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Miniaturization based Fetal Health Classification using Cardiotocographic Data

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Abstract*—With the current growth of technology towards medicine, various ultrasound methods are available to find the fetal health. It is accessed with various clinical parameters with 2-D imaging and other test. However, health prediction of fetal heart still remains an open issue due to spontaneous activities of the fetus, the minor heart size and deficiency of knowledge in fetal echocardiography. The machine learning techniques can find out the classes of fetal heart rate which can be used for earlier forecasting. With this overview, we have used Cardiotocographic Fetal heart rate dataset extracted from UCI Machine Learning Repository for predicting the fetal heart rate health classes. The classification of fetal heart rate are achieved in four ways. Firstly, the data set is preprocessed with Feature Scaling and Missing Values. Secondly, raw data set is fitted to all the classifiers and the performance is analyzed. Thirdly, the raw data set is subjected to dimensionality reduction using PCA with 10 components and then fitted to all the classifiers and the performance is analyzed. Fourth, data set is subjected to variants of PCA like Kernel PCA, Incremental PCA, Sparse PCA and Minibatch Sparse PCA with 10 components and then fitted to all the classifiers and the performance is analyzed. Fifth, performance analysis is done using metrics like Precision, Recall, Accuracy and F-score before and after feature scaling. The implementation is done using python language under Spyder platform with Anaconda Navigator. Experimental results shows that Kernel SVM classifier is found to retain the accuracy of 98.5% in PCA, Kernel PCA, Incremental PCA, Sparse PCA and Minibatch Sparse PCA after feature scaling.

***Index Terms*— machine learning, scaling, PCA, accuracy, precision and feature reduction.**

I. INTRODUCTION

The periodic changes of the fetus must be monitored through the clinical parameters in order to access the fetal health. The death rate of the fetal can be controlled by foreseeing the changes in the clinical parameters of the fetal health. With the technological growth, the ultrasound methods are used for the assessment of fetal health and other changes in the needed attributes. The genetic algorithms can also be used for the prediction of any diseases in the fetal health by interpreting the observation received through the parameter changes. The feature selection can be done using Generic Algorithm which is heuristic search algorithm which includes the processes of encoding, Fitness function evaluation, Selection via roulette wheel mechanism, Crossover, Mutation, Multi-objective optimization and Repository maintenance.

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II. LITERATURE REVIEW

This paper deals with the analysis of periodic changes to detect sinusoidal heart rate. Random forest is used for the data preprocessing and sinusoidal pattern is calculated using fuzzy theoretic method [1]. This deals with the prediction of fluctuations in the fetal distress and a superior system using deep learning is designed. Empirical model decomposition is used to decompose any one-dimensional timing signal S(t) into Intrinsic Mode Function (IMF) with different frequencies. LSMT is used to classify the data. The deep learning algorithms has most accuracy for detecting fetal heart distress [2]. This paper is used to predict fetal risk using machine learning for prevention of any immature death. The minimum redundancy maximum relevance technique is used for the dataset reduction [3]. In this paper, detail heart rate is classified using two methods and the superior method is found out between them. To use hybrid k-means, the feature extraction is done using k means clustering to perform the classification [4]. The 2D ultrasound is used to determine and measure the fetus heart rate. They process images to calculate FHR. Number of Pixel from the image is processed and gives the information about fetal heart condition as each area of the heart or part of heart images are processed using 2D ultrasound. They found out, change atrium area is better than the changes in the ventricle area with accuracy more than 90% [5].
This paper classifies and compare CTG data system using supervised SVM and decision tree to get which have best performance and accuracy [6]. This paper uses non-parametric Bayesian methods to classify the fetal heart rate. They have used non-parametric Bayesian Method and SVM-based method to classify the FHR and result are compared to find the performance of both methods. Bayesian method have better performance than SVM-based method [7]. This paper find any congenital diseases and cardiac anomalies on fetal heart using full convolution neural network (FCN). They are using FCN to detect the location of heart and analysis the any anomalies using FCN. They have concluded that FCN-16 strict model has lower error than other frames while classifying [8]. This paper try to achieve efficient fetal acidosis detection to help doctors during delivery. They are using sparse-SVM to determine and classify features and calculate performance. They have concluded that classification done by automatic selection is far better than clinical practice [9]. The Classification and regression tree (CART) to detect high-risk during pregnancy. They found that accuracy obtained using entropy calculation and GINI index is 88.87% and 90.12% respectively [10]. This paper classify the fetal heart rate using convolution neural network (CNN) to develop a neural network which will classify heart rate automatically. They found that accuracy is high of CNN than of SVM and MLP. CNN is an efficient for fetal heart monitoring system [11]. They have used classification based on association (CBA) to classify fetal health status. They have found that the accuracy of model was increased after using feature selection method. They found out that random forest and XGBoost have good performance for classifying fetal health status [12]. This paper uses SVM as classifier to implement the f-score. They have used f-score method to sort the features. F-score method is used for feature selection while SVM will classify the feature. F-score have great accuracy in predicting fetal health status [13]. This paper focus on evolutionary multi objective generic algorithm (MOGA) by use of which the factors causing fetal death is extracted with help of cardiotocographic analysis [14]. This paper introduce the use of data-driven entropy profiling to detect fetal arrhythmia automatically. The fetal QRS extraction technique is used to extract fetal heart rate from the data set and then entropy features are applied for profiling of the dataset [15].

III. PROPOSED WORK

The CTG Cardiotocographic Fetal heart rate dataset with 36 independent variables and 1 dependent variable has been used for implementation. The prediction of fetal health is done with the following contributions.

(i) Firstly, the data set is preprocessed with Feature Scaling and Missing Values.
(ii) Secondly, raw data set is fitted to all the classifiers and the performance is analysed. Thirdly, the raw data set is subjected to dimensionality reduction using PCA with 10 components and then fitted to all the classifiers and the performance is analysed.
(iii) Fourth, data set is subjected to variants of PCA like Kernel PCA, Poly Kernel PCA, Sigmoid Kernel PCA, Cosine Kernel PCA, Incremental PCA, Sparse PCA and Minibatch Sparse PCA with 10 components and then fitted to all the classifiers and the performance is analysed.
(iv) Fifth, performance analysis is done using metrics like Precision, Recall, Accuracy and F-score before and after feature scaling. The overall workflow is shown in Fig. 1.

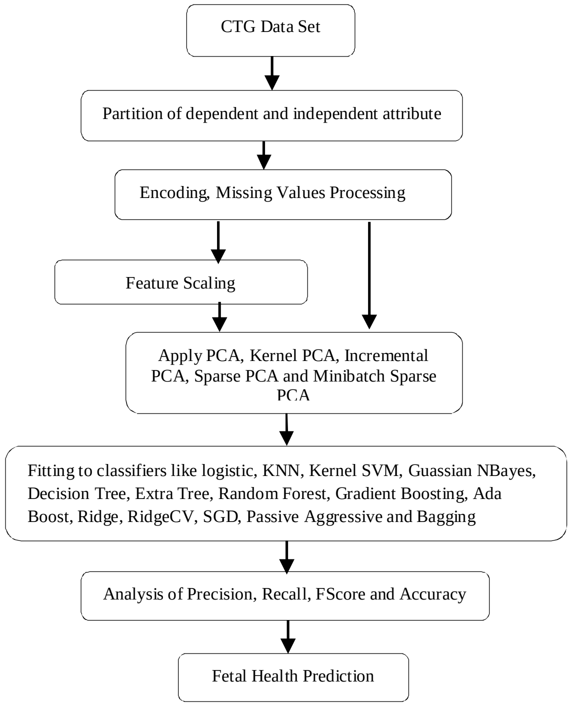

Figure 1. Overall Architecture Flow

IV. Results and Discussion

A. Implementation Setup

The CTG dataset extracted from the UCI machine learning repository is used for implementation. The dataset consists of the 36 independent features (b, e, LBE, LB, AC, FM, UC, ASTV, MSTV, ALTV, MLTV, DL, DS, DP, DR, Width, Min, Max, Nmax, Nzeros, Mode, Mean, Median, Variance, Tendency, A, B, C, D, E, AD, DE, LD, FS, SUSP, CLASS) and 1 'NSP' Target feature. The code is implemented with python under Anaconda Navigator with Spyder IDE. The data set is splitted with 80:20 for training and testing dataset.

B. Dataset Exploratory Analysis

The target class distribution and the correlation of the dataset is shown is Fig. 2.

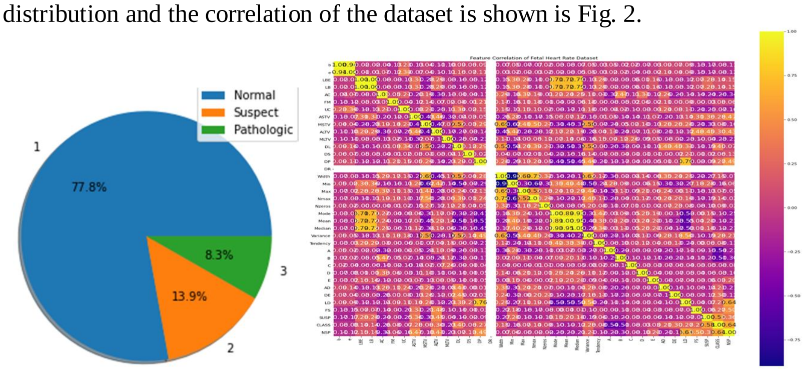

Figure 2. Correlation and Target Distribution

C.Classifier Analysis Before and After Feature Scaling

The raw data set is fitted to all the classifier like logistic regression, KNN, Kernel SVM, Decision Tree, Random Forest, Gradient Boosting, Ada Boost, Ridge, RidgeCV, SGD, Passive Aggressive and Bagging classifier with and without the presence of feature scaling and performance is shown in Table I and Table II.

TABLE I. PERFORMANCE OF RAW DATA BEFORE SCALING

Classifier	Precision	Recall	FScore	Accuracy
Logistic	0.84	0.85	0.84	0.85
KNN	0.71	0.80	0.74	0.80
KSVM	0.59	0.77	0.66	0.77
GNBayes	0.99	0.99	0.99	0.99
DTree	0.99	0.99	0.99	0.99
ETree	0.98	0.98	0.98	0.98
RForest	0.99	0.99	0.99	0.99
GBoost	0.99	0.99	0.99	0.99
AdaBoost	0.97	0.97	0.97	0.97
Ridge	0.98	0.98	0.98	0.98
RidgeCV	0.98	0.98	0.98	0.98
SGD	0.78	0.81	0.77	0.81
PAggress	0.82	0.83	0.83	0.83
Bagging	0.98	0.98	0.98	0.98

TABLE II. PERFORMANCE OF RAW DATA AFTER SCALING

Classifier	Precision	Recall	FScore	Accuracy
Logistic	0.98	0.98	0.98	0.98
KNN	0.98	0.98	0.98	0.98
KSVM	0.99	0.99	0.99	0.99
GNBayes	0.95	0.93	0.93	0.93
DTree	0.99	0.99	0.99	0.99
ETree	0.98	0.98	0.98	0.98
RForest	0.99	0.99	0.99	0.99
GBoost	0.99	0.99	0.99	0.99
AdaBoost	0.97	0.97	0.97	0.97
Ridge	0.98	0.98	0.98	0.98
RidgeCV	0.98	0.98	0.98	0.98
SGD	0.97	0.97	0.97	0.97
PAggress	0.98	0.98	0.98	0.98
Bagging	0.99	0.99	0.99	0.99

D. PCA Analysis Before and After Feature Scaling

The raw data set is fitted to PCA with 10 components and the PCA reduced dataset is subjected to all the classifier with and without the presence of feature scaling and performance is shown in Table III and Table IV.

TABLE III. PERFORMANCE OF RAW DATA BEFORE SCALING

Classifier	Precision	Recall	FScore	Accuracy
Logistic	0.85	0.76	0.79	0.76
KNN	0.71	0.80	0.74	0.80
KSVM	0.59	0.77	0.66	0.77
GNBayes	0.82	0.81	0.81	0.81
DTree	0.87	0.86	0.87	0.86
ETree	0.85	0.85	0.85	0.85
RForest	0.88	0.88	0.88	0.88
GBoost	0.89	0.89	0.89	0.89
AdaBoost	0.86	0.85	0.85	0.85
Ridge	0.81	0.82	0.81	0.82
RidgeCV	0.81	0.82	0.81	0.82
SGD	0.82	0.73	0.76	0.73
PAggress	0.75	0.51	0.57	0.51
Bagging	0.88	0.87	0.87	0.87

TABLE IV. PERFORMANCE OF RAW DATA AFTER SCALING

Classifier	Precision	Recall	FScore	Accuracy
Logistic	0.98	0.98	0.98	0.98
KNN	0.98	0.98	0.98	0.98
KSVM	0.99	0.99	0.99	0.99
GNBayes	0.97	0.97	0.97	0.97
DTree	0.98	0.98	0.98	0.98
ETree	0.96	0.96	0.96	0.96
RForest	0.99	0.99	0.99	0.99
GBoost	0.98	0.98	0.98	0.98
AdaBoost	0.92	0.84	0.86	0.84
Ridge	0.95	0.95	0.94	0.95
RidgeCV	0.95	0.95	0.94	0.95
SGD	0.96	0.96	0.96	0.96
PAggress	0.97	0.97	0.97	0.97
Bagging	0.99	0.99	0.99	0.99

E. Kernel PCA Analysis Before and After Feature Scaling

The raw data set is fitted to Kernel PCA with 10 components and then applied to all the classifier with and without the presence of feature scaling and performance is shown in Table V and Table VI.

F. Incremental PCA Analysis Before and After Feature Scaling

The raw data set is fitted to Incremental PCA with 10 components and then applied to all the classifier with and without the presence of feature scaling and performance is shown in Table VII and Table VIII.

G. Sparse PCA Analysis Before and After Feature Scaling

The raw data set is fitted to Sparse PCA with 10 components and then applied to all the classifier with and without the presence of feature scaling and performance is shown in Table IX and Table X.

TABLE V. PERFORMANCE OF RAW DATA BEFORE SCALING

Classifier	Precision	Recall	FScore	Accuracy
Logistic	0.85	0.76	0.79	0.76
KNN	0.71	0.80	0.74	0.80
KSVM	0.59	0.77	0.66	0.77
GNBayes	0.82	0.81	0.81	0.81
DTree	0.87	0.86	0.87	0.86
ETree	0.85	0.85	0.85	0.85
RForest	0.88	0.88	0.88	0.88
GBoost	0.88	0.88	0.88	0.88
AdaBoost	0.86	0.85	0.85	0.85
Ridge	0.81	0.82	0.81	0.82
RidgeCV	0.81	0.82	0.81	0.82
SGD	0.81	0.70	0.74	0.70
PAggress	0.80	0.49	0.56	0.49
Bagging	0.89	0.89	0.89	0.89

TABLE VI. PERFORMANCE OF RAW DATA AFTER SCALING

Classifier	Precision	Recall	FScore	Accuracy
Logistic	0.98	0.98	0.98	0.98
KNN	0.98	0.98	0.98	0.98
KSVM	0.99	0.99	0.99	0.99
GNBayes	0.97	0.97	0.97	0.97
DTree	0.98	0.98	0.98	0.98
ETree	0.96	0.96	0.96	0.96
RForest	0.99	0.99	0.99	0.99
GBoost	0.98	0.98	0.98	0.98
AdaBoost	0.95	0.94	0.94	0.94
Ridge	0.95	0.95	0.94	0.95
RidgeCV	0.95	0.95	0.94	0.95
SGD	0.97	0.97	0.97	0.97
PAggress	0.96	0.96	0.96	0.96

TABLE VII. PERFORMANCE OF RAW DATA BEFORE SCALING

Classifier	Precision	Recall	FScore	Accuracy
Logistic	0.85	0.78	0.80	0.78
KNN	0.71	0.80	0.74	0.80
KSVM	0.59	0.77	0.66	0.77
GNBayes	0.82	0.81	0.81	0.81
DTree	0.88	0.86	0.87	0.86
ETree	0.86	0.86	0.86	0.86
RForest	0.88	0.88	0.88	0.88
GBoost	0.89	0.89	0.89	0.89
AdaBoost	0.85	0.82	0.83	0.82
Ridge	0.81	0.82	0.81	0.82
RidgeCV	0.81	0.82	0.81	0.82
SGD	0.83	0.80	0.81	0.80
PAggress	0.77	0.62	0.66	0.62
Bagging	0.89	0.88	0.89	0.88

TABLE VIII. PERFORMANCE OF RAW DATA AFTER SCALING

Classifier	Precision	Recall	FScore	Accuracy
Logistic	0.98	0.98	0.98	0.98
KNN	0.98	0.98	0.98	0.98
KSVM	0.99	0.99	0.99	0.99
GNBayes	0.96	0.96	0.96	0.96
DTree	0.97	0.97	0.97	0.97
ETree	0.94	0.94	0.94	0.94
RForest	0.98	0.98	0.98	0.98
GBoost	0.97	0.97	0.97	0.97
AdaBoost	0.91	0.86	0.88	0.86
Ridge	0.95	0.94	0.94	0.94
RidgeCV	0.95	0.94	0.94	0.94
SGD	0.97	0.97	0.97	0.97
PAggress	0.97	0.97	0.97	0.97
Bagging	0.98	0.98	0.98	0.98

TABLE IX. PERFORMANCE OF RAW DATA BEFORE SCALING

Classifier	Precision	Recall	FScore	Accuracy
Logistic	0.84	0.76	0.78	0.76
KNN	0.70	0.79	0.73	0.79
KSVM	0.59	0.77	0.66	0.77
GNBayes	0.84	0.81	0.81	0.81
DTree	0.90	0.90	0.90	0.90
ETree	0.88	0.87	0.88	0.87
RForest	0.91	0.91	0.91	0.91
GBoost	0.91	0.92	0.91	0.92
AdaBoost	0.84	0.83	0.83	0.83
Ridge	0.81	0.82	0.81	0.82
RidgeCV	0.81	0.82	0.81	0.82
SGD	0.83	0.77	0.79	0.77
PAggress	0.81	0.46	0.52	0.46
Bagging	0.91	0.92	0.91	0.92

TABLE X. PERFORMANCE OF RAW DATA AFTER SCALING

Classifier	Precision	Recall	FScore	Accuracy
Logistic	0.97	0.97	0.97	0.97
KNN	0.98	0.98	0.98	0.98
KSVM	0.98	0.98	0.98	0.98
GNBayes	0.92	0.92	0.92	0.92
DTree	0.97	0.97	0.97	0.97
ETree	0.96	0.96	0.96	0.96
RForest	0.97	0.97	0.97	0.97
GBoost	0.97	0.97	0.97	0.97
AdaBoost	0.89	0.89	0.89	0.89
Ridge	0.95	0.95	0.94	0.95
RidgeCV	0.95	0.95	0.94	0.95
SGD	0.97	0.97	0.97	0.97
PAggress	0.97	0.97	0.97	0.97
Bagging	0.96	0.96	0.96	0.96

H. MiniBatch Sparse PCA Analysis Before and After Feature Scaling

The raw data set is fitted to Minibatch Sparse PCA with 10 components and then applied to all the classifier with and without the presence of feature scaling and performance is shown in Table XI and Table XII.

TABLE XI. PERFORMANCE OF RAW DATA BEFORE SCALING

Classifier	Precision	Recall	FScore	Accuracy
Logistic	0.84	0.78	0.80	0.78
KNN	0.78	0.78	0.73	0.78
KSVM	0.59	0.77	0.66	0.77
GNBayes	0.69	0.52	0.55	0.52
DTree	0.79	0.79	0.79	0.79
ETree	0.75	0.73	0.74	0.73
RForest	0.81	0.81	0.80	0.81
GBoost	0.80	0.81	0.80	0.81
AdaBoost	0.76	0.77	0.76	0.77
Ridge	0.79	0.80	0.77	0.80
RidgeCV	0.79	0.80	0.77	0.80
SGD	0.78	0.48	0.54	0.48
PAggress	0.76	0.38	0.43	0.38
Bagging	0.80	0.82	0.80	0.82

TABLE XII. PERFORMANCE OF RAW DATA AFTER SCALING

Classifier	Precision	Recall	FScore	Accuracy
Logistic	0.96	0.96	0.96	0.96
KNN	0.98	0.98	0.98	0.98
KSVM	0.99	0.99	0.99	0.99
GNBayes	0.95	0.95	0.94	0.95
DTree	0.97	0.97	0.97	0.97
ETree	0.97	0.97	0.97	0.97
RForest	0.98	0.97	0.97	0.97
GBoost	0.97	0.97	0.97	0.97
AdaBoost	0.89	0.60	0.65	0.60
Ridge	0.95	0.94	0.93	0.94
RidgeCV	0.95	0.94	0.93	0.94
SGD	0.95	0.95	0.95	0.95
PAggress	0.95	0.95	0.95	0.95
Bagging	0.96	0.96	0.96	0.96

I. Poly Kernel PCA Analysis Before and After Feature Scaling

The raw data set is fitted to Poly Kernel PCA with 10 components and then applied to all the classifier with and without the presence of feature scaling and performance is shown in Table XIII and Table XIV.

TABLE XIII. PERFORMANCE OF RAW DATA BEFORE SCALING

Classifier	Precision	Recall	FScore	Accuracy
Logistic	0.80	0.50	0.55	0.50
KNN	0.80	0.79	0.74	0.79
KSVM	0.59	0.77	0.66	0.77
GNBayes	0.74	0.45	0.50	0.45
DTree	0.81	0.80	0.80	0.80
ETree	0.82	0.81	0.81	0.81
RForest	0.84	0.85	0.84	0.85
GBoost	0.83	0.83	0.83	0.83
AdaBoost	0.80	0.81	0.80	0.81
Ridge	0.82	0.79	0.72	0.79
RidgeCV	0.59	0.55	0.56	0.55
SGD	0.65	0.59	0.62	0.59
PAggress	0.73	0.40	0.46	0.40
Bagging	0.85	0.85	0.85	0.85

TABLE XIV. PERFORMANCE OF RAW DATA AFTER SCALING

Classifier	Precision	Recall	FScore	Accuracy
Logistic	0.95	0.96	0.95	0.96
KNN	0.97	0.96	0.96	0.96
KSVM	0.96	0.96	0.96	0.96
GNBayes	0.89	0.79	0.82	0.79
DTree	0.98	0.98	0.98	0.98
ETree	0.94	0.94	0.94	0.94
RForest	0.98	0.98	0.98	0.98
GBoost	0.97	0.97	0.97	0.97
AdaBoost	0.88	0.86	0.87	0.86
Ridge	0.94	0.94	0.94	0.94
RidgeCV	0.95	0.94	0.94	0.94
SGD	0.95	0.95	0.95	0.95
PAggress	0.95	0.95	0.95	0.95
Bagging	0.96	0.96	0.96	0.96

J. Sigmoid Kernel PCA Analysis Before and After Feature Scaling

The raw data set is fitted to Sigmoid Kernel PCA with 10 components and then applied to all the classifier with and without the presence of feature scaling and performance is shown in Table XV and Table XVI.

TABLE XV. PERFORMANCE OF RAW DATA BEFORE SCALING

Classifier	Precision	Recall	FScore	Accuracy
Logistic	0.80	0.79	0.74	0.79
KNN	0.59	0.77	0.66	0.77
KSVM	0.74	0.45	0.50	0.45
GNBayes	0.81	0.80	0.80	0.80
DTree	0.82	0.81	0.81	0.81
ETree	0.84	0.85	0.84	0.85
RForest	0.83	0.83	0.83	0.83
GBoost	0.80	0.81	0.80	0.81
AdaBoost	0.65	0.59	0.62	0.59
Ridge	0.73	0.40	0.46	0.40
RidgeCV	0.85	0.85	0.85	0.85
SGD	0.81	0.80	0.80	0.80
PAggress	0.82	0.81	0.81	0.81
Bagging	0.84	0.85	0.84	0.85

TABLE XVI. PERFORMANCE OF RAW DATA AFTER SCALING

Classifier	Precision	Recall	FScore	Accuracy
Logistic	0.91	0.92	0.91	0.92
KNN	0.95	0.95	0.95	0.95
KSVM	0.96	0.96	0.95	0.96
GNBayes	0.91	0.91	0.91	0.91
DTree	0.95	0.95	0.95	0.95
ETree	0.91	0.91	0.91	0.91
RForest	0.95	0.95	0.95	0.95
GBoost	0.96	0.96	0.96	0.96
AdaBoost	0.89	0.85	0.86	0.85
Ridge	0.88	0.88	0.86	0.88
RidgeCV	0.89	0.88	0.86	0.88
SGD	0.92	0.92	0.92	0.92
PAggress	0.91	0.91	0.91	0.91
Bagging	0.93	0.94	0.93	0.94

K. Cosine Kernel PCA Analysis Before and After Feature Scaling

The raw data set is fitted to Cosine Kernel PCA with 10 components and then applied to all the classifier with and without the presence of feature scaling and performance is shown in Table XVII and Table XVIII.

TABLE V. PERFORMANCE OF RAW DATA BEFORE SCALING

Classifier	Precision	Recall	FScore	Accuracy
Logistic	0.65	0.77	0.68	0.77
KNN	0.81	0.80	0.76	0.80
KSVM	0.79	0.79	0.74	0.79
GNBayes	0.73	0.75	0.74	0.75
DTree	0.83	0.83	0.83	0.83
ETree	0.81	0.81	0.81	0.81
RForest	0.87	0.87	0.87	0.87
GBoost	0.86	0.86	0.86	0.86
AdaBoost	0.83	0.81	0.82	0.81
Ridge	0.74	0.77	0.69	0.77
RidgeCV	0.75	0.78	0.73	0.78
SGD	0.75	0.78	0.71	0.78
PAggress	0.77	0.79	0.74	0.79
Bagging	0.87	0.87	0.87	0.87

TABLE VI. PERFORMANCE OF RAW DATA AFTER SCALING

Classifier	Precision	Recall	FScore	Accuracy
Logistic	0.93	0.93	0.92	0.93
KNN	0.98	0.98	0.98	0.98
KSVM	0.97	0.97	0.97	0.97
GNBayes	0.94	0.94	0.93	0.94
DTree	0.94	0.94	0.94	0.94
ETree	0.93	0.93	0.93	0.93
RForest	0.96	0.96	0.96	0.96
GBoost	0.96	0.96	0.96	0.96
AdaBoost	0.89	0.86	0.87	0.86
Ridge	0.89	0.89	0.88	0.89
RidgeCV	0.89	0.89	0.88	0.89
SGD	0.92	0.92	0.91	0.92
PAggress	0.93	0.92	0.92	0.92
Bagging	0.96	0.96	0.95	0.96

V. CONCLUSIONS

An attempt is done in this work to analyze the performance metrics of all the tested classifiers with different dimensionality reduction algorithms like PCA, Kernel PCA, Poly Kernel PCA, Sigmoid Kernel PCA, Cosine Kernel PCA, Incremental PCA, Sparse PCA and Minibatch Sparse PCA. The dimensionality reduction is done with 10 components. The dimensionality reduced PCA is subjected with all the classifiers to analyze the performance. Experimental results shows that kernel support vector machine, KNN and decision tree classifier is found to retain the accuracy 95% to 99% after feature scaling for all the dimensionality reduction algorithms.

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