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RESEARCH ARTICLE

Prediction of Movie Quality via Adaptive Voting Classifier

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ABSTRACT Information retrieval from huge social web data is a challenging task for conventional search engines. Recently, information filtering recommender systems may help to find movies, however, their services are limited because of not considering movie quality aspects in detail. Prediction of movies can be improved by using the characteristics of social web content about a movie such as social-quality, tag quality, and a temporal aspect. In this paper, we have proposed to utilize several features of social quality, user reputation and temporal features to predict popular or highly rated movies. Moreover, enhanced optimization-based voting classifier is proposed to improve the performance on proposed features. Voting classifier uses the knowledge of all the candidate classifiers but ignores the performance of the model on different classes. In the proposed model, weight is assigned to each model based on its performance for each class. For the optimal selection of weights for the candidate classifiers, Genetic Algorithm is used and the proposed model is called Genetic Algorithm Voting (GA-V) classifier. After labeling the suggested features by using a fixed threshold, several classifiers like Bayesian logistic regression, Naïve Bayes, BayesNet, Random Forest, SVM, Decision Tree, LSTM and AdaboostM1 are trained on MovieLens dataset to find high-quality/popular movies in different categories. All the traditional ML models are compared with GA-V in terms of precision, recall and F1 score. The results show the significance of the proposed features and proposed GA-V classifier.

INDEX TERMS Weighted voting classifier, movie recommendation, classification, feature engineering.

I. INTRODUCTION

The rapid growth of social web has changed the behavior of internet surfers. Users may contribute to social web applications such as recommender systems, wikis and online discussion forums in the form of comments, reviews, tags, keywords and ratings. Online recommendation systems assist users in finding the desired information. For this purpose, movie recommender websites encourage its users to provide feedback in the form of ratings to improve the recommendation process. Online movie recommender systems (MRS) such as IMDB1 and MovieLens2 suggests favorite movie(s) to users based on their watch list and movie rating preferences as presented in Figure 1.

MovieLens and Internet Movie Database (IMDB) datasets are widely used to find interesting or popular movies by recommender systems [2].The IMDB dataset reflects the information about the movie's title (TV shows, short films, and so forth), cast (information about actors, actresses, crew, and directors), and trailers. Data mining techniques have been successfully applied in social web domain to address several problems such as movie classification, video quality prediction, document clustering and information retrieval [3]. Classification techniques such as decision tree and support vector machines have been used to predict movie popularity in the content distribution networks [4], actor, director and

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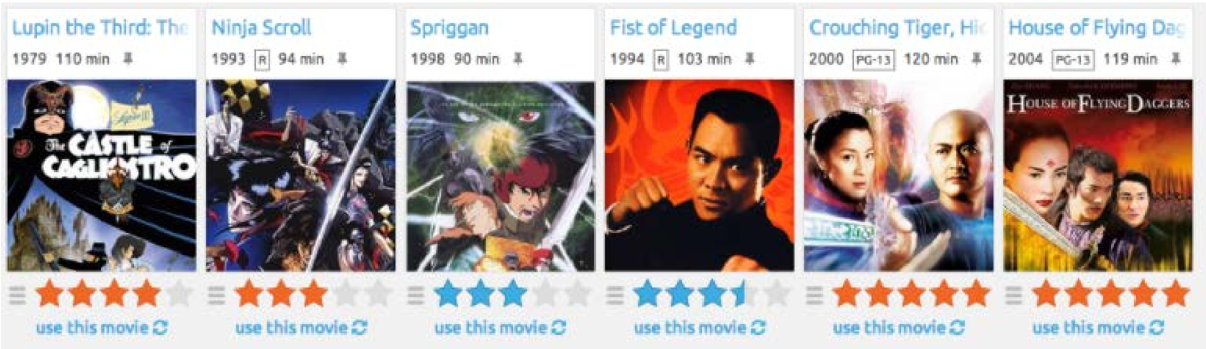


FIGURE 1. **MovieLens recommended movies [1].**

show-time features have been used to predict movie popularity. Bayesian networks model performed better than decision tree for movie popularity prediction [4], [5].

In an IMDB dataset study [6], [7] several relationships have been illustrated for successful movies prediction as below.

- Discovering films popularity based on their budget
- A famous actor
- Movie ratings, genre and title

Machine learning (ML) and semantic orientation techniques are used for movie reviews mining [8]. Movie ratings are predicted through opinion and semantic orientation features [9]. Movies are classified through features like writers, producers, words, actors and genres [4], [10], [11]. However, genres and words are found effective in movie classification [12]. Classifier's comparison is performed on MovieLens dataset to identify the best classifier for analyzing movie data based on users' ratings [13]. Movie forums are platforms for users to share their experiences and opinions about movies. Text mining techniques have been used to assess the impact of movie discussion forums on box office using features such as rating and sentiments [6]. Social network analysis and sentiment features like positivity, time and discussion intensity have been used to predict academy awards nominations and box office success [7]. It is of worth to measure user reputation who rate movies because ratings may be low and biased. Therefore, ratings without measuring user reputation cannot reflect the movie quality in the true sense. User reputation is computed based on ratings provided for movies or products by the users. Other features include rating frequency and degree of consistency [14]. Features such as category, Maltin, academy award, length, MPAA rating are used to develop a feature based movie rating system [15].

Research efforts have been made for movies quality prediction and movies recommendation. However, the problem of Movie quality prediction has been partially tackled with limited features [10], [13], [16]–[20]. This triggers the need for exploring new techniques to improve the prediction performance of the movie recommender. Current online movie recommendation sites consider general features indicating movie quality [7], [10], [12], [21]. For example, IMDB considers ratings, Meta score, reviews, critics and popularity, and MovieLens considers ratings, average stars and tags features to represent movie quality. In the last decade, social web applications (SWA) like YouTube, Amazon, IMDB, MovieLens, Reddit, last.fm and Myspace have gained tremendous popularity in public due to their services and rich features such as ratings, reviews, sentiments, up-votes and down-votes etc. The aforementioned features of SWA have been applied in information retrieval [9], [16], [17], [22]–[24], online reviews recommendations [8], [25], news article recommendations [3], [26], [27], friends recommendation [7], [10], [28], [29] etc. However, features such as user authority, social quality and temporal aspects have not been used to assess movies.

Multiple ML techniques have been used to predict the quality of the movies. From the traditional ML techniques Bayesian Logistic Regression (BLR), BayesNet (BN), Naïve Bayes (NB),Random Forest (RF), AdaBoostM1 (AB), Decision Tree (DT), Support Vectors Machine (SVM) and Long Short Term Memory (LSTM) are used to classifiy the movies and results are compared with the proposed GA based ensemble technique. The voting classifier is one of the common techniques used to make ensemble classification models. In the voting classifier, each candidate is trained on the dataset, and the training performance of each model is observed. Next, The test data is given to each model, and the label is decided by majority voting. Finally, the final label to the test sample is assigned if the label has more votes than the others. The problem with the voting classifier is that, it ignores the confidence of the candidate classifier. The confidence of the model represents its performance on training data. For example, if model A has higher accuracy than model B, then model A is more confident in predicting the accurate label for test data. The value of the vote from the confident classifier should be more than a less confident classifier. The proposed study use the weighted voting classifier to assign the weight to each classifier based on their performance on test data. The Genetic Algorithm (GA) is used to find the best combination of weights for each classifier and the target variable. Each classifier has different weight based on the number of classes in the dataset. Some algorithms are biased towards one class and not for other classes. So, the weight for each class should be different. To compute the weight of each classifier, the performance measure F1 score is considered. F1 score is used to compute the fitness of the chromosomes when the Genetic Algorithm selects the best classifiers.

In response to the aforementioned problems, in this study, movie domain related quality prediction features are proposed. The contribution of this study can be summarized as follows:

- The high-quality movies are predicted in different categories like comedy, adventure, action, animation and drama.
- Leveraging to SWA features, novel features such as social-quality, user reputation and tag quality are proposed to mine movie quality in an improved way.
- The combination of aforementioned features, as well as independent features, are used to analyze the impact on predicting a quality movie to viewers
- Proposed a weighted voting classifier based on evolutionary algorithm (GA)
- Assigned weights to each candidate classifier based on the fitness value (F1 score as a performance metric)
- The proposed model improves the ability of movie quality prediction by applying the potential aspects.
- The proposed features significantly outperform ratings-based quality prediction approaches.

We have selected movie rating as a baseline feature which has been used as a key feature in several movie recommendation works [12]–[14], [21], [30]. In order to assess movie quality, several state-of-the-art classifiers such as Bayesian logistic regression, Naïve Bayes, BayesNet, Random Forest and AdaboostM1 are trained based on the labeled features using a fixed rating threshold (i.e. 3.3). A reputed user is the one who provide rating frequently for movies. A threshold value after experimentation is set to 3.3 for reputed user who rated movies. Thus, the average rating, greater than or equal to 3.3, received by a movie is considered as popular. MovieLens dataset is used to evaluate the performance of the proposed features. The results are shown in term of classification accuracy, error and performance that shows significant improvement on social, temporal and all (combined) features for Random Forest and AdaboostM1 classifiers. However, Bayesian logistic regression classification accuracy is less than the other classifiers on all features as compared by [31], [32].

The rest of the paper is structured as follows: section II discusses the existing techniques and models for the movies recommendation; Section III explain the proposed features and their importance using different metrics. Section IV describes the proposed weighted voting classifier for movie recommendation. Section V presents the results of proposed models and compares them with the existing state of the are ML techniques to show the effectiveness of the proposed model. Finally section VI conclude the contributions with some possible future directions.

II. RELATED WORK

Movie quality prediction is widely studied problem [3], [33], [34]. This section represents the current research work in the field of making movie quality predictions by applying various techniques. Broadly, these techniques can be divided into two types: features based movie quality prediction (MQP) and collaborative & content-based MQP techniques. MovieLens3 and Internet Movie Database (IMDb4) are benchmark data sources for the analysis and evaluation [2], [35], [36].

A. FEATURES BASED MOVIE QUALITY PREDICTION TECHNIQUES

Several features have been presented for predicting movie quality/movie recommendation. Features are based on the movie's context, ratings, opinions and user reputation. Contextual information such as time, location and social context is used for movie recommendation [37] using IMDB dataset. Features such as category, Maltin, academy award, length, and MPAA rating are used to develop a feature-based movie rating system [15], where two approaches clique based and feature-based, are compared in terms of correlation coefficient between actual rating and by targetted user and movies. Various techniques [4], [12], [21] consider movie cast, genre and temporal features for finding quality movies. However, these techniques did not pay attention to user reputation and rating quality features that can impart effective knowledge in predicting quality movies [14], [38]. Limited use of movie ratings has been used as a primary measure in predicting movie quality, for example, only rating-frequency is used in many techniques [6], [9], [21]. Rating diversity and rater reputation truly reflects rating quality.

Moreover, spam rating and sparse ratings can decrease movie recommendation quality [38].Other features include rating frequency and degree of consistency [14], [39]. User reputation, rating accuracy, and influence are considered as effective measures in recommendation systems [38], [40]. Cast popularity is considered as base criteria for predicting the popularity of a movie [15]. Movie selection criteria such as clique and feature based techniques are compared. Users with similar movie ratings form a clique and in the feature-based approach, movie features are extracted which a user has rated [41]. In feature based approach, movie length, genre, Maltin and MPAA rating are used. In most cases, features outperformed a human critic. Reviews are used in predicting movie performance [42], whereas regression or stochastic models are used to predict movie quality on IMDb dataset [43], [44]. In [7], social network and sentiment features are combined to predict movie success. IMDb forum posts are weighed to predict the trends and events in the movie business. A movie rating approach based on data mining of 240 movies from IMDb is presented by [6]. Multiple features (titles, companies, actors and genre) are used to predict the movie popularity for Content Distribution/ Delivery Network (CDD) [4]. In CDD case, features such as directors, budgets and cast give good results. The warm start and cold start recommendation systems are also proposed by the researchers.

The link prediction for the cold start recommendation system is proposed to boost the performance of existing recommendation systems [45]. Social trust is an essential factor to be considered in the recommendation systems [46]. The pairwise trust prediction via matrix factorization is proposed by [47], to the intensity of the trust level in social networks. The proposed work used the user reputation features along with social and temporal features. The more detailed use of user reputation features improves the performance of the recommendations system [48].

Movie box-office success is examined through several approaches [44], [49], [50] using various text mining [6] and clustering techniques [10]. It is observed that opinions or critics are significant in predicting a film's success or failure [50]. Tag content shows the user interest about a movie and tag based feedback can improve recommendation and quality tags make a movie more favorite [51]. Tagommender recommends movies based on their associated tags [52]. Sentiment classification (SC) is helpful to identifying user opinions about movies [8]. Sentiment analysis of movie reviews is conducted using Senti WordNet based on the linguistic features (verb, adverb and adjectives) [53]. Predictor and influencer are two possible perspectives on the role of critics [54]. Winners at academy awards are predicted by [9].

The correlation between the quality of the movie and its budget is measured through data mining techniques to find the important factors in movie success [21]. Movie rating analysis is carried out through data mining techniques [21]. Firefly, a well-known social filtering system [55], presents albums and artists for rating in which "likes" and "dislikes" of the users are maintained. Users' similarity is measured through common interests. The IMDb dataset is used to predict movie success [54], [56], [57], however, aspects such as communication behavior and social network structure as a determinant of movie success are not addressed.

B. COLLABORATIVE AND CONTENT-BASED MOVIE QUALITY PREDICTION TECHNIQUES

There are a number of existing recommenders [8], [25], [58] for social web applications such as, news article recommendations [3], [26], [27], friends recommendation [7], [16], [29] for different applications such as news, products, music, movies and online reviews etc. Features such as, ratings, reviews, likes, dislikes are used in recommender systems. Some examples of popular recommender systems include books [59], movies [4], [44], [60], reviews [4] and restaurant ratings [61]. Aforementioned features are further used by classifiers such as K-Nearest Neighbor for generating recommendations [62]. Content-based filtering techniques use item features for recommendations [33], [63], [64]. The items with similar properties become the candidates for recommendation results [65]. Collaborative techniques [30], [33], [66] recommend items to users based on their neighbors' interests. Sentiments and rating features are used for recommendation by [63]. Hybrid recommender systems give recommendations by combining the features of collaborative and filtering techniques [67]–[69]. Association rule mining and classification techniques like Bayesian, decision tree [4], [60] have been used for the recommender systems [4], [60], [62]. Social network services like Digg5, Reddit6, Flickr7, Delicious8, Twitter9, Myspace10, LastFM11, Amazon12can recommend movies based on the user behaviors such as comment, visit, trust information, etc, to the user more accurately.

Multiple classification based ensemble techniques have been proposed to improve the performance of the state of the art ML algorithms and the variants of ML algorithms are also proposed [70]. Majority voting is commonly used technique because of its straightforwardness. The label is assigned based on the majority votes [71], [72]. But in reality, these assumptions are not more accurate because of different behaviour of models on real data. Another technique which is based on probability of the selection of class variable is support functions [73].The study [74] proposed multiple rules by which class posteriori probability is combined [74]. Other, weighted classifiers are also proposed based on particle swarm optimization [75], Differential Evaluation based [72] and fuzzy sets [76]. The proposed weighted voting classifier presents another look in which the string representation (chromosome representation), selection, crossover and mutation of the chromosome for GA is presented.

III. PROPOSED FEATURES FOR MOVIE QUALITY PREDICTION

To address the problem of movie quality prediction, three types of features include Social-quality features (Soc), User reputation features (Urep) and Temporal features (Temp) are proposed. We propose that the quality of a movie can be best described by its qualitative as well as quantitative characteristics. For example, high number of positive movie ratings show that it attracts huge audience attention. Secondly, having relevant tags show that movie title is comprehensive (highly relevant to the movie theme) and users can easily express their sentiments and thoughts through tags. Thirdly, temporal features capture the growth of audience in short span of time. For example, a movie is said to be popular if it receives high rating by a popular user within a short time after its release. Movie quality prediction process is shown in Figure 2. The collected ratings along with three proposed features sets are organized in a matrix form and their combination with the MovieLens dataset are loaded into the classification model to classify movies as high-quality or low-quality movies. Movie instances consist of features derived from different movie aspects. Each movie instance, Mk, can be expressed as: $M_k = Soc_k$, $Temp_k$, $Urep_k$, Cnt_k, $class_k$, where $class_k =$ high quality or low-quality

Following terms are used for proposed features.

Reputed user: users who frequently rate movies and their rated movies should have an average rating greater than or equal to 3.3. Furthermore, they apply popular tags to movies. We proposed a reputed user, with the following characteristics:

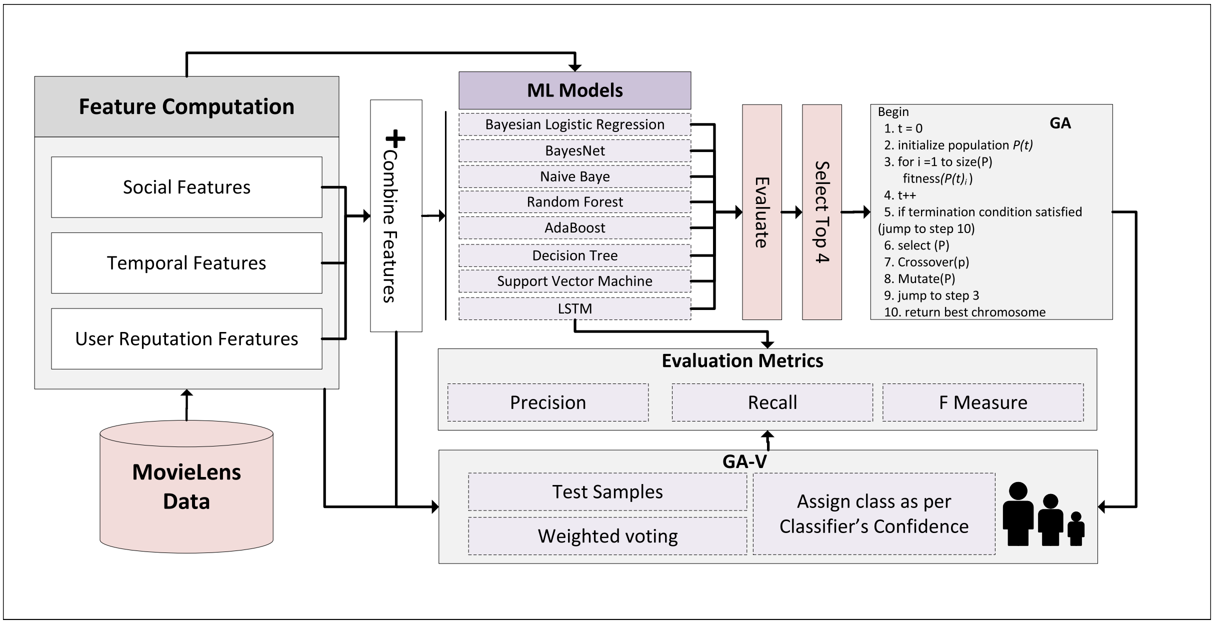


FIGURE 2. **Proposed model for movie quality prediction.**

1) A user who frequently watch popular movies (movies with an overall high rating average)
2) A user who almost gives ratings for every movie he watches. In addition, for most of the rated movies, many other reputed users also rate those movies.
3) A user who applies popular tags (a tag which is highly similar to the movie title) to the movies.

Popular movie: a movie having popular tags received from reputed users. Movie should have an average rating greater than or equal to 3.3.

Popular tag: a tag applied to a popular movie by a reputed user.

A. SOCIAL-QUALITY FEATURES

Social-quality features characterize movie quality in multiple dimensions like movie rating frequency, rating diversity and tag quality. These features are related to degree distribution in the tripartite movie-user-tag graph [38]. The following features are proposed and extracted from MovieLens dataset;

Soc-1: Total ratings received by a movie.

Soc-2: The mean of total ratings for the movie.

Soc-3: Mean of best ratings for the movie, the best rating is assumed an average score of 3 or more.

Soc-4: The standard deviation of a movie's overall ratings.

Soc-5: Mean of movie ratings by reputed users

Soc-6: Number of tags applied to a movie

Soc-7: Semantic similarity score between movie tags and movie category title

Soc-8: Number of sentimental tags of a movie

Soc-9: Total ratings by popular users

Social features (Soc-1 to 3) are based on rating quality of a movie. It is expected that if a movie has high rating frequency and has an overall high average rating, then it is a popular movie and can be classified as a high-quality. The soc-4 feature is based on a movie rating diversity, a movie with overall low rating diversity is a good one. Standard deviation has been computed to check the diversity in movie ratings. Soc-5 expresses about how much a movie receives ratings from reputed users. Soc-6 relates to tag frequency of a movie. A movie tag is taken as having high quality if its text is highly similar to movie's category name as the movie subject can be understood from its tags. Computation of semantic similarity of tags to movie category title is based on pairs of words. The maximum depth of taxonomy [77], [78] is taken into account for computing semantic similarity between movie tag (t) and movie category title (mct). For Soc-7, Similarity between movie tag and movie category title has been computed by equation 2.

$$Sim_{sem}(t, mct) = -\log \frac{length(t, mct)}{2 \times deep\_max} \tag{1}$$

Here, length (t, mct) is the shortest path between t and mct and $deep\_max$ is the maximum depth of the taxonomy. Sim_{sem} (t, mct) is the semantic similarity between a tag t and a movie category title mct that lies between 0 and $\log(2deep\_max+1)$. The similarity is computed based on the shortest path between the synonym set (synsets) associated with tag t and movie category title mct [77], [78]. We computed the similarity of a tag and a movie category title by taking the average shortest synset distance between all the terms in the tag and the movie category title. If terms of t and mct have the same sense, then length $(t, mct) = 0$. In practice, we add 1 to both length (t, mct) and 2 $deep\_max$ to avoid log(0).

In Soc-8, relates movie-tag sentiment score is computed using Senti WordNet [42]. Senti WordNet is a

WordNet extension. It adds three measures for each synonym set (synset) which are PosScore, NegScore and ObjScore which show positive sentiment, negative sentiment and Objective score respectively for each synset.

B. USER REPUTATION FEATURES

These features are concerned to capture user reputation with respect to the set of movie ratings (the user has provided in the past) [38]. If a user rates popular movies and apply popular tags to movies then he is reputed user.

Following features have been extracted from MovieLens dataset;

Urep-1: The number of movies rated by the user.

Urep-2: The number of popular movies rated by the user.

Urep-3: Total popular tags applied by the user.

Urep-4: Number of other popular raters of the movie which is rated by this user.

According to Urep-4, neighbors of reputed users are considered. It is expected that a movie is of high-quality if it is viewed or received feedback by reputed neighbors.

C. TEMPORAL FEATURES

A movie is said to be popular if it receives high rating by a popular user within a short time after its release. A movie is popular if popular users rate the movie within a short period after its release. Duration of one week from the time of movie release time has been considered as a short period,

Temp-1: Number of ratings in a week.

Temp-2: Number of high ratings in a week.

Temp-3: Number of ratings from popular users in a week.

The above-mentioned features indicate the effect of time aspect (longevity) in assessing movie quality. Longevity of a movie can be defined as the amount of time between its release-time and the time of the earliest ratings received.

The five quartile summary of the features are shown in Figure 3. Five Numbers, Minimum, first quartile, average, third quartile and maximum number from each feature is shown in each boxplot.

IV. CLASSIFICATION AND MOVIES QUALITY PREDICTION

The experiments are conducted on Windows 11 operating system with 32GB of RAM. Python is used as a core programming language. Libraries of python including pandas (for data science) NumPy (for numerical calculations) SkLearn (for data reprocessing and ML techniques) and Keras (for Deep learning techniques) are used. Anaconda and Jupyter notebook are used to conduct the experiments.

A supervised learning approach is adopted to predict high-quality movies. A concept of the high-quality movie is introduced in which a movie with high scores of ratings, movie rater reputation, tag quality, positive sentiments, and good ratings in the initial period of launching is considered as high-quality. Movie instances are labeled as high-quality or low-quality.

Traditional voting classifiers use the knowledge of all the candidate classifiers but ignore the performance of each classifier on training data. Therefore, the trust level of each classifier should be different based on their performance on training data. The weighting strategy is used to assign the weight to each classifier based on the performance of each class. The selection of the candidate classifier is based on their performance on the proposed feature. On average, LSTM, SVM, NB, and AdaBoost perform well from traditional ML techniques on training data. Therefore, all these four classifiers are used as candidate classifiers.

Voting is a technique to merge the knowledge of candidates for classification problems. The model of the voting classifier is based on the trained ensemble, ML, or deep learning models. All the candidates are trained on one parameter set like 10 fold or hold out. Same data samples are passed to each classifier to predict the class for each sample. Finally, the voting classifier assigns the final label to the sample based on the number of votes. However, the problem is that all the candidates have different performances. The performance is also different for each class. If a model performs well for one class, it can make many mistakes for other classes. The F1 score considers the positive rate from all the positives, so the F1 score is the best measure to select the classifier with the best performance for each class. A Genetic Algorithm (GA) is used to assign the weights to each classifier.

Suppose we have N number of candidate classifiers ($CF + 1, CF_2, \ldots CF_3$) and M number of target variables. The weighted voting classifier can be expressed as follows:

First of all, find the weights of the votes for each classifier, which optimize the function like $F_i(V)$; $i \leq 1$. V represents the array of size $N \times M$. The combination of i and j from V shows the weight of the vote $V(i, j)$ (Weight of ith classifier for jth class). The class for which the classifier is more confident, more weight is assigned, and less weight is assigned for other cases. The array $V(i, j)$ is used when the final class to the particular sample will be assigned. Here the function F_i is a performance measure of the classification problem. For a classification problem, specifically, precision, recall, and F1 score are used. To assign the weight to each class, we have selected the F1 score.

A. POPULATION INITIALIZATION AND STRING REPRESENTATION FOR GA

If we have N number of classifiers and M number of classes (M = 2), the length of the chromosomes will be $N \times M$. Each chromosome represents the performance score of the classifiers along with their class.

B. FITNESS FUNCTION

For the fitness of the performance of the classifier, we have selected the F1 score. For N number of classifiers we have fitness for each classifier $F_i i = 1, 2 \ldots N$. the predicted variable's weight provided by the ith classifier is $I(n, i)$ (n is classifier and i is the class). The overall score of a class for a particular sample is:

$$f(c_i) = \sum I(n, i) \times F_n, \quad \forall n = 1 \ldots N \;\; and \;\; c_i = op(s, n) \tag{2}$$

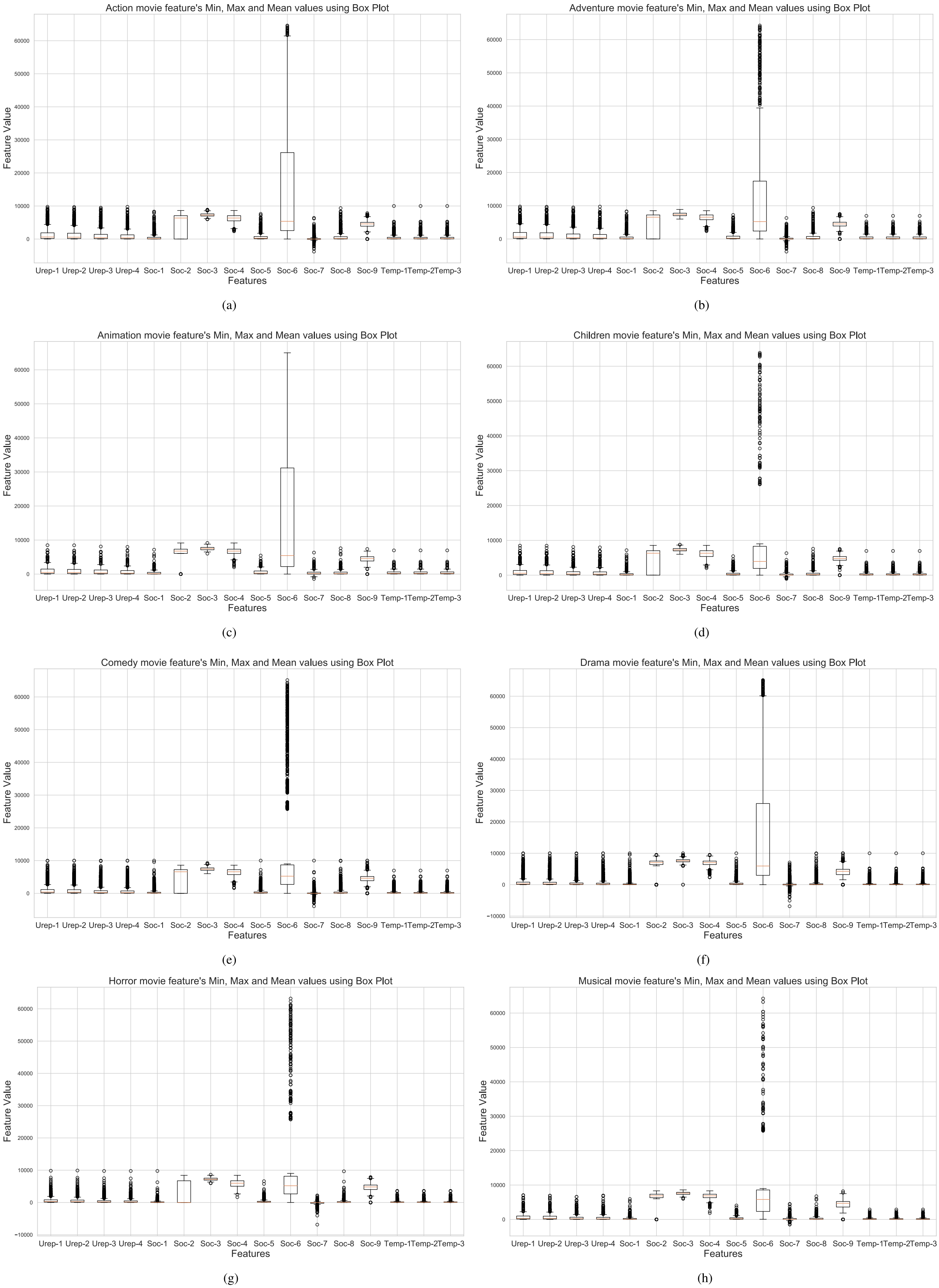
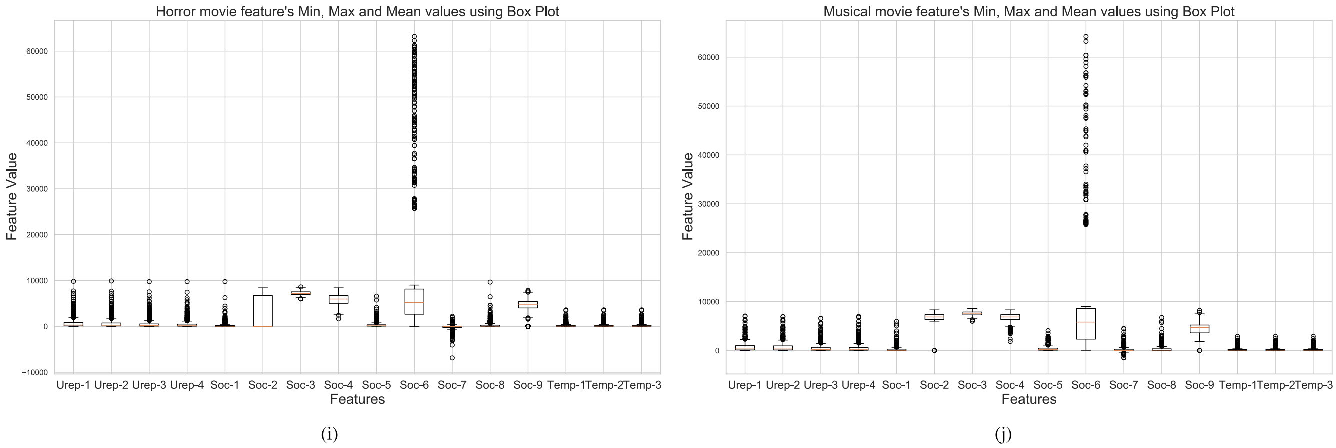


FIGURE 3. **(a)–(j) Minimum, maximum and average value representation using boxplot for all combined features of all the movie category.**



(i) (j)

FIGURE 3. ***(Continued.)*** **(a)–(j) Minimum, maximum and average value representation using boxplot for all combined features of all the movie category.**

where, $op(s, n)$ is the output label provided by the n classifier. The average F1 score value is used as the fitness of the chromosome.

C. SELECTION

In our proposed weighted voting classifier, we have used the roulette wheel selection technique. During the search, multiple solutions are generated, and the best solutions are selected using fitness values. Here, the selection of the chromosome is based on probability. If f_i is the value of fitness for ith chromosome, its selection probability will be:

$$p_i = \frac{f_i}{\sum j = 1Nf_j} \tag{3}$$

D. CROSSOVER

The adaptive technique [79] is used for crossover probability. If we assume f_{max} is the maximum, $\bar{f}$ is average fitness value of the population and f' is the large fitness value of crossed solutions.

$$\mu_c = k_1 \times \frac{(f_{max} - f')}{(f_{max} - \bar{f})}, if\ f' > \bar{f}$$
$$\mu_c = k_3, if\ f' \leq \bar{f} \tag{4}$$

where, the value of k_1 and k_3 are kept as 1.0. When the offspring of two poor chromosomes is good, the value of μ_c will be increased, and if the solutions themselves are good, the value will be decreased to reduce the likelihood of distorting the solution by crossover.

E. MUTATION

Same as crossover, mutation is performed with some probability μ_m for each chromosome. Again, mutation probability is selected adaptively [79].

$$\mu_c = k_2 \times \frac{(f_{max} - f')}{(f_{max} - \bar{f})}, if\ f' > \bar{f}$$
$$\mu_c = k_4, if\ f' \leq \bar{f} \tag{5}$$

TABLE 1. **Confusion matrix.**

	Non-Relevant	Relevant
Not Retrieved	*TN(True Negatives)*	*FN (False Negatives)*
Retrieved	*FP (False Positives)*	*TP (True Positives)*

For mutation the value of k_2 and k_4 are set on 0.5. The adaptive technique will help GA to come to the light from the darkness of the local optimum.

Classification of movie quality prediction is essential in differentiating between popular and unpopular movies. The popularity of a movie can be distinguished by the classifiers using a set of features. Therefore, UserReputation, Social and Temporal features (described in section 3) are input to classifiers. In this perspective, well-known classifiers are chosen, such as Bayesian logistic regression (BLR), adaboostM1 (AB), Naïve Bayes (NB), BayesNet (BN), Random Forest (RF), Support Vector Machine, and LSTM. These classifiers are trained over MovieLens dataset [26] for movie quality prediction, and the results are compared with the proposed weighted voting classifier.

Bayesian Logistic Regression can be used to predict best-rated movies by avoiding over-fitting [31], [32]. BLR classifier can be trained and used to predict popular movies using UserReputation features, Social Features, Temporal features, and their combination (all) features of each categorized movie. The predictive statistical analysis can be carried out using the Bayes rule for binary, or multiple classes [80].

The error of any "weak" learning algorithm can be reduced by improving performance with the help of "boosting". The well-known boosting algorithm is Adaboost [80], [81]. AB is one of the well-known versions of the AdaBoost algorithm for predicting a popular movie. This algorithm takes an input of the labeled proposed features of movies of each category to classify a popular movie using a simple rule.

Naive Bayes classifier can be used to minimize the intractable feature's complexity by considering the

TABLE 2. Comparison of performance of traditional ML algorithms and proposed GA-V classifier in terms of average, minimum and maximum precision recall and F1 score using user-reputation features.

Movie Category	Classifier	Precision	Recall	F1 Score	Movie Category	Classifier	Precision	Recall	F1 Score
	BLR	60.14±0.27	1.00±0.00	75.55±0.19		BLR	42.57±0.17	1.00±0.00	59.66±1.42
	BN	86.96±0.56	62.61±0.85	72.86±1.41		BN	73.31±1.21	70.22±0.96	71.77±0.87
	NB	93.77±0.37	55.73±1.38	69.94±2.01		NB	86.51±1.20	48.53±0.32	62.1±1.36
	RF	84.31±0.96	82.64±0.63	83.58±1.87		RF	78.15±0.74	73.83±0.22	75.94±1.03
Action	AB	77.78±0.41	80.82±1.55	78.94±0.85	Horror	AB	72.91±0.25	69.8±1.64	71.45±0.95
	D-Tree	78.37±0.96	77.99±0.44	78.13±1.08		D-Tree	73.59±0.87	73.95±0.57	73.67±0.22
	SVM	72.38±1.02	72.42±1.33	72.40±0.57		SVM	78.66±0.2	78.60±0.77	77.87±0.28
	LSTM	75.80±0.71	73.82±0.51	74.22±0.23		LSTM	79.68±0.14	79.53±0.74	78.83±0.61
	GA-V	94.79±0.85	91.19±0.32	92.14±0.14		**GA-V**	79.90±0.74	85.50±	83.03±0.53
	BLR	61.56±0.54	1.00±0.00	76.26±0.48		BLR	43.83±0.96	1.00±0.00	60.97±1.05
	BN	82.45±0.37	78.54±0.95	80.45±0.41		BN	54.72±0.41	71.22±0.85	61.26±0.74
	NB	93.44±1.65	54.94±2.85	69.28±1.05		NB	80.25±0.41	57.19±1.34	66.76± 1.43
	RF	83.81±0.95	83.86±0.63	83.84±0.24		RF	50.27±4.04	42.97±2.08	46.26±0.96
Adventure	AB	84.42±0.85	0.767±0.75	80.23±0.91	Drama	AB	33.31±0.57	42.98±0.45	37.59±1.05
	D-Tree	70.57±0.85	69.84±1.75	70.05±1.01		D-Tree	25.07±5.85	50.27±2.17	33.32±5.21
	SVM	75.22±2.01	70.63±0.85	70.72±1.34		SVM	83.33±0.84	75.08±1.07	73.34±0.76
	LSTM	73.42±0.85	71.03±0.75	71.28±0.86		LSTM	83.38±1.85	75.34±1.28	73.34±0.95
	GA-V	84.13±0.87	91.70±0.76	88.01± 0.91		**GA-V**	82.06±0.86	90.36±0.76	77.39±0.72
	BLR	71.84±0.45	1.00±0.00	83.65±0.37		BLR	47.36±4.12	1.00±0.00	64.34±2.01
	BN	94.96±0.75	59.64±1.24	73.82±0.99		BN	83.12±1.08	70.76±1.13	76.24± 1.36
	NB	96.41±0.23	57.46±2.22	72.56±1.45		NB	91.30±0.79	52.52±2.09	66.74±1.24
	RF	83.25±0.28	84.66±0.75	83.97±1.22		RF	77.51±0.92	73.15±3.06	75.27±1.07
Animation	AB	86.33±0.46	73.93±1.75	79.74±1.63	Musical	AB	81.67±0.73	69.47±1.17	75.54±0.17
	D-Tree	81.19±0.75	80.77±0.73	80.96±0.89		D-Tree	73.43±0.74	73.27±0.96	73.28±1.38
	SVM	61.16±0.35	78.21±0.86	68.64±0.37		SVM	78.82±0.83	75.25±1.24	74.75±1.37
	LSTM	61.16±2.08	78.21±2.36	68.64±1.88		LSTM	78.82±0.83	75.25±1.38	74.75±1.48
	GA-V	89.26±0.37	79.25±1.09	84.24±0.38		**GA-V**	88.24±0.94	86.32±0.37	83.99±0.96
	BLR	58.75±1.85	1.00±0.00	74.78±1.05		BLR	59.57±1.46	1.00±0.00	74.61±0.72
	BN	80.63± 0.75	61.87±1.74	69.72±2.65		BN	85.40±0.96	56.61±1.47	67.71±0.81
	NB	89.71±0.41	45.90±2.75	60.63±4.27		NB	89.44±1.36	49.97±5.17	63.31±3.14
	RF	68.52±0.74	71.57±1.30	70.21±0.36		RF	80.79±1.37	79.73±0.85	80.21±0.78
Children	AB	77.11±1.35	72.49±0.91	74.61±0.52	Mystery	AB	82.30±0.94	61.87±1.37	70.69±2.03
	D-Tree	69.40±0.14	68.80±0.37	68.88±0.11		Tree	57.02±0.00	57.02±0.00	57.02±0.00
	SVM	76.73±0.25	74.40±0.71	74.32±0.37		SVM	72.52±0.78	66.94±1.07	67.00±0.61
	LSTM	75.66±0.05	73.60±0.71	73.55±0.37		LSTM	70.18±0.64	68.60±0.37	68.92±0.84
	GA-V	79.26±0.31	82.48±0.74	80.33±0.11		**GA-V**	72.45±0.77	86.96±0.14	83.45± 0.37
	BLR	50.63±3.25	1.00±0.00	67.27±2.09		BLR	50.50±3.45	1.00±0.00	67.10±2.66
	BN	76.27±1.35	66.83±0.86	71.21±0.73		BN	78.50±1.38	64.51±2.06	70.82±1.55
	NB	87.77±0.57	49.12±2.78	63.07±1.11		NB	88.50±0.92	50.51±1.89	64.33±1.43
	RF	78.96±0.63	76.21±1.41	77.51±1.03		RF	77.50±0.37	75.54±0.77	76.56±0.39
Comedy	AB	76.96±1.38	67.14±1.33	71.48± 1.19	Romance	AB	79.46±0.21	64.51±0.39	71.12±1.02
	D-Tree	69.40±0.03	68.80±1.08	68.88±1.68		Tree	75.69±0.85	75.45±1.03	75.46±0.92
	SVM	76.73±1.06	74.40±0.43	74.32±0.28		SVM	73.19±1.09	73.13±0.95	73.14±1.08
	LSTM	75.66±0.88	73.60±0.71	73.55± 0.76		LSTM	74.41±0.73	71.58±0.19	71.04±0.41
	GA-V	81.64±0.11	71.22±0.76	76.74±0.19		**GA-V**	85.63±0.18	73.22±0.46	80.02±0.72

conditional independence assumption. Thus, the number of estimated parameters dramatically reduces from $2(2^n - 1)$ to 2^n. NB classifier assigns a probability to each category of movie features according to their target classes. The output is minimized to a single probability-based predicted value for each movie category's entire set of features. However, NB is highly sensitive to classifying erroneous probability estimates for the features of movie categories due to its numeric predictions [82].

BayesNet encodes probabilistic relationships among the labeled features of each movie category [52]. Based on the following advantages of the BN classifier, it's commonly used to analyze data in close connection with the statistical methods. 1. BN handles missing data and encodes dependencies of features set and target class. 2. BN learns a connecting relationship in order to obtain knowledge by predicting the consequences of intervention. 3. BN combines the prior knowledge and features set. 4. BN avoids overfitting of data.

A random forest classifier is the mixture of tree predictors [83]. Each feature depends on the movie features independently with similar distribution for all features of the movie in a movie-quality prediction system. The general error of a movie to its forest classifier depends upon the advantage of the individual features of a movie and the correlation between them. RF classifier can be defined in the context of movie features for a user to predict a high-quality/popular movie as follows.

Definition: A random forest classifier consists of a collection of features structured classifiers with random labeled feature vectors of a movie by casting a vote for the most popular movie class according to the features input.

A support vector machine is a robust classifier and regressor because of its vital kernel tricks. The kernel tricks of SVM transform the feature space into kernelized feature space. SVM is selected as a candidate of GA-V to make the classifier strong with the RBF kernel of SVM. The proposed feature

TABLE 3. Comparison of performance of traditional ML algorithms and proposed GA-V classifier in terms of average, minimum and maximum precision recall and F1 score using social features.

Movie Category	Classifier	Precision	Recall	F1 Score	Movie Category	Classifier	Precision	Recall	F1 Score
Action	BLR	72.76±0.65	87.47±0.85	79.45±0.18	Horror	BLR	77.74±1.56	61.60±0.25	68.45±1.96
	BN	88.57±0.18	77.24±1.28	82.65±0.76		BN	79.63±0.78	72.84±0.18	77.56±1.81
	NB	93.94±0.58	61.11±0.28	73.94±1.02		NB	84.35±1.00	53.28±1.85	65.76±2.18
	RF	89.43±0.45	89.21±0.22	89.24±0.87		RF	86.22±0.75	79.71±0.87	82.89±0.67
	AB	85.30±1.06	84.66±0.78	84.91±0.17		AB	81.92±0.53	77.21±1.28	79.40±1.20
	Tree	83.34±1.89	83.29±0.19	83.31±1.07		Tree	84.69±0.27	84.65±0.94	84.67±0.91
	SVM	81.44±0.87	81.06±0.29	81.19±0.74		SVM	80.90±1.23	80.93±0.84	80.48±1.24
	LSTM	82.73±0.02	82.73±0.00	82.73±0.01		LSTM	83.13±0.05	83.26±0.10	83.12±0.21
	GA-V	94.31±0.81	90.02±0.18	91.36±0.39		**GA-V**	85.22±0.86	79.21±1.08	88.28±0.67
Adventure	BLR	70.66±0.85	91.65±0.12	79.72±0.85	Drama	BLR	71.43±0.74	71.64±0.65	71.44±0.18
	BN	89.47±0.05	78.30±0.81	83.25±0.72		BN	83.33±0.37	71.24±0.97	76.39±0.25
	NB	95.63±0.73	61.22±1.28	79.53±1.85		NB	85.27±0.28	85.73±0.75	85.70±0.95
	RF	89.82±0.29	86.74±0.75	88.29±0.73		RF	75.61±0.81	42.92±0.76	54.53±0.83
	AB	88.48±0.76	79.40±1.09	83.72±0.46		AB	83.33±0.29	71.14±0.73	76.95±0.49
	Tree	81.10±0.28	80.95±0.94	81.01±1.51		Tree	25.24±0.28	50.85±0.91	33.33±3.09
	SVM	80.10±0.39	80.16±0.76	80.13±0.29		SVM	65.51±3.84	65.05±2.21	64.99±2.19
	LSTM	82.10±0.72	81.75±0.61	81.84±0.06		LSTM	18.51±2.72	30.40±3.30	23.93±1.39
	GA-V	94.96±0.58	82.19±0.41	86.32±0.39		**GA-V**	89.66±0.19	81.29±0.85	86.95±0.19
Animation	BLR	81.34±0.81	92.16±0.43	86.63±0.63	Musical	BLR	82.63±0.48	66.19±0.75	73.38±0.26
	BN	91.13±0.75	83.05±1.68	87.32±0.61		BN	82.63±0.38	74.84±0.82	78.53±0.19
	NB	96.22±0.39	66.53±0.85	78.60±0.28		NB	89.25±0.94	61.94±1.75	73.18±0.68
	RF	91.42±0.49	91.56±0.68	91.25±0.58		RF	83.96±0.72	81.32±0.19	82.58±0.82
	AB	91.45±0.72	91.24±0.54	91.27±0.37		AB	81.73±0.39	72.53±0.85	76.84±0.43
	Tree	85.62±0.48	85.90±0.68	85.74±0.75		Tree	81.18±0.48	81.19±0.78	81.18±0.43
	SVM	81.96±0.68	83.33±0.49	81.63±0.87		SVM	78.81±0.59	77.23±1.75	77.08±0.19
	LSTM	85.62±0.79	85.90±0.72	85.74±0.73		LSTM	86.42±0.81	86.14±0.98	86.14±0.93
	GA-V	86.95±0.73	94.12±0.59	92.01±0.87		**GA-V**	88.12±0.81	83.21±0.	87.96±0.49
Children	BLR	70.46±0.86	78.54±0.58	74.22±0.74	Mystery	BLR	64.59±1.48	91.13±0.85	75.59±0.74
	BN	86.74±0.89	69.39±1.36	72.73±1.20		BN	83.61±0.87	73.4 ±1.36	78.47±1.96
	NB	93.69±0.94	50.45±2.85	65.67±1.29		NB	91.15±0.39	58.57±1.08	71.25±0.75
	RF	83.85±0.94	84.17±0.65	84.10±0.18		RF	84.71±0.78	89.66±0.19	87.13±0.78
	AB	78.69±0.78	83.76±0.29	81.11±0.84		AB	86.24±0.19	70.12±0.94	77.31±1.28
	Tree	71.32±0.28	71.20±1.08	71.24±1.24		Tree	69.14±1.28	69.42±1.48	69.24±1.57
	SVM	78.44±1.27	78.40±1.22	78.42±1.07		SVM	80.86±0.84	80.99±0.54	80.88±0.91
	LSTM	80.04±0.75	80.00±0.19	80.02±0.25		LSTM	80.06±0.28	80.17±0.95	80.09±0.74
	GA-V	83.96±0.58	85.39±0.74	84.96±0.08		**GA-V**	89.67±1.25	87.41±0.75	88.10±0.86
Comedy	BLR	81.51±0.96	70.78±0.15	75.54±0.84	Romance	BLR	81.89±0.64	66.81±0.84	73.50±0.18
	BN	81.52±1.22	68.41±1.08	74.44±0.94		BN	81.14±0.18	67.14±1.85	73.48±1.25
	NB	90.71±0.81	52.36±1.25	66.29±0.84		NB	88.21±0.11	50.24±2.91	64.41±1.28
	RF	86.07±0.25	81.76±0.85	84.31±0.18		RF	83.56±0.96	80.97±0.10	82.27±0.74
	AB	79.70±0.19	74.32±0.72	76.94±1.25		AB	81.42±0.46	69.74±0.83	75.18± 1.20
	Tree	78.77±0.29	78.77±0.28	78.77±0.84		Tree	74.41±0.75	74.42±0.76	74.41±0.28
	SVM	58.26±0.81	57.80±0.76	56.75±0.72		SVM	77.89±0.46	77.26±0.47	77.23±0.94
	LSTM	80.97±0.76	80.69±0.78	80.67±1.40		LSTM	80.12±0.27	79.84±0.74	79.85±0.64
	GA-V	84.36±0.75	87.91±1.02	85.61±0.39		**GA-V**	81.08±0.61	84.63±0.39	82.00±0.91

space is extended to kernelized feature space and classifies the data into vast feature space. RBF kernel is used to transform the data to kernelized feature space. LSTM is selected from the deep learning family to predict the movie quality.

The proposed GA-V selects the best four classifiers (RF, ND, SVM, and LSTM) as a candidate to vote for each sample. Figure 2 shows the flow of classification and weight assignment using GA. First, n number of weights (as per target variable) are assigned to each classifier. The final label is assigned to each sample based on the voting.

V. EXPERIMENTS AND RESULTS

To validate the proposed features and proposed GA-V classifier, 10-fold cross validation technique is used. Experiments are conducted on standard benchmark MovieLens dataset. This dataset was assembled by GroupLens project [26]. MovieLens is divided into three sub-databases that are movie, user ratings and tags databases. About 955,80 tags and 10,000,054 ratings are applied to 10681 movies by 71567 users by online movie recommender service of MovieLens. The rating of the entire MovieLens dataset ranges between 1 and 5 inclusive. To fit a model, we have preprocessed and labeled the MovieLens dataset by presenting UserReputation, Social, Temporal features and also a combined set of these features named as All. After preprocessing, 10677 labeled instances were considered with the use of four UserReputation features, nine Social features, three temporal features and a combination of all these features as Total features. In this context, several classifiers including Bayesian logistic Regression classifier are used to predict the popular movie with an objective to get high accuracy as reported by [31], [32] for text classification. Several experiments were performed by utilizing the 10-fold cross validation test on MovieLens dataset to measure the effectiveness of several classifiers as discussed in section 3.1. These classifiers are trained on UserReputation, Social, Temporal and a combination of all of these features to verify their classification accuracy, error and performance. The goal is to

TABLE 4. Comparison of performance of traditional ML algorithms and proposed GA-V classifier in terms of average, minimum and maximum precision recall and F1 score using temporal features.

Movie Category	Classifier	Precision	Recall	F1 Score	Movie Category	Classifier	Precision	Recall	F1 Score
Action	BLR	60.12±1.85	100±0.00	75.78±0.75	Horror	BLR	42.55±3.48	100±0.00	59.62±1.68
	BN	92.55±0.12	93.17±0.72	92.89±0.58		BN	80.15±0.28	97.45±0.54	88.16±0.84
	NB	97.22±0.73	56.93±0.28	71.78±0.64		NB	94.84±1.67	61.29±0.16	73.65±0.68
	RF	92.65±0.56	93.14±0.96	92.82±0.58		RF	82.38±0.75	88.55±1.68	85.31±0.75
	AB	92.53±0.84	93.21±0.94	92.84±0.72		AB	80.56±0.81	96.74±0.43	88.31±0.84
	D-Tree	92.79±0.45	92.76±0.84	92.69±0.73		D-Tree	94.24±0.45	93.95±0.28	94.00±0.84
	SVM	87.69±0.74	85.79±0.94	86.02±0.71		SVM	89.90±0.41	89.77±0.87	89.62±1.19
	LSTM	88.82±0.48	87.47±0.81	87.64±1.84		LSTM	87.84±0.75	86.98±0.64	86.53±0.81
	GA-V	93.21±0.58	90.98±0.49	92.84±0.64		**GA-V**	96.32±0.71	95.87±0.84	95.98±0.61
Adventure	BLR	61.76±0.84	100±0.00	76.22±0.73	Drama	BLR	43.83±0.71	100±0.00	60.09±0.64
	BN	91.62±0.42	94.84±0.34	93.46±0.61		BN	100±0.00	85.70±0.72	92.36±0.35
	NB	96.82±1.42	64.48±0.87	76.73±0.97		NB	100±0.00	28.56±0.84	46.44±0.92
	RF	92.78±0.19	94.58±0.74	93.84±0.48		RF	100±0.00	85.77±0.74	92.34±1.71
	AB	92.73±0.52	94.38±0.50	93.46±0.84		AB	100±0.00	85.77±0.51	92.32±0.54
	D-Tree	91.29±0.64	91.27±0.71	91.22±0.65		D-Tree	25.04±0.45	50.00±0.54	33.43±0.24
	SVM	85.25±0.61	82.14±0.57	82.28±0.98		SVM	65.45±0.64	65.25±0.71	62.43±0.08
	LSTM	85.98±0.84	83.33±0.64	83.48±0.12		LSTM	61.54±0.75	65.45±0.84	64.95±0.38
	GA-V	91.12±0.66	95.87±0.57	94.45±0.25		**GA-V**	98.65±0.69	85.01±0.75	94.12±0.35
Animation	BLR	71.85±2.42	100±0.00	82.36±0.77	Musical	BLR	47.37±0.81	100±0.00	64.34±2.15
	BN	91.31±0.64	97.95±0.91	94.42±0.38		BN	93.27±0.96	86.38±0.38	89.61±0.40
	NB	98.61±0.70	72.95±0.46	83.83±1.60		NB	95.94±0.88	58.88±0.40	72.92±0.34
	RF	91.17±0.38	97.93±0.74	94.42±0.79		RF	95.12±0.47	85.61±0.19	90.17±0.74
	AB	91.11±0.57	97.93±0.89	94.46±0.54		AB	92.48±0.41	86.33±0.57	89.58±0.42
	D-Tree	94.61±1.67	95.19±0.48	94.87±0.83		D-Tree	90.18±0.16	90.10±0.49	90.10±0.47
	SVM	71.56±0.87	83.75±0.71	79.49±1.28		SVM	85.93±0.56	85.15±0.72	85.13±0.48
	LSTM	92.31±0.51	92.31±0.93	92.31±0.38		LSTM	83.60±0.64	81.19±1.84	81.00±0.81
	GA-V	97.12±0.24	95.11±0.34	95.89±0.71		**GA-V**	89.25±0.78	91.22±0.81	91.96±0.29
Children	BLR	58.76±0.68	100±0.00	75.24±0.75	Mystery	BLR	59.35±0.28	100±0.00	74.65±0.71
	BN	82.24±0.68	99.22±0.69	89.93±0.23		BN	96.24±0.22	89.60±0.87	92.71±0.71
	NB	94.12±0.34	51.63±0.98	66.27±0.33		NB	99.34±0.34	61.85±2.68	76.82±2.94
	RF	82.82±0.87	97.68±0.47	89.61±0.72		RF	96.25±0.18	89.67 ±0.47	92.73±0.58
	AB	82.22±0.39	99.27±0.43	89.92±0.37		AB	96.14±0.31	89.61±0.31	92.72±0.47
	D-Tree	85.67±0.24	84.80±0.87	84.53±0.97		D-Tree	90.46±0.29	89.26±0.73	89.36±1.71
	SVM	80.70±0.41	79.20±1.37	79.22±0.68		SVM	86.06±0.83	78.51±0.71	78.47±0.82
	LSTM	80.70±0.78	79.20±0.68	79.22±0.72		LSTM	87.94±0.73	84.30±0.81	84.44±0.84
	GA-V	82.36±0.74	99.87±0.41	90.01±0.64		**GA-V**	87.94±0.28	84.30±0.87	84.44±1.72
Comedy	BLR	50.26±2.45	100±0.00	67.22±0.97	Romance	BLR	50.52±3.64	100±0.00	67.14±0.51
	BN	92.56±0.68	89.36±0.49	91.14±0.56		BN	97.84±0.41	89.34±0.75	93.45±0.52
	NB	96.21±0.76	53.82±0.87	69.37±0.54		NB	98.34±0.35	69.74±0.41	81.33±0.78
	RF	92.61±0.58	89.62±0.29	91.12±0.67		RF	97.8 ±0.41	89.33±1.79	93.48±0.88
	AB	92.62±0.44	89.63±0.45	91.11±0.69		AB	97.81±0.94	89.34±0.74	93.43±0.64
	D-Tree	91.59±0.78	91.56±0.15	91.56±1.68		D-Tree	89.17±0.42	89.15±0.29	89.15±0.75
	SVM	76.55±0.67	73.53±0.87	72.61±0.28		SVM	90.62±0.45	88.63±0.87	88.55±0.74
	LSTM	87.78±0.28	86.83±0.71	86.77±0.60		LSTM	95.24±0.53	94.83±0.88	94.83±0.71
	GA-V	95.84±0.50	89.66±0.30	93.29±0.78		**GA-V**	97.25±0.80	96.74±0.41	95.88±0.63

find the best or popular movie in given categories of MovieLens Dataset based on the proposed features and GA-V. The precise classification of movie categories features can improve the ability of movie quality prediction system. The proposed feature are passed to the state of the art ML model and proposed GA-V classifier with same data distribution and training environment.

A. PERFORMANCE OF CLASSIFIERS ON FEATURES

For a fair comparison, the same training parameters are used to train all the classifiers, where ten-fold is used to train the model on training and validation data. The experimental environment also remains the same for all classifiers, and the fame metric, i.e. F1 score, is used to identify the optimal classifier for the voting. To measure the prediction performance, confusion matrix can be used to evaluate the classifier's results. The confusion matrix has four categories, as given by Table 1, to analyze the performance such as precision, recall, sensitivity and specificity.

First, precision is the ratio of number of relevant movies retrieved to the total number of irrelevant and relevant movies retrieved. Precision can be computed by equation (6).

$$Precision = \frac{TP}{TP + FP} \tag{6}$$

Second, recall is the ratio of the number of relevant movies retrieved to the total number of relevant movies retrieved and the number of relevant movies not retrieved by the classifier. Recall can be computed by equation (7).

$$Recall = \frac{TP}{TP + FN} \tag{7}$$

Lastly, F1 score is the harmonic mean of precision and recall which can be computed by using equation (8). F1 score is also used as a fitness function for GA-V. F–measure plays important role in the performance of proposed GA-V classifier.

$$F1score = 2 \times \frac{Precision \times Recall}{Precision + Recall} \tag{8}$$

TABLE 5. Comparison of performance of Traditional ML algorithms and proposed GA-V classifier in terms of average, minimum and maximum precision recall and F1 score on all (user reputation, social & temporal) features.

Movie Category	Classifier	Precision	Recall	F1 Score	Movie Category	Classifier	Precision	Recall	F1 Score
Action	BLR	85.22±0.56	83.55±0.54	85.14±1.64	Horror	BLR	81.47±0.61	61.63±0.41	70.34±0.75
	BN	93.48±0.71	84.42±0.69	88.72±0.68		BN	87.12±0.69	81.61±0.19	84.35±0.71
	NB	96.63±0.40	62.90±0.71	76.21±0.13		NB	91.74±0.67	58.24±0.89	71.21±0.54
	RF	95.63±0.58	91.31±0.16	94.44±0.26		RF	98.30±0.74	97.71±0.71	98.54±0.58
	AB	92.64±0.69	93.28±0.69	93.26±0.67		AB	83.82±0.74	95.14±0.71	89.41±0.26
	D-Tree	95.56±0.38	95.54±0.68	95.52±0.57		D-Tree	98.15±0.48	98.14±0.57	98.13±0.64
	SVM	87.36±1.36	86.63±0.	86.78±0.78		SVM	87.24±0.29	86.98±0.91	86.69±0.35
	LSTM	88.69±0.39	88.30±0.69	88.39±0.71		LSTM	87.54±0.72	87.44±0.94	87.24±0.48
	GA-V	94.12±0.68	97.63±0.47	96.74±0.48		**GA-V**	99.47±0.67	98.96±0.58	99.73±0.78
Adventure	BLR	84.65±0.74	84.52±0.38	84.16±0.64	Drama	BLR	71.45±0.62	71.43±0.74	71.45±0.25
	BN	94.62±0.08	83.63±0.33	88.81±0.39		BN	85.73±0.61	85.71±0.24	85.70±0.42
	NB	96.28±0.67	64.73±0.97	77.65±1.97		NB	83.03±0.49	71.41±0.58	76.95±0.48
	RF	93.62±0.71	93.57±0.72	95.84±0.58		RF	100±0.00	85.37±0.67	92.53±0.96
	AB	92.58±0.69	94.83±0.85	93.48±0.58		AB	100±0.00	85.57±0.39	92.33±0.54
	D-Tree	95.64±0.18	95.63±0.33	95.64±0.20		D-Tree	25.55±0.94	50.25±0.91	33.33±0.69
	SVM	82.70±1.68	81.75±0.97	81.90±0.58		SVM	65.55±0.78	65.7 ±0.68	64.3 ±0.57
	LSTM	85.70±0.88	85.32±0.51	85.40±0.12		LSTM	65.55±0.18	65.45±0.67	64.37±0.64
	GA-V	97.21±0.45	96.23±0.97	96.08±0.35		**GA-V**	85.65±0.44	98.45±0.64	96.5 ±0.64
Animation	BLR	81.37±0.64	94.47±0.69	87.37±0.64	Musical	BLR	83.37±0.25	67.25±0.11	74.75±0.15
	BN	97.81±0.74	84.63±0.66	90.34±0.97		BN	89.26±0.99	91.31±0.64	90.42±0.68
	NB	99.32±0.89	72.35±0.77	83.77±0.74		NB	91.27±0.34	61.95±0.68	73.98±0.39
	RF	96.33±0.80	96.83±0.44	96.64±0.83		RF	96.95±0.46	96.94±0.64	96.92±0.54
	AB	94.37±0.29	96.87±0.61	95.55±0.67		AB	91.82±0.50	90.65±0.34	91.23±0.28
	D-Tree	94.82±0.18	94.87±0.94	94.75±0.71		D-Tree	85.18±0.57	85.15±0.69	85.15±0.78
	SVM	83.55±0.88	84.62±0.71	83.33±0.74		SVM	81.51±0.97	79.21±0.97	78.99±0.59
	LSTM	88.24±0.58	88.46±0.69	88.33±0.74		LSTM	81.92±0.67	81.19±0.28	81.16±0.78
	GA-V	98.54±0.41	93.27±0.64	95.97±0.28		**GA-V**	96.91±0.87	97.52±0.94	97.08±0.41
Children	BLR	74.33±0.68	81.43±0.79	77.77±0.42	Mystery	BLR	76.17±0.48	87.31±0.73	81.25±0.43
	BN	89.43±0.69	75.68±0.81	81.92±0.75		BN	93.28±0.28	88.44±0.67	90.63±0.82
	NB	94.22±0.71	53.33±0.57	68.18±0.31		NB	95.84±0.34	66.28±0.43	78.14±0.36
	RF	92.42±0.54	98.83±0.71	95.61±0.28		RF	97.52±0.95	98.87±0.38	98.13±0.84
	AB	87.58±0.67	94.32±0.34	90.82±0.18		AB	95.72±0.36	92.24±0.61	94.13±0.36
	D-Tree	93.57±0.10	93.74±0.87	93.60±0.26		D-Tree	90.40±0.38	90.08±0.64	90.14±0.84
	SVM	84.83±0.12	84.96±0.94	84.80±0.55		SVM	80.93±0.36	80.99±0.39	80.96±0.58
	LSTM	84.02±0.41	84.09±0.41	84.00±0.43		LSTM	82.72±0.72	82.64±0.35	82.67±0.67
	GA-V	98.54±0.25	99.74±0.48	99.38±0.58		**GA-V**	95.44±0.48	97.25±0.11	96.4 ±0.64
Comedy	BLR	83.52±0.67	74.55±0.25	78.64±0.67	Romance	BLR	83.64±0.16	73.21±0.11	77.92±0.60
	BN	91.48±0.15	84.25±0.37	87.74±0.87		BN	93.28±0.48	90.26±1.72	91.74±0.28
	NB	93.65±0.18	57.44±0.49	71.14±0.81		NB	93.34±0.72	61.48±0.84	74.12±0.67
	RF	98.45±0.14	99.55±0.87	98.61±0.78		RF	98.29±0.38	98.97±0.69	98.98±0.67
	AB	92.58±0.21	90.47±0.69	91.53±0.28		AB	97.45±0.48	91.58±0.55	94.14±0.84
	D-Tree	97.72±0.37	97.70±0.51	97.70±0.54		D-Tree	96.75±0.31	96.64±0.31	96.64±0.97
	SVM	65.01±0.84	63.17±0.46	61.68±0.68		SVM	85.77±0.45	84.75±0.67	84.71±0.17
	LSTM	93.36±0.23	93.09±0.78	93.09±0.54		LSTM	93.67±0.74	93.02±0.74	93.02±0.54
	GA-V	99.21±0.85	99.75±0.64	99.64±0.28		**GA-V**	98.24±0.54	99.73±0.425	98.98±0.64

As precision and recall are the complementary measures with an inverse relationship, therefore F1 score is used to normalize the performance of classification results.

In Table 2, performance measures (Precision, Recall and F1 scores) are presented for each movie category using User reputation features. As a result, RF classifier has the higher F1 score on User Reputation features as compared to all other traditional classifiers except the movie category children. AB is the only classifier with slightly lower F1 score values for each movie category. Similarly, BN and BLR are the quick successors of RF and AB classifiers. Also, NB is relatively below to BLR and BN. RF classifier has shown better performance on User Reputation features for predicting a popular movie. LSTM and SVM have almost equal performance in terms of all the measures. The proposed GA-V classifier outperform for all the categories. The knowledge of ML and deep learning is merged to find the best label for each sample of the dataset.

Similarly, RF, BN and AB classifiers have competitive performance on social and temporal features. NB, BLR has less classification performance for a popular movie based on social and temporal features in a movie category of a movie recommender system. Table 3 and 4 presented the comparative performance for selecting the best classifier using proposed features for a movie category. Based on social and temporal features, we can conclude that classification accuracy varies on a different dataset with different features after a comparison with [31], [32]. However, RF and AB classifiers have more computational cost as compared to BN and NB. In addition, BLR and NB have almost same for movie quality prediction system. The Proposed GA-V classifier performs well for each movie category. The merged knowledge makes good predictions.

To strengthen our argument, all features are combined to train the aforementioned classifier for their performance. RF also performed better than the rest of the traditional classifier, and GA-V performs better from all the classifiers for all movie categories. In short, GA-V classifier can be effectively used in movie quality prediction system due to its better F1 score, classification accuracy and less classification error. RF is the second best possible choice in such systems to find popular movies in different categories. However, better features may lead to improvement of these classifiers performance. Table 5, presents and helps researchers to choose a classifier according to their features in relevance to proposed work for developing an accurate movie quality prediction system.

B. CLASSIFIERS ACCURACY AND ERROR ON PROPOSED FEATURES

All these classifiers are trained separately by using UserReputation, Social, Temporal and All features. A mixed behavior of classifiers can be observed on UserReputation, Social and Temporal features. However, Naïve Bayes and BayesNet performed efficiently, not only on all features but also on respective features independently. Naive Bayes models are popular due to their simplicity in allowing each attribute to contribute towards the final decision equally and independently from the other attributes. For movie quality prediction, Naïve Bayes models are well suited to capture the complexity of the underlying decision-making process, considering the many (inter)dependencies such as ratings, tags, sentiments etc. While Decision Tree classifier training process is complex, and they can get out of hand with the number of nodes created in some cases. Another disadvantage of Decision Tree models is that the algorithm separates the samples linearly. Depending on their nature, the movies data might not be linearly separable, and thus decision trees are unsuitable for movie quality prediction. AdaboostM1 and Random forest classifiers are relatively slow with better classification accuracy. Also, Bayesian logistic regression performed efficiently on all input data with less classification accuracy. SVM also performs consistent for all the categories. We have used the RBF kernal of SVM which transform the feature space to another feature space. SVM extend the proposed feature space to kernelized feature space and find the separation line. The proposed model use the brain of all the candidate classifiers, so it performs well as compared to state of the art ML and DL models. Consequently, we can conclude that GA-V classifier is better for assessing a popular movie based on the proposed features for each movie category. Random Forest, SVM and AdaboostM1 classifier can be considered as a second choice in movie quality prediction systems.

A percentage complement of classifier accuracy refers to classifier error. Therefore, a classifier with promising the lowest classification error is considered to be the best classifier. For this purpose, comparisons of several classifiers error have been performed. From the stand alone classifiers, RF and AB classifiers can be justified based on the lowest classification error for each movie category using the proposed set of input features. BLR classifier performs worst in term of classifier error. And the proposed GA-V have minimum error on proposed features.

VI. CONCLUSION AND FUTURE WORK

An improved movie quality prediction mechanism is proposed by utilizing a new set of novel features to measure the movie quality from different angles such as social quality, user reputation and temporal aspects. Furthermore, the GA based weighted voting classifier is proposed to validate the significance of proposed features. The proposed method use the knowledge of best classifiers and assign weights according to their confidence. The propsoed method is compared with existing ML, DL and ensemble (AdaBoost) models. The results shows the significance of the propsoed features and model in terms if precision, recall and F1 score.The aim of this work is to evaluate the effectiveness of social web domain features in identifying quality movies. Leveraging the aspects of social web applications such as online reviews recommendation, product recommendations and news article recommendations, experimental results indicate that our suggested features contributed significant results for identifying a quality movie.For the future, the existing featurs can be extended to new features and compared with the existing features. For the classifier, the weight assigning based on F1 score can be replaced with multiple evaluation measures including precision, recall and accuracy. the weight can be assigned to each model based on multiple fitness values.

VII. AUTHOR CONTRIBUTIONS

Conceptualization: Muhammad Shahzad Faisal, Khalid Iqbal, Atif Rizwan, Ali Daud; Methodology: Muhammad Shahzad Faisal, Khalid Iqbal, Atif Rizwan, Ali Daud, and Heba Fasihuddin; Software: Muhammad Shahzad Faisal, and Atif Rizwan; Validation: Muhammad Shahzad Faisal, Khalid Iqbal, Ali Daud, and Ameen Banjar; Formal Analysis: Atif Rizwan, Khalid Iqbal, Atif Rizwan, and Ameen Banjar; Investigation: Muhammad Shahzad Faisal, Atif Rizwan, and Khalid Iqbal; Resources: Heba Fasihuddin, Ameen Banjar, and Ali Daud; Data Curation: Muhammad Shahzad Faisal and Atif Rizwan; Writing—Original Draft Preparation: Muhammad Shahzad Faisal, Atif Rizwan, and Khalid Iqbal; Writing—Review And Editing, Ali Daud, Heba Fasihuddin, and Ameen Banjar; Visualization: Muhammad Shahzad Faisal, Khalid Iqbal, Atif Rizwan, and Ameen Banjar; Supervision: Ali Daud and Heba Fasihuddin; Project Administration: Ali Daud and Atif Rizwan; Funding Acquisition: Heba Fasihuddin, Ameen Banjar, and Ali Daud. All authors have read and agreed to the published version of the manuscript.

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REFERENCES

[1] *MovieLens*. Accessed: Mar. 3, 2021. [Online]. Available: https://movielens.org/

[2] F. M. Harper and J. A. Konstan, "The movielens datasets: History and context," *ACM Trans. Interact. Intell. Syst.*, vol. 5, no. 4, pp. 1–19, 2016.

[3] R. Kosala and H. Blockeel, ''Web mining research: A survey,'' *ACM SIGKDD Explorations Newslett.*, vol. 2, no. 1, pp. 1–15, 2000.

[4] F. Zhu and X. Zhang, ''Impact of online consumer reviews on sales: The moderating role of product and consumer characteristics,'' *J. Marketing*, vol. 74, pp. 133–148, Mar. 2010.

[5] M. A. Hall and E. Frank, ''Combining naive Bayes and decision tables,'' in *Proc. FLAIRS Conf.*, 2118, pp. 318–319, 2008.

[6] I.-P. Chiang, ''Using text mining techniques to analyze how movie forums affect the box office,'' *Int. J. Electron. Commerce Stud.*, vol. 5, no. 1, pp. 91–96, Jun. 2014.

[7] J. Krauss, S. Nann, D. Simon, K. Fischbach, and P. Gloor, ''Predicting movie success and academy awards through sentiment and social network analysis,'' in *Proc. Eur. Conf. Inf. Syst. (ECIS)*, 2008, pp. 2026–2037.

[8] Q. Ye, W. Shi, and Y. Li, ''Sentiment classification for movie reviews in Chinese by improved semantic oriented approach,'' in *Proc. 39th Annu. Hawaii Int. Conf. Syst. Sci. (HICSS)*, vol. 3, Jan. 2006, p. 53b.

[9] P. Chaovalit and L. Zhou, ''Movie review mining: A comparison between supervised and unsupervised classification approaches,'' in *Proc. 38th Annu. Hawaii Int. Conf. Syst. Sci.*, 2005, p. 112.

[10] K. R. Apala, M. Jose, S. Motnam, C.-C. Chan, K. J. Liszka, and F. de Gregorio, ''Prediction of movies box office performance using social media,'' in *Proc. IEEE/ACM Int. Conf. Adv. Social Netw. Anal. Mining*, Aug. 2013, pp. 1209–1214.

[11] W. Carrer-Neto, M. L. Hernández-Alcaraz, R. Valencia-García, and F. García-Sánchez, ''Social knowledge-based recommender system. Application to the movies domain,'' *Expert Syst. Appl.*, vol. 39, no. 12, pp. 10990–11000, Sep. 2012.

[12] S. Kabinsingha, S. Chindasorn, and C. Chantrapornchai, ''A movie rating approach and application based on data mining,'' *Int. J. Eng. Innov. Technol.*, vol. 2, no. 1, pp. 77–83, 2012.

[13] S. Dhawan and K. Singh, ''Analysing user ratings for classifying online movie data using various classifiers to generate recommendations,'' in *Proc. Int. Conf. Futuristic Trends Comput. Anal. Knowl. Manage. (ABLAZE)*, Feb. 2015, pp. 295–300.

[14] M. Chen and J. P. Singh, ''Computing and using reputations for internet ratings,'' in *Proc. 3rd ACM Conf. Electron. Commerce (EC)*, 2001, pp. 154–162.

[15] J. Alspector, A. Koicz, and N. Karunanithi, ''Feature-based and clique-based user models for movie selection: A comparative study,'' *User Model. User-Adapted Interact.*, vol. 7, no. 4, pp. 279–304, 1997.

[16] C. Basu, H. Hirsh, and W. Cohen, ''Recommendation as classification: Using social and content-based information in recommendation,'' in *Proc. AAAI/IAAI*, 1998, pp. 714–720.

[17] J. Davidson, B. Livingston, D. Sampath, B. Liebald, J. Liu, P. Nandy, T. Van Vleet, U. Gargi, S. Gupta, Y. He, and M. Lambert, ''The Youtube video recommendation system,'' in *Proc. 4th ACM Conf. Recommender Syst. (RecSys)*, 2010, pp. 293–296.

[18] T. Amjad, Y. Ding, A. Daud, J. Xu, and V. Malic, ''Topic-based heterogeneous rank,'' *Scientometrics*, vol. 104, no. 1, pp. 313–334, Jul. 2015.

[19] A. Daud, R. Abbasi, and F. Muhammad, ''Finding rising stars in social networks,'' in *Database Systems for Advanced Applications* (Lecture Notes in Computer Science), vol. 7825, W. Meng, L. Feng, S. Bressan, W. Winiwarter, and W. Song, Eds. Berlin, Germany: Springer, 2013, doi: 10.1007/978-3-642-37487-6_4.

[20] A. Daud, M. Ahmad, M. S. I. Malik, and D. Che, ''Using machine learning techniques for rising star prediction in co-author network,'' *Scientometrics*, vol. 102, no. 2, pp. 1687–1711, 2015.

[21] M. Saraee, S. White, and J. Eccleston, ''A data mining approach to analysis and prediction of movie ratings,'' *WIT Trans. Inf. Commun. Technol.*, vol. 33, p. 10, 2004.

[22] D. L. Lee, H. Chuang, and K. Seamons, ''Document ranking and the vector-space model,'' *IEEE Softw.*, vol. 14, no. 2, pp. 67–75, Mar. 1997.

[23] T. Amjad, A. Daud, D. Che, and A. Akram, ''MuICE: Mutual influence and citation exclusivity author rank,'' *Inf. Process. Manage.*, vol. 52, no. 3, pp. 374–386, May 2016.

[24] C. Faisal, M. Shahzad, A. Daud, F. Imran, and S. Rho, ''A novel framework for social web forums' thread ranking based on semantics and post quality features,'' *J. Supercomput.*, vol. 72, no. 11, pp. 4276–4295, 2016.

[25] L. Akritidis, D. Katsaros, and P. Bozanis, ''Identifying the productive and influential bloggers in a community,'' *IEEE Trans. Syst., Man, Cybern., C (Appl. Rev.)*, vol. 41, no. 5, pp. 759–764, Sep. 2011.

[26] P. Resnick, N. Iacovou, M. Suchak, P. Bergstrom, and J. Riedl, ''Grouplens: An open architecture for collaborative filtering of netnews,'' in *Proc. ACM Conf. Comput. Supported Cooperat. Work*, 1994, pp. 175–186.

[27] W. Sack, ''Conversation map: A content-based usenet newsgroup browser,'' in *From Usenet to CoWebs* (Computer Supported Cooperative Work), C. Lueg and D. Fisher, Eds. London, U.K.: Springer, 2003, doi: 10.1007/978-1-4471-0057-7_5.

[28] N. Agarwal, H. Liu, L. Tang, and P. S. Yu, ''Modeling blogger influence in a community,'' *Social Netw. Anal. Mining*, vol. 2, no. 2, pp. 139–162, Jun. 2012.

[29] I. Ha, K. J. Oh, M. D. Hong, and G. S. Jo, ''Social filtering using social relationship for movie recommendation,'' in *Computational Collective Intelligence. Technologies and Applications* (Lecture Notes in Computer Science), vol. 7653, N. T. Nguyen, K. Hoang, and P. Jędrzejowicz, Eds. Berlin, Germany: Springer, 2012, doi: 10.1007/978-3-642-34630-9_41.

[30] A. Deng, Y. Zhu, and B. Shi, ''A collaborative filtering recommendation algorithm based on item rating prediction,'' *J. Softw.*, vol. 14, no. 9, pp. 1621–1628, 2003.

[31] K. Iqbal, X.-C. Yin, H.-W. Hao, S. Asghar, and H. Ali, ''Bayesian network scores based text localization in scene images,'' in *Proc. Int. Joint Conf. Neural Netw. (IJCNN)*, Jul. 2014, pp. 2218–2225.

[32] K. Iqbal, X.-C. Yin, X. Yin, H. Ali, and H.-W. Hao, ''Classifier comparison for MSER-based text classification in scene images,'' in *Proc. Int. Joint Conf. Neural Netw. (IJCNN)*, Aug. 2013, pp. 1–6.

[33] G. Adomavicius and A. Tuzhilin, ''Toward the next generation of recommender systems: A survey of the state-of-the-art and possible extensions,'' *IEEE Trans. Knowl. Data Eng.*, vol. 17, no. 6, pp. 734–749, Jun. 2005.

[34] Z.-K. Zhang, T. Zhou, and Y.-C. Zhang, ''Tag-aware recommender systems: A state-of-the-art survey,'' *J. Comput. Sci. Technol.*, vol. 26, no. 5, pp. 767–777, Sep. 2011.

[35] W. Zhang and S. Skiena, ''Improving movie gross prediction through news analysis,'' in *Proc. IEEE/WIC/ACM Int. Joint Conf. Web Intell. Intell. Agent Technol.*, vol. 1, Sep. 2009, pp. 301–304.

[36] Q. Zhao, S. Chang, F. M. Harper, and J. A. Konstan, ''Gaze prediction for recommender systems,'' in *Proc. 10th ACM Conf. Recommender Syst.*, Sep. 2016, pp. 131–138.

[37] X. H. Pham, J. J. Jung, and S.-B. Park, ''Exploiting social contexts for movie recommendation,'' *Malaysian J. Comput. Sci.*, vol. 27, no. 1, pp. 68–79, 2014.

[38] M. P. O'Mahony and B. Smyth, ''A classification-based review recommender,'' in *Research and Development in Intelligent Systems XXVI*, M. Bramer, R. Ellis, and M. Petridis, Eds. London, U.K.: Springer, 2010, doi: 10.1007/978-1-84882-983-1_4.

[39] A. Irshad, S. A. Chaudhry, S. Kumari, M. Usman, K. Mahmood, and M. S. Faisal, ''An improved lightweight multiserver authentication scheme,'' *Int. J. Commun. Syst.*, vol. 30, no. 17, p. e3351, Nov. 2017.

[40] W. Hu, Y. Zhang, Y. Zhou, and Z. Xue, ''Contribution-based user reputation modeling in collaborative recommender systems,'' in *Proc. 9th Int. Conf. Ubiquitous Intell. Comput. 9th Int. Conf. Autonomic Trusted Comput.*, Sep. 2012, pp. 172–179.

[41] W. Hill, L. Stead, M. Rosenstein, and G. Furnas, ''Recommending and evaluating choices in a virtual community of use,'' in *Proc. SIGCHI Conf. Hum. Factors Comput. Syst. (CHI)*, 1995, pp. 194–201.

[42] S. Baccianella, A. Esuli, and F. Sebastiani, ''Sentiwordnet 3.0: An enhanced lexical resource for sentiment analysis and opinion mining,'' in *Proc. 7th Int. Conf. Lang. Resour. Eval. (LREC)*, 2010.

[43] R. Sharda and E. Meany, ''Forecasting gate receipts using neural network and rough sets,'' in *Proc. Int. DSI Conf.*, 2000, pp. 1–5.

[44] P. K. Chintagunta, S. Gopinath, and S. Venkataraman, ''The effects of online user reviews on movie box office performance: Accounting for sequential rollout and aggregation across local markets,'' *Marketing Sci.*, vol. 29, no. 5, pp. 944–957, 2010.

[45] M. Dadgar and A. Hamzeh, ''How to boost the performance of recommender systems by social trust? Studying the challenges and proposing a solution,'' *IEEE Access*, vol. 10, pp. 13768–13779, 2022.

[46] T. Hassan, B. Edmison, T. Stelter, and D. S. McCrickard, ''Learning to trust: Understanding editorial authority and trust in recommender systems for education,'' in *Proc. 29th ACM Conf. Modeling, Adaptation Personalization*, Jun. 2021, pp. 24–32.

[47] P. D. Meo, ''Trust prediction via matrix factorisation,'' *ACM Trans. Internet Technol.*, vol. 19, no. 4, pp. 1–20, 2019.

[48] L. Burbach, J. Nakayama, N. Plettenberg, M. Ziefle, and A. C. Valdez, ''User preferences in recommendation algorithms: The influence of user diversity, trust, and product category on privacy perceptions in recommender algorithms,'' in *Proc. 12th ACM Conf. Recommender Syst.*, 2018, pp. 306–310.

[49] A. Chen, ''Forecasting gross revenues at the movie box office,'' Univ. Washington, Seattle, WA, USA, Working Paper, 2002.

[50] N. Terry, M. Butler, and D. A. De'Armond, "The determinants of domestic box office performance in the motion picture industry," *Southwestern Econ. Rev.*, vol. 32, pp. 137–148, Aug. 2011.
[51] S. Sen, J. Vig, and J. Riedl, "Tagommenders: Connecting users to items through tags," in *Proc. 18th Int. Conf. World Wide Web*, 2009, pp. 671–680.
[52] D. Heckerman, D. Geiger, and D. M. Chickering, "Learning Bayesian networks: The combination of knowledge and statistical data," *Mach. Learn.*, vol. 20, no. 3, pp. 197–243, Sep. 1995.
[53] V. K. Singh, R. Piryani, A. Uddin, and P. Waila, "Sentiment analysis of movie reviews and blog posts," in *Proc. 3rd IEEE Int. Advance Comput. Conf. (IACC)*, Feb. 2013, pp. 893–898.
[54] J. Eliashberg and S. M. Shugan, "Film critics: Influencers or predictors?" *J. Marketing*, vol. 61, no. 2, pp. 68–78, 1997.
[55] U. Shardanand and P. Maes, "Social information filtering: Algorithms for automating 'word of mouth,'" in *Proc. Conf. Hum. Factors Comput. Syst. (SIGCHI)*, 1995, pp. 210–217.
[56] C. Dellarocas, X. Zhang, and N. F. Awad, "Exploring the value of online product reviews in forecasting sales: The case of motion pictures," *J. Interact. Marketing*, vol. 21, no. 4, pp. 23–45, Nov. 2007.
[57] D. Kaplan, "And the oscar goes to…A logistic regression model for predicting academy award results," *J. Appl. Econ. Policy*, vol. 25, no. 1, pp. 23–41, 2006.
[58] G. Fei, A. Mukherjee, B. Liu, M. Hsu, M. Castellanos, and R. Ghosh, "Exploiting burstiness in reviews for review spammer detection," in *Proc. Int. AAAI Conf. Web Social Media*, vol. 7, 2013, pp. 175–184.
[59] K. Anwar, J. Siddiqui, and S. S. Sohail, "Machine learning-based book recommender system: A survey and new perspectives," *Int. J. Intell. Inf. Database Syst.*, vol. 13, nos. 2–4, pp. 231–248, 2020.
[60] W. Duan, B. Gu, and A. B. Whinston, "Do online reviews matter?—An empirical investigation of panel data," *Decis. Support Syst.*, vol. 45, no. 4, pp. 1007–1016, 2008.
[61] X. Lu, S. Ba, L. Huang, and Y. Feng, "Promotional marketing or word-of-mouth? Evidence from online restaurant reviews," *Inf. Syst. Res.*, vol. 24, no. 3, pp. 596–612, 2013.
[62] B. Wang, Q. Liao, and C. Zhang, "Weight based KNN recommender system," in *Proc. 5th Int. Conf. Intell. Hum.-Mach. Syst. Cybern.*, vol. 2, Aug. 2013, pp. 449–452.
[63] H.-M. Chuang, L.-C. Wang, and C.-C. Pan, "A study on the comparison between content-based and preference-based recommendation systems," in *Proc. 4th Int. Conf. Semantics, Knowl. Grid*, Dec. 2008, pp. 477–480.
[64] R. Hooda, K. Singh, and S. Dhawan, "A study of recommender systems on social networks and content-based web systems," *Int. J. Comput. Appl.*, vol. 97, no. 4, pp. 23–28, Jul. 2014.
[65] C. Rana and S. K. Jain, "Building a book recommender system using time based content filtering," *WSEAS Trans. Comput.*, vol. 11, no. 2, pp. 2224–2872, 2012.
[66] Y. H. Cho, J. K. Kim, and S. H. Kim, "A personalized recommender system based on web usage mining and decision tree induction," *Exp. Syst. Appl.*, vol. 23, no. 3, pp. 329–342, Oct. 2002.
[67] M. K. Khribi, M. Jemni, and O. Nasraoui, "Toward a hybrid recommender system for e-learning personalization based on web usage mining techniques and information retrieval," in *Proc. E-Learn: World Conf. E-Learn. Corporate, Government, Healthcare, Higher Educ.*, 2007, pp. 6136–6145.
[68] G. Lekakos and P. Caravelas, "A hybrid approach for movie recommendation," *Multimedia Tools Appl.*, vol. 36, nos. 1–2, pp. 55–70, Jan. 2008.
[69] D.-R. Liu and Y.-Y. Shih, "Hybrid approaches to product recommendation based on customer lifetime value and purchase preferences," *J. Syst. Softw.*, vol. 77, no. 2, pp. 181–191, Aug. 2005.
[70] A. Rizwan, N. Iqbal, R. Ahmad, and D.-H. Kim, "WR-SVM model based on the margin radius approach for solving the minimum enclosing ball problem in support vector machine classification," *Appl. Sci.*, vol. 11, no. 10, p. 4657, May 2021.
[71] L. I. Kuncheva and J. J. Rodriguez, "A weighted voting framework for classifiers ensembles," *Knowl. Inf. Syst.*, vol. 38, no. 2, pp. 259–275, Feb. 2014.
[72] A. Rizwan, A. N. Khan, N. Iqbal, R. Ahmad, and D. H. Kim, "Enhanced optimization-based voting classifier and chained multi-objective regressor for effective groundwater resource management," *IEEE Access*, vol. 9, pp. 168329–168341, 2021.
[73] M. Woźniak, M. Graña, and E. Corchado, "A survey of multiple classifier systems as hybrid systems," *Inf. Fusion*, vol. 16, pp. 3–17, May 2014.
[74] J. Kittler, M. Hatef, R. P. W. Duin, and J. Matas, "On combining classifiers," *IEEE Trans. Pattern Anal. Mach. Intell.*, vol. 20, no. 3, pp. 226–239, Mar. 1998.
[75] A. Kausar, M. Ishtiaq, M. A. Jaffar, and A. M. Mirza, "Optimization of ensemble based decision using PSO," in *Proc. World Congr. Eng.*, vol. 1, 2010, pp. 1–6.
[76] R. Burduk, "Recognition task with feature selection and weighted majority voting based on interval-valued fuzzy sets," in *Computational Collective Intelligence. Technologies and Applications* (Lecture Notes in Computer Science), vol. 7653, N. T. Nguyen, K. Hoang, and P. Jędrzejowicz, Eds. Berlin, Germany: Springer, 2012, doi: 10.1007/978-3-642-34630-9_21.
[77] C. Leacock and M. Chodorow, "Combining local context and WordNet similarity for word sense identification," *WordNet: Electron. Lexical Database*, vol. 49, no. 2, pp. 265–283, 1998.
[78] L. Meng, R. Huang, and J. Gu, "A review of semantic similarity measures in WordNet," *Int. J. Hybrid Inf. Technol.*, vol. 6, no. 1, pp. 1–12, 2013.
[79] M. Srinivas and L. M. Patnaik, "Adaptive probabilities of crossover and mutation in genetic algorithms," *IEEE Trans. Syst., Man, Cybern.*, vol. 24, no. 4, pp. 656–667, Apr. 1994.
[80] Y. Freund and R. E. Schapire, "Experiments with a new boosting algorithm," in *Proc. ICML*, vol. 96, 1996, pp. 148–156.
[81] M. de Gemmis, P. Lops, G. Semeraro, and P. Basile, "Integrating tags in a semantic content-based recommender," in *Proc. ACM Conf. Recommender Syst. (RecSys)*, 2008, pp. 163–170.
[82] M. Hall, E. Frank, G. Holmes, B. Pfahringer, P. Reutemann, and I. H. Witten, "The WEKA data mining software: An update," *ACM SIGKDD Explorations Newslett.*, vol. 11, no. 1, pp. 10–18, 2009.
[83] L. Breiman, "Random forests," *Mach. Learn.*, vol. 45, no. 1, pp. 5–32, 2001.

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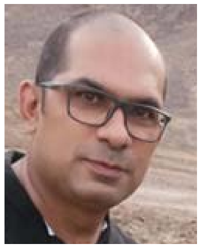

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