e-ISSN : 0976-5166
p-ISSN : 2231-3850

KNOWLEDGE DATA ANALYSIS ON MIGRAINE HEADACHES BY USING OPTIMAL CLASSIFIERS

Dr. K. Nattar Kannan[1] , Dr. Gunasekar Thangarasu[2]

Professor, Department of Artificial Intelligence and Machine Learning, Saveetha School of Engineering, Saveetha Institute of Medical and Technical Sciences (SIMATS),Chennai.[1].

Professor, Head of Department, Professional Industry Driven Education (PRIDE), MAHSA University, Malaysia[2].

kannannattar@gmail.com[1],gunasekar97@gmail.com[2]

Abstract

Machine learning (ML) is largely used to develop automatic predictors in migraine classification but automatic predictors for medication overuse (MO) in migraine are still in their infancy. This research work finds Naïve Bayes and Naïve Bayes Updateable classifier of statistical learning are producing an efficient results compare with functional learning models. In Statistical learning Naïve Bayes and Naïve Bayes Updateable algorithms are having same as well as highest efficient outcome which is 93.50% of accuracy; In Functional learning, Quadratic Discriminant Analysis is having 93% of accuracy which is highest efficient outcome compare with other functional models. In Statistical learning Naïve Bayes and Naïve Bayes Updateable algorithms are having same as well as highest efficient outcome which is 0.93 of PPV; In Functional learning, Quadratic Discriminant Analysis is having highest PPV which is 0.93 of PPV. In Statistical learning Naïve Bayes and Naïve Bayes Updateable algorithms are having same as well as highest efficient outcome which is 0.94 of TPR; In Functional learning, Quadratic Discriminant Analysis is having highest TPR which is 0.93 of TPR compare with other functional learning. In Statistical learning Naïve Bayes and Naïve Bayes Updateable algorithms are having same as well as highest efficient outcome which is 0.99 of AUCROC; In Functional learning, Quadratic Discriminant Analysis and Multi-Layer Perceptron are having highest AUCROC and same AUCROC value which is 0.97 of AUCROC compare with other functional learning. In Statistical learning Naïve Bayes and Naïve Bayes Updateable algorithms are having same as well as highest efficient outcome which is 0.97 of AUCPRC; In Functional learning, Quadratic Discriminant Analysis is having highest AUCPRC value which is 0.93 of AUCPRC Compare with other functional learning. In Statistical learning Naïve Bayes and Naïve Bayes Updateable algorithms are having same as well as highest efficient outcome which is 0.93 of F1-Score;. In Functional learning, Quadratic Discriminant Analysis is having highest F1-Score value which is 0.93 of F1-Score value Compare with other functional learning. In Statistical learning Naïve Bayes and Naïve Bayes Updateable algorithms are having same as well as highest efficient outcome which is 0.89 of k value; In Functional learning, Quadratic Discriminant Analysis is having highest k value which is 0.88 of k value Compare with other functional learning. In Statistical learning, Naïve Bayes and Naïve Bayes Updateable algorithms are having same as well as highest efficient outcome which is 0.90 of phi coefficient value; In Functional learning, Quadratic Discriminant Analysis is having highest phi coefficient value which is 0.88 of phi coefficient value Compare with other functional learning. This work finds that statistical learning models produce better outcome with lowest errors compare with functional model

Keywords: Migraine, Functional Learning, Headache, Statistical learning, KDD

I Introduction

Migraine is a primary form of headache characterized by recurrent episodes of debilitating headache, sometimes preceded by transient neurological symptoms named aura.[1] Its pathophysiology recognizes a unique mixture of bio-psycho-social aspects, which may all trigger the attack in susceptible individuals, unveiling a biological predisposition of a dysexcitable brain to convert non-painful stimulation into headache pain. This ultimately leads to impressive disability, significant productivity loss, huge economic burden and healthcare resource use. Current validated diagnostic criteria, in fact, distinguish migraine according to the attack frequency (episodic or chronic) or to the presence/absence of aura [2,3,4], but do not disentangle he different endophenotypes of this highly heterogeneous headache disorder[4]. Thus, there is still an unmet need to develop classifications models that embody the newest AI technologies and can be used to predict MO in individual migraine patients for a personalized patient care.

This paper organizes, In section 2 presents related works of this research work; In Section 3 presents materials and methods; In Section 4 shows results and discussion and finally Section 5 conclusion of this research work.

II Literature Survey

Preventative migraine medications are often underutilized, leaving patients at-risk of medication overuse, disease progression, higher disability and increased healthcare costs [5-9]. Daily or weekly analgesic use, in fact, disproportionately increases the risk for chronic migraine as documented by a large prospective population survey [10]. When considering a specialized headache center setting, the odds for developing chronic migraine 1 year later in patients with episodic migraine with MO is 19.4 times higher than in those without [11]. The risk of chronic migraine progression is further incremented when overusing involves acute medications containing barbiturates, compared with acetaminophen, as hinted by the American Migraine Prevalence and Prevention (AMPP) study [13, 14]. MOH is the epitome of hard to treat neurological disorders due to its disappointing response to treatment and frequent relapse. Artificial intelligence (AI) with machine learning (ML) has shown great potential in building automatic predictors in the field of migraine but detectors for MO are still in their infancy [21]. In fact, many AI models have been applied for nearly 10 years to implement medical decision support systems for the diagnosis of migraine and for predicting migraine treatment outcomes [14-23].

III Materials and Methods

This section focuses terms and definition of this research work. The dataset borrowed from kaggle repository[24]. It consists 400 records with following 24 labels. Age, Duration, Frequency, Location, Character, Intensity, Nausea, Vomit, Photophobia, Photophobia, Visual Sensory, Dysphasia, Dysarthria, Vertigo, Tinnitus, Hypocausts, iplopia, Defect Ataxia, Conscience, Paresthesia, DPF and Type. This dataset Consists there are 7 different types which is called classes. They are Sporadic hemiplegic migraine,Basilar-type aura,Migraine without aura,Typical aura with migraine,Typical aura without migraine,Familial hemiplegic migraine and other.

This work implements that the following proposed methods by 1:9 fold cross validation in open source data mining tool namely Weka.3.9.5.[25]

- Statistical Learning
    - Bayes Net
    - Naïve Bayes
    - Naïve Bayes Multinomial Updateable
    - Naïve Bayes Updateable
    - Naïve Bayes Multinomial
- Functional Learning
    - Latent Dirichlet allocation
    - Sequential minimal optimization
    - Quadratic Discriminant Analysis
    - Multinomial Logistic Regression
    - Multilayer Perceptron

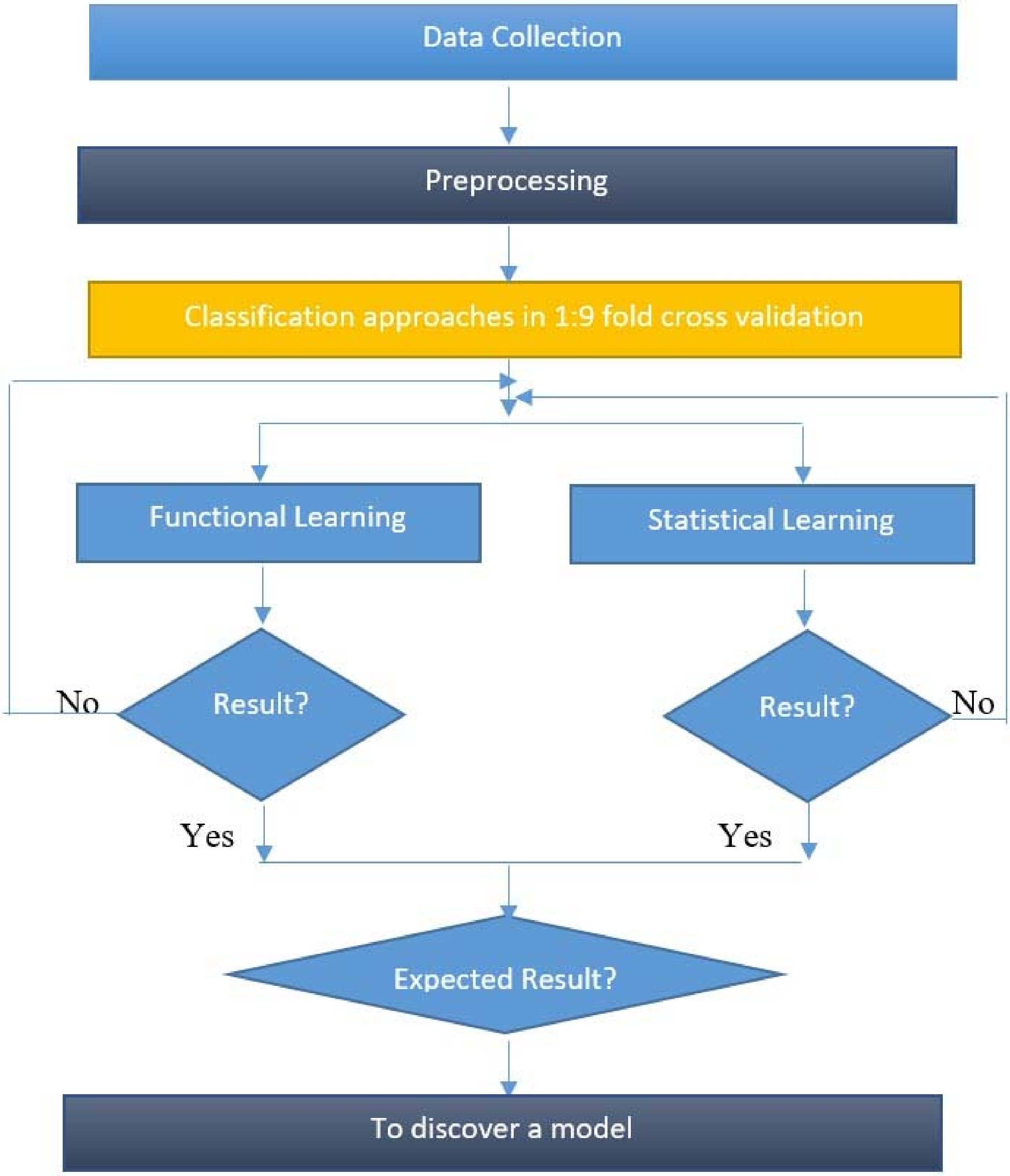

Figure 1: Proposed System Architecture

IV Results and Discussions

In this section focuses on the results and discussions of the research work. The below table 1 presents that the performance of various accuracies, Positive Predictive Value (PPV), True Positive Rate (TPR), AUCROC, and AUCPRC of statistical and functional learning on borrowed dataset.

Table 1: Performance of Model Evaluation on Statistical Vs Functional Learning

Category	Classifiers	Accuracy	Positive Predictive Value	True Positive Rate	AUCROC	AUCPRC
Statistical Learning	Bayes Net	90.75%	0.90	0.90	0.98	0.95
	Naïve Bayes	93.50%	0.93	0.94	0.99	0.97
	Naïve Bayes Multinomial Updateable	85.50%	0.85	0.86	0.97	0.92
	Naïve Bayes Updateable	93.50%	0.93	0.94	0.99	0.97
	Naïve Bayes Multinomial	85.50%	0.85	0.86	0.97	0.92
Functional Learning	Latent Dirichlet Allocation	90.25%	0.90	0.90	0.96	0.92
	Sequential minimal optimization	89.00%	0.88	0.89	0.92	0.83
	Quadratic Discriminant Analysis	93.00%	0.93	0.93	0.97	0.93
	Multinomial Logistic Regression	88.75%	0.89	0.89	0.94	0.84
	Multilayer Perceptron	89.50%	0.90	0.90	0.97	0.92

In Statistical Learning, Bayes Net is having 90.75% of accuracy,0.90 of PPV,0.90 of TPR,0.98 of AUCROC and 0.95 of AUCPRC values; Naïve Bayes is having 93.50% of accuracy,0.93 of PPV,0.94 of TPR,0.99 of AUCROC and 0.97 of AUCPRC values; Naïve Bayes Multinomial Updateable is having 85.50% of accuracy,0.85 of PPV,0.86 of TPR,0.97 of AUCROC and 0.92 of AUCPRC values; Naïve Bayes Updateable is having 93.50% of accuracy,0.93 of PPV,0.94 of TPR,0.99 of AUCROC and 0.97 of AUCPRC values; Naïve Bayes Updateable is having 85.50% of accuracy,0.85 of PPV,0.90 of TPR,0.86 of AUCROC and 0.97 of AUCPRC values.

In Functional Learning, Latent Dirichlet Allocation is having 90.25% of accuracy,0.90 of PPV,0.90 of TPR,0.96 of AUCROC and 0.92 of AUCPRC values; Sequential minimal optimization is 89% of accuracy,0.88 of PPV,0.89 of TPR,0.92 of AUCROC and 0.83 of AUCPRC values; Quadratic Discriminant Analysis is having 93% of accuracy,0.93 of PPV,0.93 of TPR,0.97 of AUCROC and 0.93 of AUCPRC values; Multinomial Logistic Regression is having 88.75% of accuracy,0.89 of PPV,0.89 of TPR,0.94 of AUCROC and 0.84 of AUCPRC values; Multilayer Perceptron is having 89.50% of accuracy,0.90 of PPV,0.90 of TPR,0.97 of AUCROC and 0.92 of AUCPRC values.

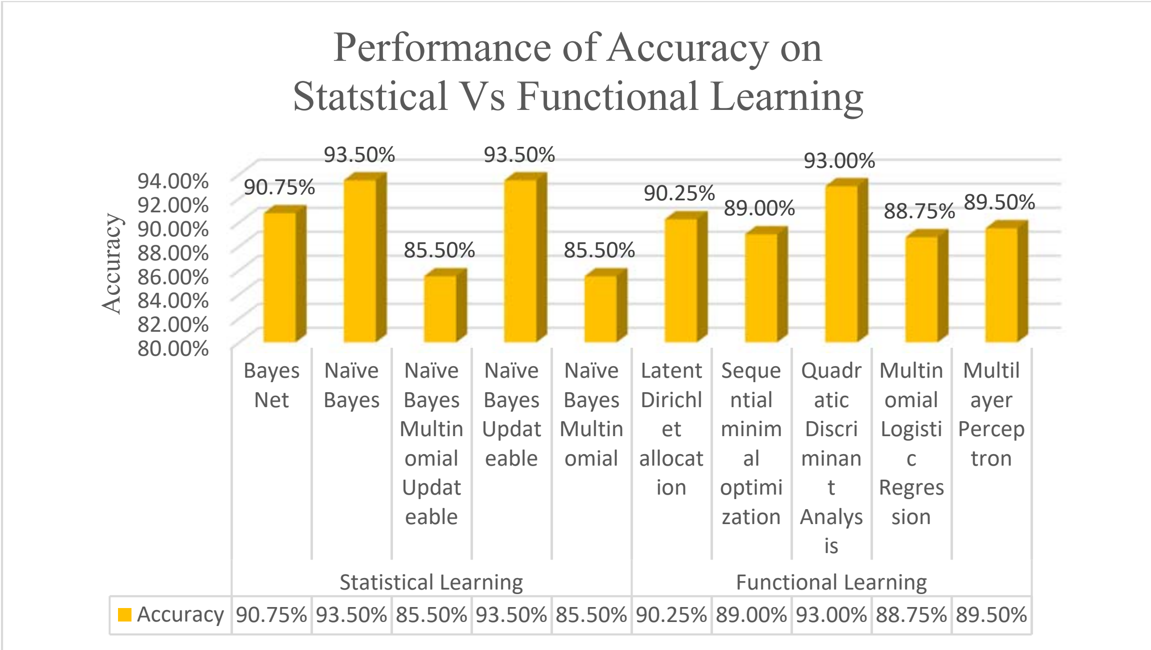

Figure 2: Performance of Accuracy on Statistical Vs Functional Learning

The figure 2 shows that the various accuracy performances of statistical and functional learning on borrowed dataset. In Statistical learning Naïve Bayes and Naïve Bayes Updateable algorithms are having same as well as highest efficient outcome which is 93.50% of accuracy; the Naive Bayes and Naïve Bayes Multinomial are having lowest as well same outcome which is 85.50% of accuracy. In Functional learning, Multinomial Logistic Regression is having lowest accuracy level which is 88.75%; Quadratic Discriminant Analysis is having 93% of accuracy which is highest efficient outcome compare with other functional models.

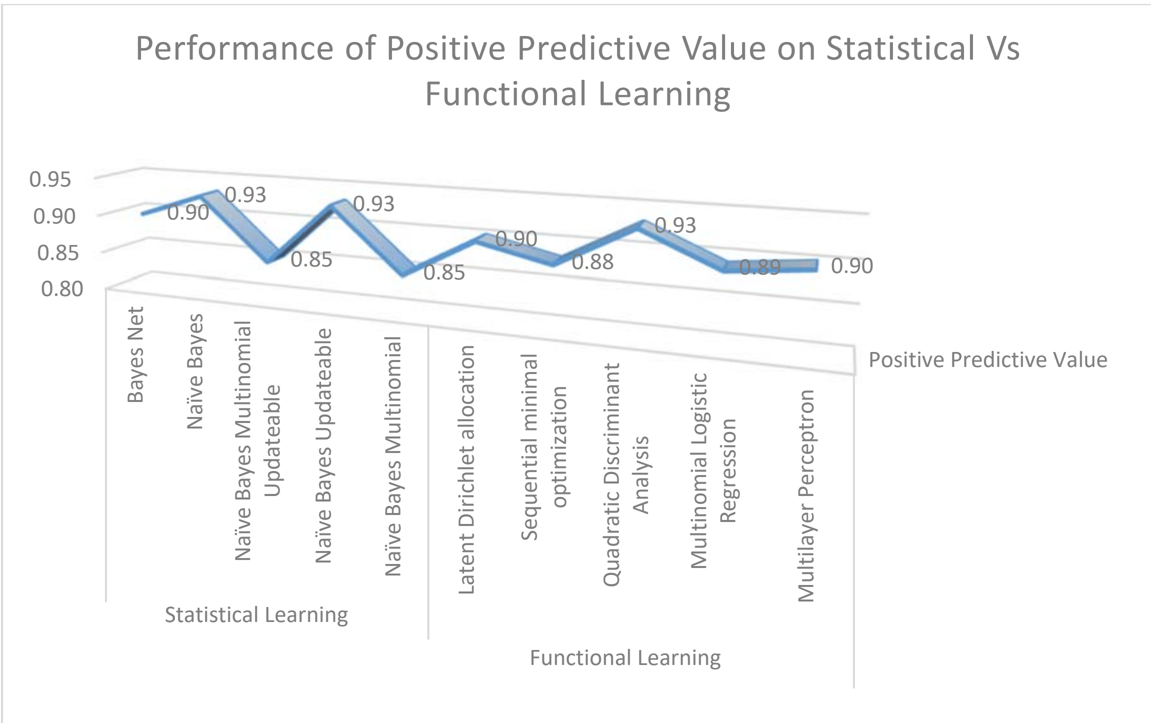

Figure 3: Performance of PPV on Statistical Vs Functional Learning

The figure 3 shows that the various PPV performances of statistical and functional learning on borrowed dataset. In Statistical learning Naïve Bayes and Naïve Bayes Updateable algorithms are having same as well as highest efficient outcome which is 0.93 of PPV; the Naive Bayes and Naïve Bayes Multinomial are having lowest as well same outcome which is 0.85 of PPV. In Functional learning, SMO is having lowest PPV level which is 0.88 of PPV; Quadratic Discriminant Analysis is having highest PPV which is 0.93 of PPV.

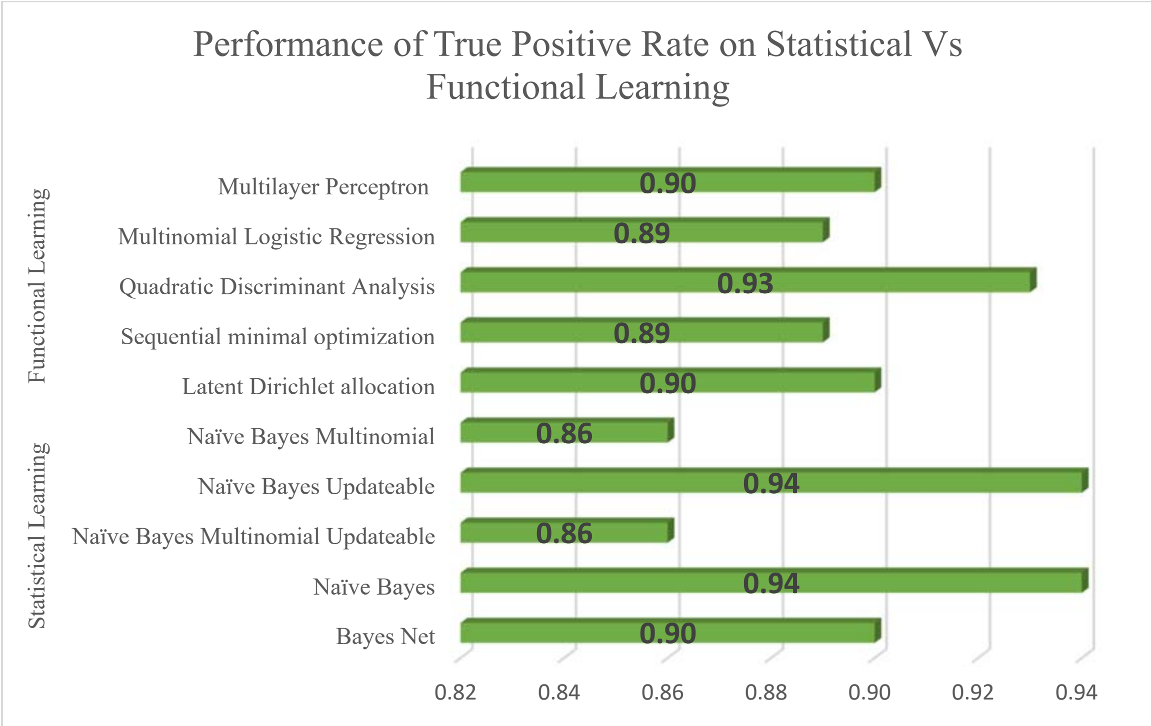

Figure 4: Performance of TPR on Statistical Vs Functional Learning

The figure 4 shows that the various TPR performances of statistical and functional learning on borrowed dataset. In Statistical learning Naïve Bayes and Naïve Bayes Updateable algorithms are having same as well as highest efficient outcome which is 0.94 of TPR; the Naive Bayes and Naïve Bayes Multinomial are having lowest as well same outcome which is 0.86 of TPR. In Functional learning, SMO and Multinomial Logistic Regression is having lowest TPR level which is 0.89 of TPR; Quadratic Discriminant Analysis is having highest TPR which is 0.93 of TPR compare with other functional learning.

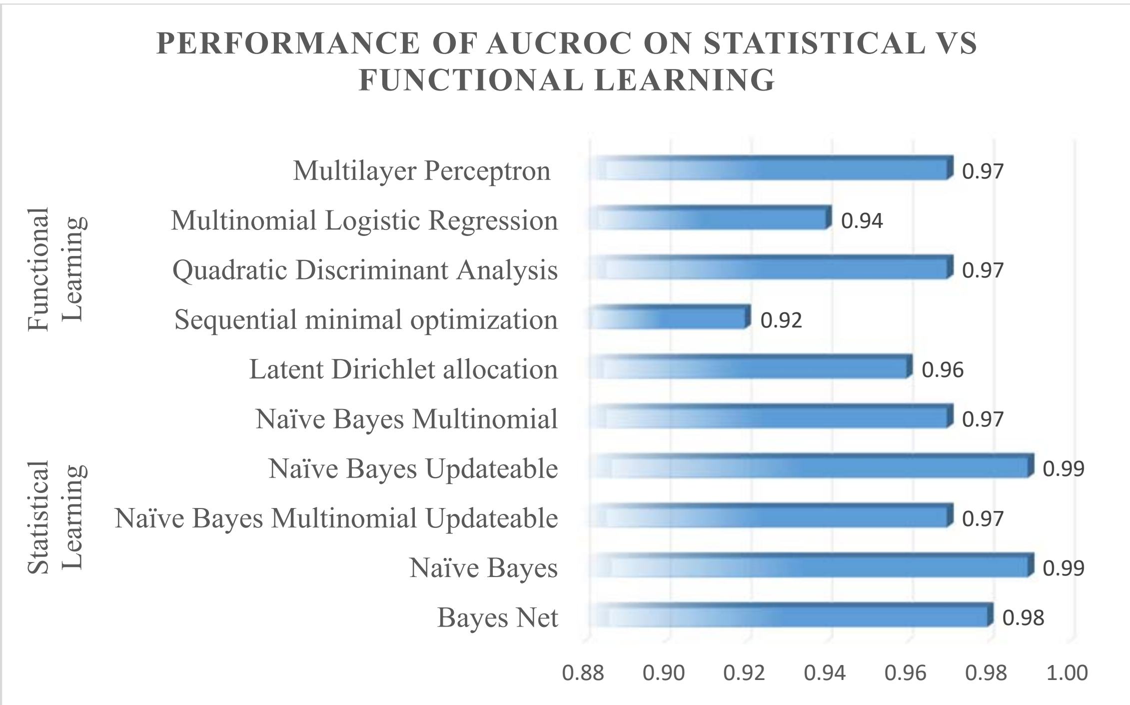

Figure 5: Performance of AUCROC on Statistical Vs Functional Learning

The figure 5 shows that the various AUCROC performances of statistical and functional learning on borrowed dataset. In Statistical learning Naïve Bayes and Naïve Bayes Updateable algorithms are having same as well as highest efficient outcome which is 0.99 of AUCROC; the Naive Bayes and Naïve Bayes Multinomial are having lowest as well same outcome which is 0.97 of AUCROC. In Functional learning, SMO is having lowest AUCROC

e-ISSN : 0976-5166
p-ISSN : 2231-3850

level which is 0.92 of AUCROC; Quadratic Discriminant Analysis and Multi-Layer Perceptron are having highest AUCROC and same AUCROC value which is 0.97 of AUCROC compare with other functional learning.

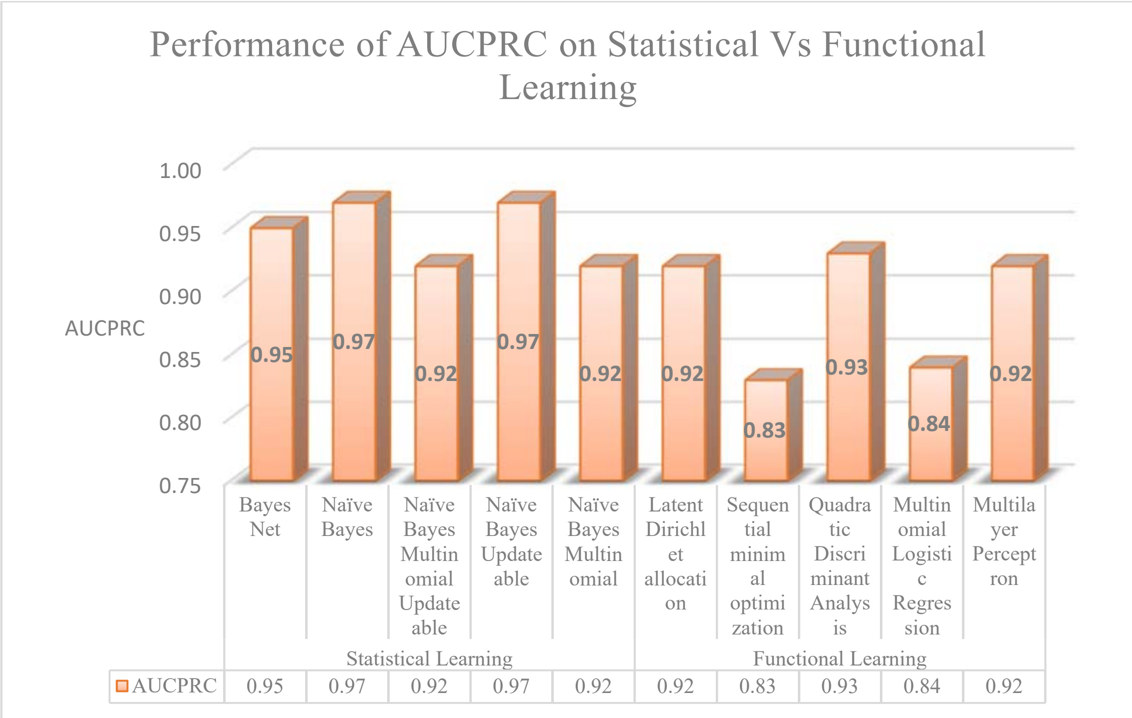

Figure 6: Performance of AUCPRC on Statistical Vs Functional Learning

The figure 6 shows that the various AUCPRC performances of statistical and functional learning on borrowed dataset. In Statistical learning Naïve Bayes and Naïve Bayes Updateable algorithms are having same as well as highest efficient outcome which is 0.97 of AUCPRC; the Naive Bayes and Naïve Bayes Multinomial are having lowest as well same outcome which is 0.92 of AUCPRC. In Functional learning, SMO is having lowest AUCPRC level which is 0.83 of AUCPRC; Quadratic Discriminant Analysis is having highest AUCPRC value which is 0.93 of AUCPRC Compare with other functional learning.

Table 2: Performance of F1 Score, K, Phi Coefficient, and Time (In Sec) on Statistical Vs Functional Learning

Category	Classifiers	F1-Score	Cohen's Kappa	Phi Coefficient	Time (In Seconds)
Statistical Learning	Bayes Net	0.90	0.84	0.85	0.08
	Naïve Bayes	0.93	0.89	0.90	0.00
	Naïve Bayes Multinomial Updateable	0.84	0.72	0.75	0.02
	Naïve Bayes Updateable	0.93	0.89	0.90	0.02
	Naïve Bayes Multinomial	0.84	0.72	0.75	0.01
Functional Learning	Latent Dirichlet allocation	0.90	0.83	0.84	0.33
	Sequential minimal optimization	0.88	0.80	0.80	0.02
	Quadratic Discriminant Analysis	0.93	0.88	0.88	0.03
	Multinomial Logistic Regression	0.89	0.80	0.83	0.91
	Multilayer Perceptron	0.90	0.82	0.83	2.48

Above table 2 presents that the performance of various F1 Score, Cohen's Kappa statistic, Phi Coefficient, Time(In Seconds) to build a model of statistical and functional learning on borrowed dataset. In Statistical Learning, Bayes Net is having 0.90 of F1-Score value, 0.84 of Cohen's kappa statistic value, 0.85 of phi coefficient value, and it takes 0.08 seconds to make its model; Naïve Bayes is having 0.93 of F1-Score value, 0.89 of Cohen's kappa statistic value, 0.90 of phi coefficient value, and it takes zero seconds to make its model; Naïve Bayes Multinomial Updateable is having 0.84 of F1-Score value, 0.72 of Cohen's kappa statistic value, 0.75 of phi coefficient value, and it takes 0.02 seconds to make its model;Naïve Bayes Updateable is having 0.93 of F1-Score value, 0.89 of Cohen's kappa statistic value, 0.90 of phi coefficient value, and it takes 0.02 seconds to make its model; Naïve Bayes Updateable is having 0.84 of F1-Score value, 0.72 of Cohen's kappa statistic value, 0.75 of phi coefficient value, and it takes 0.01 seconds to make its model.

In Functional Learning, Latent Dirichlet Allocation is having 0.90 of F1-Score value, 0.83 of Cohen's kappa statistic value, 0.84 of phi coefficient value, and it takes 0.33 seconds to make its model; Sequential minimal optimization is having 0.88 of F1-Score value, 0.80 of Cohen's kappa statistic value, 0.80 of phi coefficient value, and it takes 0.02 seconds to make its model; Quadratic Discriminant Analysis is having 0.93 of F1-Score value, 0.88 of Cohen's kappa statistic value, 0.88 of phi coefficient value, and it takes 0.03 seconds to make its model; Multinomial Logistic Regression is having 0.89 of F1-Score value, 0.80 of Cohen's kappa statistic value, 0.83 of phi coefficient value, and it takes 0.91 seconds to make its model; Multilayer Perceptron is having 0.90 of F1-Score value, 0.82 of Cohen's kappa statistic value, 0.83of phi coefficient value, and it takes 2.48 seconds to make its model.

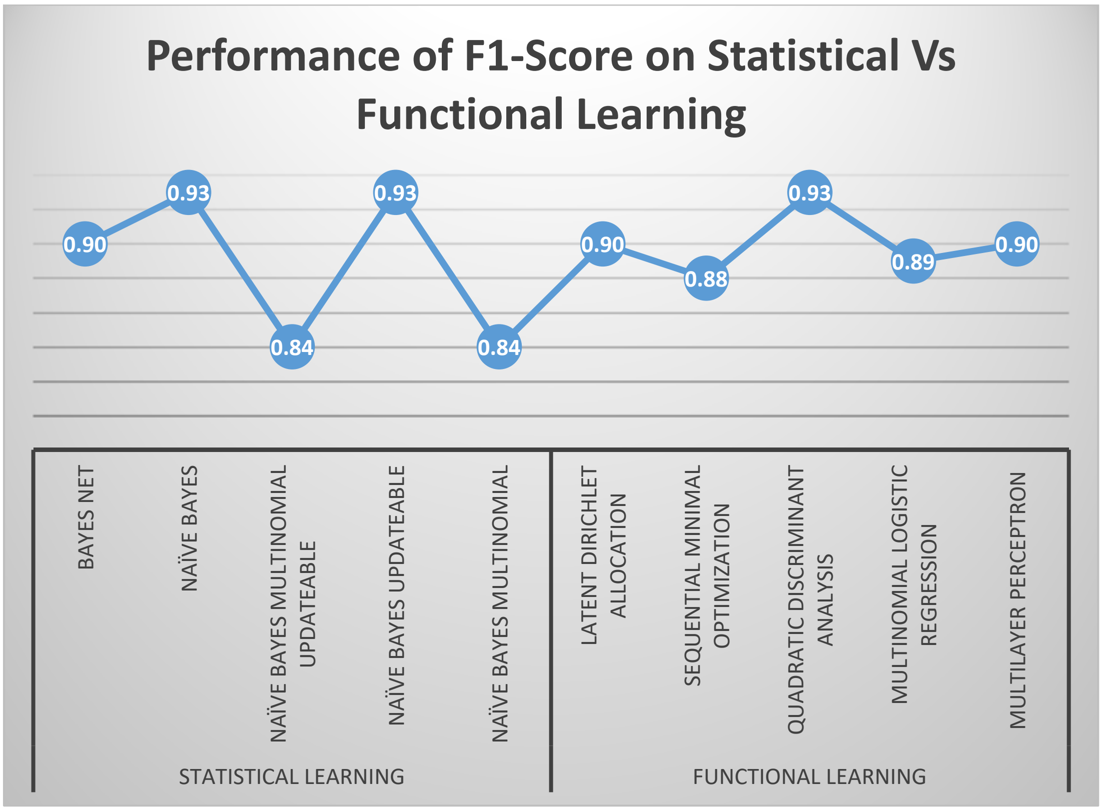

Figure 7: Performance of F1-Score on Statistical Vs Functional Learning

The figure 7 shows that the various F1-Score performances of statistical and functional learning on borrowed dataset. In Statistical learning Naïve Bayes and Naïve Bayes Updateable algorithms are having same as well as highest efficient outcome which is 0.93 of F1-Score; the Naive Bayes and Naïve Bayes Multinomial are having lowest as well same outcome which is 0.84 of F1-Score. In Functional learning, SMO is having lowest F1-Score level which is 0.88 of F1-Score; Quadratic Discriminant Analysis is having highest F1-Score value which is 0.93 of F1-Score value Compare with other functional learning.

e-ISSN : 0976-5166
p-ISSN : 2231-3850

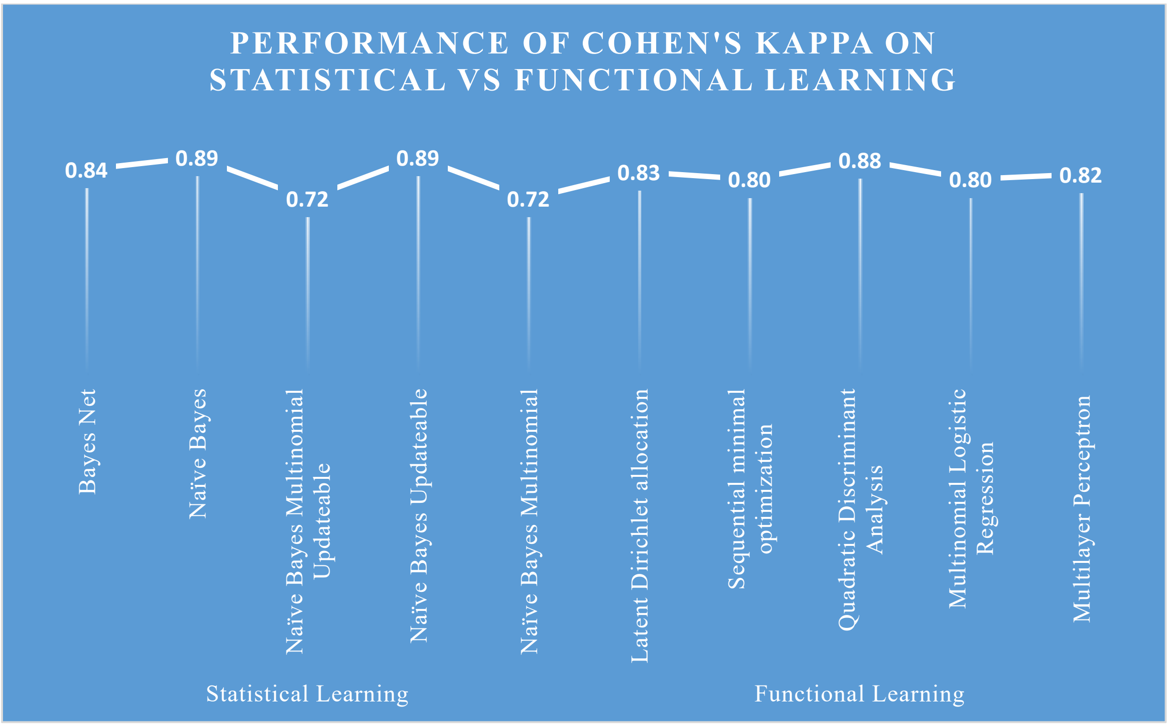

Figure 8: Performance of Kappa statistic on Statistical Vs Functional Learning

The figure 8 shows that the various Cohen's kappa statistic (k) performances of statistical and functional learning on borrowed dataset. In Statistical learning Naïve Bayes and Naïve Bayes Updateable algorithms are having same as well as highest efficient outcome which is 0.89 of k value; the Naive Bayes and Naïve Bayes Multinomial are having lowest as well same outcome which is 0.72 of k value. In Functional learning, SMO is having lowest k level which is 0.80 of k value; Quadratic Discriminant Analysis is having highest k value which is 0.88 of k value Compare with other functional learning.

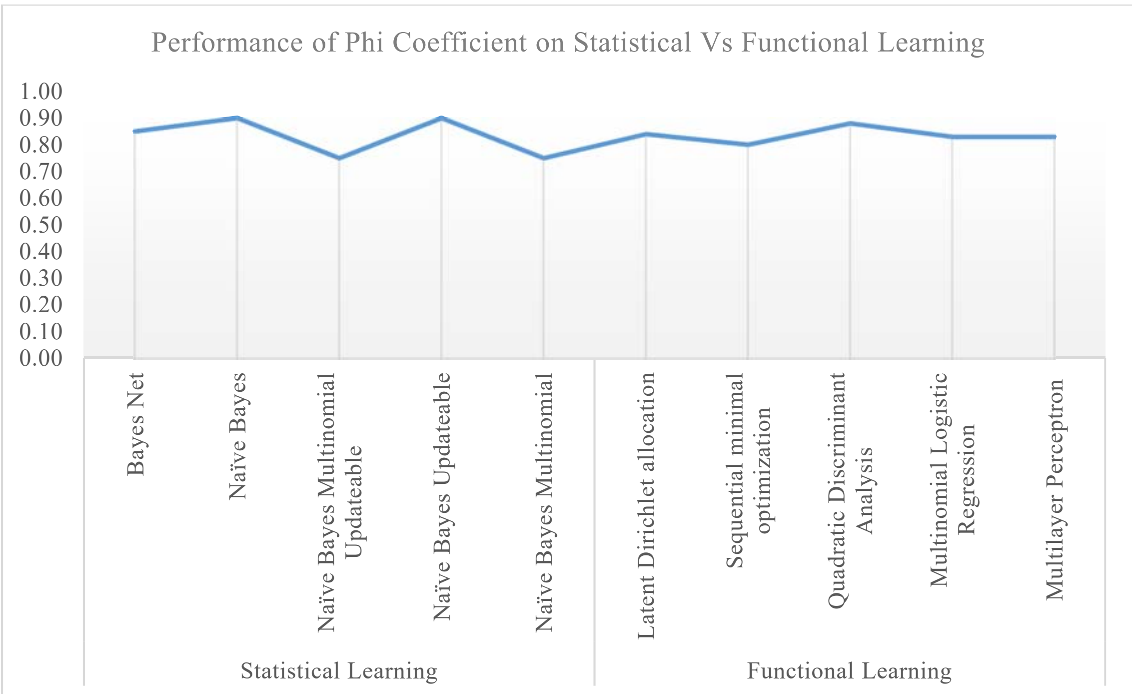

Figure 9: Performance of Phi Coefficient on Statistical Vs Functional Learning

The figure 9 shows that the various phi coefficient performances of statistical and functional learning on borrowed dataset. In Statistical learning, Naïve Bayes and Naïve Bayes Updateable algorithms are having same as well as highest efficient outcome which is 0.90 of phi coefficient value; the Naive Bayes and Naïve Bayes Multinomial are having lowest as well same outcome which is 0.75 of phi coefficient value. In Functional learning, SMO is having lowest phi coefficient value which is 0.80 of phi coefficient value; Quadratic Discriminant Analysis is having highest phi coefficient value which is 0.88 of phi coefficient value Compare with other functional learning.

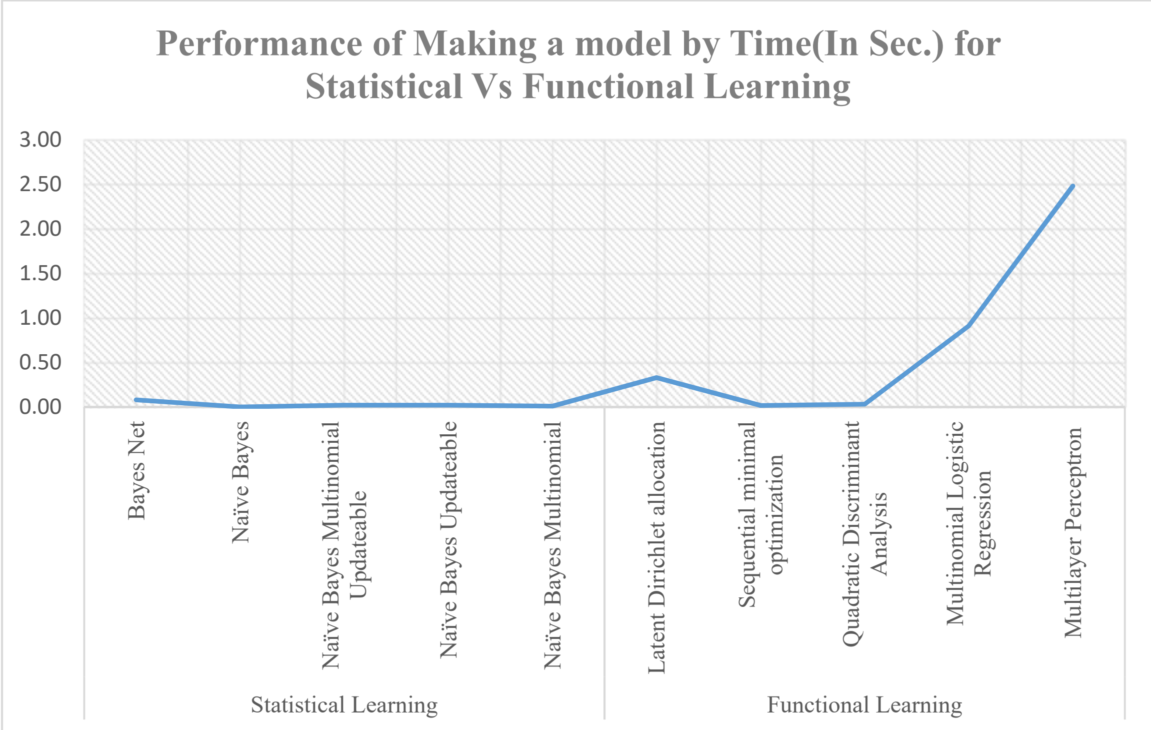

Figure 10: Performance of Time for making a model on Statistical Vs Functional Learning

The figure 10 shows that the various phi coefficient performances of statistical and functional learning on borrowed dataset. In Statistical learning Naïve Bayes is taking least time consumption which is zero seconds and Bayes Net is taking 0.08 seconds which is maximum time consumption to build its models. In functional learning, Multi-Layer Perceptron is taking more time consumption which is 2.48 seconds and SMO is taking least consumption to make a model which is 0.02 seconds.

Table 3: Performance of Errors on Statistical Vs Functional Learning

Category	Classifiers	Average Absolute Deviation	Root Average Squared Deviation	Relative Mean Squared Deviation	Root Relative Squared Deviation
Statistical Learning	Bayes Net	0.04	0.14	21.89%	49.15%
	Naïve Bayes	0.03	0.12	14.99%	41.35%
	Naïve Bayes Multinomial Updateable	0.06	0.17	34.58%	59.89%
	Naïve Bayes Updateable	0.03	0.12	14.99%	41.35%
	Naïve Bayes Multinomial	0.06	0.17	34.58%	59.89%
Functional Learning	Latent Dirichlet allocation	0.03	0.16	19.39%	54.12%
	Sequential minimal optimization	0.21	0.30	122.19%	105.10%
	Quadratic Discriminant Analysis	0.02	0.14	11.86%	48.58%
	Multinomial Logistic Regression	0.04	0.17	21.91%	59.03%
	Multilayer Perceptron	0.04	0.15	21.21%	51.61%

Above table 3 presents that the performance of Average Absolute Deviation, Root Average Squared Deviation, Relative Mean Squared Deviation and Root Relative Squared Deviation, of statistical and functional learning on borrowed dataset.

In Statistical Learning, Bayes Net is having 0.04 of average absolute deviation value, 0.14 of root average squared deviation,21.89% of relative mean squared deviation and 49.15% of root relative squared deviation; Naïve Bayes is having 0.03 of average absolute deviation value, 0.12 of root average squared deviation,14.99% of relative mean squared deviation and 41.35% of root relative squared deviation; Naïve Bayes Multinomial Updateable is 0.06 of average absolute deviation value, 0.17 of root average squared deviation,34.58% of relative mean squared deviation and 59.89% of root relative squared deviation; Naïve Bayes Updateable is having 0.03 of average absolute deviation value, 0.12 of root average squared deviation,14.99% of relative mean squared deviation and 41.35% of root relative squared deviation; Naïve Bayes Updateable is 0.06 of average absolute deviation value, 0.17 of root average squared deviation,34.58% of relative mean squared deviation and 59.89% of root relative squared deviation;

In Functional Learning, Latent Dirichlet Allocation is having 0.03 of average absolute deviation value, 0.16 of root average squared deviation,19.39% of relative mean squared deviation and 54.12% of root relative squared deviation; Sequential minimal optimization is having 0.21 of average absolute deviation value, 0.30 of root average squared deviation,122.19% of relative mean squared deviation and 105.10% of root relative squared deviation; Quadratic Discriminant Analysis is 0.02 of average absolute deviation value, 0.14 of root average squared deviation,11.86% of relative mean squared deviation and 48.58% of root relative squared deviation; Multinomial Logistic Regression is having 0.04 of average absolute deviation value, 0.17 of root average squared deviation,21.91% of relative mean squared deviation and 59.03% of root relative squared deviation; Multilayer Perceptron is 0.04 of average absolute deviation value, 0.15 of root average squared deviation,21.21% of relative mean squared deviation and 51.61% of root relative squared deviation.

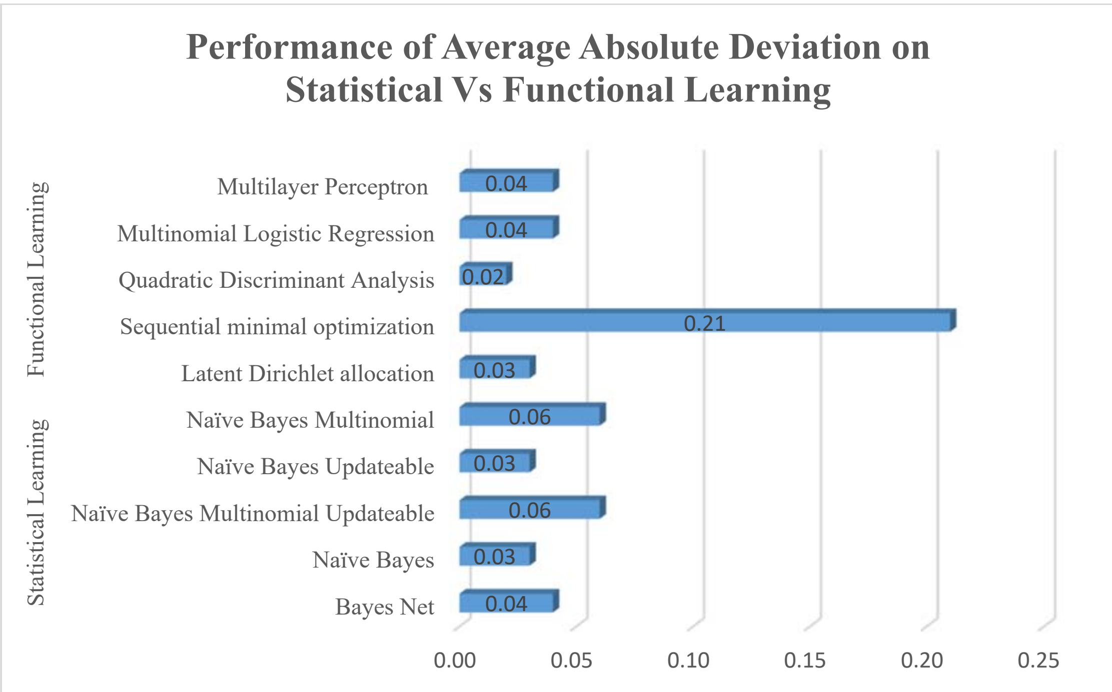

Figure 11: Performance of AAD on Statistical Vs Functional Learning

The figure 11 shows that the various AAD performances of statistical and functional learning on borrowed dataset.

In Statistical learning, Naïve Bayes updateable and Naïve Bayes are showing least errors which is 0.03 of AAD. Naïve Bayes Multinomial Updateable and Naïve Bayes Multinomial are showing same level of errors which is 0.06 of AAD.In Functional Learning, SMO is showing maximum level of errors which is 0.21 of AAD and QDA is showing least level of errors which is 0.02 of AAD.

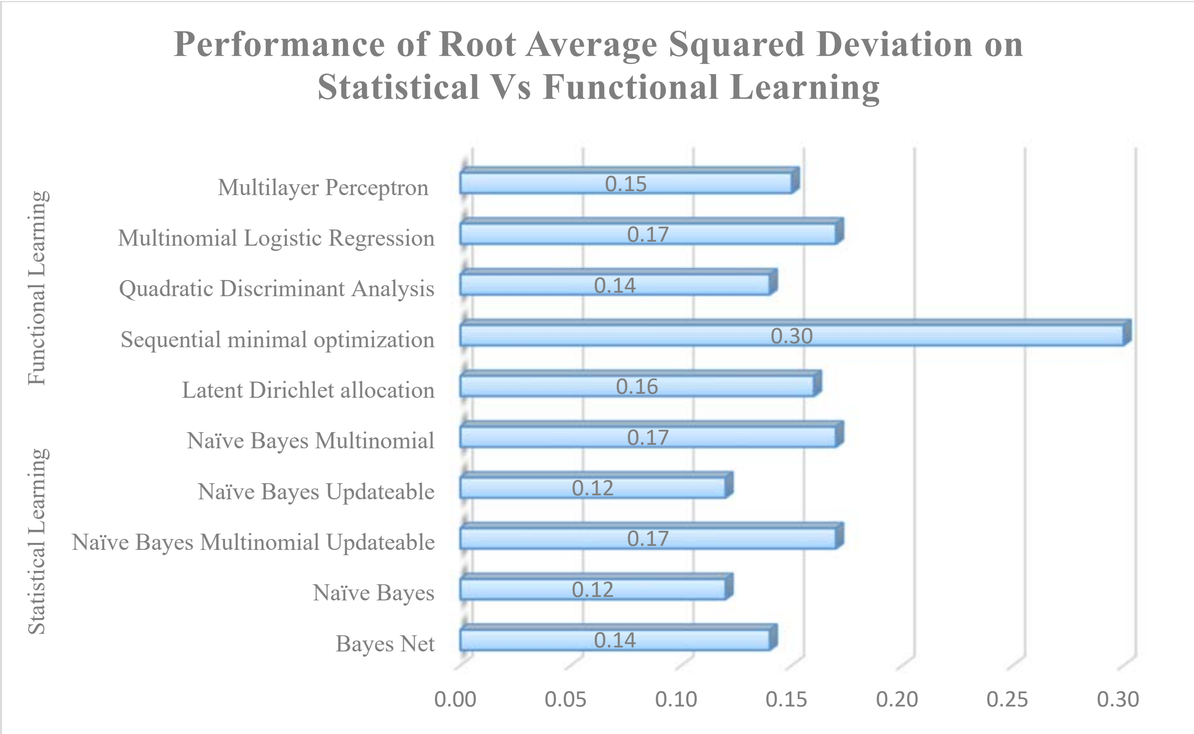

Figure 12: Performance of RASD on Statistical Vs Functional Learning

The figure 12 shows that the various RASD performances of statistical and functional learning on borrowed dataset. In Statistical learning, Naïve Bayes updateable and Naïve Bayes are showing least errors which is 0.17 of RASD. Naïve Bayes Multinomial Updateable and Naïve Bayes Multinomial are showing same level of errors which is 0.12 of RASD.In Functional Learning, SMO is showing maximum level of errors which is 0.30 of RASD and QDA is showing least level of errors which is 0.14 of RASD.

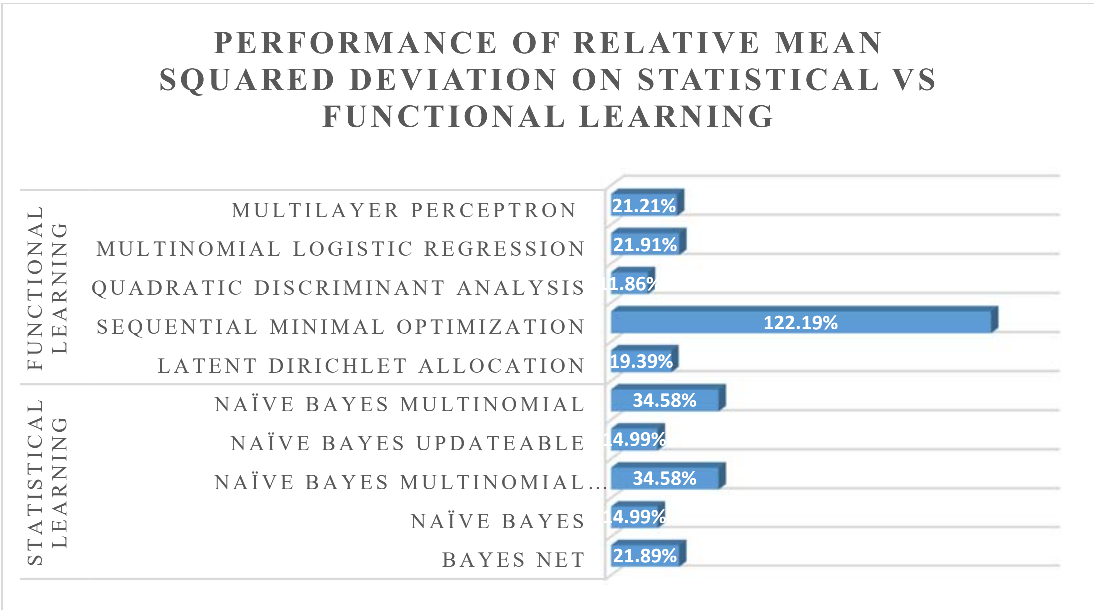

Figure 13: Performance of RMSD on Statistical Vs Functional Learning

The figure 13 shows that the various RASD performances of statistical and functional learning on borrowed dataset. In Statistical learning, Naïve Bayes updateable and Naïve Bayes are showing least errors which is 34.58% of RMSD. Naïve Bayes Multinomial Updateable and Naïve Bayes Multinomial are showing same level of errors which is 14.99% of RMSD.In Functional Learning, SMO is showing maximum level of errors which is 122.19% of RMSD and QDA is showing least level of errors which is 11.86% of RMSD.

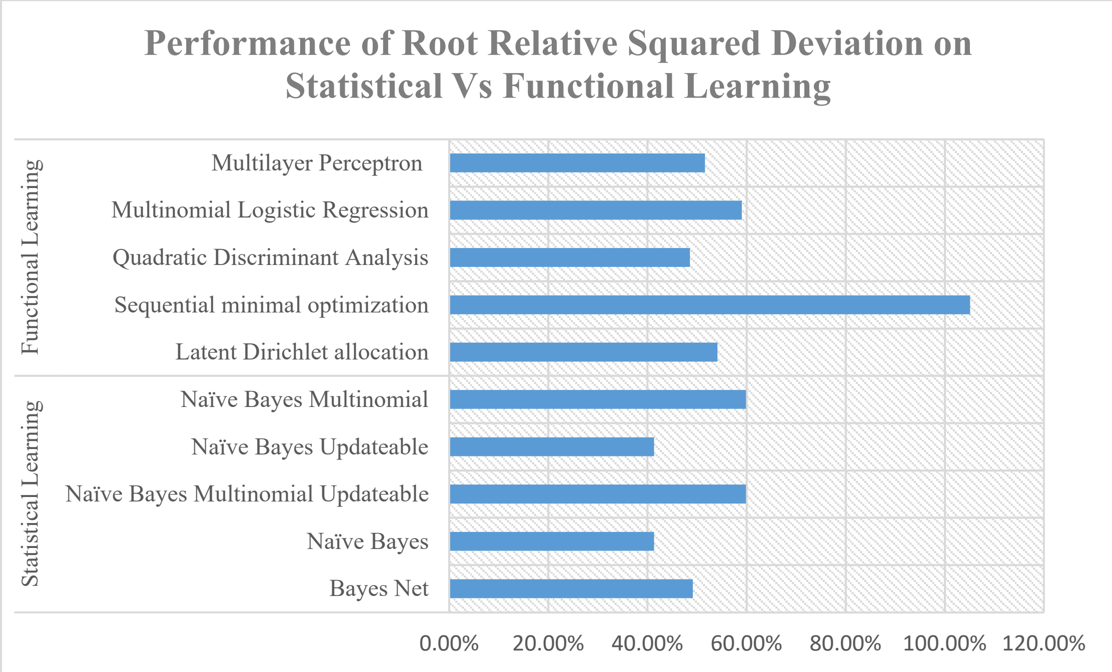

Figure 13: Performance of RRSD on Statistical Vs Functional Learning

The figure 13 shows that the various RRSD performances of statistical and functional learning on borrowed dataset. In Statistical learning, Naïve Bayes updateable and Naïve Bayes are showing least errors which is 59.89% of RRSD. Naïve Bayes Multinomial Updateable and Naïve Bayes Multinomial are showing same level of errors which is 41.35% of RRSD.In Functional Learning, SMO is showing maximum level of errors which is 105.10% of RRSD and QDA is showing least level of errors which is 48.58% of RRSD.

V Conclusions

This research work conclude that In Statistical learning, Naïve Bayes and Naïve Bayes Updateable algorithms are having same as well as highest efficient outcome which is 93.50% of accuracy; In Functional learning, Quadratic Discriminant Analysis is having 93% of accuracy which is highest efficient outcome compare with other functional models. In Statistical learning Naïve Bayes and Naïve Bayes Updateable algorithms are having same as well as highest efficient outcome which is 0.93 of PPV; In Functional learning, Quadratic Discriminant Analysis is having highest PPV which is 0.93 of PPV.In Statistical learning Naïve Bayes and Naïve Bayes Updateable algorithms are having same as well as highest efficient outcome which is 0.94 of TPR;In Functional learning, Quadratic Discriminant Analysis is having highest TPR which is 0.93 of TPR compare with other functional learning. In Statistical learning Naïve Bayes and Naïve Bayes Updateable algorithms are having same as well as highest efficient outcome which is 0.99 of AUCROC; In Functional learning, Quadratic Discriminant Analysis and Multi-Layer Perceptron are having highest AUCROC and same AUCROC value which is 0.97 of AUCROC compare with other functional learning. In Statistical learning Naïve Bayes and Naïve Bayes Updateable algorithms are having same as well as highest efficient outcome which is 0.97 of AUCPRC; In Functional learning, Quadratic Discriminant Analysis is having highest AUCPRC value which is 0.93 of AUCPRC Compare with other functional learning.

VI. Conflicts of interest

The authors have no conflicts of interest to declare.

References

[1] Patrizia Ferroni, Fabio M. Zanzotto, Noemi Scarpato, Antonella Spila, Luisa Fofi, Gabriella Egeo, Alessandro Rullo, Raffaele Palmirotta, Piero Barbanti, Fiorella Guadagni,, Machine learning approach to predict medication overuse in migraine patients, Computational and Structural Biotechnology Journal, Volume 18,2020,Pages 1487-1496,ISSN 2001-0370,

[2] https://doi.org/10.1016/j.csbj.2020.06.006

[3] Headache Classification Committee of the International Headache Society (IHS) (2018) The International Classification of Headache Disorders, 3rd edition. Cephalalgia 38: 1-211.

[4] Barbanti P, Egeo G (2015) Pharmacological trials in migraine: it's time to reappraise where the headache is and what the pain is like. Headache 55: 439-441.

[5] Ford JH, Schroeder K, Buse DC, Joshi S, Gelwicks S, et al (2019) Predicting initiation of preventive migraine medications: exploratory study in a large U.S. medical claims database. Curr Med Res Opin DOI: 10.1080/03007995.2019.1657716.

[6] Schwedt TJ, Alam A, Reed ML, Fanning KM, Munjal S, et al (2018) Factors associated with acute medication overuse in people with migraine: results from the 2017 migraine in America symptoms and treatment (MAST) study. J Headache Pain 19: 38.

[7] May A, Schulte LH (2016) Chronic migraine: risk factors, mechanisms and treatment. Nat Rev Neurol. 12: 455-464.
[8] Chen PK, Wang SJ (2019) Medication Overuse and Medication Overuse Headache: Risk Factors, Comorbidities, Associated Burdens and Nonpharmacologic and Pharmacologic Treatment Approaches. Curr Pain Headache Rep 23: 60.
[9] Wakerley BR (2019) Medication-overuse headache. Pract Neurol 19: 399-403.
[10] Zwart JA, Dyb G, Hagen K, Svebak S, Holmen J (2003) Analgesic use: a predictor of chronic pain and medication overuse headache: the Head-HUNT Study. Neurology 61: 160- 164.
[11] Katsarava Z, Schneeweiss S, Kurth T, et al (2004) Incidence and predictors for chronicity of headache in patients with episodic migraine. Neurology 62: 788-790.
[12] Bigal ME, Serrano D, Buse D, Scher A, Stewart, WF, Lipton RB (2008) Acute migraine medications and evolution from episodic to chronic migraine: A longitudinal populationbased study. Headache 48: 1157-1168.
[13] Wang SJ, Fuh JL, Lu SR, Juang KD. Outcomes and predictors of chronic daily headache in adolescents: A 2-year longitudinal study. Neurology. 2007;68:591-596.
[14] Krawczyk B, Simić D, Simić S, Woźniak M (2013) Automatic diagnosis of primary headaches by machine learning methods. Cent Eur J Med 8: 157-165.
[15] Çelik U, Yurtay N, Koç ER, Tepe N, Güllüoğlu H, et al (2015) Diagnostic Accuracy Comparison of Artificial Immune Algorithms for Primary Headaches. Comput Math Methods Med 2015: 465192.
[16] Keight R, Aljaaf AJ, Al-Jumeily D, Hussain AJ, Özge A, et al (2017) An intelligent systems approach to primary headache diagnosis. International Conference on Intelligent Computing. Dordrecht: Springer.
[17] Vandewiele G, De Backere F, Lannoye K, Vanden Berghe M, Janssens O, et al (2018) A decision support system to follow up and diagnose primary headache patients using semantically enriched data. BMC Med Inform Decis Mak 18: 98.
[18] Khayamnia M, Yazdchi M, Heidari A, Foroughipour M (2019) Diagnosis of common headaches using hybrid expert-based systems. J Med Signals Sens 9: 174-180
[19] Yang H, Zhang J, Liu Q, Wang Y (2018) Multimodal MRI-based classification of migraine: using deep learning convolutional neural network. Biomed Eng Online 17: 138.
[20] Chong CD, Gaw N, Fu Y, Li J, Wu T, et al (2017) Migraine classification using magnetic resonance imaging resting-state functional connectivity data. Cephalalgia 37: 828-844.
[21] Garcia-Chimeno Y, Garcia-Zapirain B, Gomez-Beldarrain M, Fernandez-Ruanova B, Garcia-Monco JC (2017) Automatic migraine classification via feature selection committee and machine learning techniques over imaging and questionnaire data. BMC Med Inform Decis Mak 17: 38.
[22] Parrales Bravo F, Del Barrio García AA, Gallego MM, Gago Veiga AB, Ruiz M, et al (2019) Prediction of patient's response to OnabotulinumtoxinA treatment for migraine. Heliyon 5: e01043.
[23] Athreya A, Iyer R, Neavin D, Wang L, Weinshilboum R, et al (2018) Augmentation of hysician Assessments with Multi-Omics Enhances Predictability of Drug Response: A Case Study of Major Depressive Disorder. IEEE Comput Intell Mag 13: 20-31.
[24] Ferroni, P, Zanzotto, F.M, Scarpato, N, Riondino, S, Nanni, U, et al (2017) Risk assessment for venous thromboembolism in chemotherapy treated ambulatory cancer patients: a precision medicine approach. Med Decis Making 37: 234-242.
[25] 24 https://www.kaggle.com/datasets/weinoose/migraine-classification
[26] https://www.cs.waikato.ac.nz/ml/weka/

Authors Profile

Dr. K.Nattar Kannan, B.E., M.E., Ph.D., is Professor in the Department of Artificial Intelligence and Machine Learning, Saveetha School of Engineering, Saveetha Institute of Medical And Technical Sciences (SIMATS), Chennai. He has completed his Ph.D. degree in Computer Science and Engineering from Manonmaniam Sundaranar University, Tamilnadu, India in 2016, and M.E. degree in Computer Science and Engineering from Manonmaniam Sundaranar University, Tamilnadu, India in 2008, and a B.E. degree in Computer Science & Engineering from Dr. Sivanthi Aditanar College of Engineering, Thiruchendur, and Tamilnadu, India in 2002. He has over 20 years of teaching experience, including 8 years of overseas (Malaysia) experience. He is a life member of the ISTE chapter and IAENG. He has published 15 research publications during his career. He has presented more than five research papers at national and international conferences. He is the applicant of 3 patents in IPR .He has received project funds from Tamilnadu State Council for Science and Technology. His current research interests involve Wireless Sensor Networks, Machine Learning, Artificial Intelligence, and the Internet of Things.

Dr. Gunasekar Thangarasu is presently working as Department Head in Professional, Industry Driven Education at MAHSA University, Malaysia. He received his PhD in the field of Information Technology at University Technology PETRONAS, Malaysia. He has been working in the capacity of a reviewer for renowned journals. He has published more than 25 journals. Besides, he has also attended more than 35 conferences in the area of Computing. With the experience gained as a lecturer cum programme co-ordinator since 2003, he has involved in academic programme management, development of new curriculam, providing professional industrial training and supervision of final year student's projects.