International Journal on Emerging Technologies **11**(2): 603-609(2020)

ISSN No. (Print): 0975-8364
ISSN No. (Online): 2249-3255

Outfit Selection Recommendation System using Classification Techniques

N. Srinivasa Gupta[1], D. Sai Thanishvi[2] and B. Valarmathi[3]
[1]Associate Professor, Department of Manufacturing, School of Mechanical Engineering,
Vellore Institute of Technology, Vellore (Tamilnadu), India.
[2]M.Tech Integrated (Software Engineering) Student, Department of Software and Systems Engineering,
School of Information Technology and Engineering, Vellore Institute of Technology, Vellore (Tamilnadu), India.
[3]Associate Professor, Department of Software and Systems Engineering,
School of Information Technology and Engineering, Vellore Institute of Technology, Vellore (Tamilnadu), India.

(Corresponding author: B.Valarmathi)
(Received 03 January 2020, Revised 27 February 2020, Accepted 02 March 2020)
(Published by Research Trend, Website: www.researchtrend.net)

ABSTRACT: Recommendation of outfit helps the people in taking the right decision while purchasing and also increases the sales. The analysis of the accuracy of the classified dataset using various data mining techniques and algorithms is the key concept of this paper. The accuracy when the algorithms are applied on the balanced dataset, imbalanced dataset, dataset with attribute reduction and without attribute reduction is compared. To perform the attribute reduction, we are using cfsSubsetEval, consistencySubsetEval and chisquaredAttributeEval. The algorithms that are used to classify the dataset are Random Forest, Naive Bayes, zeroR, Multilayer Perception, RBF Network and AdaboostM1. The main challenge is thatthe virtual dataset is imbalanced through which we got poor results with less accuracies. This dataset is balanced using SMOTE analysis to obtain higher accuracies and also attribute reduction is performed to compare the accuracies obtained. In comparison with the existing method, the maximum accuracy rate produced by the Poonkuzhali Sugumaran and Vinodh Kumar Sukumaran [1] was 98% using hybrid classifier ID3 and AdaBoost algorithms. In the proposed method, the dataset when balanced by SMOTE analysis and classified by Random Forest algorithm, it results in 99.86% of accuracy in recommending the outfit.

Keywords: AdaboostM1, ANN, Data Mining, Multilayer perception, Naive Bayes, Random Forest, RBF Network, SMOTE, ZeroR.

Abbreviations: ANN, Artificial Neural Network;RBF, Radial Basis Function; SMOTE, Synthetic Minority Oversampling Technique; UCI,University of California Irvine.

I. INTRODUCTION

This basic need of every human is a dress. The fashion style and sense are emerging tremendously everywhere in the recent years. There are millions of clothing styles in various ranges of price and quality. Everyone needs the best outfit that suits perfectly out of it. We can recommend the suitable outfit for the users with the help of data mining processes and tools.

Sutar and Khade (2014) proposed a picture or image catching by utilizing HAAR feature for getting body parameters to classify and extract the most ideal outfits from the system by utilizing HIGEN MINER calculation [2]. Akshaya *et al*., (2018) suggested the outfits based on client evaluations by KNN Algorithm [3]. Hank *et al.,* (2018) suggested the some assessments. The assessment demonstrated that the capacity to identify garments and clients in smart fitting room lodges empowers the product recommendation system to produce better suggestions [4]. Bindu and Deepika (2019) proposed the user recommendation system, which employed collaborative and content based filtering to give recommendations [5]. Martin *et al*., (2012) used a linear regression method to predict clothing insulation factors [6]. Lin *et al*., (2019) proposed a neural co-supervision learning framework for improving outfit recommendation [7]. Will Serrano (2019) proposed an intelligent recommender system (IRS) based on the Random Neural Network. IRS goes about as an interface between the client and the diverse Recommender Systems that iteratively adjusts to the apparent client pertinence. Likewise, a significance metric that consolidates both importance and rank is introduced, this measurement is utilized to approve and analyse the presentation of the proposed calculation. IRS beats the Big Data recommender systems subsequent to learning iteratively from its client [8]. Rocha *et al*., (2017) suggested a two primary parts: the user modeling and the dress proposal, which was liable for suggesting style apparel things to ladies. To show the information about body types as well as the information for clothing recommendation, they utilized a set of If-Then rules [9]. Sharma *et al*., (2019) proposed framework structure was planned on the client's biometric profile and historical data of item request or product order. They gathered the client's historical data from a fashion organization managing altered made-to-gauge articles of clothing. The proposed system was based on various data mining methods like clustering, classification and association mining [10]. Wakita *et al*., (2016) proposed a fashion brand suggestion framework utilizing a deep learning technique. This framework improves the probability that a client will discover his/her preferred clothes items. The client should initially decide his/her preferred d fashion brands [11]. Hou *et al*., (2019) initially presented a fine-grained interpretable semantic space. Then they built a Semantic Extraction Network (SEN) and Fine-grained Preferences Attention

(FPA) module to extend clients and things into this space, individually. With SAERS, they were fit for giving material suggestions to clients, yet in addition clarifying the motivation behind why they suggested the fabric through instinctive visual property semantic features in a customized way. Broad examinations led on real world datasets plainly exhibit the adequacy of our methodology contrasted and the best in class strategies [12]. Quanping (2015) used a modified collaborative filtering algorithm attached with fashion attributes like colour, material, style and etc. [13]. Yu *et al.*, (2018) proposed to present the aesthetic data, which is exceptionally significant with client preference, into clothing recommender frameworks. To accomplish this, They first presented the aesthetic features mined by a pre- trained neural network system. Taking into account that the aesthetic preference shifts fundamentally from client to client and by time, they at that point proposed another tensor factorization method to join the aesthetic features in a customized way [14]. Dai (2015) concentrated on the pictures upper body dressing and with human model in the pictures [15]. Chavare *et al.*, (2019) investigated different techniques for deep learning to improve recommendation value of recommender framework. They proposed the collaborative filtering using deep neural network system. This strategy will acquire connection among item and user. At that point the framework will consider over a significant time span relationship of item and user. They emphasised on building start to finish neural systems considering past behaviour. They anticipated the exact recommendation using deep learning [16]. The exhaustive overview of the recommender framework was introduced in this paper. They likewise proposed some potential directions in defeating issues like cold start and absence of rating standards in rating based suggestions, and so on [17].

WEKA is a visualization tool that helps us with data analysis and predictive modelling. It offers user-friendly interface which supports to perform many data mining and visualization techniques.

In the existing method, the drawback was they used the virtual dataset from the UCI Machine Learning Repository without any pre-processing or balancing which might decrease the rate of accuracy. In the proposed method, we performed pre-processing on the virtual dataset using SMOTE analysis and balanced the dataset which increases the rate of accuracy.

The fashion dataset is used in this paper and is divided into different phases. Firstly, the raw data is balanced and then classified using various algorithms. The second phase of the paper is where after pre-processing the data, we perform attribute reduction using various techniques and then classify it. In the next phase, the raw data are directly classified without any pre-processing and attribute reduction. The last phase is where we apply attribute reduction using various techniques to the raw data without pre-processing and then classify the data using different algorithms tocompare the accuracy. Finally, we combine all the phases and analyze the results.

II. METHODS

In this paper, we have four phases in which we analyse theclassification of the dataset and provide the best algorithm and the technique to be followed to achieve highest accuracy. The four phases are balancing data with attribute reduction and then classifying it, balancing data without attribute reduction and classifying it, classifying the imbalanced data with attribute reduction and classifying the imbalanced data without attribute reduction. The techniques and the algorithms used for this process are discussed below.

A. Balancing Data

The dataset is pre-processed and balanced using Synthetic Minority Oversampling Technique (SMOTE) analysis. SMOTE is a statistical technique to balance the data and increase the number of minority cases in the dataset and the percentage of the cases that to be increased can be changed in the module's properties.

B. Attribute Reduction

The attribute selection also known as feature selection is performed and the attributes that have least priority are reduced.

– **cfsSubsetEval:** Correlation-based Feature Selection Evaluator considers degree of redundancy between features and also the predictive ability of each feature and evaluates the attributes and provides us the attributes subset that to be considered.

– **ChisquaredAttributeEval:** The evaluation is performed and the attribute subset is selected considering the class and applying the chi-square test on it.

– **ConsistencySubsetEval:** When it comes to consistency, there is no chance that subset attributes consistency will be less than that of the whole set of attributes. This evaluatorsearches for the subset that is smallest and which has the less consistency that is equal to the consistency of whole set of attributes.

C. Algorithms

To perform the classification of the dataset, we consider some data mining algorithms and neural networks explained below.

– **Random Forest:** It is a supervised classification algorithm developed by Leo Brieman and Adele Cutler. It grows many classification trees and the accuracy is directly proportional to the number of trees. It is often used in scientific work, Banking, Stock market, E-commerce since it runs efficiently on large datasets.

– **Naive Bayes:** It is a supervised machine learning algorithm that works very fast when compared to other algorithms. This algorithm works on Bayes theorem of probability and helps in predicting the class of dataset while it assumes that the feature presence is not related to the other feature. It is used for very large datasets.

– **ZeroR:** It is a simplest classification method which predicts the majority category and is used when there is a need of very basic and low level classification algorithms. This algorithm is purely based on the target value. It constructs a table for the frequencies of the target value and selects the most frequent one.

– **Multilayer Perception:** It is a feed-forward Artificial Neural Network (ANN) which contains at least three layers that includes hidden layer with input and output layers. Since it can differentiate data that is linearly inseparable, it is used in research processes.

– **RBF Network:** Radial Basis Function Network consists of hidden layer along with the input and output layers. In this Artificial Neural Network (ANN), the hidden layer consists of hidden neurons where the Gaussian function is used as an activation function. It is used in classification, time series prediction, function approximation and interpolation.

– **AdaboostM1:** Adaptive boosting is a machine learning meta-algorithm that can be used in conjunction with many other algorithms to increase performance. It is a best out-of-the-box classifier.

D. Framework for the proposed system

The outfit dataset is divided into two categories, one is balanced dataset after applying SMOTE analysis and the second one is the imbalanced dataset. Then on the balanced dataset, we apply attribute reduction and classify the dataset to compare the accuracies. The balanced data without attribute reduction is also classified to compare the accuracies. We apply attribute reduction on the imbalanced dataset and classify it to compare the accuracies. Also theimbalanced dataset is directly classified without any attribute reduction and the accuracies are compared. The framework of this system is shown in detail in Fig. 1.

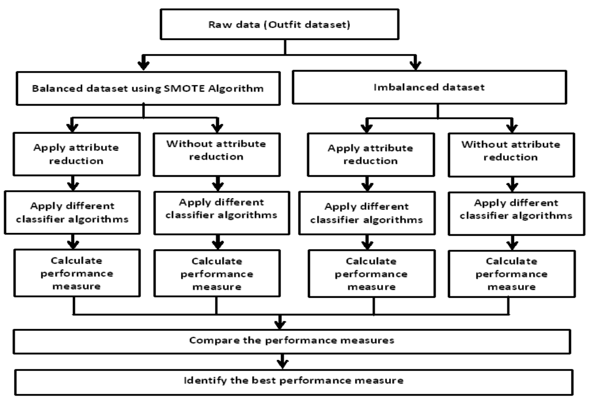

Fig. 1. Framework for the proposed system.

III. RESULTS AND DISCUSSION

In comparison with the existing method, the maximum accuracy rate produced by the Sugumaran and Sukumaran [1] was 98% using hybrid classifier ID3 and AdaBoost algorithms.

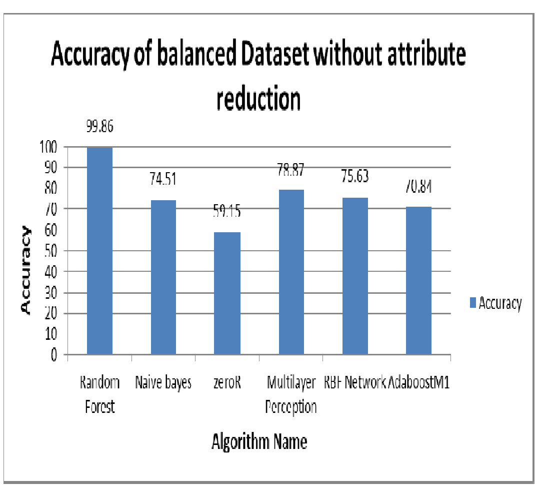

Fig. 2. Accuracy of balanced dataset using SMOTE algorithm without attribute reduction.

The proposed system provides the highest accuracy of 99.86% when the dataset is balanced using SMOTE and then classified using Random Forest algorithm. The analysis is performed and the results are discussed below.

Since we performed pre-processing and balanced the dataset the accuracy we obtained after classifying with Random Forest algorithm is 99.86% whereas classifying the imbalanced dataset with the same Random Forest algorithm gives 99.6%. So, here the accuracy rate increases when we classify the balanced dataset rather than the imbalanced dataset.

A. Balanced data classification without attribute reduction

The dataset is balanced using SMOTE analysis and then classified using six different algorithms and the accuracies are given below in Table 1.

The accuracies are compared when classified with Random Forest, Naive Bayes, ZeroR, Multilayer Perception, RBF Network and AdaboostM1.

Among all these, the highest accuracy of 99.86% is achieved when the dataset is balanced using SMOTE and then classified using Random Forest algorithm.

The accuracy of the balanced dataset using SMOTE algorithm without attribute reduction is represented in the form of bar graph where the x-axis represents the algorithm name and the y-axis represents the accuracies of the respective algorithms as shown in Fig. 2 in which random forest gives the highest accuracy of 99.86%.

Table 1: Accuracy of balanced dataset using SMOTE algorithm without attribute reduction.

S.No.	Balancing technique	Algorithm	Accuracy
1.	SMOTE	Random Forest	99.86%
2.		Naive Bayes	74.51%
3.		zeroR	59.15%
4.		Multilayer Perception	78.87%
5.		RBF Network	75.63%
6.		AdaboostM1	70.84%

B. Balanced data classification with Attribute reduction

The dataset is balanced using SMOTE analysis and the attribute selection is performed using cfsSubsetEval, ChisquaredAttributeEval and classifierSubsetEval. The accuracies are compared after classifying the dataset using six different algorithms Random Forest, Naive Bayes, ZeroR, Multilayer Perception, RBF Network and AdaboostM1 as shown in the Table 2, 3, 4.

Table 2: Accuracy of balanced dataset using SMOTE algorithm and with attribute reduction using cfsSubsetEval.

S.No.	Algorithm	Accuracy
1.	Random Forest	86.46%
2.	Naive Bayes	54.30%
3.	zeroR	44.57%
4.	Multilayer Perception	84.20%
5.	RBF Network	60.65%
6.	AdaboostM1	44.08%

Table 3: Accuracy of balanced dataset using SMOTE algorithm and with attribute reduction using consistencySubsetEval.

S.No.	Algorithm	Accuracy
1.	Random Forest	94.22%
2.	Naive bayes	58.67%
3.	zeroR	44.57%
4.	Multilayer Perception	91.11%
5.	RBF Network	64.31%
6.	AdaboostM1	49.08%

Among these, the highest accuracy of 99.72% is achieved when the dataset is balanced using SMOTE and the chisquaredAttributeEval is used to reduce the attributes and the Random Forest to classify the dataset as shown in the Table 4.

Table 4: Accuracy of balanced data using SMOTE algorithm and with attribute reduction using ChisquaredAttributeEval.

S.No.	Algorithm	Accuracy
1.	Random Forest	99.72%
2.	Naive Bayes	60.08%
3.	zeroR	44.57%
4.	Multilayer Perception	67.98%
5.	RBF Network	68.12%
6.	AdaboostM1	49.08%

The accuracy of the balanced dataset using SMOTE technique with attribute reduction using cfsSubsetEval is represented in the form of bar graph where the x-axis represents the algorithm name and y-axis represents the accuracy of the respective algorithms as shown in Fig. 3 in which Random forest algorithm has the highest accuracy of 86.46%.

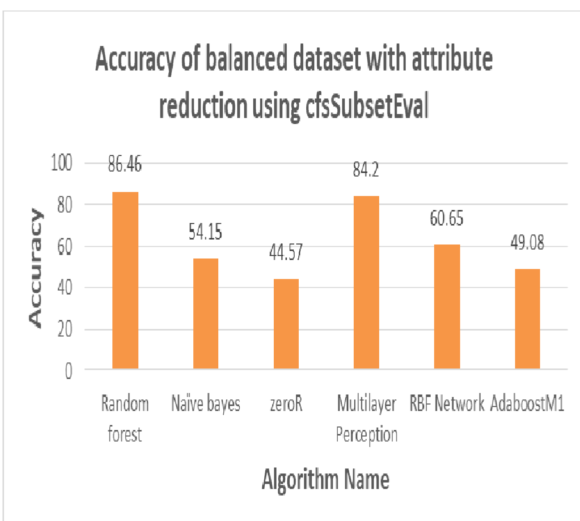

Fig. 3. Accuracy of balanced dataset using SMOTE algorithm and with attribute reduction using cfsSubsetEval.

The accuracy of the balanced dataset using SMOTE technique with attribute reduction using consistencySubsetEval is represented in the form of bar graph where the x-axis represents the algorithm name and y-axis represents the accuracy of the respective algorithms as shown in Fig. 4 in which Random forest algorithm has the highest accuracy of 94.22%.

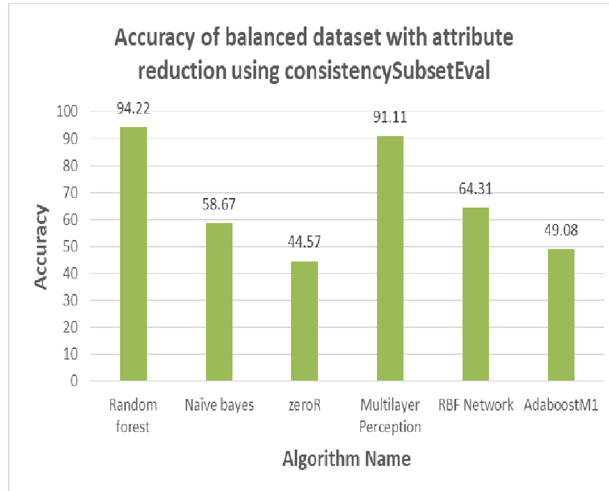

Fig. 4. Accuracy of balanced dataset using SMOTE algorithm and with attribute reduction using consistencySubsetEval.

The accuracy of the balanced dataset using SMOTE technique with attribute reduction using Chi-squared attribute evaluator is represented in the form of bar graph where the x-axis represents the algorithm name and y-axis represents the accuracy of the respective algorithms as shown in Fig. 5 in which Random forest algorithm has the highest accuracy of 99.72%.

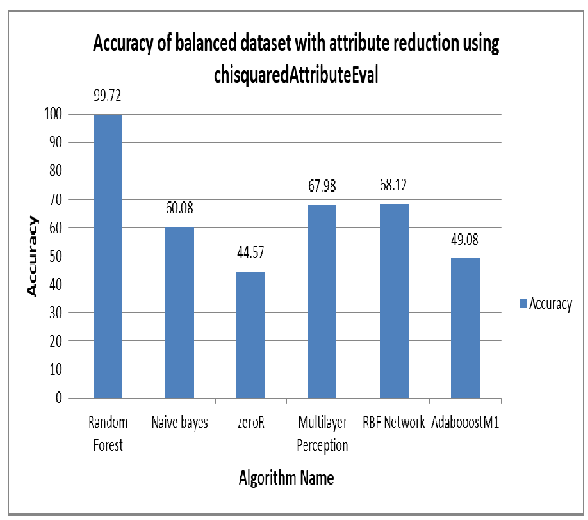

Fig. 5. Accuracy of balanced dataset using SMOTE algorithm and with attribute reduction using chisquaredAttributeEval.

After balancing the dataset using SMOTE technique, attribute reduction using cfsSubsetEval, consistency SubsetEval and chisquaredAttributeEval is performed and then six classification algorithms are applied on the dataset and the accuracies are compared as shown in the Table 5.

Table 5: Comparison of accuracies of balanced dataset with attribute reduction using cfsSubsetEval, consistencySubsetEval and chisquaredAttribute Eval.

S.No.	Algorithm	Accuracy using cfsSubsetEval	Accuracy using consistencySubsetEval	Accuracy using chisquaredAttributeEval
1.	Random Forest	86.46%	94.22%	99.72%
2.	Naïve Bayes	54.30%	58.67%	60.08%
3.	zeroR	44.57%	44.57%	44.57%
4.	Multilayer Perception	84.2%	91.11%	67.98%
5.	RBF Network	60.65%	64.31%	68.12%
6.	AdaboostM1	44.08%	49.08%	49.08%

The comparison of accuracies that are obtained when the dataset is classified after balancing using SMOTE technique and then attribute reduction using cfsSubsetEval, consistencySubsetEval and chisquaredAttributeEval is represented in the form of bar graph where the x-axis represents the algorithm name and y-axis represents the accuracies as shown in Fig. 6 in which Random forest algorithm classification and chisquaredAttributeEval gives highest accuracy of 99.72%.

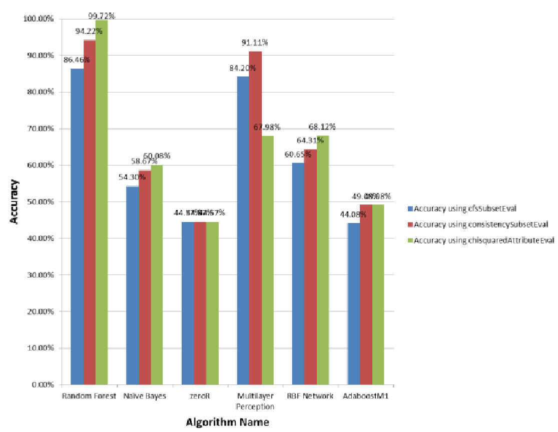

Fig. 6. Comparison of accuracies of balanced dataset with attribute reduction using cfsSubsetEval, consistencySubsetEval and chisquaredAttributeEval.

C. Imbalanced data Classification without attribute reduction

The dataset downloaded from the UCI repository is directly classified without any pre-processing or attribute selection and the accuracies are compared as given below in Table 6.

Among these, the highest accuracy of 99.6% is achieved when the dataset is classified using Random Forest algorithm.

Table 6: Accuracy of imbalanced dataset without attribute reduction.

S. No.	Algorithm	Accuracy
1.	Random Forest	99.6%
2.	Naive bayes	72.6%
3.	zeroR	58%
4.	Multilayer Perception	76%
5.	RBF Network	71.2%
6.	AdaboostM1	64.6%

The accuracy of the imbalanced dataset is represented in the form of bar graph where x-axis represents algorithm name and y-axis represents accuracy obtained with the respective algorithm as shown in Fig. 7 where the random forest algorithm gives highest accuracy of 99.6%.

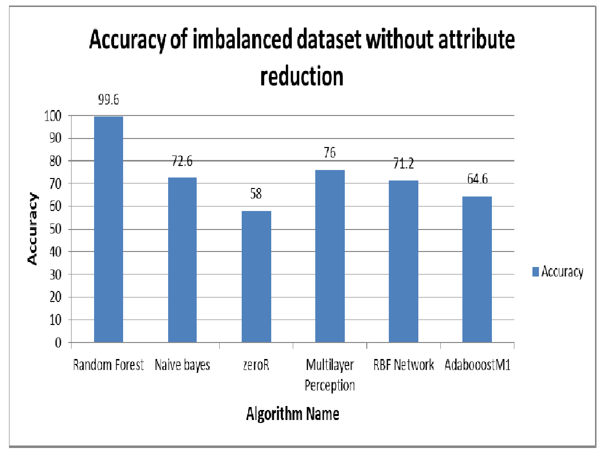

Fig. 7. Accuracy of imbalanced dataset without attribute reduction.

D. Imbalanced data classification with attribute reduction

Attribute selection is performed on the dataset using the techniques cfsSubsetEval, ChisquaredAttributeEval, classifierSubsetEval and then classified using six different algorithms like Random Forest, Naive bayes, ZeroR, Multilayer Perception, RBF Network and AdaboostM1 as shown in Table 7, 8, 9.

Table 7: Accuracy of the imbalanced dataset with attribute reduction using cfsSubsetEval.

S. No.	Algorithm	Accuracy
1.	Random Forest	95.19%
2.	Naive bayes	54.51%
3.	zeroR	40.68%
4.	Multilayer Perception	87.57%
5.	RBF Network	64.6%
6.	AdaboostM1	46.89%

Table 8: Accuracy of imbalanced dataset with attribute reduction using consistencySubsetEval.

S. No.	Algorithm	Accuracy
1.	Random Forest	98.2%
2.	Naive Bayes	58.72%
3.	zeroR	40.68%
4.	Multilayer Perception	93.78%
5.	RBF Network	67.13%
6.	AdaboostM1	46.89%

Among these, the highest accuracy of 99.59% is achieved when the attribute reduction is performed on the dataset using chisquaredAttributeEval and then classified using Random Forest algorithm as shown in the Table 9.

Table 9: Accuracy of imbalanced dataset with attribute reduction using chisquaredAttributeEval.

S. No	Algorithm	Accuracy
1.	Random Forest	99.59%
2.	Naive bayes	59.32%
3.	zeroR	40.68%
4.	Multilayer Perception	95.79%
5.	RBF Network	72.14%
6.	AdaboostM1	46.89%

The accuracy of the imbalanced dataset with attribute reduction using cfsSubsetEval is represented in the form of bar graph where x-axis represents algorithm name and y-axis represents accuracy obtained with the respective algorithm as shown in Fig. 8 where random forest algorithm gives the highest accuracy of 95.19%. The accuracy of the imbalanced dataset with attribute eduction using consistencySubsetEval is represented in the form of bar graph where x-axis represents algorithm name and y-axis represents accuracy as shown in Fig. 9 where random forest algorithm gives the highest accuracy of 98.2%. The accuracy of the imbalanced dataset with attribute reduction using chi-squared attribute evaluator is represented in the form of bar graph where x-axis represents algorithm name and y-axis represents accuracy obtained with the respective algorithm as shown in Fig. 10 where random forest algorithm gives the highest accuracy of 99.59%.

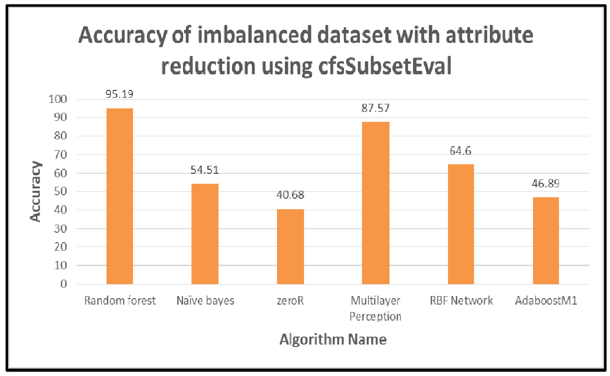

Fig. 8. Accuracy of imbalanced dataset with attribute reduction using cfsSubsetEval.

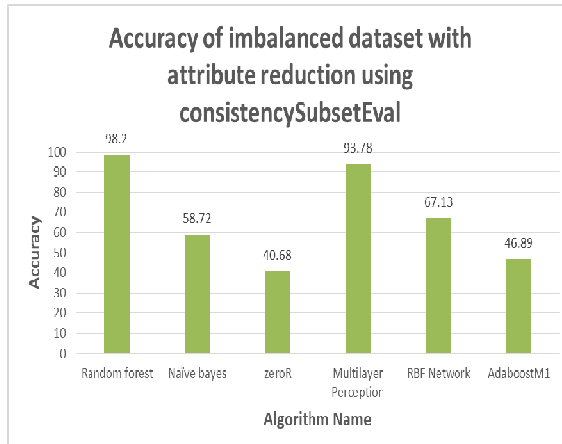

Fig. 9. Accuracy of imbalanced dataset with attribute reduction using consistencySubsetEval.

Table 10: Comparison of accuracies of imbalanced dataset with attribute reduction using cfsSubsetEval, consistencySubsetEval and chisquaredAttributeEval.

S. No.	Algorithm	Accuracy using cfsSubsetEval	Accuracy using consistencySubsetEval	Accuracy using chisquaredAttributeEval
1.	Random Forest	95.19%	98.2%	99.59%
2.	Naïve Bayes	54.51%	58.72%	59.32%
3.	zeroR	40.68%	40.68%	40.68%
4.	Multilayer Perception	87.57%	93.78%	95.79%
5.	RBF Network	64.6%	67.13%	72.14%
6.	AdaboostM1	46.89%	46.89%	46.89%

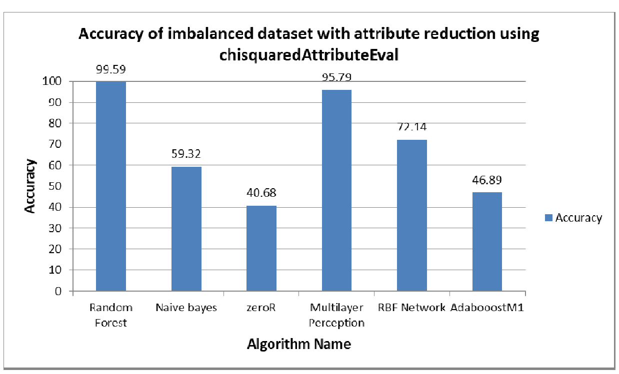

Fig. 10. Accuracy of imbalanced dataset with attribute reduction using chisquaredAttributeEval.

For the imbalanced dataset, attribute reduction using cfsSubsetEval, consistencySubsetEval and chisquaredAttributeEval is performed and then six classification algorithms are applied on the dataset and the accuracies are compared as shown in the Table 10. The comparison of accuracies that are obtained when the dataset is classified after performing attribute reduction using cfsSubsetEval, consistencySubsetEval and chisquaredAttributeEval is represented in the form of bar graph where the x-axis represents the algorithm name and y-axis represents the accuracies as shown in Fig. 11 in which Random forest algorithm classification and chisquaredAttributeEval gives highest accuracy of 99.59%.

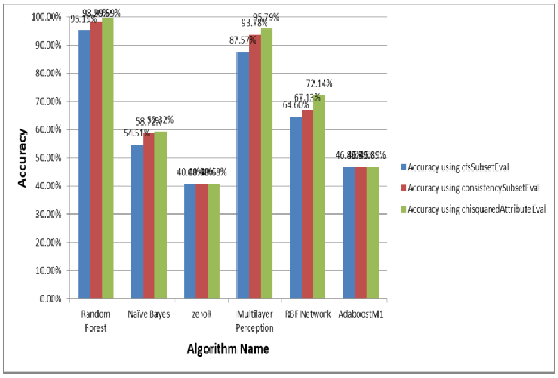

Fig. 11. Comparison of accuracies of imbalanced dataset with attribute reduction using cfsSubsetEval, consistencySubsetEval and chisquaredAttributeEval.

IV. CONCLUSION

Many researches were done on recommending the outfit with various algorithms but there is lack in providing the best method to continue this process of recommending and hence we used different algorithms to classify the dataset by applying some techniques on itand compared all the accuracies to provide the best method. The highest accuracy is found when the dataset is balanced using SMOTE analysis and then classified using Random Forest algorithm which is 99.86%. On an average, the Random Forest algorithm andthe chisquaredAttributeEval have the highest accuracy rate. Hence, it is recommended to use the Random Forest algorithm to classify this dataset and chisquaredAttributeEval for the attribute reduction according to our research. Also this research highly recommends to make the dataset balanced before classifying it. This research might help in selecting the algorithms and other techniques while performing any type of classification.

V. FUTURE SCOPE

In future, we would also like to work on more concepts and will try to provide more information about this recommendation system. We like to explore the system using fuzzy logic and genetic algorithms and study more about it.

Conflict of Interest. There is no conflict of interest involving the content enlisted in the given paper.

REFERENCES

[1]. Sugumaran, P., & Sukumaran, V. (2019). Recommendations to improve dead stock management in garment industry using data analytics. *Mathematical biosciences and engineering: MBE*, *16*(6), 8121-8133.

[2]. Sutar, S. H., & Khade, A. H. (2014). Recommendation System for Outfit Selection (RSOS). *arXiv preprint arXiv:1402.6692*, 1-6.

[3]. Akshaya, S. O., Kamali, P. & Sudha, P. (2018). Outfit Recommendation System using KNN Algorithm. *International Journal of Engineering Research and Technology (IJERT), 6*(7), 1-4.

[4]. Hanke, J., Hauser, M., Dürr, A., & Thiesse, F. (2018). Redefining the Offline Retail Experience: Designing Product Recommendation Systems for Fashion Stores, 1-14.

[5]. Bindu, V. S., & Deepika, V. (2019). Data Mining based Recommendation System in Social Networking. *International Journal of Research in Engineering, 2*(1), 113-115.

[6]. Martin, M., Jeyasingh., Kumaravel, Appavoo. & Sakthivel, P. (2012). Data Mining for Prediction of Clothing Insulation. *International Journal of Modern Engineering Research (IJMER)*, *2*(2), 1-5.

[7]. Lin, Y., Ren, P., Chen, Z., Ren, Z., Ma, J., & de Rijke, M. (2019). Improving outfit recommendation with co-supervision of fashion generation. In *The World Wide Web Conference*, 1095-1105.

[8]. Serrano, W. (2019). Intelligent Recommender System for Big Data Applications Based on the Random Neural Network. *Big Data and Cognitive Computing*, *3*(1), 1-29.

[9]. Rocha, H. J. B., de Barros Costa, E., Silva, E. T., Lima, N. C., & Cavalcanti, J. (2017). A Knowledge-based Approach for Personalised Clothing Recommendation for Women. In *ICEIS, 1,* 610-617.

[10]. Sharma, S., Koehl, L., Bruniaux, P., & Zeng, X. (2019). Customized Garment Fashion Recommendation System using Data Mining Techniques. *Computer Science and Information Technology (CS & IT),* 373-385.

[11]. Wakita, Y., Oku, K., & Kawagoe, K. (2016). Toward fashion-brand recommendation systems using deep-learning: preliminary analysis. *Int J Konwl Eng*, *2*(3), 128-131.

[12]. Hou, M., Wu, L., Chen, E., Li, Z., Zheng, V. W., & Liu, Q. (2019). Explainable fashion recommendation: a semantic attribute region guided approach. Proceedings of the *Twenty-Eighth International Joint Conference on Artificial Intelligence (IJCAI),* 1-8.

[13]. Quanping, H. (2015). Analysis of collaborative filtering algorithm fused with fashion attributes. *International Journal of u-and e-Service, Science and Technology*, *8*(10), 159-168.

[14]. Yu, W., Zhang, H., He, X., Chen, X., Xiong, L., & Qin, Z. (2018). Aesthetic-based clothing recommendation. In *Proceedings of the 2018 World Wide Web Conference*, 649-658.

[15]. Dai, W. (2015). Clothing Fashion Style Recommendation System. A Thesis Presented to Department of Electrical and Computer Engineering in North-eastern University of Boston.

[16]. Chavare, S., Awati, C. J., Deshmukh, R. J., Patil, S. S., & Kolekar, A. B. (2019). A Review on Smart deep Learning for Recommendation System. *International Journal of Scientific and Technology Research, 8*(9), 1529-1532.

[17]. Sohail, S. S., Siddiqui, J., & Ali, R. (2017). Classifications of Recommender Systems: A review. *Journal of Engineering Science & Technology Review*, *10*(4), 132-153.

How to cite this article: Gupta, S. N., Thanishvi, D. S. and Valarmathi, B. (2020). Outfit Selection Recommendation System using Classification Techniques. *International Journal on Emerging Technologies*, *11*(2): 603–609.