International Journal on Recent and Innovation Trends in Computing and Communication
ISSN: 2321-8169 Volume: 11 Issue: 11s
DOI: https://doi.org/10.17762/ijritcc.v11i11s.8299
***Article Received:** 07 July 2023 **Revised:** 29 August 2023 **Accepted:** 20 September 2023*

Exploratory Data Analysis on Blueberry yield through Bayes and Function Models

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Abstract—Agricultural researchers are using machine learning to predict crop yield. Many machine learning algorithms need lots of data. One of the major challenges in training and experimenting with machine learning algorithms is the availability of training data in sufficient quality and quantity remains a limiting factor. The Linear Discriminant Analysis produces 95.88% of accuracy which is most efficient of selected models; The Nave Bayes Multinomial has 69.88% accuracy, while the Linear Discriminant Analysis has 0.96 precision. The NBM has 0.71 precision, while Linear Discriminant Analysis has 0.95 recall. The Linear Discriminant Analysis produces 0.99 of ROC, which is the most efficient outcome of selected models. The NBM gives least ROC, which is 0.80. The Linear Discriminant Analysis produces 0.99 of PRC, which is the most efficient outcome of selected models. The NBM gives least PRC, which is 0.72. The LDA explores efficient outcome with low deviations. Four machine-learning-based predictive models were then built using the simulated dataset. This simulated data provides researchers with actual field observation data and those who want to test machine learning algorithms' response to real data with crop yield prediction models.

Keywords- Linear Discriminant Analysis (LDA); yield; Naïve Bayes Multinomial (NBM); wild blueberry;Prediction;

I. INTRODUCTION

The blueberry (Vaccinium corymbosum L.) is a blooming plant species in the genus Va The blueberry, scientifically known as Vaccinium corymbosum L., is a species of flowering plant that belongs to the heather family and the genus Vaccinium. It is most typically found in Eurasia and North America [1]. Blueberries are prized for their anti-inflammatory, anti-oxidant, and neurocognitive-boosting characteristics [2]. Blueberries also have a variety of other benefits. Blueberry agricultural fields in the European Union spanned an area of 27,630 hectares in 2020, according to data from FAOSTAT [3], and Poland placed first with a cultivated area of 9700 hectares and an average yield of 57,010 hg/ha.

It is necessary to pay attention to the plantation in order to discover important factors that affect plant growth and condition during the growing season in order to achieve an increased yield, improved fruit quality, and a more stable economic situation when producing blueberries. A number of internal (genetic) and external (growing practices, stimulants, climate) factors influence the amount of blueberries that can be harvested from a plant [4].These elements almost always correspond with one another, but the way in which they interact has not been well researched as of yet.During the growth season, shortly prior to harvest, models are employed for estimating purposes in order to provide yield predictions [5,6,7,8]. The ability to make informed choices about work planning and the allocation of storage space is facilitated by having prior knowledge of the yield that is anticipated for a particular year. It may also increase agricultural profitability and maintain a balance in the quantity of inputs needed, such as water, fertilizers, and pesticides. Consumption of these goods in moderation leads to a decrease in the amount of energy required on the farm, as well as a reduction in the amount of human labour required. Last but not least, a decrease in total production costs might lead to increased profitability for a plantation [9,10]. The estimation of theoretical yields is one of the applications for yield prediction that is employed while conducting agricultural damage assessments [11]. It should also be mentioned that in addition to the prediction of the yield quantity, the yield lost has potential applications in practice, as shown in research carried out by Khan's team [12], as well as its yield quality, for instance in the form of fruit freshness prediction [13]. This was demonstrated by the research that was conducted.

This paper organizes the second section contains literature survey, in section three shows definition and proposed methods

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and section four presents outcome and discussions and finally section 5 represents the conclusions..

II. LITERATURE REVIEW

Data nature, data type, and data source are three of the most important criteria that are used in the research on fruit yield forecasting of orchard crops. These criteria are used to divide yield determination methods into categories. As a result, the primary classification divides them into direct and indirect methods [10]. According to this classification, indirect methods are described as yield prediction methods, while direct methods are described as yield estimation methods; however, this nomenclature is not commonly used.

The data used in direct methods come from direct measurements of yield-forming generative organs. "direct methods" These could include the number of flowers, buds, or fruits, as well as their geometric dimensions and/or their weight. They can be performed manually or automatically using a variety of ground platforms, some of which are stationary [14,15,16], while others are mobile [17,18,19] or aerial [20,21,22,23].

In the case of indirect methods, the process of yield prediction involves the creation of a predictive model using characteristics that are only tangentially related to the yield as inputs. These characteristics can be broken down into a few different categories. The most significant ones are characteristics that are ascribed to plants, as well as climate, soil conditions, and agro technical processes [10]. The most common types of data that can be attributed to climate are meteorological data on historical and current air and soil parameters, such as the amount of natural precipitation and solar activity, also known as insolation or solar radiation [24]. The data that are used in yield forecasting and the description of the soil environment refer both to small soil parameters that change over time, such as the texture of the surface or subsurface layer, as well as to medium and short-term variables, such as the soil's pH, organic matter (OM) content, salinity (EC), or the content of individual plant nutrients, both macro and micro elements [25,26]. These data are broken down into two categories: small soil parameters that change over time and medium and short-term variables. Plant data that are input into prediction models using indirect data typically include information about the growth status of plants or their organs in successive vegetation phases. This information can be expressed in the form of vegetation indices, the degree of plant compactness (canopy/biomass), the time and rate of reaching characteristic developmental phases, such as flowering and fruit setting. Indirect data can be collected from a variety of sources, including observations, experiments, and surveys. These data are derived from remote sensing (RS), satellites, or unmanned aerial vehicles (UAVs) for the most part [27, 28,29,30].

Information from measurements made locally at the site of plant growth and information interpolated from network measurements conducted over larger areas can both be used as data sources for prediction models, and these sources can be used regardless of the type and nature of the prediction models themselves. Not only are data from individual measurement stations being gathered more frequently, but also data from a grid of sensors that have been mounted on plantations and are being read by Internet of Things devices [31]. When looking at access to databases for predictive models, it is important to note that the data can be any of the three types: private, public, or commercial [32]. It is becoming increasingly necessary to employ methods for managing large data sets, also known as Big Data [33-38], during the phase of storing, processing, sharing, and analysing the collected data due to the abundance of different types, natures, and sources of data that are used in predictive models for orchard crops.

III. MATERIALS AND METHODS

The dataset used for predictive modelling was generated by the Wild Blueberry Pollination Simulation Model, which is an open-source, spatially-explicit computer simulation program (Figure 1) that enables exploration of how various factors, including plant spatial arrangement, outcrossing and self-pollination, bee species compositions and weather conditions, in isolation and combination, affect pollination efficiency and yield of the wild blueberry agro-ecosystem. The simulation model has been validated by the field observation and experimental data collected in Maine USA and Canadian Maritimes during the last 30 years [2] and now is a useful tool for hypothesis testing and theory development for wild blueberry pollination researches. A simulated wild blueberry field on Julian date 136 of the production season. The green dots are quadrats in which stems are in bud (before bloom) stage, yellow dots are quadrats in which stems are in bloom, red dots are quadrats in which flowers on stems have become fruit (after bloom). Mixed yellow (flower) and green (bud) stem show the pattern of successive waves of flowering within a clone. Red stems with different color saturation indicate the percentage of fruit set, i.e., bright red stems have higher fruit set than the dark red ones. Black area are bare spots in the field caused by herbicide applications and erosion [2].

This article presents the dataset of 777 records. A detailed description of the extracted features is shown in Table 1.

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Table1: Dataset Description

S.No	Name of the attribute	low	High	Description
1	Clone_size	10m2	40m2	average blueberry clone size
2	Honey_bee	0 bees/ m2/min	18.43 bees/m2/min	Density of Honeybee
3	Bumble_bee	0 bees/ m2/min	0.583 bees/m2/min	Density of Bumblebee
4	Andrena_bee	0 bees/ m2/min	0.75 bees/m2/min	Density of Andrena bee
5	Osmia_bee	0 bees/ m2/min	0.75 bees/m2/min	Density of Osmia bee
6	Max_UpperTRange	69.7 °C	94.6°C	Maximum Upper band air temperature
7	Min_UpperTRange	39°C	57.2°C	Minimum Upper band air temperature
8	Average_UpperTRange	58.2 °C	79°C	Average Upper band air temperature
9	Max_LowerTRange	50.2 °C	68.2°C	Maximum Lowest daily air temperature
10	Min_LowerTRange	24.3 °C	33°C	Minimum Lower band air temperature
11	Average_LowerTRange	41.2	55.9	Average Lower band air temperature
12	Raining_Days	1 day	34 day	Number of bloom season days with above-zero precipitation
13	Average_Raining_Days	0.06 day	0.56 day	Bloom season average rain days
14	Fruit_set	0.192732	0.652144	Set of Fruit
15	Fruit_mass	0.311921	0.53566	Mass of Fruit
16	No_seeds	22.0792	46.58511	Seed
17	Outcome_yield	1637.704	8969.402	Yield
18	Class	Low	High	Outcome

The following models are selected in this research work for getting efficient model. They are

- Naïve Bayes : It is one of the fast and easy ML algorithms to predict a class of datasets. · It can be used for Binary as well as Multi-class Classifications.
- Naïve Bayes Multinomial: ***It*** is a probabilistic learning method that is mostly used in Natural Language Processing (NLP).
- Linear Discriminant Analysis (LDA): It is one of the commonly used dimensionality reduction techniques in machine learning to solve more than two-class classification problems.
- Quadratic Discriminant Analysis QDA: It is quite similar to LDA except we relaxed the assumption that the mean and covariance of all the classes were equal.

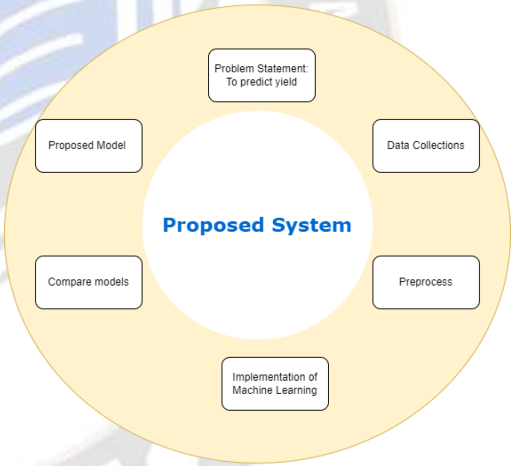

Fig 1: Proposed System

The above selected algorithms are implemented with data ratio of 90%of training and 10% of testing data in weka 9.3.5 machine learning tool.

IV. OUTCOME AND DISCUSSIONS

This section focuses on the outcome of selected models in borrowed dataset. The below table shows that the performance of time, accuracy, precision and recall of selected Bayes and Function models.

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Table 2: Performance of Bayes and Function Models

S.NO	Bayes & Function Learning	Time	Accuracy	Precision	Recall
1	NB	0.02s	94.46%	0.95	0.94
2	NBM	0s	69.88%	0.71	0.69
3	LDA	0.56s	95.88%	0.96	0.95
4	QDA	0.04s	82.23%	0.84	0.822

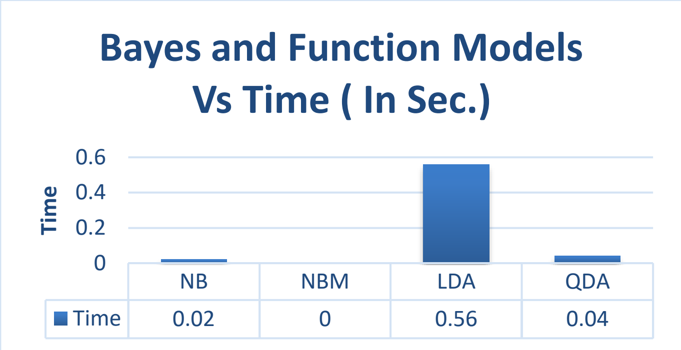

Fig 2: Time performance of Bayes and Function Models

The above diagram 2 shows that the time performance of Bayes and function models. The NBM takes least time for making its model which is 0 seconds. The LDA takes most time for creating its model which is 0.56 seconds. The QDA consumes 0.04 seconds for making its model. The NB consumes 0.02 seconds for creating this model.

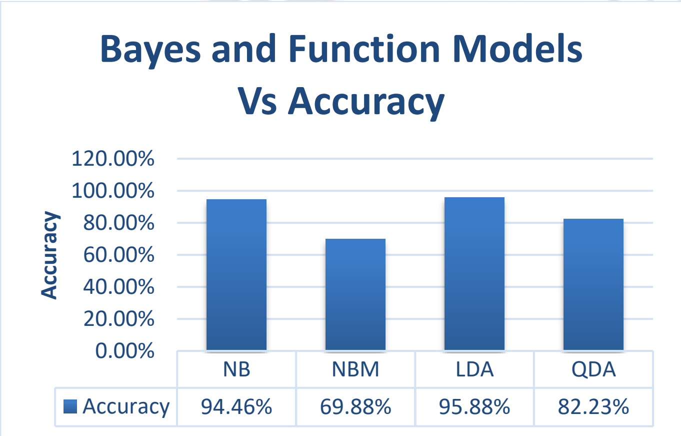

Fig 3: Accuracy performance of Bayes and Function Models

The above diagram 3 shows that the efficiency performance of Bayes and function models. The LDA produces 95.88% of accuracy which is most efficient of selected models; The NBM gives least accuracy which is 69.88%; The NB gives 94.46% of accuracy; The QDA shows 82.23% of accuracy.

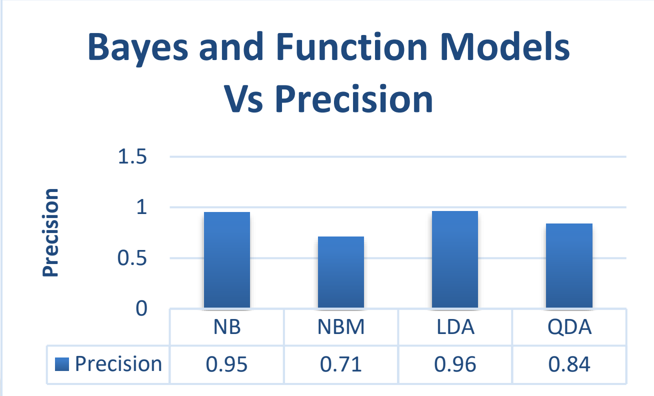

Fig 4: Precision performance of Bayes and Function Models

The above diagram 4 shows that the precision performance of Bayes and function models. The LDA produces 0.96 of precision which is most efficient outcome of selected models; The NBM gives least precision which is 0.71; The NB gives 0.95 of precision; The QDA shows 0.84 of precision.

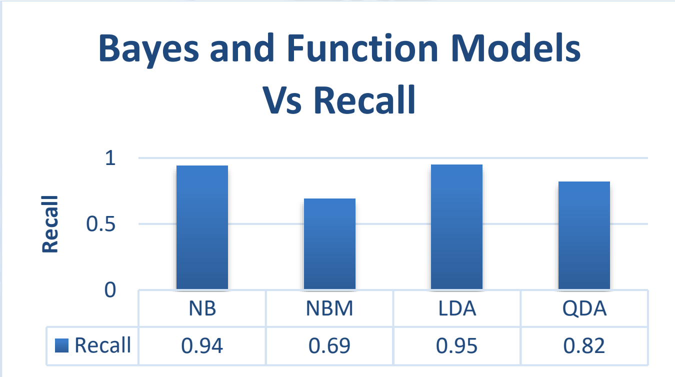

Figure 5: Recall performance of Bayes and Function Models

The above diagram 5 shows that the recall performance of Bayes and function models. The LDA produces 0.95 of recall which is most efficient outcome of selected models; The NBM gives least recall which is 0.69; The NB gives 0.94 of recall; The QDA shows 0.82 of recall.

Table 3: ROC and PRC of Bayes and Function Models

S.No	Bayes & Function Learning	ROC	PRC
1	NB	0.98	0.97
2	NBM	0.8	0.72
3	LDA	0.99	0.99
4	QDA	0.97	0.95

The above table 3 shows the Receiver Operating Characteristic Curve and Precision Recall Curve performance of selected classifiers

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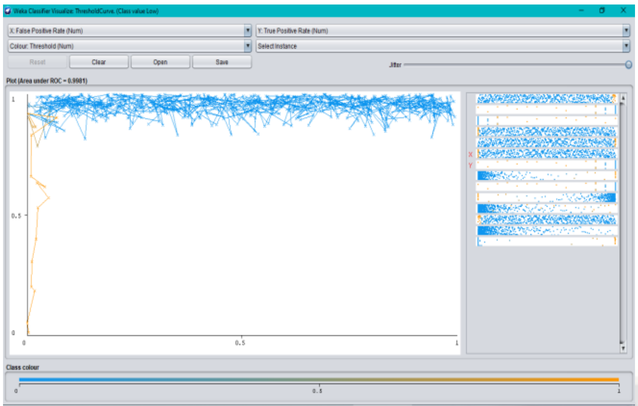


Fig 6. a. ROC of LDA in low yield category

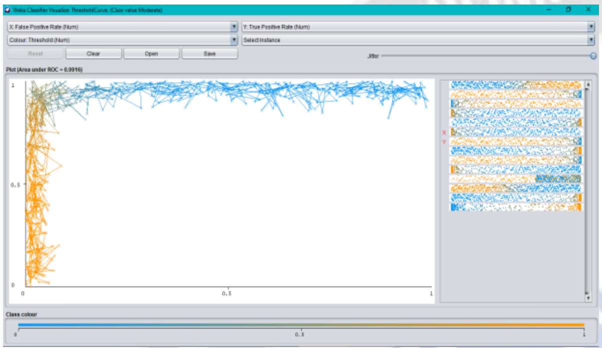
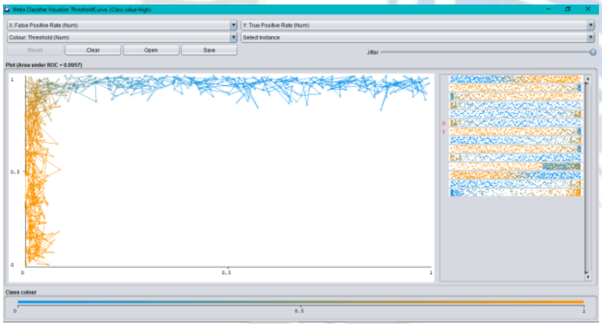


Fig 6. b. ROC of LDA in moderate yield category



6. c. ROC of LDA in high yield category

The diagrams 6.a, b and c shows that the ROC distribution of LDA in low, moderate and high yield categories

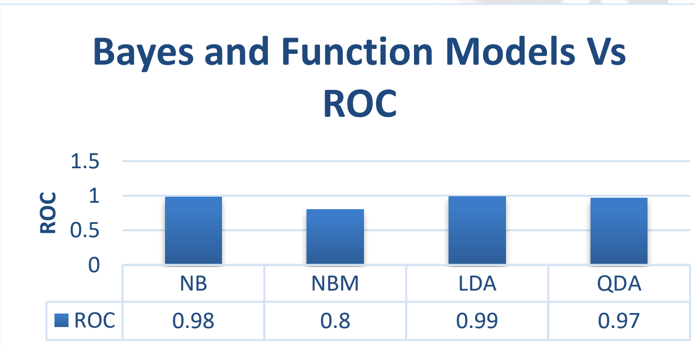


Fig 7: ROC performance of Bayes and Function Models

The above diagram 7 shows that the ROC performance of Bayes and function models. The LDA produces 0.99 of ROC which is most efficient outcome of selected models; The NBM gives least ROC which is 0.80; The NB gives 0.98 of ROC; The QDA shows 0.97 of ROC.

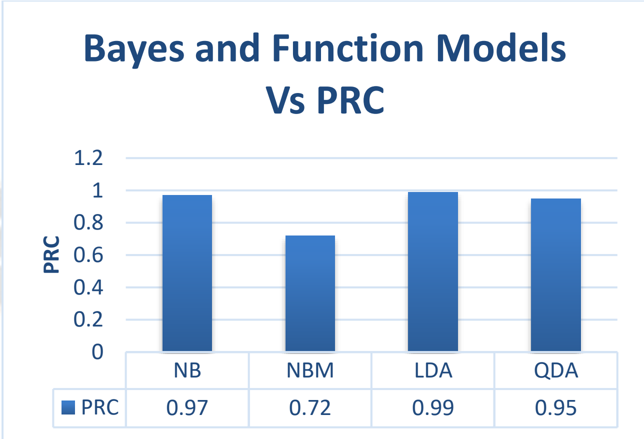


Fig 8: PRC performance of Bayes and Function Models

The above diagram 8 shows that the PRC performance of Bayes and function models. The LDA produces 0.99 of PRC which is most efficient outcome of selected models; The NBM gives least PRC which is 0.72; The NB gives 0.97 of ROC; The QDA shows 0.95 of ROC.

Table 4: Statistical performance of Bayes and Function Models

S.No	Bayes & Function Learning	Kappa	F-Measure	MCC
1	NB	0.89	0.94	0.91
2	NBM	0.42	0.7	0.43
3	LDA	0.92	0.95	0.92
4	QDA	0.64	0.81	0.68

The above table 4 shows that the kappa, F-Measure and Matthews Correlation Coefficient performance of selected Bayes and Function models.

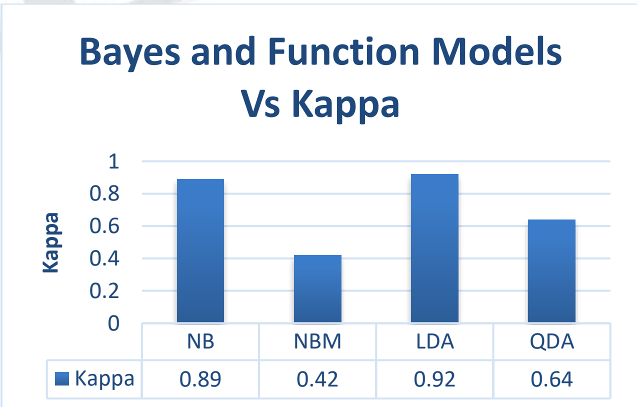


Fig 9: Kappa performance of Bayes and Function Models

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The above diagram 9 shows that the kappa performance of Bayes and function models. The LDA produces 0.92 of kappa which is most efficient outcome of selected models; The NBM gives least kappa which is 0.42; The NB gives 0.89 of kappa; The QDA shows 0.64 of kappa.

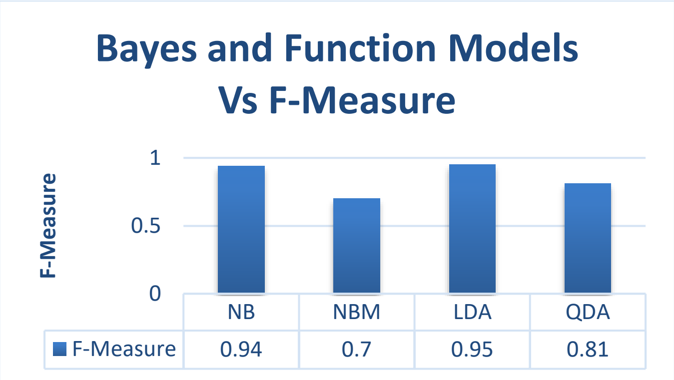

Fig 10: F-Measure performance of Bayes and Function Models

The above diagram 10 shows that the F-Measure performance of Bayes and function models. The LDA produces 0.95 of F-Measure which is most efficient outcome of selected models; The NBM gives least F-Measure which is 0.70 of F-Measure; The NB gives 0.94 of F-Measure; The QDA shows 0.81 of F-Measure.

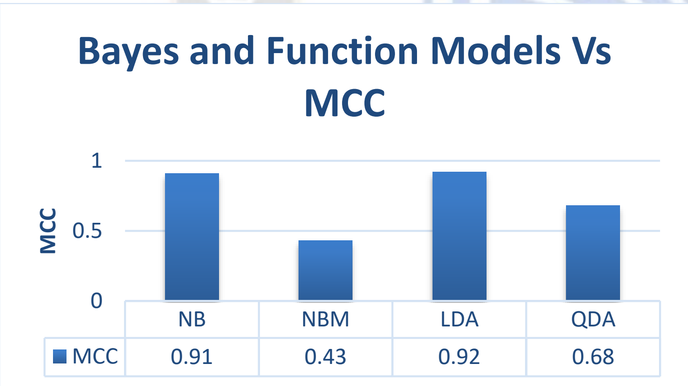

Fig 11: MCC performance of Bayes and Function Models

The above diagram 11 shows that the MCC performance of Bayes and function models. The LDA produces 0.92 of MCC which is most efficient outcome of selected models; The NBM gives least F-Measure which is 0.91 of MCC; The NB gives 0.91 of MCC; The QDA shows 0.68 of MCC.

Table 5: Deviation performance of Bayes and Function Models

S.No	Bayes & Function Learning	MAE	RMSE	RAE	RRSE
1	NB	0.04	0.18	12.88%	42.94%
2	NBM	0.2	0.44	58.35%	107.69%
3	LDA	0.06	0.15	19.18%	38.39%
4	QDA	0.11	0.33	34.80%	80.43%

The table 5 shows that the deviations distributions of Bayes and function models like mean absolute performance, root mean squared error, relative absolute error and root relative squared error.

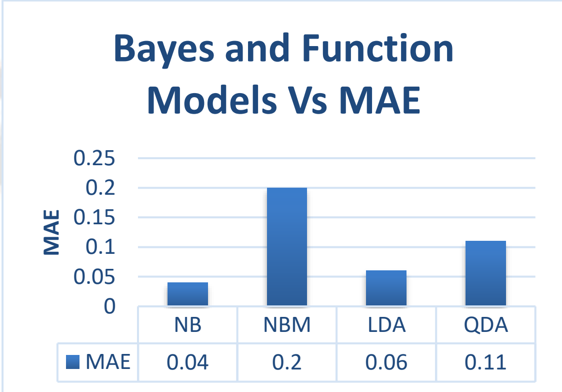

Fig12: MAE performance of Bayes and Function Models

The above diagram 12 shows that the MAE performance of Bayes and function models. The LDA produces 0.06 of MAE which is best performance of selected models; The NBM gives worst performance which is 0.2 of MAE; The NB gives 0.04 of MAE; The QDA shows 0.11 of MAE.

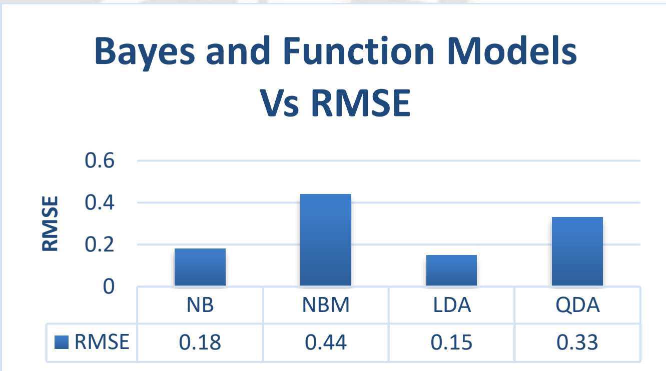

Fig 13: RMSE performance of Bayes and Function Models

The above diagram 13 shows that the RMSE performance of Bayes and function models. The LDA produces 0.15 of RMSE which is best performance of selected models; The NBM gives worst performance which is 0.44 of RMSE; The NB gives 0.18 of RMSE; The QDA shows 0.33 of RMSE.

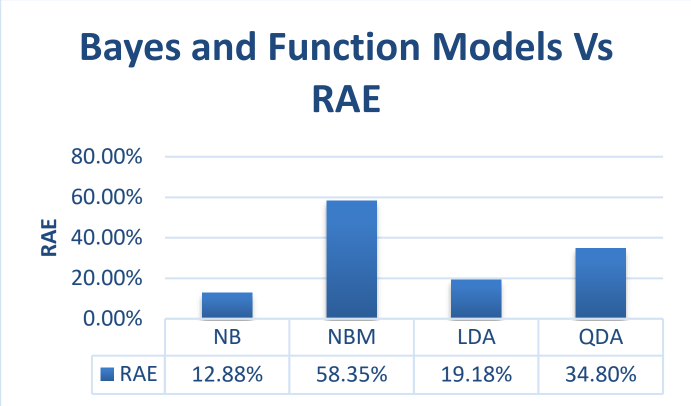

Fig 14: RAE performance of Bayes and Function Models

The above diagram 14 shows that the RAE performance of Bayes and function models. The LDA produces 19.18% of RAE which is best performance of selected models; The NBM gives worst performance which is 58.35% of RAE; The NB gives 12.88% RAE; The QDA shows 34.80% of RAE.

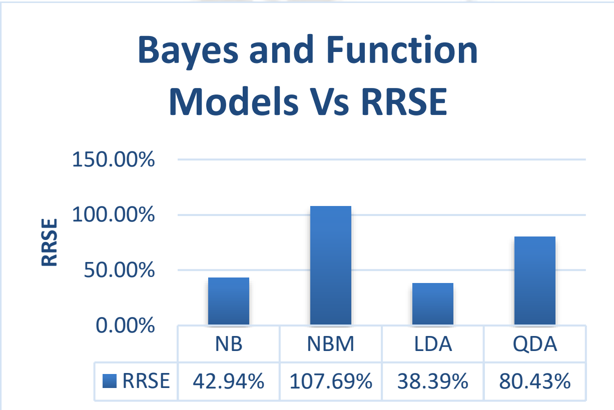

Fig 15: RRSE performance of Bayes and Function Models

The above diagram 15 shows that the RRSE performance of Bayes and function models. The LDA produces 38.39% of RRSE which is best performance of selected models; The NBM gives worst performance which is 107.69% of RRSE; The NB gives 42.94% RRSE; The QDA shows 80.43% of RRSE.

V. CONCLUSION

This research work concludes that the LDA shows best outcome with low deviations.The LDA produces 0.06 of MAE which is best performance of selected models; The NBM gives worst performance which is 0.2 of MAE; The LDA produces 0.15 of RMSE which is best performance of selected models; The NBM gives worst performance which is 0.44 of RMSE; The LDA produces 19.18% of RAE which is best performance of selected models; The NBM gives worst performance which is 58.35% of RAE; The LDA produces 38.39% of RRSE which is best performance of selected models; The NBM gives worst performance which is 107.69% of RRSE. This work recommends that the LDA model compare with other models.

ACKNOWLEDGMENT

The preferred spelling of the word “acknowledgment” in America is without an “e” after the “g”. Avoid the stilted expression, “One of us (R.B.G.) thanks . . .” Instead, try “R.B.G. thanks”. Put applicable sponsor acknowledgments here; DO NOT place them on the first page of your paper or as a footnote.

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