Turkish Online Journal of Qualitative Inquiry (TOJQI)
Volume 12, Issue 6, July, 2021: 7716-7729

Research Article

Cross Validation Component Based Reduction for Divorce Rate Prediction

M. Shyamala Devi[1*], D.Umanandhini[2], A. Peter Soosai Anandaraj[3], S. Sridevi[4]

Abstract

Concurring to information from the Centres for Illness Control and Anticipation, instruction and religion are both capable indicators of lasting or dissolving unions. The chance of a marriage finishing in separate was lower for individuals with more knowledge, with over half of relational unions of those who did not complete high school having finished in separate compared with roughly 30 percent of relational unions of college graduates. With this overview, the divorce rate dataset from UCI dataset repository is used for predicting the divorce class target with the following contributions. Firstly, the Divorce rate dataset is subjected with the data cleaning and exploratory data analysis. Secondly, the data set is settled with different classifiers to look at the classification before and after feature scaling. Thirdly, the dataset is processed with various cross validation of training and testing dataset i.e 80:20, 30:70, 40:60, 50:50 to improve the accuracy of all the classifiers. Fourth, the dataset is processed with 15, 20 and 30 components of principal component analysis and then applied with all classifier algorithm to analyze the accuracy of divorce rate prediction. Fifth, the performance analysis is done with precision, recall, accuracy, fscore and running time to infer the classification before and after feature scaling. Experimental results show that the Random Forest classifier is found to have the accuracy of 98% for all PCA reduced dataset with 15, 20 and 30 components. The result shows that Random Forest classifier is found to have the accuracy of 98% for 40:60, 50:50 of training and testing dataset.

Keywords: *Machine learning, scaling, precision, accuracy, classification, crossvalidation*

[1,2,3,4]Department of Computer Science & Engineering, Vel Tech Rangarajan Dr. Sagunthala R&D Institute of Science and Technology.

Email: shyamaladevim@veltech.edu.in

Introduction

When we are dealing with the relationship between man and woman, one of them is marriage. Great connections does not occur directly within a day. They take involvement, dedication, absolution and most of all the exertion. The current period, in arrange to preserve a great relationship ended up more challenging. In decades of logical inquire about into cherish, closeness and connections have instructed us that a number of behaviors can anticipate when a few is on strong ground or headed for serious troubles. Couples that wed later tend to have connections that final longer. The prior the couple gets together, the more noteworthy the chance of afterward separate. Interests, that holds in case couples move in together whereas they're more youthful (as in adolescent a long time), as well. There are numerous ranges of closeness that can improve a marriage/relationship, offer assistance it to stay solid and offer assistance it to induce back on track when it has ended up far off and troublesome.

Related works

Background

The investigate strategy utilized in this paper is to begin with calculating the forecast precision of the SVM calculation by tuning its hyperparameter (C and bit values). Sometime recently calculating the expectation exactness, Correlation-based include choice, that was executed on the dataset to get the foremost critical qualities. Information investigation was performed utilizing devices broadly utilized in machine learning or information mining[1]. This paper explores about that data mining strategies is applied on the separate information set, it was watched that the foremost fruitful result is gotten with ANN model connected at the side correlation-based highlight choice[2]. This paper predicts the number of marriages and the unemployment rate, the medium age at marriage and the education level index using divorce rate prediction using data mining techniques. In this paper, an application of data mining techniques is presented so as to highlight the opportunity of using these methods in the field of demography and social statistics, with the final goal of predicting the divorce rate for a certain year at district level[3]. In this paper, Students' key statistic characteristics and their marks on many composed assignments can constitute the preparing set for a directed machine learning calculation[4].

Machine learning, in specific, can foresee patients' survival from their information and can individuate the foremost critical highlights among those included in their therapeutic records. In this paper, both highlight positioning approaches clearly recognize serum creatinine and launch division as the two most pertinent highlights, that point construct the machine learning survival expectation models on these two components alone[5]. In this paper, they have utilized imperative highlights by expelling the repetitive highlights that don't contribute to the forecast by utilizing optimized machine learning calculation (PSO) for the standard information set accessible to anticipate the separate rate[6]. This paper foresee whether one or two is aiming to get separated or not. The feature weights are initialized with arbitrary numbers, at that point after validation, the weights are balanced based on approval[7].The common objective of this paper is to construct a show that anticipate the likelihood of separate particularly separate of the populace within the data mining technologies. Half breed demonstrate is made by combining solid characteristics created based on the CRISP-DM demonstrate by embracing it to scholarly research The result of this dataset demonstrates that applying information mining to classify occasions to anticipate the likelihood of separate is exceptionally efficient[8]. Dataset is taken from the stock information of a specific company named Infratel. The information set contains data like past closing, opening, tall, moo, and volume of the stocks of that company. ANN is very able of securing the unexpected and unheralded changes taken note in framework since as it were one specific window is conveyed for foreseeing the coming occurrence[9]. This paper propose the information mining procedures for classification and foreseeing in social science issue through authoritative records. Results: ROC bend and the Area under Curve (AUC) accomplished 60%, esteem affirm the great precision model[10].

Proposed Work

The main contribution of this paper is to perform analysis of the dataset accuracy with different levels of cross validation and the dimensionality reduction through feature extraction methods [11]. The overall architecture of this paper is shown in Figure.1. The divorce rate classification is predicted using machine learning algorithms with the following contributions.

(i) Firstly, the Divorce rate dataset is subjected with the data cleaning and exploratory data analysis.

(ii) Secondly, the data set is settled with different classifiers to look at the classification before and after feature scaling.

(iii) Thirdly, the dataset is processed with various cross validation of training and testing dataset i.e 80:20, 30:70, 40:60, 50:50 to improve the accuracy of all the classifiers.

(iv) Fourth, the dataset is processed with 15, 20 and 30 components of principal component analysis and then applied with all classifier algorithm to analyze the accuracy of divorce rate prediction.

(v) Fifth, the performance analysis is done with precision, recall, accuracy, fscore and running time to infer the classification before and after feature scaling

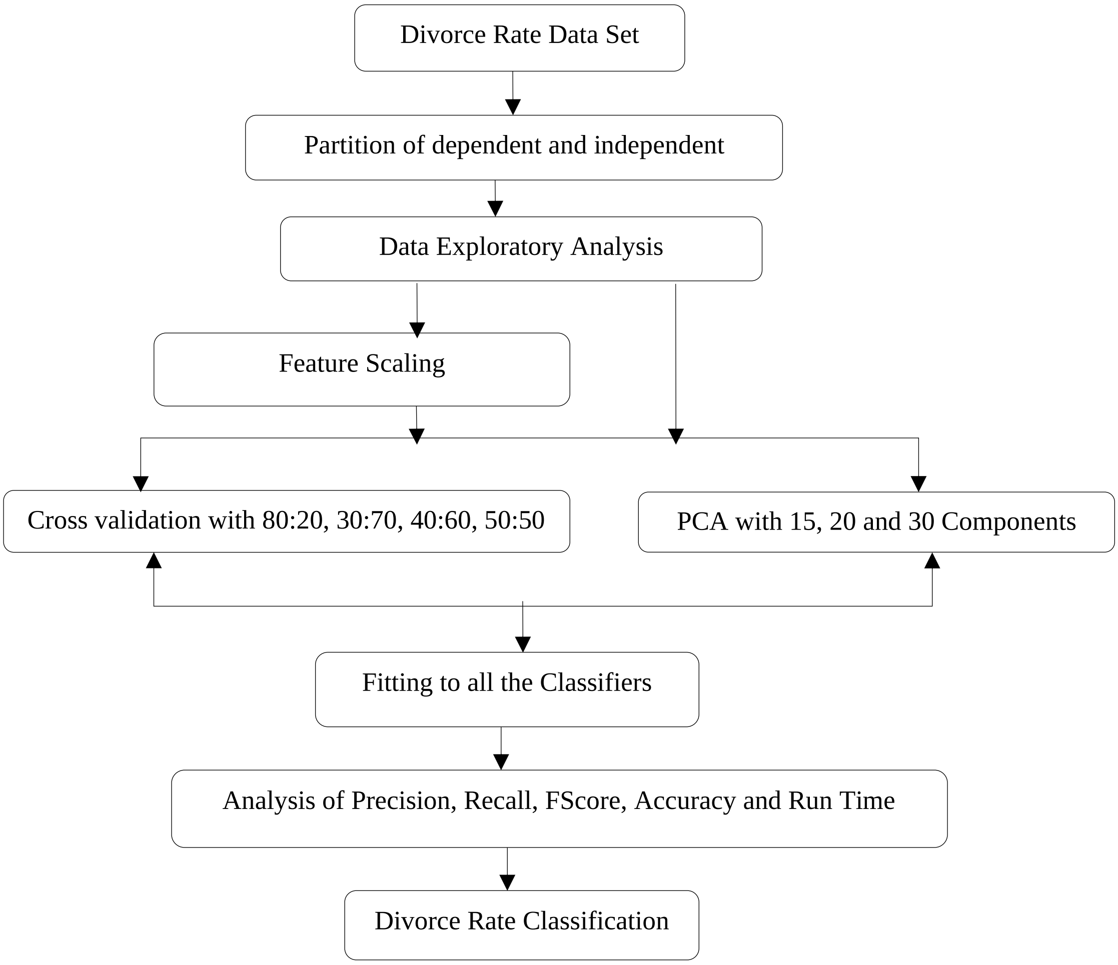

Figure 1. Overall Workflow of the system

Exploratory Data Analysis

The divorce rate dataset from UCI dataset repository is used for predicting the divorce rate class target[12]. The dataset have 170 records with 54 attributes and 1 target attribute and is shown in Figure. 2. The python scripting language is coded in Spyder editor with Anaconda navigator for execution[13]. The dataset correlation and target class distribution is shown in Figure. 3.

1. When one of our apologies apologizes when our discussions go in a bad direction, the issue does not extend.
2. I know we can ignore our differences, even if things get hard sometimes.
3. When we need it, we can take our discussions with my wife from the beginning and correct it.
4. When I argue with my wife, it will eventually work for me to contact him.
5. The time I spent with my wife is special for us.
6. We don't have time at home as partners.
7. We are like two strangers who share the same environment at home rather than family.
8. I enjoy our holidays with my wife.
9. I enjoy traveling with my wife.
10. My wife and most of our goals are common.
11. I think that one day in the future, when I look back, I see that my wife and I are in harmony with each other.
12. My wife and I have similar values in terms of personal freedom.
13. My husband and I have similar entertainment.
14. Most of our goals for people (children, friends, etc.) are the same.
15. Our dreams of living with my wife are similar and harmonious
16. We're compatible with my wife about what love should be
17. We share the same views with my wife about being happy in your life
18. My wife and I have similar ideas about how marriage should be
19. My wife and I have similar ideas about how roles should be in marriage
20. My wife and I have similar values in trust
21. I know exactly what my wife likes.
22. I know how my wife wants to be taken care of when she's sick.
23. I know my wife's favorite food.
24. I can tell you what kind of stress my wife is facing in her life.
25. I have knowledge of my wife's inner world.
26. I know my wife's basic concerns.
27. I know what my wife's current sources of stress are.
28. I know my wife's hopes and wishes.
29. I know my wife very well.
30. I know my wife's friends and their social relationships.
31. I feel aggressive when I argue with my wife.
32. When discussing with my wife, I usually use expressions such as you always or you never
33. I can use negative statements about my wife's personality during our discussions.
34. I can use offensive expressions during our discussions.
35. I can insult our discussions.
36. I can be humiliating when we argue.
37. My argument with my wife is not calm.
38. I hate my wife's way of bringing it up.
39. Fights often occur suddenly.
40. We're just starting a fight before I know what's going on.
41. When I talk to my wife about something, my calm suddenly breaks.
42. When I argue with my wife, it only snaps in and I don't say a word.
43. I'm mostly thirsty to calm the environment a little bit.
44. Sometimes I think it's good for me to leave home for a while.
45. I'd rather stay silent than argue with my wife.
46. Even if I'm right in the argument, I'm thirsty not to upset the other side.
47. When I argue with my wife, I remain silent because I am afraid of not being able to control my anger.
48. I feel right in our discussions.
49. I have nothing to do with what I've been accused of.
50. I'm not actually the one who's guilty about what I'm accused of.
51. I'm not the one who's wrong about problems at home.
52. I wouldn't hesitate to tell her about my wife's inadequacy.
53. When I discuss it, I remind her of my wife's inadequate issues.
54. I'm not afraid to tell her about my wife's incompetence.

Figure 2. Target Attribute Details of the Divorce Dataset

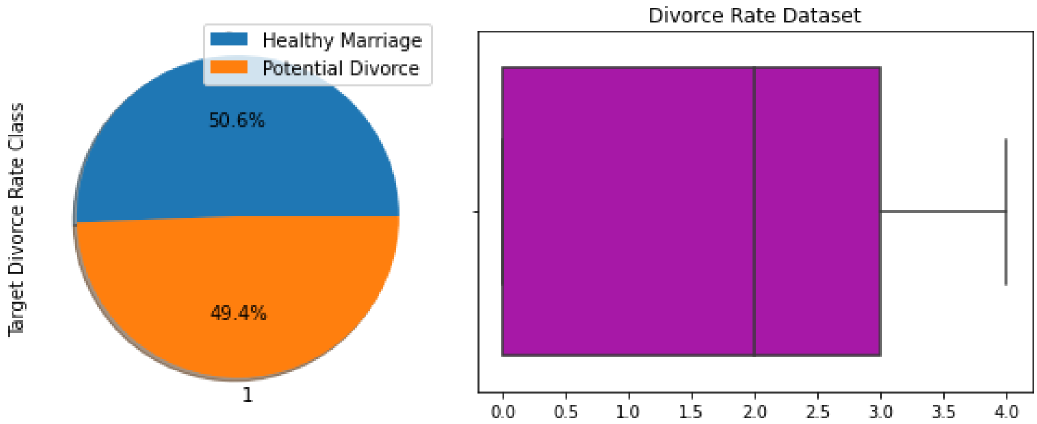

Figure 3. Target Feature Analysis of Dataset

Implementation and Discussions

The data set is splitted with 80:20 training and testing dataset and is settled with different classifiers to look at the classification before and after scaling [14] and is shown in Figure. 4. And Table. 1.

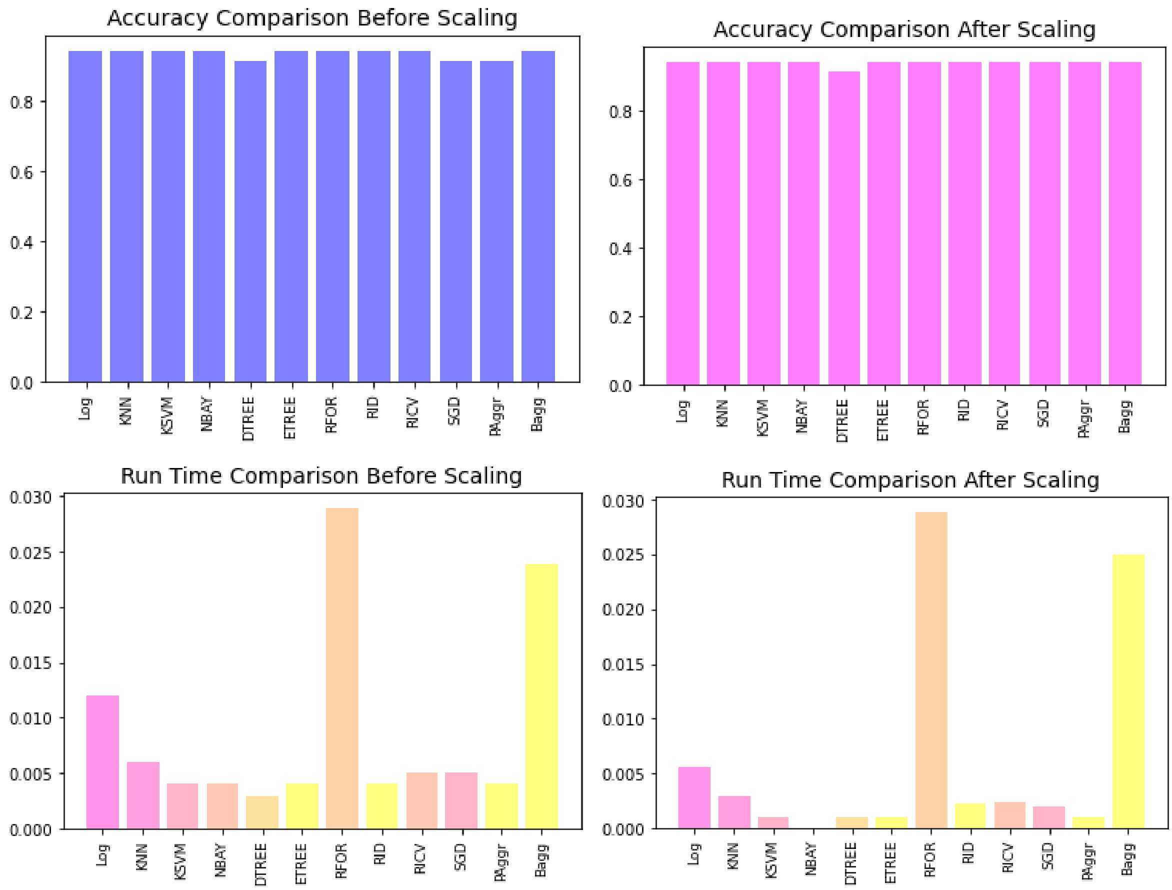

Figure 4. Performance Metrics for Raw Dataset before and after Feature scaling for 80:20

Table 1

Performance Indices for 80:20 splitting before and after Feature Scaling

Classifier	Before Feature Scaling					After Feature Scaling				
	Precision	Rcall	FScore	Accuracy	RunTime	Precision	Recall	FScore	Accuracy	RunTime
LReg	0.95	0.94	0.94	0.94	0.01	0.95	0.94	0.94	0.94	0.01
KNN	0.95	0.94	0.94	0.94	0.01	0.95	0.94	0.94	0.94	0.00
KSVM	0.95	0.94	0.94	0.94	0.00	0.95	0.94	0.94	0.94	0.00
GNB	0.95	0.94	0.94	0.94	0.00	0.95	0.94	0.94	0.94	0.00
Dtree	0.91	0.91	0.91	0.91	0.00	0.91	0.91	0.91	0.91	0.00
Etree	0.95	0.94	0.94	0.94	0.00	0.95	0.94	0.94	0.94	0.00
RFor	0.95	0.94	0.94	0.94	0.03	0.95	0.94	0.94	0.94	0.03
Ridge	0.95	0.94	0.94	0.94	0.00	0.95	0.94	0.94	0.94	0.00
RCV	0.95	0.94	0.94	0.94	0.00	0.95	0.94	0.94	0.94	0.00
SGD	0.91	0.91	0.91	0.91	0.01	0.95	0.94	0.94	0.94	0.00
PAg	0.91	0.91	0.91	0.91	0.00	0.95	0.94	0.94	0.94	0.00
Bagg	0.95	0.94	0.94	0.94	0.02	0.95	0.94	0.94	0.94	0.02

The data set is splitted with 30:70 training and testing dataset and is settled with different classifiers to look at the classification before and after feature scaling [15] and is shown in Figure. 5. and Table. 2.

Table 2

Performance Indices for 70:30 splitting before and after Feature Scaling

Classifier	Before Feature Scaling					After Feature Scaling				
	Precision	Rcall	FScore	Accuracy	RunTime	Precision	Recall	FScore	Accuracy	RunTime
LReg	0.96	0.96	0.96	0.96	0.02	0.96	0.96	0.96	0.96	0.01
KNN	0.96	0.96	0.96	0.96	0.01	0.96	0.96	0.96	0.96	0.00
KSVM	0.96	0.96	0.96	0.96	0.00	0.96	0.96	0.96	0.96	0.00
GNB	0.94	0.94	0.94	0.94	0.00	0.94	0.94	0.94	0.94	0.00
Dtree	0.92	0.92	0.92	0.92	0.00	0.92	0.92	0.92	0.92	0.00
Etree	0.96	0.96	0.96	0.96	0.00	0.96	0.96	0.96	0.96	0.00
RFor	0.96	0.96	0.96	0.96	0.03	0.96	0.96	0.96	0.96	0.03
Ridge	0.96	0.96	0.96	0.96	0.00	0.96	0.96	0.96	0.96	0.00
RCV	0.96	0.96	0.96	0.96	0.01	0.96	0.96	0.96	0.96	0.00
SGD	0.93	0.92	0.92	0.92	0.01	0.94	0.94	0.94	0.94	0.00
PAg	0.94	0.94	0.94	0.94	0.00	0.96	0.96	0.96	0.96	0.00
Bagg	0.96	0.96	0.96	0.96	0.03	0.96	0.96	0.96	0.96	0.03

Figure 5. Performance Metrics for Raw Dataset before and after Feature scaling for 70:30

The data set is splitted with 40:60 training and testing dataset and is settled with different classifiers to look at the classification before and after feature scaling [16] and is shown in Figure. 6. and Table. 3.

Table 3

Performance Indices for 60:40 splitting before and after Feature Scaling

Classifier	Before Feature Scaling					After Feature Scaling				
	Precision	Rcall	FScore	Accuracy	RunTime	Precision	Recall	FScore	Accuracy	RunTime
LReg	0.97	0.97	0.97	0.97	0.01	0.97	0.97	0.97	0.97	0.01
KNN	0.97	0.97	0.97	0.97	0.01	0.97	0.97	0.97	0.97	0.00
KSVM	0.97	0.97	0.97	0.97	0.00	0.97	0.97	0.97	0.97	0.00
GNB	0.96	0.96	0.96	0.96	0.00	0.96	0.96	0.96	0.96	0.00
Dtree	0.94	0.94	0.94	0.94	0.00	0.94	0.94	0.94	0.94	0.00
Etree	0.94	0.94	0.94	0.94	0.00	0.94	0.94	0.94	0.94	0.00
RFor	0.97	0.97	0.97	0.97	0.03	0.97	0.97	0.97	0.97	0.03
Ridge	0.97	0.97	0.97	0.97	0.00	0.97	0.97	0.97	0.97	0.00
RCV	0.97	0.97	0.97	0.97	0.00	0.97	0.97	0.97	0.97	0.00
SGD	0.91	0.91	0.91	0.91	0.00	0.96	0.96	0.96	0.96	0.00
PAg	0.94	0.94	0.94	0.94	0.00	0.97	0.97	0.97	0.97	0.00
Bagg	0.97	0.97	0.97	0.97	0.03	0.94	0.94	0.94	0.94	0.03

Figure 6. Performance Metrics for Raw Dataset before and after Feature scaling for 60:40

The data set is splitted with 50:50 training and testing dataset and is settled with different classifiers to look at the classification before and after feature scaling[17] and is shown in Figure. 7. And Table. 4.

Table 4

Performance Indices for 50:50 splitting before and after Feature Scaling

Classifier	Before Feature Scaling					After Feature Scaling				
	Precision	Rcall	FScore	Accuracy	RunTime	Precision	Recall	FScore	Accuracy	RunTime
LReg	0.98	0.98	0.98	0.98	0.02	0.98	0.98	0.98	0.98	0.00
KNN	0.98	0.98	0.98	0.98	0.02	0.98	0.98	0.98	0.98	0.00
KSVM	0.98	0.98	0.98	0.98	0.00	0.98	0.98	0.98	0.98	0.00
GNB	0.96	0.96	0.96	0.96	0.02	0.96	0.96	0.96	0.96	0.00
Dtree	0.95	0.95	0.95	0.95	0.00	0.95	0.95	0.95	0.95	0.00
Etree	0.95	0.95	0.95	0.95	0.00	0.95	0.95	0.95	0.95	0.00
RFor	0.98	0.98	0.98	0.98	0.03	0.98	0.98	0.98	0.98	0.03
Ridge	0.99	0.99	0.99	0.99	0.00	0.98	0.98	0.98	0.98	0.00
RCV	0.98	0.98	0.98	0.98	0.00	0.98	0.98	0.98	0.98	0.00
SGD	0.97	0.96	0.96	0.96	0.00	0.96	0.96	0.96	0.96	0.00
PAg	0.95	0.95	0.95	0.95	0.00	0.98	0.98	0.98	0.98	0.00
Bagg	0.98	0.98	0.98	0.98	0.02	0.98	0.98	0.98	0.98	0.03

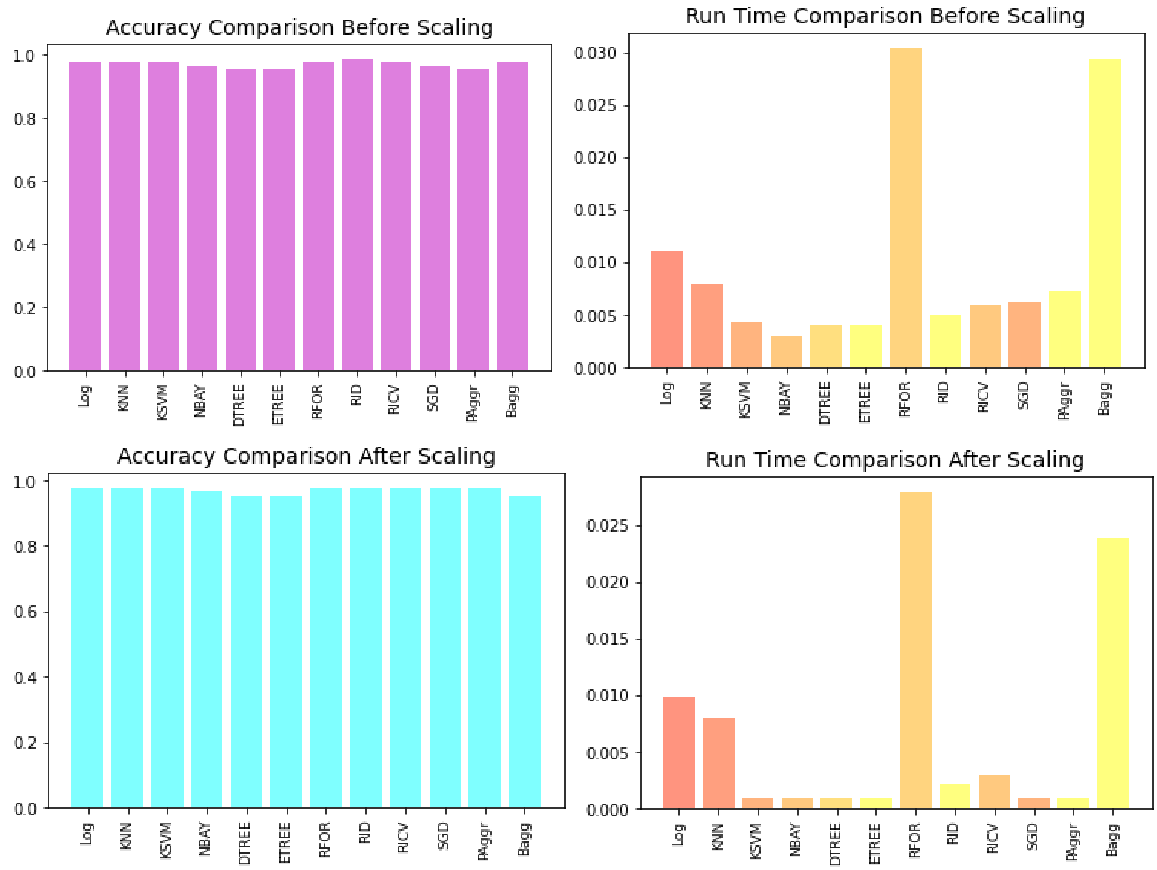

Figure 7. Performance Metrics for Raw Dataset before and after Feature scaling for 50:50

The data set is applied with PCA reduction with 15 components and is settled with different classifiers to look at the classification before and after feature scaling [18] and is shown in Figure. 8. And Table. 5.

Table 5

Performance Indices for 15 Component PCA before and after Feature Scaling

Classifier	Before Feature Scaling					After Feature Scaling				
	Precision	Rcall	FScore	Accuracy	RunTime	Precision	Recall	FScore	Accuracy	RunTime
LReg	0.95	0.94	0.94	0.94	0.02	0.95	0.94	0.94	0.94	0.01
KNN	0.95	0.94	0.94	0.94	0.01	0.95	0.94	0.94	0.94	0.00
KSVM	0.95	0.94	0.94	0.94	0.00	0.95	0.94	0.94	0.94	0.00
GNB	0.95	0.94	0.94	0.94	0.00	0.95	0.94	0.94	0.94	0.00
Dtree	0.91	0.91	0.91	0.91	0.00	0.91	0.91	0.91	0.91	0.00
Etree	0.95	0.94	0.94	0.94	0.00	0.95	0.94	0.94	0.94	0.00
RFor	0.98	0.98	0.98	0.98	0.02	0.98	0.98	0.98	0.98	0.00
Ridge	0.95	0.94	0.94	0.94	0.01	0.95	0.94	0.94	0.94	0.00
RCV	0.95	0.94	0.94	0.94	0.00	0.95	0.94	0.94	0.94	0.00
SGD	0.95	0.94	0.94	0.94	0.00	0.95	0.94	0.94	0.94	0.00
PAg	0.91	0.91	0.91	0.91	0.01	0.95	0.94	0.94	0.94	0.00
Bagg	0.95	0.94	0.94	0.94	0.03	0.95	0.94	0.94	0.94	0.02

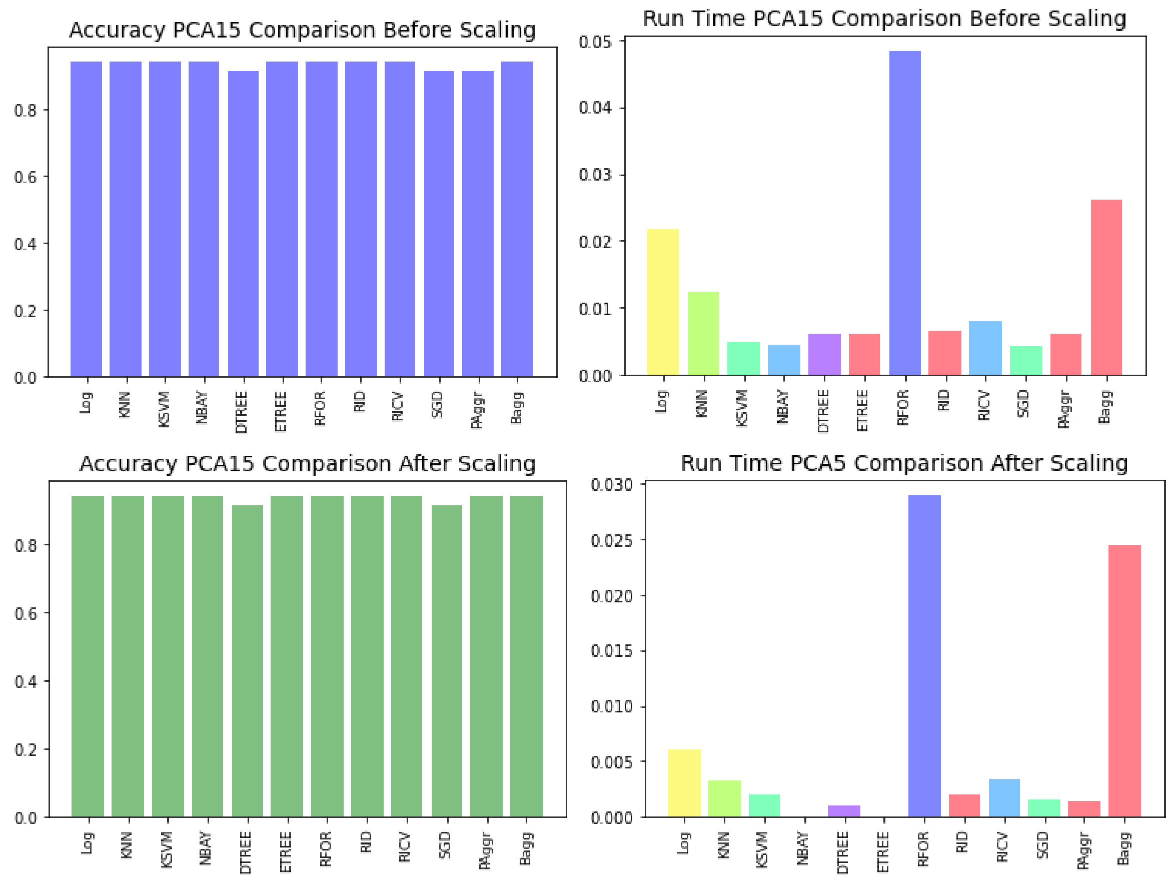

Figure 8. Performance Metrics for PCA Reduced with 15 components before and after scaling

The data set is applied with PCA reduction with 20 components and is settled with different classifiers to look at the classification before and after feature scaling[19] and is shown in Figure. 9. And Table. 6.

Table 6

Performance Indices for 20 Component PCA before and after Feature Scaling

Classifier	Before Feature Scaling					After Feature Scaling				
	Precision	Rcall	FScore	Accuracy	RunTime	Precision	Recall	FScore	Accuracy	RunTime
LReg	0.95	0.94	0.94	0.94	0.01	0.95	0.94	0.94	0.94	0.01
KNN	0.95	0.94	0.94	0.94	0.01	0.95	0.94	0.94	0.94	0.00
KSVM	0.95	0.94	0.94	0.94	0.00	0.95	0.94	0.94	0.94	0.00
GNB	0.95	0.94	0.94	0.94	0.00	0.95	0.94	0.94	0.94	0.00
Dtree	0.91	0.91	0.91	0.91	0.00	0.91	0.91	0.91	0.91	0.00
Etree	0.95	0.94	0.94	0.94	0.00	0.95	0.94	0.94	0.94	0.00
RFor	0.98	0.98	0.98	0.98	0.02	0.98	0.98	0.98	0.98	0.00
Ridge	0.95	0.94	0.94	0.94	0.01	0.95	0.94	0.94	0.94	0.00
RCV	0.95	0.94	0.94	0.94	0.01	0.95	0.94	0.94	0.94	0.00
SGD	0.97	0.97	0.97	0.97	0.00	0.95	0.94	0.94	0.94	0.00
PAg	0.91	0.91	0.91	0.91	0.00	0.95	0.94	0.94	0.94	0.00
Bagg	0.95	0.94	0.94	0.94	0.03	0.95	0.94	0.94	0.94	0.03

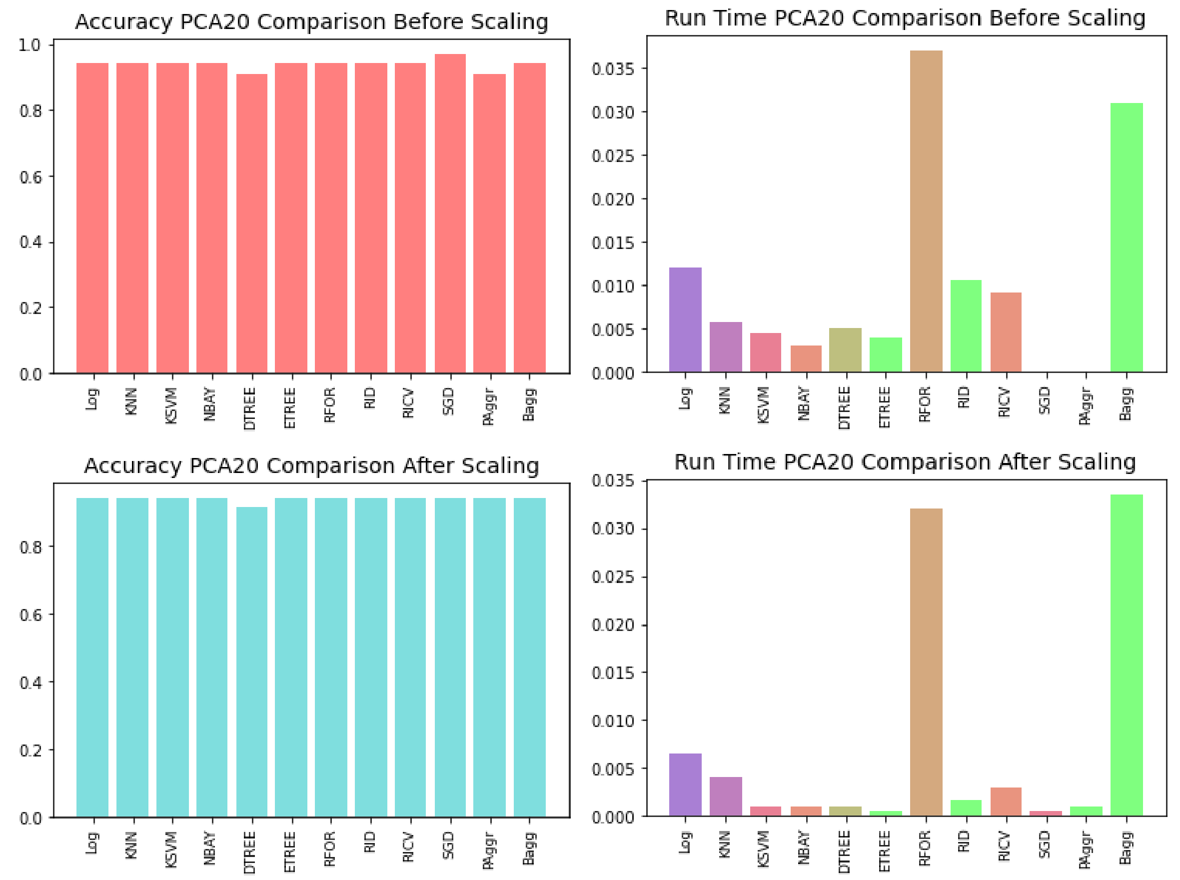

Figure 9. Performance Metrics for PCA Reduced with 20 components before and after scaling

The data set is applied with PCA reduction with 30 components and is settled with different classifiers to look at the classification before and after feature scaling [20] and is shown in Figure. 10 and Table. 7.

Table 7

Performance Indices for 30 Component PCA before and after Feature Scaling

Classifier	Before Feature Scaling					After Feature Scaling				
	Precision	Rcall	FScore	Accuracy	RunTime	Precision	Recall	FScore	Accuracy	RunTime
LReg	0.95	0.94	0.94	0.94	0.01	0.95	0.94	0.94	0.94	0.01
KNN	0.95	0.94	0.94	0.94	0.01	0.95	0.94	0.94	0.94	0.00
KSVM	0.95	0.94	0.94	0.94	0.00	0.95	0.94	0.94	0.94	0.00
GNB	0.95	0.94	0.94	0.94	0.00	0.95	0.94	0.94	0.94	0.00
Dtree	0.91	0.91	0.91	0.91	0.00	0.91	0.91	0.91	0.91	0.00
Etree	0.95	0.94	0.94	0.94	0.00	0.95	0.94	0.94	0.94	0.00
RFor	0.98	0.98	0.98	0.98	0.02	0.98	0.98	0.98	0.98	0.00
Ridge	0.95	0.94	0.94	0.94	0.00	0.95	0.94	0.94	0.94	0.00
RCV	0.95	0.94	0.94	0.94	0.01	0.95	0.94	0.94	0.94	0.00
SGD	0.94	0.94	0.94	0.94	0.01	0.95	0.94	0.94	0.94	0.00
PAg	0.91	0.91	0.91	0.91	0.00	0.95	0.94	0.94	0.94	0.00
Bagg	0.95	0.94	0.94	0.94	0.02	0.91	0.91	0.91	0.91	0.04

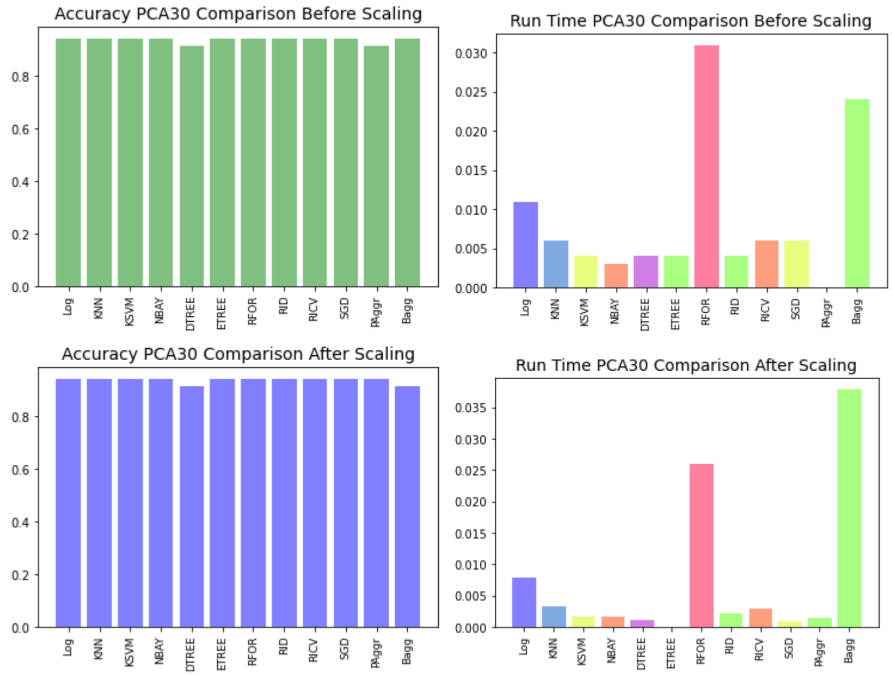

Figure 9. Performance Metrics for PCA Reduced with 30 components before and after scaling

Conclusion

An attempt is made in this paper is to perform analysis of the dataset accuracy with different levels of cross validation and the dimensionality reduction through feature extraction methods. The dataset is subject to perform cross validation by splitting the training and testing dataset with 80:20, 30:70, 40:60 and 50:50 to analyze how well the accuracy of divorce rate prediction of the dataset. The dataset is also done with principal component analysis with 15, 20 and 30 components to analyse the accuracy of divorce rate prediction. Experimental results show that the Random Forest classifier is found to have the accuracy of 98% for all PCA reduced dataset with 15, 20 and 30 components. The results shows that Random Forest classifier is found to have the accuracy of 98% for 40:60, 50:50 of training and testing dataset.

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