Multilingual Opinion Mining Movie Recommendation System Using RNN

Conference Paper · April 2020

DOI: 10.1007/978-981-15-3369-3_44

3 authors:

Tarana Singh
Gautam Buddha University

Anand Nayyar
Duy Tan University

Arun Solanki
Gautam Buddha University

Multilingual Opinion Mining Movie Recommendation System Using RNN

Tarana Singh, Anand Nayyar and Arun Solanki

Abstract Twitter is a news and social networking site where people around the world post their blogs and share their feeling, point of view, and comments regarding any communication or about any latest movie, etc. Thus, Twitter generates a massive quantity of Twitter data every day. This data is real time, which is being used in the proposed work for implementing a "movie recommendation system." To enhance the performance of the framework, sentimental analysis is also being applied to the data. Nowadays, the recommendation system is also an essential tool for online businesses and used by various e-commerce sites, music applications, entertainment sites, etc. This work proposed a movie recommendation system for the movie domain which is developed using real-time multilingual tweets. These tweets are obtained from Twitter API using the LinqToTwitter Library. Sentimental analysis is also being performed on tweets. In this work, multilingual and real-time tweets are considered. These tweets are translated into the target language using Google Translate API. The proposed work used the Stanford library for preprocessing, and RNN is used for classifying the tweets. The tweets are classified as positive, negative, and neutral tweets. Preprocessing of the tweets is done to remove unwanted words, URLs, emoticons, etc. Finally, based on the classification, the movie is suggested to the user. This proposed work is better than the current practices as the implementation is being done on real-time tweets, and sentimental analysis is also being performed to get better results. This system is achieving 91.67% accuracy, 92% precision, 90.2% recall, and 90.98% f-measure.

Keywords Recurrent neural network · Artificial neural network · Natural language processing · Text categorization · Twitter API · The movie database

T. Singh (✉) · A. Solanki
Gautam Buddha University, Greater Noida, India
e-mail: taranasingh14@gmail.com

A. Solanki
e-mail: Ymca.arun@gmail.com

A. Nayyar
Duy Tan University, Da Nang, Vietnam
e-mail: anandnayyar@duytan.edu.vn

P. K. Singh et al. (eds.), *Proceedings of First International Conference on Computing, Communications, and Cyber-Security (IC4S 2019)*, Lecture Notes in Networks and Systems 121, https://doi.org/10.1007/978-981-15-3369-3_44

1 Introduction

Recommendation systems are the subclass of the information filtering systems. These systems are used in a variety of areas, YouTube, Netflix, Amazon, Facebook, Twitter, Instagram, etc. [1–3]. Recommendation systems are basically of two kinds; for instance, content-based recommendation systems, these systems predict based on item properties [4–6]. Another sort of recommendation system is collaborative filtering [7–11]; these systems predict based on comparing the user's history [12–15]. Other than these two techniques, there is also the system named hybrid recommendation system. In this technique, both the collaborative and content-based filtering techniques are combined [16–19]. In this technique, content is used to infer ratings in case of the sparsity of ratings [20–22]. Both of these techniques are used in most recommendation systems at present. Netflix movie recommendation system is an example of a hybrid recommendation system [23, 24]. Sentiment analysis (SA) is also called opinion mining. Sentiment analysis is a logical mining of content which distinguishes and concentrates emotional data in source material. This will help in business to comprehend the social supposition of their image, item, or administration while checking on the Web discussions. However, investigation of online lifestreams is typically limited to the fundamental feeling or opinion analysis [25–28]. This is similar to digging the surface and omitting out the insights those need to be discovered. There are three approaches to sentimental analysis [29–33]. "Lexicon-based approach" of sentimental analysis is the unsupervised technique. Categorization is finished by looking at the highlights of a given content against conclusion vocabularies whose feelings are determined before the utilization [34–36]. The lexicon-based techniques to sentiment analysis are unsupervised learning because it does not require prior training to classify the data. [37–39]. "Machine learning approach" applicable to sentiment analysis mostly belongs to supervised classification. In this approach, there are two sets of documents, i.e., a training set and test set. The training set is used by an automatic classifier to learn the differentiating characteristics of materials, and a test set is used to check how well the classifier performs. Several techniques are Naïve Bayes, maximum entropy, support vector machine, etc. These techniques have achieved great success in sentiment analysis [40, 41]. The hybrid approach of sentimental analysis is the combination of both the above methods of sentimental analysis. Past research has shown that if the ML and LB both are combined, the performance of SA will improve [42].

2 Recurrent Neural Network

Recurrent neural network is a type of neural network that contains guided loops; these ends represent the promotion of activation for future entries in a sequence. Instead of accepting the same vector input X as a test example, an RNN can take the series of vector inputs $(x_1, x_2, x_3, \ldots, x_t)$ for arbitrary, where T is the value of the variable. When there is a single dimension in each x_t in our specific application, each x_t is a vector representation of a word, and $(x_1, \ldots, x_t))$ is a sequence of words in the movie review; it shares that RNN can imagine "unrolling" to copy to a network in each of all other copies of the same weight [43]. For each loop edge in the system, we connect the side to the same node in the x_t network, thereby creating a chain, which breaks any loop and gives us the standard forward neural network feed technique. First, calculate the value for it, the input gate, and the candidate value for the states of the memory cells at a time.

$$i_t = \sigma w_i x_t + U_i h_i + b_i \tag{1}$$

$$c_t = \tanh(w_i x_t + U_i h_t - 1 + bc) \tag{2}$$

Secondly, calculate the value of the function of activating the forget gate of the memory cells at time t:

$$f_t = \sigma w_f x_t + U_f h_t - 1 + b_f \tag{3}$$

Given the value of the input gate activation, the forget gate activation, and the candidate state value, now we can compute the memory cells' new state at time t:

$$c_t = i_t * c_t + f_t * c_t - 1 \tag{4}$$

With the new state of the memory cells, we can compute the latest value of the output gates and subsequently their outputs:

$$o_t = (w_o x_t + U_i h_t - 1) \tag{5}$$

Figure 1 shows the general architecture of RNN, also used in the proposed study [44–47]. This architecture used an embedded layer to break down the data into a sentence. These sentences are converted into words. In these words, the filter is applied and maps to output. In the proposed work, the main objective is to build a recommendation system for the movie domain. This system will use real-time Twitter data to generate predictions [48–50].

3 Research Paper Organization

The proposed work starts with Part I as introduction of the basics of recommendation system, sentimental analysis, and RNN. Part II discusses the latest work done by recent authors with the details of the techniques and tools used by different authors. Part III describes the architecture of the proposed recommendation system. Part IV shows the flowchart of the proposed method. Part V shows the algorithm of the

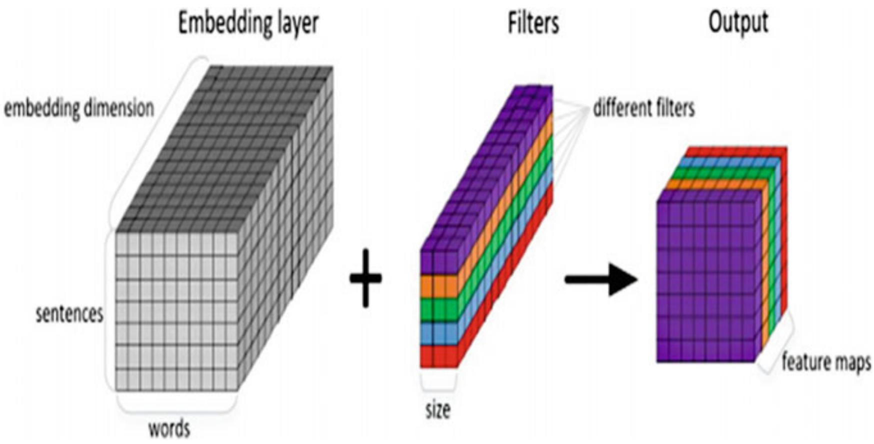

Fig. 1 RNN general architecture

proposed system. Part VI discusses the implementation of the proposed system with the help of the snapshot of the system while using the system. Part VII is presenting the results obtained in the proposed method. Part VIII is explaining the conclusion, and finally, in Part IX, the future work of the proposed system is stated. In the last part, X, in this paper, all the references are given.

4 Literature Review

Zhang et al. [36], the author, reviewed the preprocessing of tweets in detail. The author tackled various models as the results obtained by a solitary model may betray as they rely upon the data of that particular model. The author discussed that employing multiple models will assemble the exactness of the machine. The author used NB classifiers, which exhibits the most significant outcomes when appeared differently concerning SMO, SVM, and random forest. Rajput et al. [37] recommended that opinion word is utilized in many feeling characterization assignments. Positive sentiment phrases are being utilized to state any ideal conditions, while negative contemplations are being utilized to unwanted state conditions. There are some sentences and idioms, which are said to be as one as the lexicon of sentiment. There are three primary ways to deal with arranging or gathering rundown of sentiment words. The standard methodology takes too much time and is not utilized alone, and it is commonly joined with the other two computerized approaches because to keep mistakes away from mechanized techniques. Fradkin et al. [39], the author, proposed a recommendation system to foresee the user's review and information, dominatingly from massive collected data to suggest their preferences. The movie suggestion framework is a framework that helps users in characterizing users with common preferences. This framework (K-means cuckoo) has 0.68 MAE. Solanki et al. [49], the author, displayed a recommendation framework using "K-means clustering" and KNN, and these works for different estimations of "RMSE" are acquired. In this work, if authors are decreasing the no. of observations, the estimate of "RMSE" reduces. The most significant evaluation of "RMSE" got is 1.081648.

In the above discussion, there are various articles given by multiple writers who chip away at the sentimental analysis and recommendation system. In the existing systems, past researchers utilize the datasets from the given repositories, for instance, the GroupLens datasets, MovieLens datasets, and so forth; these datasets are the static datasets which are accessible on the Web on various Web sites. Previously, the authors took a shot at these available datasets to accomplish some degree of precision.

5 Architecture

Figure 2 demonstrates the working of the projected framework. It comprises three components, specifically the information component, a preparing component, and a yield component.

- **Input Module**: In this component, the client needs to give a contribution to the framework. The framework will pick the current date and area of the client. This data is additionally given to the next module, for example, the preprocessing; i.e., the output of the first module will be the input of the processing module.

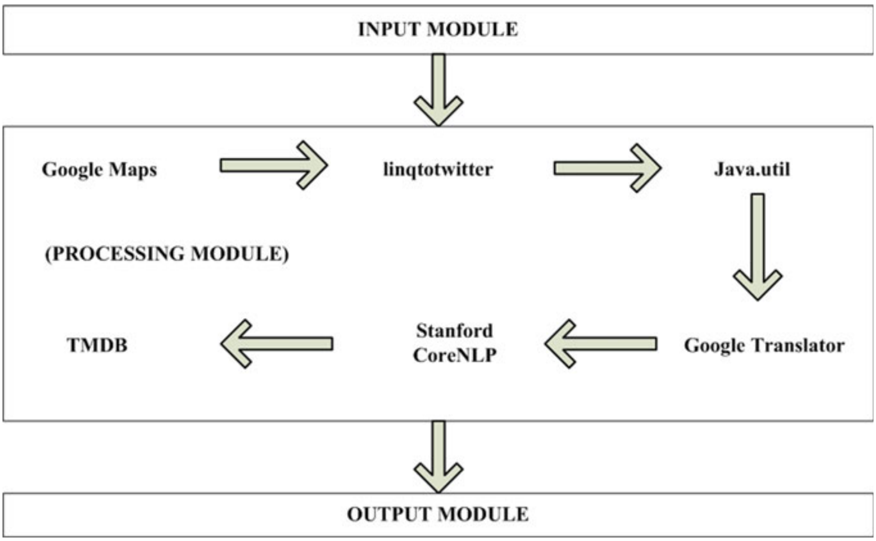

Fig. 2 Architecture of the system

- **Processing Module**: In the module, the framework procures the information from Twitter API, deciphers the multilingual information utilizing Google interpreter into the English language, and produces it accordingly.
  - **GoogleMap**: It is used to obtain the current geographical location of the user.
  - **LinqToTwitter**: It is used to link to the Twitter API to access the real-time Twitter data.
  - **Google Translate**: It is used to translate the other languages tweet into the target language, English.
  - **java.util**: It is used to access the property class to obtain the properties from the data and pass these properties to the model for training.
  - **Stanford NLP**: This library is used to train the model.
  - **TMDB**: This library is used to fetch the movie's data from the Web.

  This module will perform various operations like downloading the data, preprocessing the data, and finally applying the RNN classifier to categorize the tweets into positive, negative, and neutral categories. According to the input from the user, the system will generate a recommendation that has high positive reviews and will go to the next module that is an output module.
- **Output Module**: The yield module depicts the anticipated movie that the info client may like. The output of the processing module will be the input of this module.

6 Flowchart

Figure 3 demonstrates the stream outline of the movie recommendation framework. This chart reflects the procedure stream of the suggested framework, which portrays how the structure is functioning, how the system is managing the crude information, and how the framework predicts the beautiful motion pictures as per the contribution from the client.

7 Pseudocode of the Proposed System

Pseudocode of the proposed framework has the following steps:
Step 1: Input search text.
Step 2: System date and geographical location are automatically detected.
Step 3: Choose language.
Step 4: Search and download the data from Twitter.
Step 5: Translate the downloaded data using Google Translate.
Step 6: Preprocess the data using Stanford NLP.
Step 7: Apply RNN for the classification of the tweets.

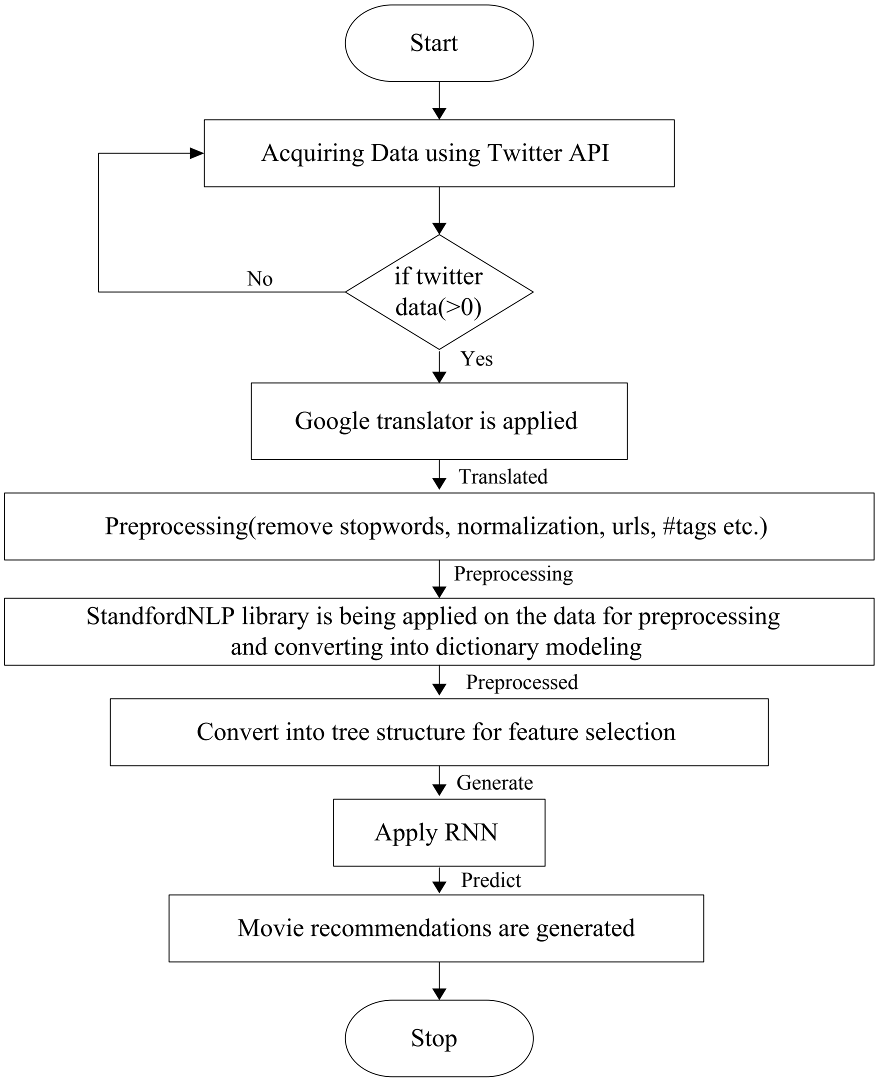

Fig. 3 Flowchart

Step 8: Movie recommendations are generated.
Step 9: Accuracy of the system is evaluated.

8 Implementation of the Proposed System

Step 1: In step 1, the proposed system search the query at client side to produce the recommendations. This framework will naturally pick the system date and geographical location using GoogleMap. The primary motivation behind the current geographic location of the client is that the proposed system can recognize in which geographical area the client is present so the framework can identify the most recent and mainstream movie. This encourages the context to produce the most appropriate recommendations to the user. Another part here is to choose the language. When we connect to the Twitter information at that point, there are the tweets in various languages like Hindi, Marathi, Spanish, and so forth recommended style to choose all language so the framework will obtain every tweet from the Twitter as presented in Fig. 4.

Step 2: After Step 1, users need to click on the search and download button, and the downloading of the twitter data will start. The downloaded information is stored in a.txt file and stored in the system for further operations as shown in Fig. 5a, b.

Step 3: In this step, the translation of the data is being performed using the Google Translator. As the information that is collected from Twitter is multilingual, that is why the conversion of the data into the target language (i.e., English) is essential. To translate the data into the targeted language, the user needs to click on the button "translate the data using Google Translate." Converted data is again stored in a.txt file for further operations as shown in Fig. 6a, b.

Step 4: The translated tweets are used to perform preprocessing. Preprocessing is done to eliminate the stop words, emoticons, hashtags, URLs, etc., and sentimental

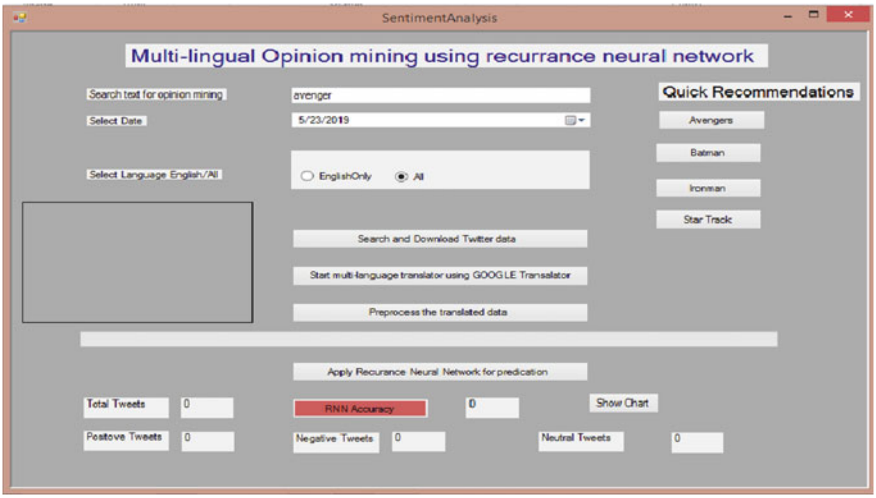

Fig. 4 Input data

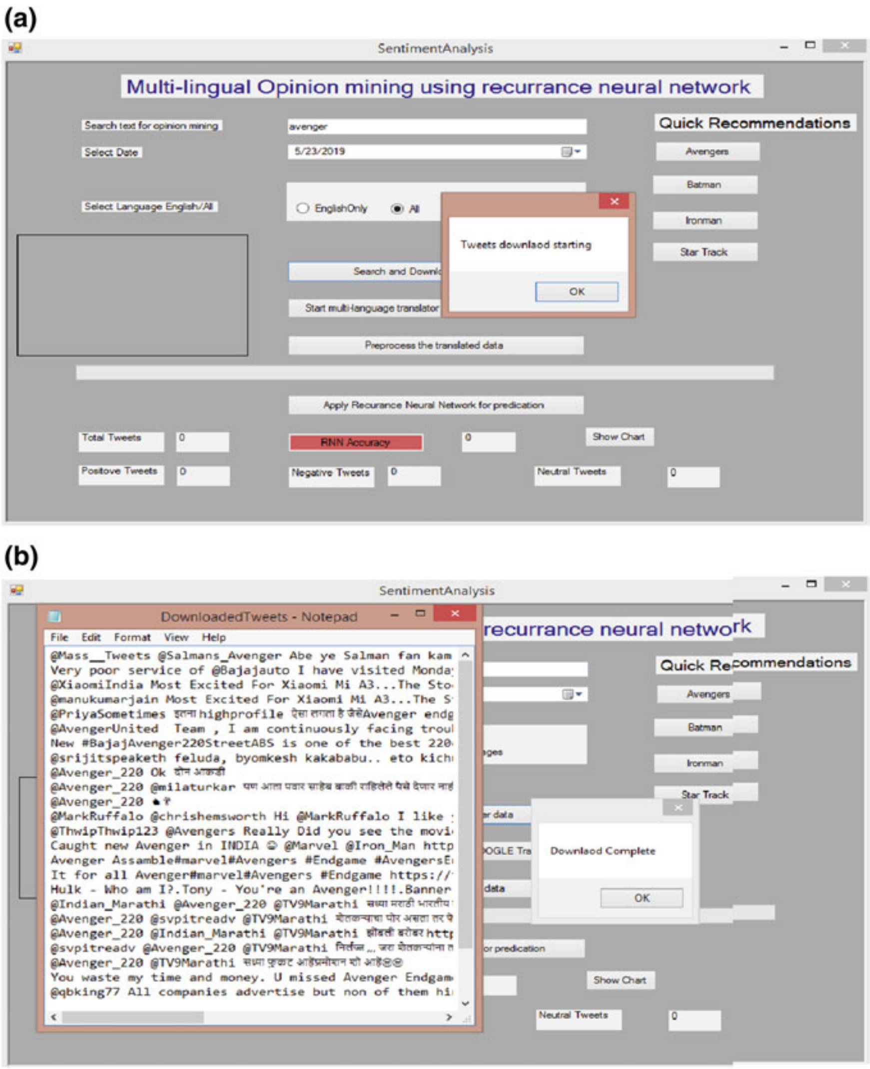

Fig. 5 **a** Tweet downloading. **b** Tweet downloading complete and .txt file of tweets

analysis is shown on the left data, which is without any unwanted words and characters. After this step is completed, we got the data on which the user can perform further tasks. After preprocessing, the processed tweets are stored in another.txt file, as shown in Fig. 7a, b. This file is used for further operations, i.e., sentimental analysis of the tweets.

Step 5: Preprocessing of the downloaded data is done in the above step using the Stanford NLP Library. Now, the classification of the preprocessed tweets is being done using RNN classification in Fig. 8. The tweets are classified into different

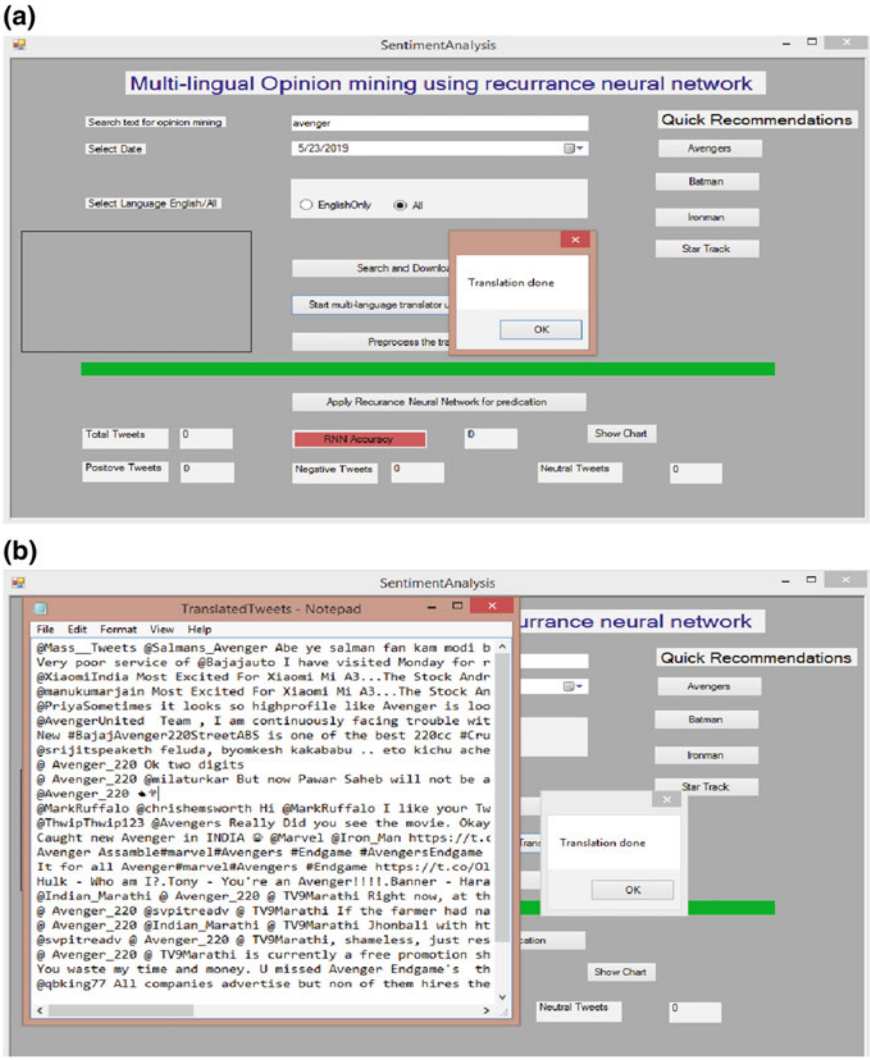

Fig. 6 **a** Translating the tweets. **b** Translated tweets

categories, namely positive tweets, negative tweets, and neutral tweets.

Step 6: In this step, based on the above classification, the recommendations to the user are being generated in the grid view. To produce the movie's recommendations in the system, the TMDB library is used. The user needs to enter the text, i.e., movie name in the searching textbox, and after all the above steps, the most prominent and exceedingly positive movie is predicted to the user by the system. The developer can manage the number of movies generated, which will be shown in the grid view. This is shown in Fig. 9.

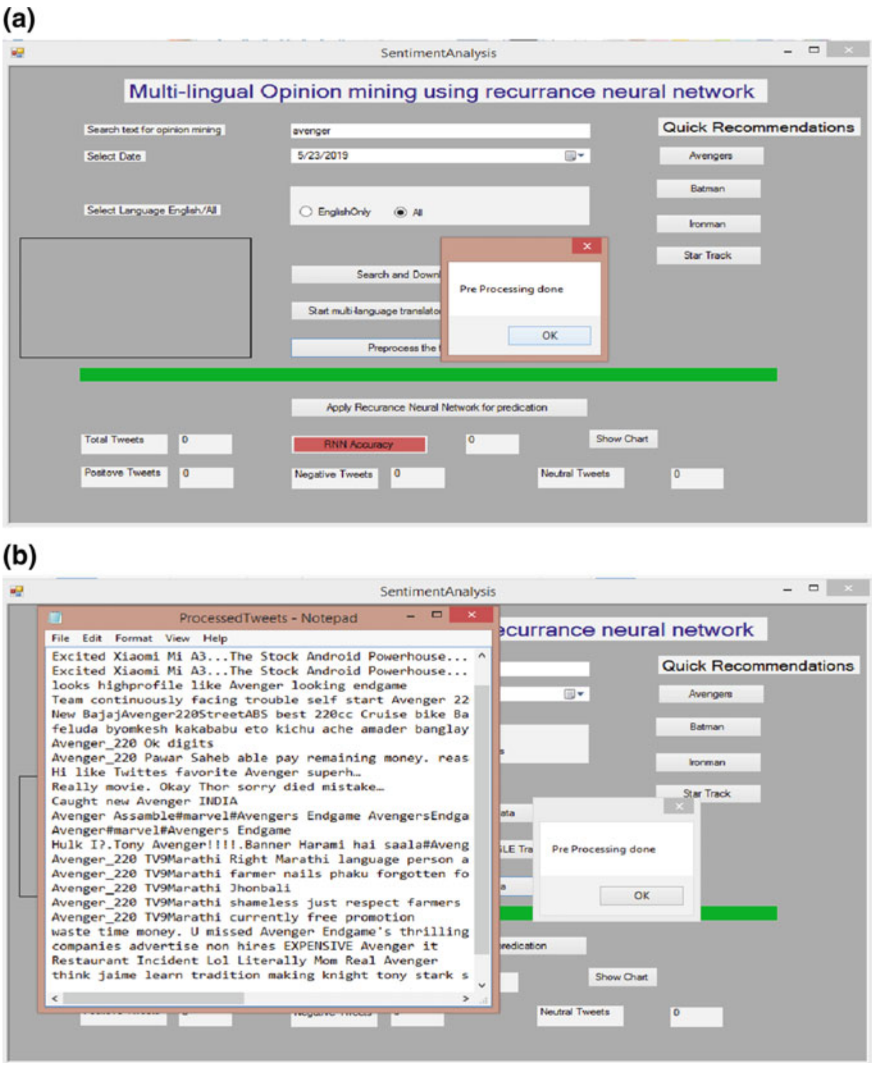

Fig. 7 **a** Preprocessing of tweets. **b** Preprocessed tweets

9 Result Analysis

In Fig. 10, the accuracy of the proposed framework is being represented, i.e., recommending the movies to the user according to the input data from the user with 91% accuracy.

Figure 11 shows the result where all the different positive, negative, and neutral tweets are being represented on the pie graph and all the values are in the %, so the pie chart is being utilized to describe the results of the proposed system.

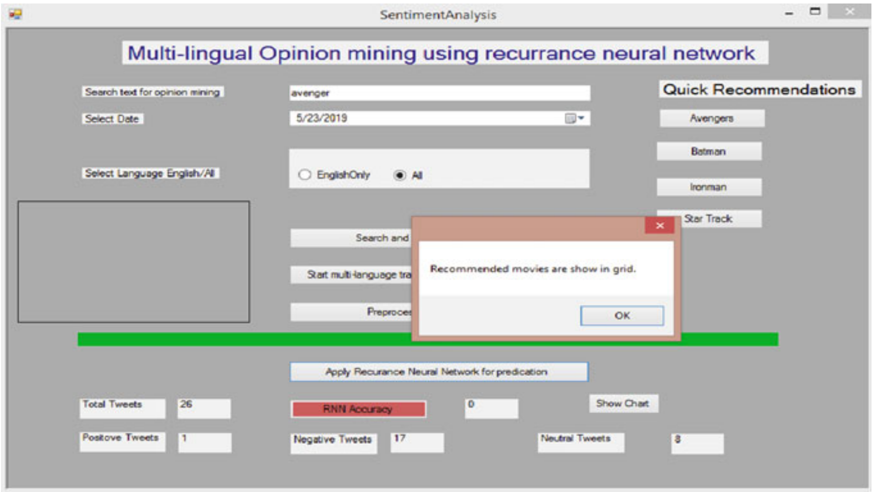

Fig. 8 Apply recurrence neural network for classification

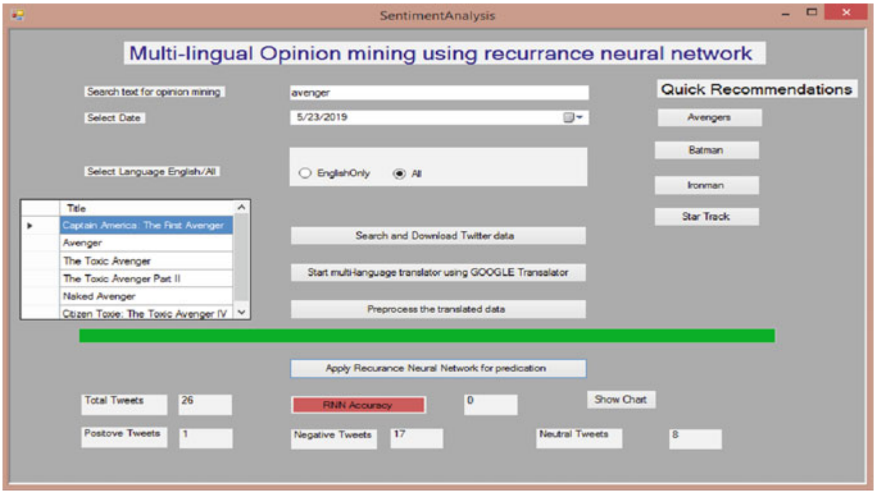

Fig. 9 Recommendations for the users

In Table 1, the result of the proposed system is represented with accuracy, precision, recall, and f-measures. The result of the proposed method is also compared with the results of the existing systems. The proposed work is improved than the already present work, as the proposed work is to obtain better outcomes [14, 27].

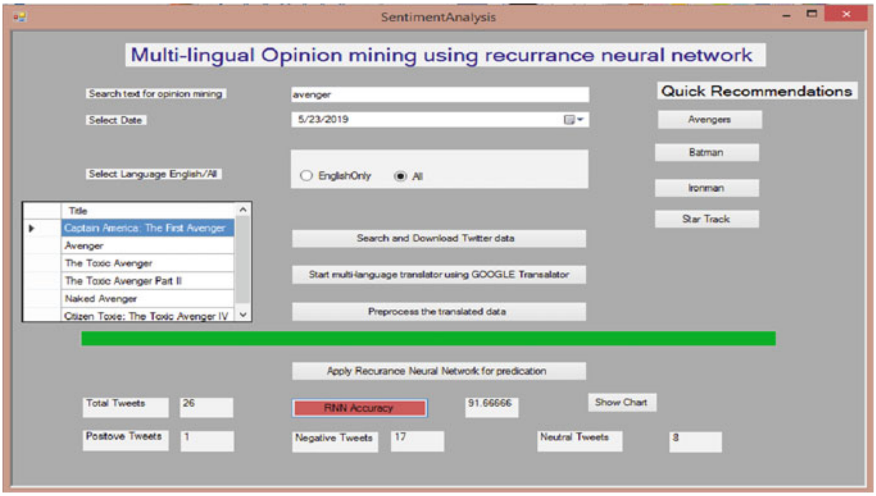

Fig. 10 Results of projected system

10 Conclusion

In this work, we have developed a movie recommendation framework using the TMDB database. RNN classification is applied for the sentimental analysis of the tweets; then, the movie recommendations are generated to the user based on the input given to the system by the user. In this proposed system, different operations are being done on the tweets like downloading of the information, interpretation

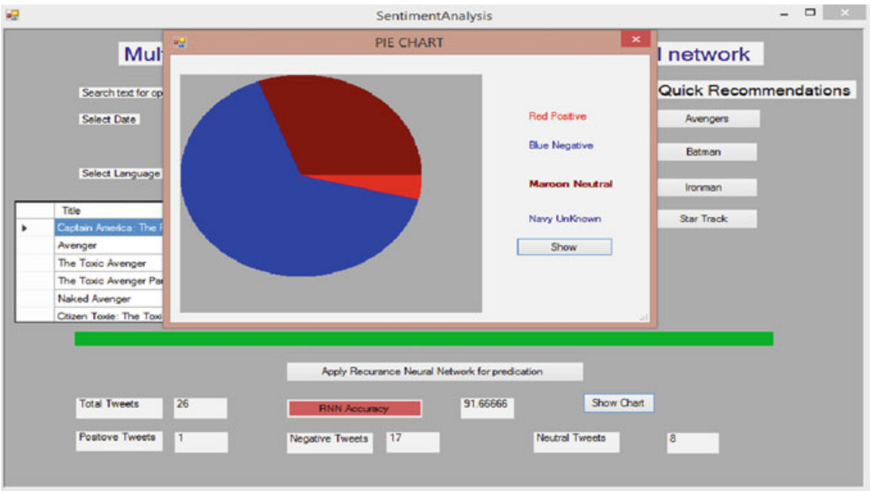

Fig. 11 PIE chart representation of results

Table 1 Result of performance measures for RNN and comparison with other classifiers

S. No.	Classifier	Dataset	Accuracy (%)	Precision (%)	Recall (%)	F-measures (%)
1	RNN (proposed work)	Twitter	91.67	92	90.2	90.98
2	Naïve Bayes (Soni)	Twitter	77.16	78.12	74.5	76.15
3	SVM (HailongZhang et al.)	Twitter	79.5	79	79	79

of the information, per-handling of the information, and afterward, the grouping of the data. For the classification of the information, the RNN classifier is being utilized, which is grouping the information with 91.67% accuracy. The discernments make it extraordinarily sure that the RNN classifier defeats each other classifier in anticipating the suspicions with the precision of 92%. This work has differentiated unmistakable request computations by getting the best results. There are various challenges for sentimental analysis heretofore. While attempting to counter this, this system used RNN classifiers which fall under AI frameworks to organize the ends did by slangs, incorrect spellings, emoticons, multilingual contentions, and different event of words and achieved a high precision. In this work, continuous Twitter information is being used utilizing different Twitter API keys to get to the report. In this way, the proposed framework is delivering the outcomes as indicated by the most recent discharge and fame of the movies in the specific geographical spam where the client is while scanning for the proposals.

11 Future Work

In the proposed work, the recommendation system is working only for the movie domain, but in the future, this system can be extended for the universal recommendation system, i.e., a system which can generate recommendations for other fields. In the future, these emoticons can be added in preprocessing to obtain the emotions of the users as these emoticons are also the part of the user's sentiments. So, in the future work, some techniques can be used for sentimental analysis.

References

1. Ziegler, C.N., McNee, S.M., Konstan, J.A., Lausen, G.: Improving recommendation lists through topic diversification. In: Proceedings of the 14th International Conference on World Wide Web, New York, NY, USA, vol. 2131, no. 34, pp. 222–234 (2005)

2. Gokulakrishnan, B., Priyanthan, P., Raghavan, T., Prasath, N., Perera, A.: Opinion mining and sentiment analysis on a twitter data stream. In: The International Conference on Advances in ICT for Emerging Regions, vol. 46, no. 12, pp. 182–188 (2012)
3. Singh, Y., Bhatia, P., Sangwan, O.: A review of studies on machine learning techniques. Int. J. Comput. Sci. Secur. **1**(1), 70–84 (2007)
4. Tejeda, A.: A quality-based recommender system to disseminate information in a university digital library. Inf. Sci. **261**(32), 52–69 (2014)
5. Fan, Y., Dong, L., Sun, X., Wang, D., Qin, W., Aizeng, C.: Research on auto-generating test-paper model based on spatial-temporal clustering analysis. In: Huang, D.S., Jo, K.H., Zhang, X.L. (eds.) Intelligent Computing Theories and Application, ICIC, Lecture Notes in Computer Science, vol. 10955, no. 2342, pp. 238–255. Springer, Cham (2018)
6. Luo, X., Zhou, M., Xia, Y., Zhu, Q.: An efficient non-negative matrix-factorization-based approach to collaborative filtering for recommender systems. IEEE Trans. Industr. Inf. **10**(2), 1231–1245 (2014)
7. Kanta, V., Bharadwaj, K.: Enhancing recommendation quality of content-based, filtering through collaborative predictions and fuzzy similarity measures. Procedia Eng. **38**(21), 939–942 (2012)
8. Lops, P., Gemmis, M., Semeraro, G.: Content-based recommender systems: state of the art and trends. In: Ricci, F., Rokach, L., Shapira, B., Kantor P. (eds.) Recommender Systems Handbook, vol. 2131, no. 34, pp. 2371–2384. Springer, Boston, MA (2011)
9. Hu, N., Bose, I., Koh, N.S., Liu, L.: Manipulation of online reviews: an analysis of ratings, readability, and sentiments. Decis Support Syst. **52**(12), 674–684 (2012)
10. Jiang, J., Lu, J., Zhang, G., Long, G.: Scaling-up Item-based collaborative filtering recommendation algorithm based on Hadoop. In: 2013 IEEE World Congress on Services, vol. 52, no. 12, pp. 4–9 July 2013
11. Adeniyi, D., Wei, Z., Yongquan, Y.: Automated web usage data mining and recommendation system using k-nearest neighbor (KNN) classification method. Saudi Comput. Soc. King Saud Univ. **2152**(120), 34–49 (2014)
12. Kataria, R., Verma, O.P.: An effective collaborative movie recommender system with cuckoo search. Egypt. Inform. J. **18**(2), 105–112 (2019)
13. Xiao, P., Liangshan, S., Xiuran, L.: Improved collaborative filtering algorithm in the research and application of personalized movie recommendations. In: Fourth International Conference on Intelligent Systems Design and Engineering Applications, vol. 56, no. 6, pp. 401–414 (2013)
14. Munoz-Organero, M., Gustavo, A. González, R., Pedro, J., Delgado, C.: A Collaborative Recommender System Based on Space- Time Similarities, IEEE Pervasive Computing, vol. 2131, no. 34, pp. 232–246 (2010)
15. Czarnowski, I., Jdrzejowicz, P.: Data reduction algorithm for machine learning and data mining. In: Nguyen, N.T., Borzemski, L., Grzech, A., Ali, M. (eds.) New Frontiers in Applied Artificial Intelligence. IEA/AIE, Lecture Notes in Computer Science, vol. 5027, no. 2032, pp. 80–94. Springer, Berlin (2008)
16. Duarte, D., Stahl, N.: Machine learning: a concise overview. In: Said, A., Torra, V. (eds.) Data Science in Practice. Studies in Big Data, vol. 46, no. 12, pp. 95–115. Springer, Cham (2019)
17. Shamri, A.: Fuzzy-genetic approach to recommender systems based on a novel hybrid user model, expert systems with applications. In: 3rd International Conference on Computer Science and Information Technology, IEEE, vol. 1267, no. 104, pp. 300–313 (2008)
18. Jinming, H.: Application and research of collaborative filtering in e-commerce recommendation system. In: 3rd International Conference on Computer Science and Information Technology, vol. 1567, no. 204, pp. 338–352 (2010)
19. Jiang, Z., Zang, W., Liu, X.: Research of K-means clustering method based on DNA genetic algorithm and P system. In: Zu, Q., Hu, B. (eds.) Human-Centered Computing. HCC Lecture Notes in Computer Science, vol. 9567, no. 214, pp. 145–158. Springer, Cham (2016)
20. Yan, B., Chen, G.: AppJoy: personalized mobile application discovery. In: Proceedings of the 9th International Conference on Mobile Systems Applications and Services—MobiSys 11, vol. 2340, no. 123, pp. 11–25 (2011)

21. Davidsson, C., Moritz, S.: Utilizing implicit feedback and context to recommend mobile applications from first use. In: Proceedings of the Ca RR 2011, vol. 1240, no. 103, pp. 19–22. ACM Press, New York (2011)
22. Bilge, A., Kaleli, C., Yakut, I., Gunes, I., Polat, H.: A survey of privacy-preserving collaborative filtering schemes. Int. J. Softw. Eng. Knowl. Eng. **40**(13), 1085–1108 (2013)
23. Veselka, M., Schindler, K.: Mutual information estimation in higher dimensions: a speed-up of a k-nearest neighbor based estimator. In: Beliczynski B., Dzielinski A., Iwanowski M., Ribeiro B. (eds.) Adaptive and Natural Computing Algorithms. ICANNGA 2007. Lecture Notes in Computer Science, vol. 4431, no. 32, pp 2231–2245, Springer, Berlin (2007)
24. Calandrino, J.A., Kilzer, A., Narayanan. A., Felten, E.W., Shmatikov, V.: You might also like: privacy risks of collaborative filtering. In: Proceedings of the IEEE Symposium on Security and Privacy, vol. 1421, no. 26, pp. 231–246, Oakland, CA, USA (2011)
25. Soni, A.: Multi-lingual sentiment analysis of twitter data by using classification algorithms accepted to publish in IEEE, vol. 1238, no. 33, pp. 1022–1034 (2017)
26. Ahuja, R., Solanki, A.: Movie recommender system using K-Means clustering and K-Nearest Neighbor. In: Accepted for Publication in Confluence-2019: 9th International Conference on Cloud Computing, Data Science & Engineering, Amity University, Noida, vol. 1231, no. 21, pp. 25–38 (2019)
27. Ko, S.K.: A smart movie recommendation system. In: Smith, M.J., Salvendy, G. (eds.) Human Interface and the Management of Information. Interacting with Information. Human Interface, 2011. Lecture Notes in Computer Science, vol. 6771, no. 12, pp. 628–642. Springer, Berlin (2011)
28. Argamon, S., Bloom, K., Esuli, A., Sebastiani, F.: Automatically determining attitude type and force for sentiment analysis. In Human Language Technology. Challenges of the Information Society Springer, vol 223 issue 23, pp. 218–231, (2009)
29. Jinming, H.: Application and research of collaborative filtering in e-commerce recommendation system. In: 2010 3rd International Conference on Computer Science and Information Technology, vol. 40, no. 13, pp. 151–164 (2010)
30. Neri, F., Aliprandi, C., Capeci, F., Cuadros, M., Tomas.: Sentiment Analysis on Social Media. In: ACM International Conference on Advances in Social Networks Analysis and Mining, vol. 39, no. 20, pp. 324-338 (2012)
31. Xie, H.T., Meng, X.W.: A personalized information service model adapting to user requirement evolution. Acta Electron. Sin. **39**(3), 643–648 (2011)
32. Polat, H., Du, W.: Privacy preserving top n recommendation for distributed data. J. Am. Soc. Inf. Sci. Technol. **59**(7), 1093–1108 (2008)
33. Yakut, I., Polat, H.: Estimating NBC-based recommendations on arbitrarily partitioned data with privacy. Knowl. Based on Syst **36**(10), 2163–2178 (2012)
34. Okkalioglu, M., Koc, M., Polat, H.: On the discovery of fake binary ratings. In: Proceedings of the 30th Annual ACM Symposium on Applied Computing, ACM, USA, vol. 122. no. 20, pp. 901–907 (2015)
35. Wang, L.C., Meng, X.W., Zhang, Y.J.: A cognitive psychology-based approach to user preferences elicitation for mobile network services. Acta Electron. Sin. **39**(11), 2547–2553 (2011)
36. Zhang, H., Gan, W., Jiang, B.: Machine Learning and Lexicon based methods for sentiment classification: a survey. In: 11th Web Information System and Application Conference IEEE, vol. 132, no. 24, pp. 262–265 (2017)
37. Rajput, R., Solanki, A.: Real-time analysis of tweets using machine learning and semantic analysis. In: International Conference on Communication and Computing Systems (ICCCS-2016), Taylor and Francis, at Dronacharya College of Engineering, Gurgaon, 9–11 Sept, vol 138 issue 25, pp. 687–692, (2016)
38. Munoz-Organero, M., Ramíez-González, G.A., Munoz-Merino, P.J., Delgado, K.: A collaborative recommender system based on space-time similarities. IEEE Pervasive Comput. 2010, vol. 12 no. 5, pp. 1023–1039 (2017)

39. Fradkin, D., Muchnik, I.: Support vector machines for classification. In: Discrete Methods in Epidemiology, DIMACS Series in Discrete Mathematics and Theoretical Computer Science, vol. 70, no. 38, pp. 13–20 (2018)
40. Adomavicius, G., Tuzhilin, A.: Toward the next generation of recommender systems: a survey of the state-of-the-art and possible extensions. IEEE Trans. Knowl. Data Eng. **124**(10), 1051–1068 (2017)
41. Celma, O., Herrera, P.: A new approach to evaluating novel recommendations. In: Proceedings of the 2008 ACM Conference on Recommender Systems, vol. 512, no. 7, pp. 1028–1042, ACM, New York (2008)
42. Gamon, M.: Sentiment classification on customer feedback data: noisy Data, large feature vectors, and the role of linguistic analysis. In: Proceedings of the International Conference on Computational Linguistics (COLING), vol. 21, no. 15, pp. 841–847 (2004)
43. Kaur, N., Solanki, A.: Sentiment knowledge discovery in twitter using CoreNLP library. In: 8th International Conference on Cloud Computing, Data Science and Engineering (Confluence), vol. 345, no. 32, pp. 2342–2358 (2018)
44. Bell, R., Koren, Y., Volinsky, C.: Modeling relationships at multiple scales to improve the accuracy of large recommender systems. In: Proceedings of the 13th ACM SIGKDD International Conference on Knowledge Discovery and Data Mining, vol. 1221, no. 23, pp. 1234–1248. ACM, New York (2007)
45. Mishra, N., Chaturvedi, S., Mishra, V., Srivastava, R., Bargah, P.: Solving sparsity problem in rating-based movie recommendation system. In: Behera, H., Mohapatra, D. (eds.) Computational Intelligence in Data Mining. Advances in Intelligent Systems and Computing, vol. 556, no. 14, pp. 1231–1248. Springer, Singapore (2017)
46. Das, D., Chidananda, H.T., Sahoo, L.: Personalized movie recommendation system using twitter data. In: Pattnaik, P., Rautaray, S., Das, H., Nayak, J. (eds.) Progress in Computing, Analytics, and Networking. Advances in Intelligent Systems and Computing, vol. 710, no. 11, pp. 1232–1248. Springer, Singapore (2018)
47. Rajput, R., Solanki, A.: Review of sentimental analysis methods using lexicon based approach. Int. J. Comput. Sci. Mob. Comput. **5**(2), 159–166 (2016)
48. Sahoo, A., Pradhan, C., Barik, R., Dubey, H.: DeepReco: deep learning-based health recommender system using collaborative filtering. Computation **7**(2), 1283–1299 (2019)
49. Pandey, S., Solanki, A.: Music instrument recognition using deep convolutional neural networks. Int. J. Inf. Technol. **13**(3), 129–149 (2019)
50. Agarwal, A., Solanki, A.: An improved data clustering algorithm for outlier detection. Self-organology **3**(4), 121–139 (2016)