Detecting Severity of Diabetic Retina by Functional Learning with Image Processing Techniques

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Abstract:

A machine learning using image processing offers great potential for large-scale healthcare screening and may help choose the best treatment for individual patients. Diagnostic advances in metabolism and endocrinology enabled retinal and ocular disease studies. Diabetic retinopathy (DR) causes blindness worldwide. Machine learning systems can accurately detect DR using digital fundus photos or optical coherence tomography. Thus, AI can be used to construct accurate and efficient methods for early DR diagnosis and screening without particular clinic resources. Machine learning allows early diagnosis with high specificity and sensitivity based on minimally created variables, enabling tailored DR progression real-time monitoring and in-time ophthalmic or endocrine therapy. The Multi Logistic Regression (MLR) shows 75% of accuracy which is highest than other models. The Sequential Minimal Optimization (SMO) shows 69% of accuracy which is lowest than other models. The MLR and Quadratic Discriminant Analysis shows the same as well maximum precision value compare than others which is 0.76 of precision value. The MLR shows maximum recall value i.e., 0.75 of recall. The SMO shows least recall 0.69 value. The MLR shows maximum ROC value 0.83. The SMO shows least ROC value 0.70. The MLR has the maximum PRC value which is 0.83. The Sequential Minimal Optimization shows the minimum PRC value which is 0.64. The Multi-Layer Perceptron takes more time for making its model which is 3.03 seconds. The Quadratic Discriminant Analysis and Linear Discriminant Analysis takes same time for creating their models which is zero seconds. The MLR has moderate agreement with the data which is 0.50 of kappa. The SMO has least fair agreement with the data which is 0.39. The Multi-Layer Perceptron has least F-Measure value which is 0.20 and the MLR has maximum F-Measure value which is 0.75. The Fisher's Linear Discriminant Analysis and Linear Discriminant Analysis has same Matthews Correlation Coefficient value which is 0.47. The Multi Logistic Regression had 0.51 which is highest Matthews Correlation Coefficient value. This research work explores the Multi Logistic Regression model gives best performance with lowest deviations than other functional models.

Key terms: SMO, Linear Discriminant Analysis, MLR, Multi-Layer Perceptron, and Fisher's Linear Discriminant Analysis

II Introduction

Diabetics' major cause of blindness is diabetic retinopathy (DR) [1]. Chronic high blood glucose levels damage retinal capillaries, impairing light perception and signal transmission. By 2030, 191 million people worldwide will have DR, which is most common in working-age people [2]. Despite DR progressing to blindness, early detection is difficult because to its invisible visual indicators. Regular screening and early diagnosis lower vision loss risk by 57.0% and treatment costs [2]. Retinal photography screening for DR is safe, simple, tolerable, and benefit-validated by multiple longitudinal studies [3, 4]. Early detection allows patients to receive effective treatments with intravitreal anti-VEGF doses and laser therapy for severe DR. Many nations lack resources for nationwide screening. Insufficiently trained ophthalmologists require a simple and scalable community screening option. DR, a major public health issue, fits all screening criteria proposed by numerous international bodies [5].This paper organizes section 2 focuses on literature survey; in section 3 presents materials and methods; in section 4 shows results and interpretations, and finally section 5 has conclusion of this research work.

III Literature Survey

Hand-engineered methods have been shown to detect DR in retinal fundus images. Traditional ML patterns for DR analysis use hand-engineered features [7-11]. In [8-12], mathematic morphology, thresh-holding and deformable models, retinal lesion tracking, matching filter models, clustering-based models, and hybrid techniques were examined for DR diagnosis. In [13-14], algorithms extracted haemorrhages, blood vessel texture, and micro-aneurysms from colour fundus images. Reviews exudate detection and retinal vascular segmentation techniques [15-16]. Analyzed optic disc segmentation and glaucoma. Because choosing the best hand-engineered features requires expertise, these strategies are not generalised.

Machine Learning learning applications in e-healthcare have grown recently due to the availability of big data sets and low-cost computing resources [17-19].ML-based solutions outperform manual methods for a variety of computer vision tasks. To develop automatic computer-aided decision support systems for DR diagnosis, many DL-based models and algorithms have been developed to analyse retinal fundus images. ML-based medical image processing applications have been tested to extract DR-related signs.[20] DR screening programmes have attempted computer-aided systems using advanced algorithms and telemedicine to detect DR early. Ophthalmologists are referred via automatic DR grading systems. Ophthalmologists labour less using these systems, making analysis and treatment cheaper.

III Materials and Methods

This section focuses on the materials and methods of the research work. The diabetic retinopathy data set has collected from public data repository, namely UCI repository [31]. This dataset contains features extracted from the Messidor image set to predict whether an image contains signs of diabetic retinopathy or not. The below table describes the attributes of collected dataset.

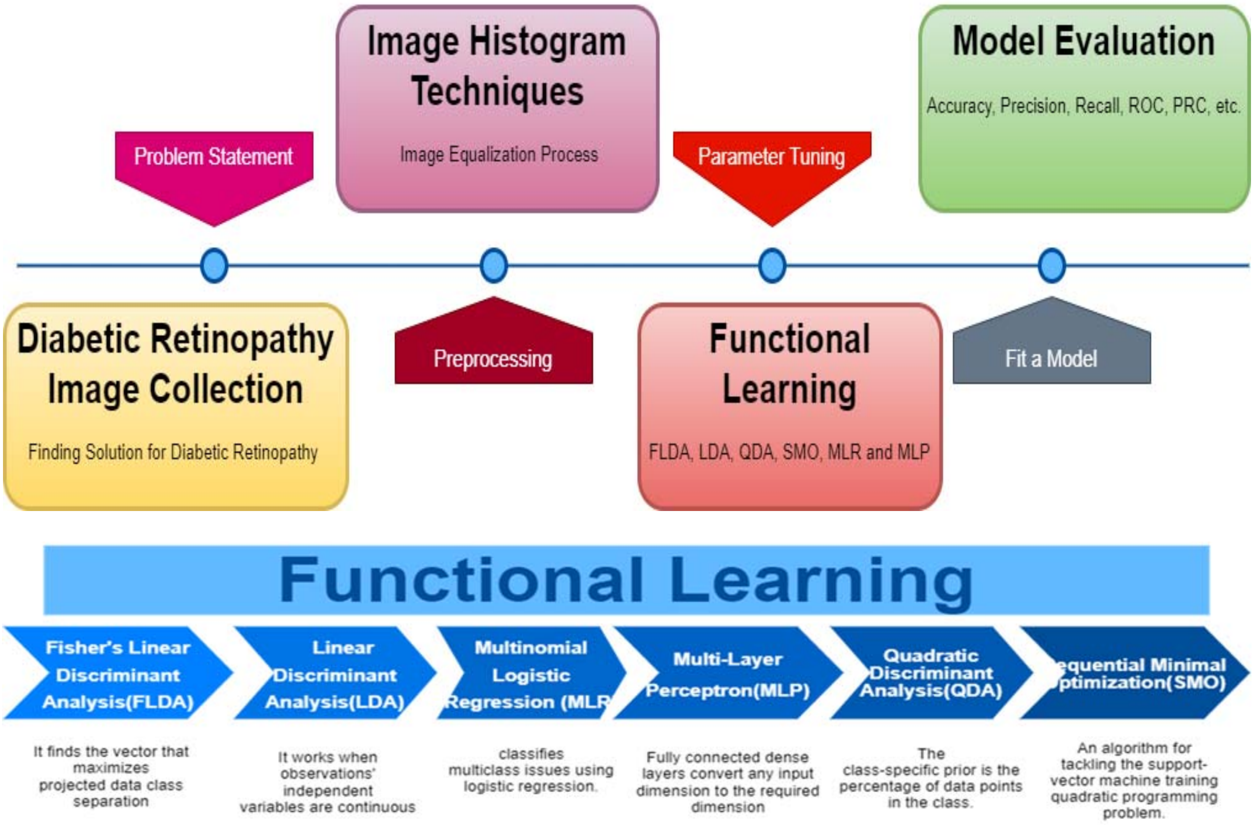

Figure 1: Proposed Architecture

The architecture shows the flow process of this research work. The collected dataset to be applied image filtering and features selection through ensemble learning models in weka 3.9.5 open source tool.

This work considers following functional algorithms:

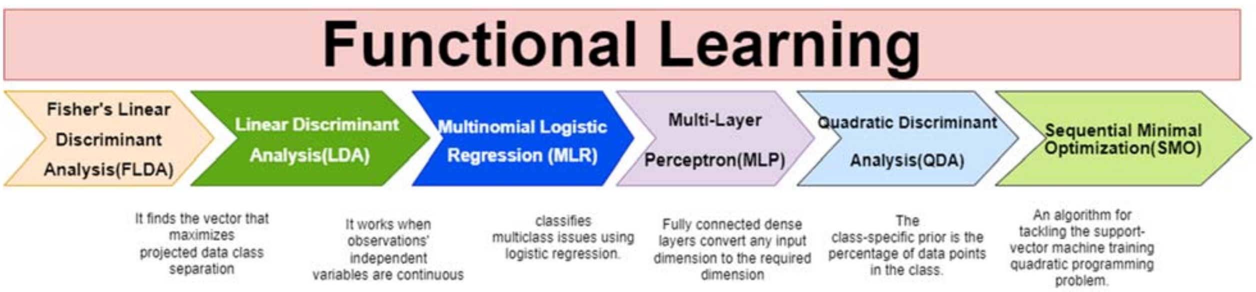

Figure 2: List of ML Models

The above algorithms are implemented in Weka 3.9.5 with 10% of testing and 90% of training

IV Outcome and Interpretations

This section focuses the outcome of the selected classifiers like FLDA, LDA, MLR, MLP,QDA and SMO on functional models.

Table 2: Classifiers Vs Outcomes

Classifier	Accuracy	Precision	Recall	ROC	PRC
FLDA	71.42%	0.75	0.71	0.79	0.79
LDA	72.11%	0.74	0.72	0.80	0.79
MLR	75%	0.76	0.75	0.83	0.83
MLP	72%	0.72	0.72	0.80	0.79
QDA	69.77%	0.76	0.70	0.79	0.78
SMO	69%	0.70	0.69	0.70	0.64

The above table 2 shows the accuracy, precision, recall, receiver operating characteristic curve(ROC) and precision recall curve (PRC) value on like FLDA ,LDA, MLR, MLP, QDA, and SMO of functional models.

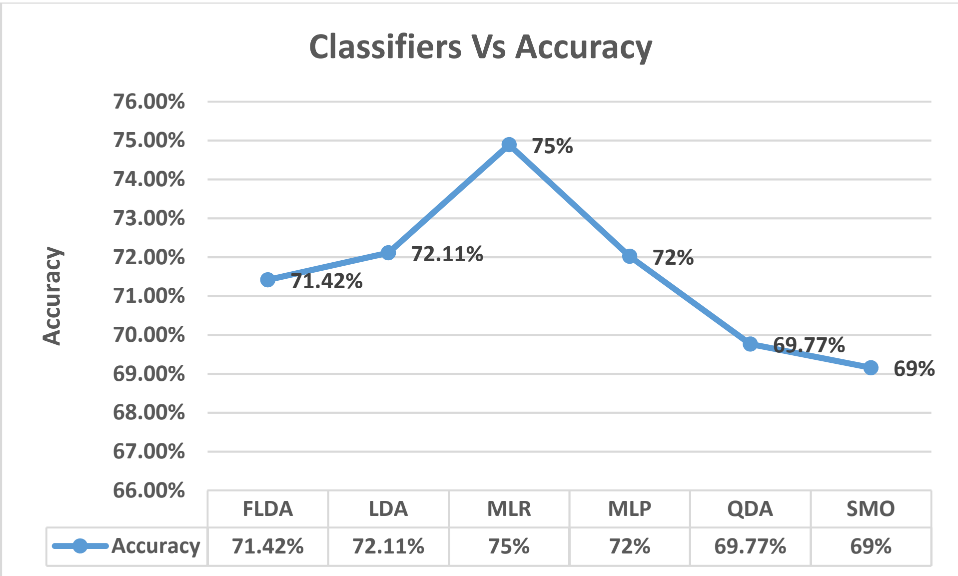

Figure 3: Classifiers Vs Accuracy

The above figure 3 depicts the accuracy levels of FLDA, LDA, MLR, MLP, QDA, and SMO of functional models. The MLR shows 75% of efficiency which is highest than other models. The SMO shows 69% of efficiency which is lowest than other models. The LDA,MLP,FLDA and QDA shows 72.11% of accuracy,72% of accuracy,71.42% of accuracy and 69.77% of accuracy respectively.

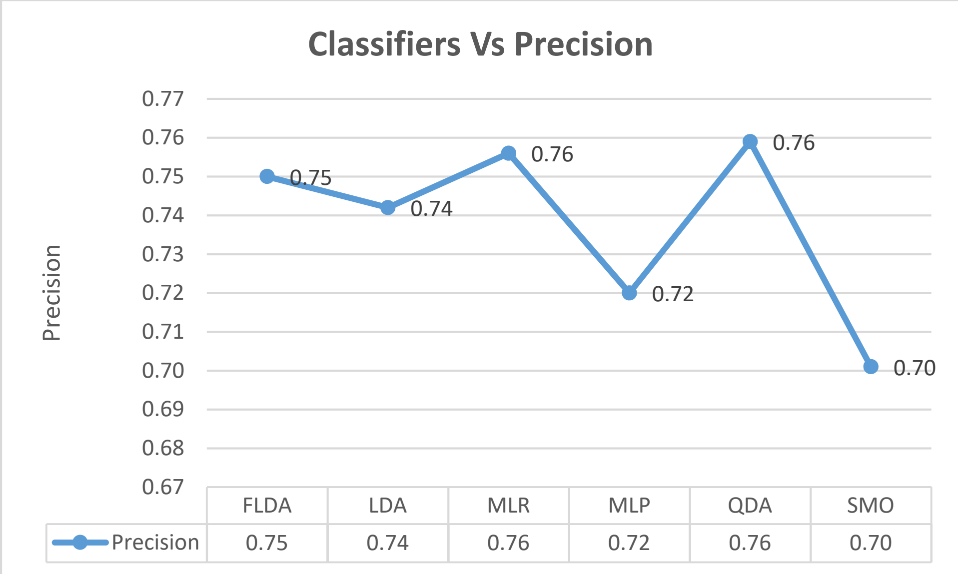

Figure 4: Classifiers Vs Precision

The above figure 4 depicts the various precision levels of FLDA, LDA, MLR, MLP, QDA, and SMO of functional models. The MLR and QDA shows the same as well maximum precision value compare than others which is 0.76 of precision value. The FLDA, LDA, MLP and SMO shows 0.75, 0.74, 0.72 and 0.70 of precision value respectively.

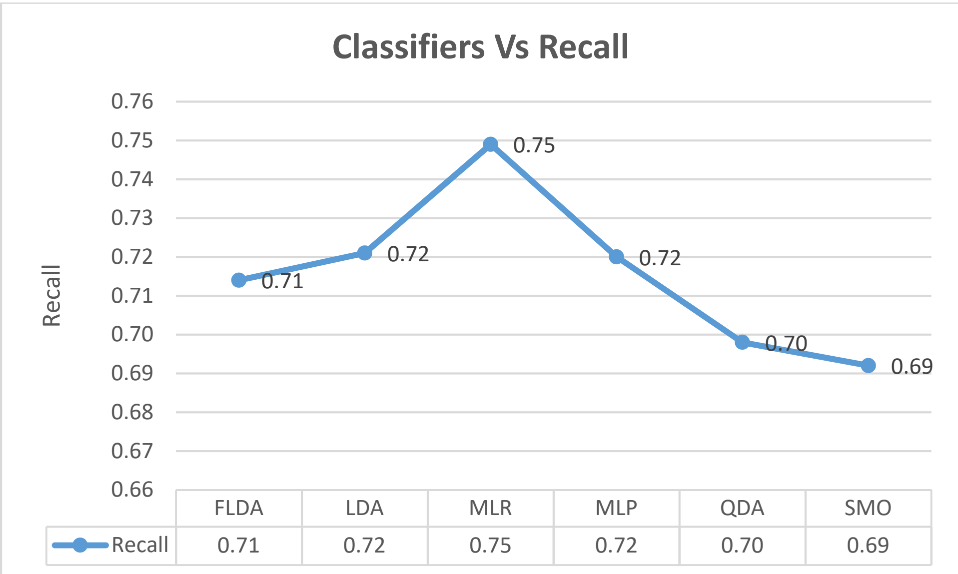

Figure 5: Classifiers VsRecall

The above figure 5 depicts the various recall levels FLDA,LDA,MLR,MLP,QDA,and SMO of functional models.The MLR shows maximum recall value i.e., 0.75 of recall. The SMO shows least recall 0.69 value. The LDA and MLP has same recall value which is 0.72. The FLDA and QDA has 0.71 of recall value and 0.70 of recall value.

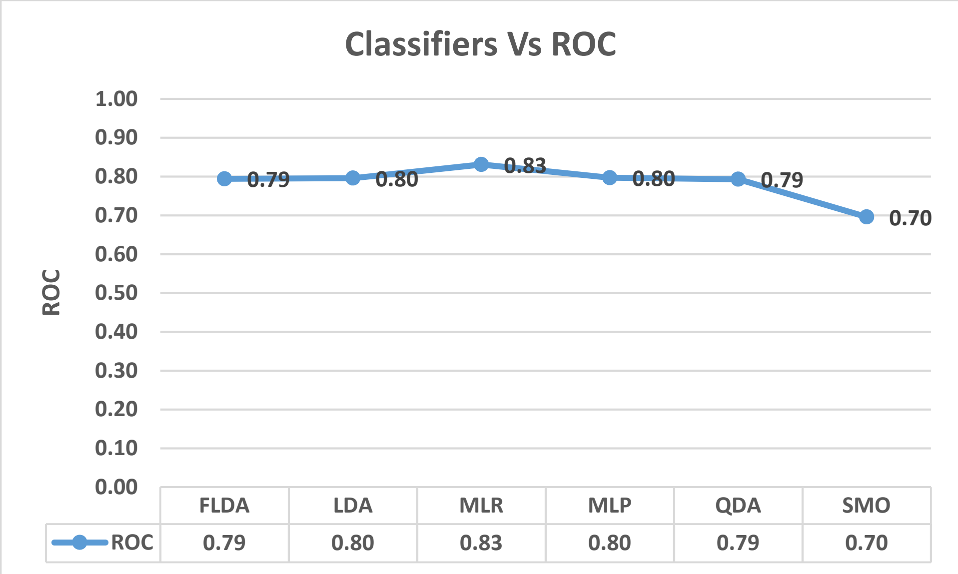

Figure 6: Classifiers Vs ROC

The above figure 6 depicts the various ROC levels of FLDA,LDA,MLR,MLP,QDA,and SMO of functional models. The MLR shows maximum ROC value 0.83. The SMO shows least ROC value 0.70. The FLDA and QDA shows same ROC value 0.79. The LDA and MLP shows same ROC value 0.80.

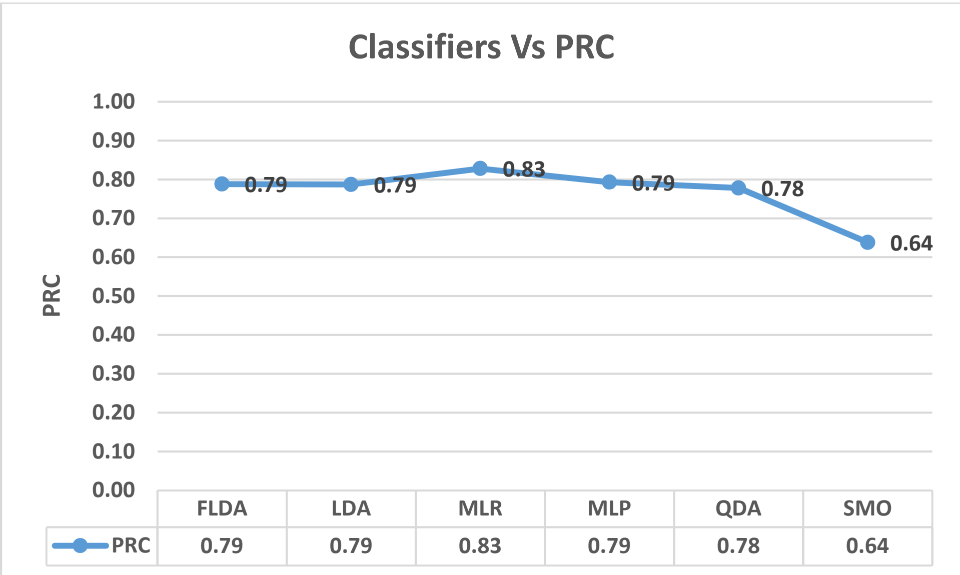

Figure 7: Classifiers VsPRC

The above figure 7 depicts the various PRC levels of FLDA,LDA,MLR,MLP,QDA,and SMO of functional models.The MLR shows the maximum PRC value which is 0.83. The SMO shows the minimum PRC value which is 0.64. The MLP,LDA and FLDA shows same PRC value which is 0.79 and QDA shows 0.78 of PRC value.

Table 3: Classifiers Vs Outcomes

Classifier	Time	Kappa	F-Measure	MCC
FLDA	0.01	0.44	0.71	0.47
LDA	0.00	0.45	0.72	0.47
MLR	0.06	0.50	0.75	0.51
MLP	3.03	0.44	0.20	0.44
QDA	0.00	0.41	0.69	0.46
SEQUENTIAL MINIMAL OPTIMIZATION	0.93	0.39	0.69	0.39

The above table 3 depicts the time consumption, Kappa, F-Measure, Matthews Correlation Coefficient value (MCC) of FLDA,LDA,MLR,MLP,QDA,and SMO of functional models.

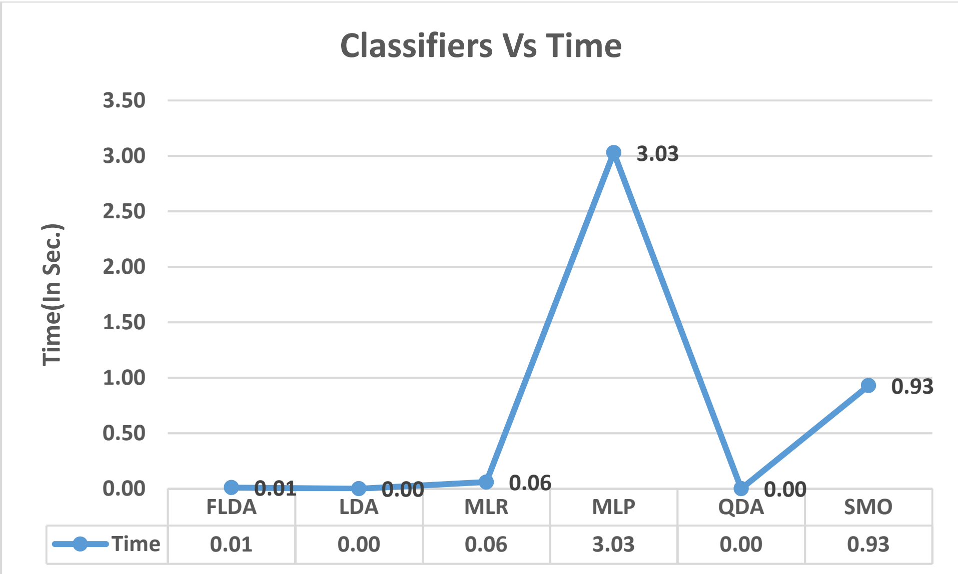

Figure 8: Classifiers Vs Time

The above figure 8 depicts the various time consumption in seconds for making models of FLDA,LDA,MLR,MLP,QDA,and SMO of functional models. The MLP takes more time for making its model which is 3.03 seconds. The QDA and LDA takes same time for creating their models which is zero seconds. The SMO takes 0.93 seconds, MLR takes 0.06 seconds, and FLDA takes 0.01 seconds for building their models.

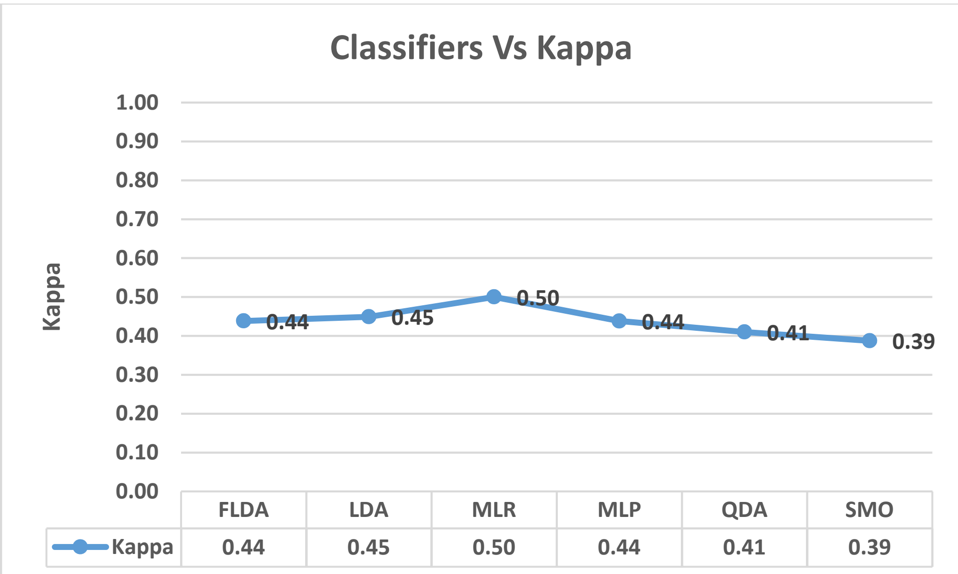

Figure 9: Classifiers VsKappa

The above figure 9 depicts the various kappa levels of FLDA,LDA,MLR,MLP,QDA,and SMO of functional models.The MLR has moderate agreement with the data which is 0.50 of kappa. The SMO has least fair agreement with the data which is 0.39. The LDA has 0.45 of kappa co efficient value. The FLDA and MLP has same kappa value which is 0.44. The QDA has 0.41 of kappa value.

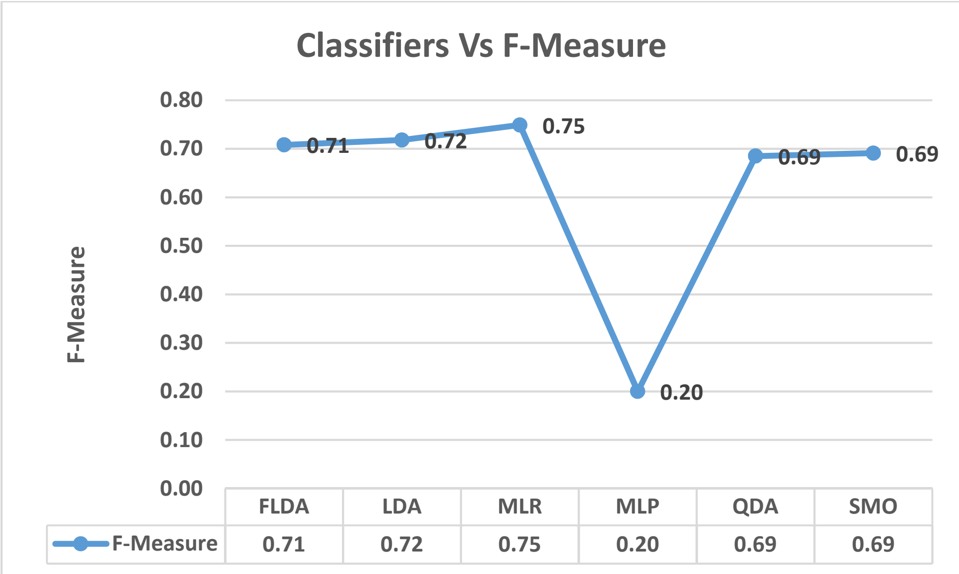

Figure 10: Classifiers Vs F-Measure

The above figure 10 depicts the various F-Measure levels of FLDA,LDA,MLR,MLP,QDA,and SMO of functional models.The MLP has least F-Measure value which is 0.20 and the MLR has maximum F-Measure value which is 0.75. The QDA and SMO has same F-Measure value 0.69. The LDA and FLDA has 0.72 and 0.71 of F-Measure value.

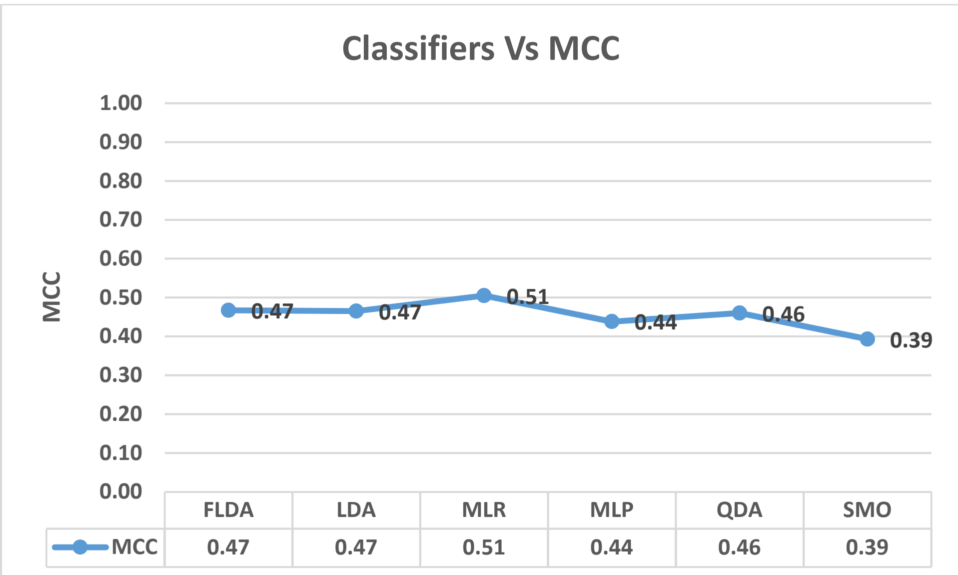

Figure 11: Classifiers VsMCC

The above figure 11 depicts the various MCC levels of FLDA,LDA,MLR,MLP,QDA,and SMO of functional models.The FLDA and LDA has same MCC value which is 0.47. The MLR had 0.51 which is highest MCC value. The SMO has MCC value 0.39 which is least than other models. The QDA and MLP has 0.46 and 0.44 of MCC values.

Table 4: Classifiers Vs Errors

Classifier	MAE	RMSE	RAE	RRSE
FLDA	0.48	0.48	96.86%	96.92%
LDA	0.40	0.43	79.80%	86.71%
MLR	0.32	0.41	65%	81.37%
MLP	0.33	0.44	66%	87.22%
QDA	0.30	0.53	60.74%	106.14%
SEQUENTIAL MINIMAL OPTIMIZATION	0.31	0.55	62%	111.28%

The above table 4 depicts the Mean Absolute Error (MAE), Relative Absolute Error (RAE),Root Measure Squared Error (RMSE), and Relative Root Squared Error (RRSE) of FLDA,LDA,MLR,MLP,QDA,and SMO of functional models.

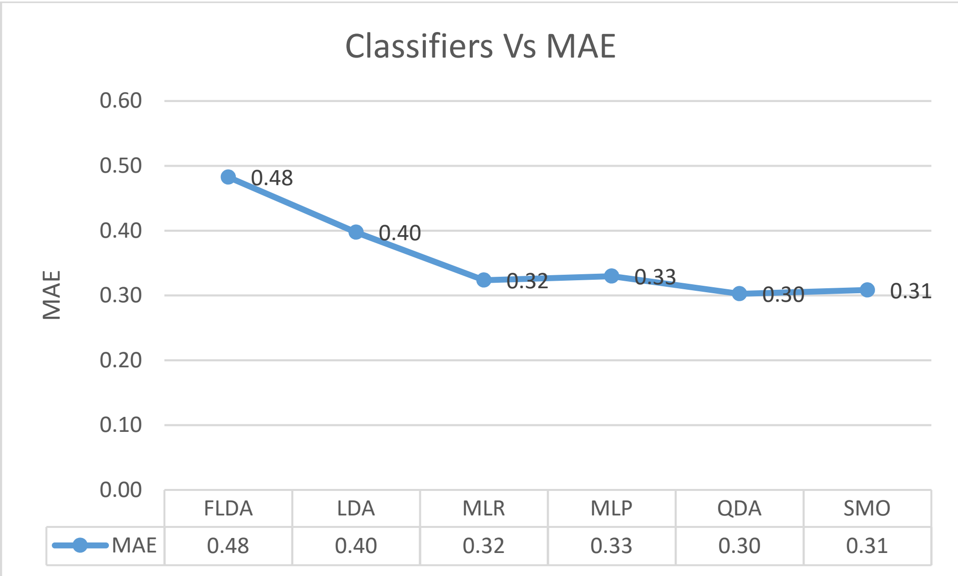

Figure 12: Classifiers VsMAE

The above figure 12 depicts the various MAE levels of FLDA,LDA,MLR,MLP,QDA,and SMO of functional models. The FLDA has worst performance which is 0.48 of MAE. The SMO has best performance which is 0.31 of MAE. The LDA, MLP, MLR, and QDA has 0.40 of MAE, 0.33 of MAE, 0.32 of MAE and 0.30 of MAE.

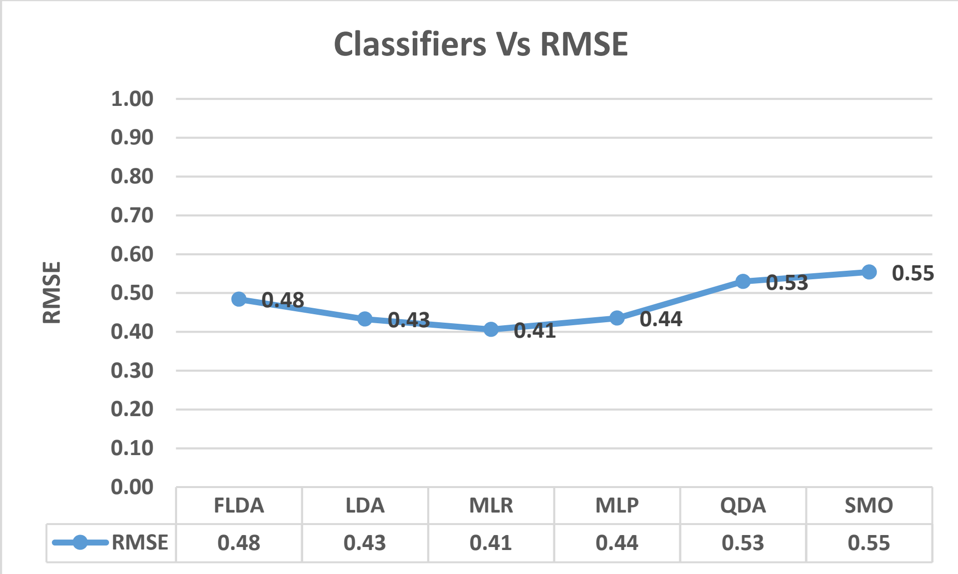

Figure 13: Classifiers Vs RMSE

The above figure 13 depicts the various RMSE levels of FLDA,LDA,MLR,MLP,QDA,and SMO of functional models.The SMO has worst performance which is 0.55 of RMSE; the MLR has best performance which is 0.41 of RMSE; the FLDA is 0.48 of RMSE, the LDA is 0.43 of RMSE, the MLP is 0.44 of RMSE and the QDA is 0.53 of RMSE.

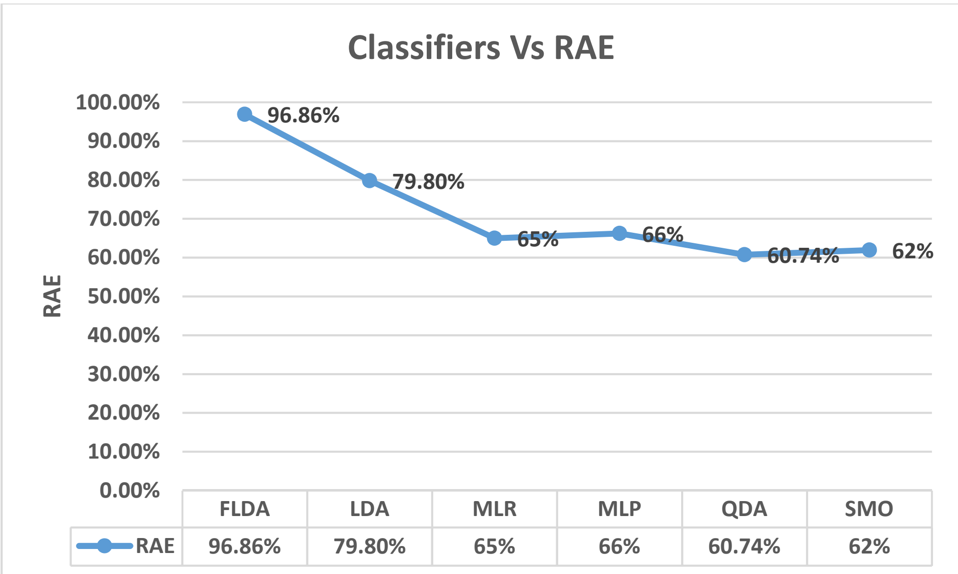

Figure 14: Classifiers Vs RAE

The above figure 14 depicts the various RAE levels of FLDA,LDA,MLR,MLP,QDA,and SMO of functional models. The FLDA is having worst performance, it has 96.86% of RAE and SMO is having best performance, it has 62% of RAE. The LDA is 79.80% of RAE, MLR is 65% of RAE and MLP is 66% of RAE and QDA is 60.74% of RAE.

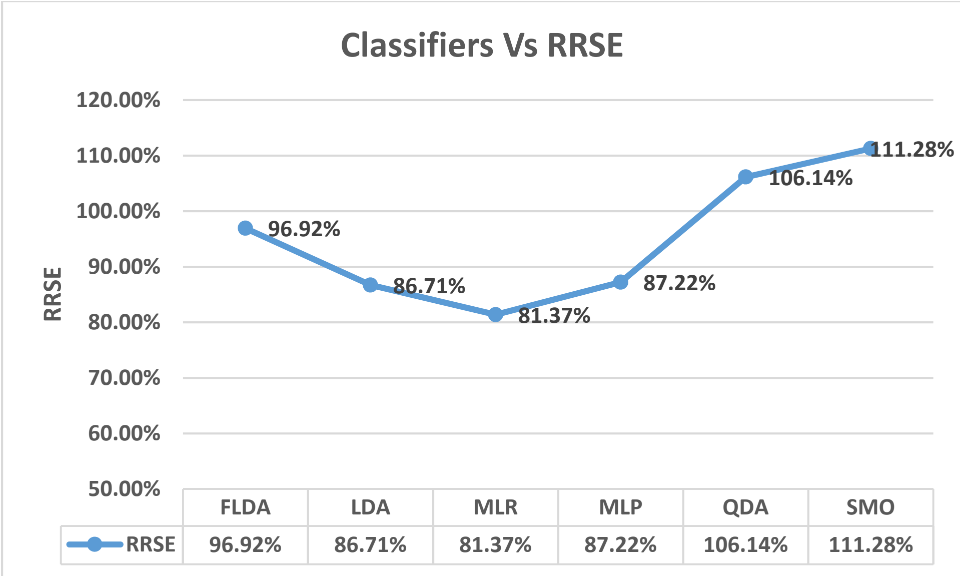

Figure 15: Classifiers Vs RRSE

The above figure 15 depicts the various RRSE levels of FLDA,LDA,MLR,MLP,QDA,and SMO of functional models. The SMO performance is low which 111.28% of RRSE is and MLR performance is good which 81.37% of RRSE. The FLDA,LDA,MLP and QDA has 96.92%,86.71%,87.22% and 106.14% of RRSE values respectively.

V Conclusion

This research work shows the Multi Logistic Regression model has most accurate at 75% , 0.76 of precision, 0.75 of recall, 0.83 of ROC, 0.83 of PRC, Kappa 0.50indicates moderate data agreement, 0.75 of F-Measure and 0.51of Matthews Correlation Coefficient with least deviations. This work recommends that the MLR model performed well compare with other models.

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Conflicts of interest

The authors have no conflicts of interest to declare.

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Authors Profile

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Dr. T. Sasipraba, obtained her B.E and M.E., from the University of Madras and Ph.D from Sathyabama University. She joined Sathyabama University in 1995 as a Lecturer and her 19 years of meritorious career in the same University has promoted her as Vice Chancellor of the university in the year 2020. During the course of her career at Sathyabama University Dr.T.Sasipraba has made exceptional contributions in the areas of research and developments, international linkages and Publications. For her outstanding contributions over the years, Dr.T.Sasipraba has received numerous awards from Sathyabama University and from Cognizant Technology Solutions. She has published more than 127 papers in refereed international journals and conference proceedings and has guided many Ph.D. Scholars in the field of Computer Science and Engineering.