KNN Algorithm tested on bread dataset to check the outcome. It has obtained 69.23% accuracy to confidently predict the outcome of bread.

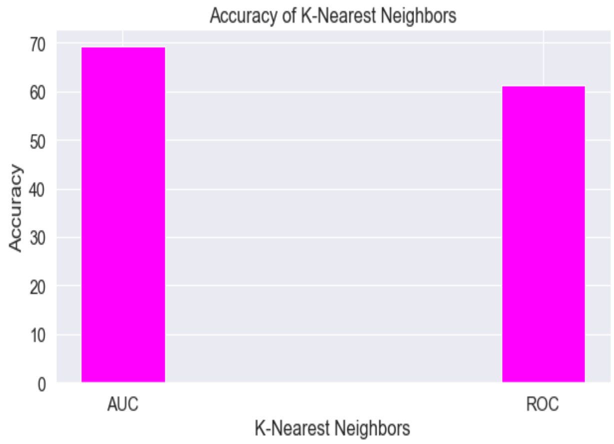

Figure 15. K-Nearest Neighbour Performance

4.1.2 Logistic Regression

Logistic Regression tested on bread dataset to check the outcome. It has obtained 72.31% accuracy to confidently predict the outcome of bread.

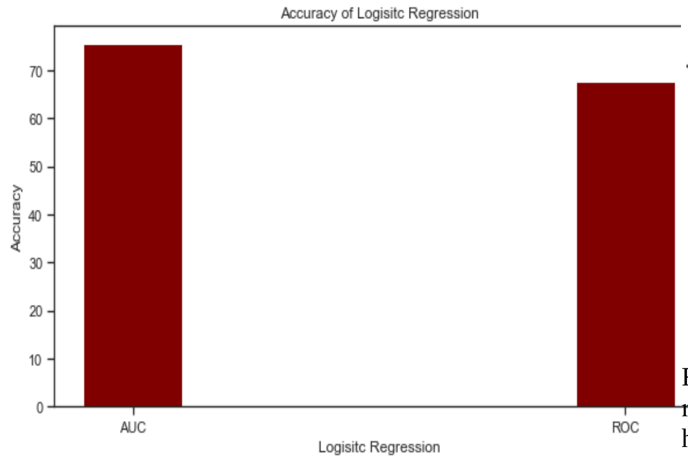

Figure 26. Performance of Logistic Regression

4.1.3 Naïve Bayes

Naive Bayes tested on bread dataset to check the outcome. It has obtained 81.54% accuracy to confidently predict the outcome of bread.

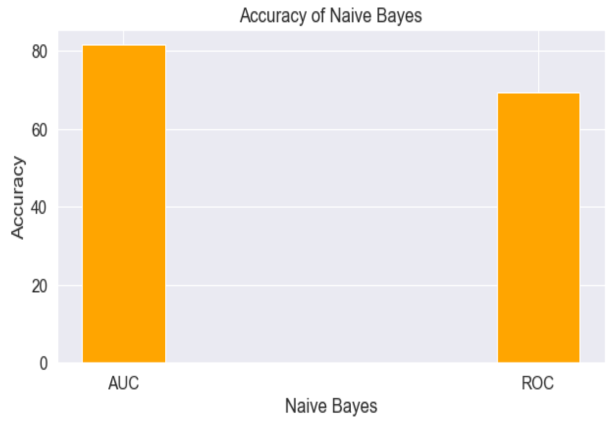

Figure 17. Performance of Naïve Bayes

4.1.4 Support Vector Machine

SVM tested on bread dataset to check the outcome. It has obtained 76.92% accuracy to confidently predict the outcome of bread.

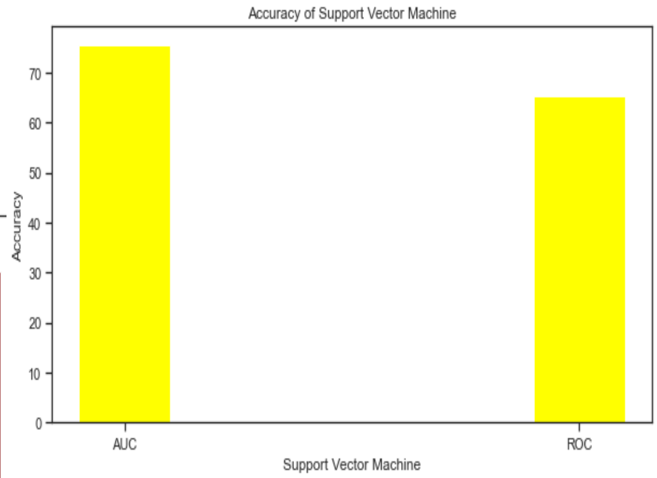

Figure 18. Performance of SVM

Figure below shows the comparative analysis of linear machine learning models. In which Gaussian Naïve Bayes has shown the highest accuracy of 81.54%.

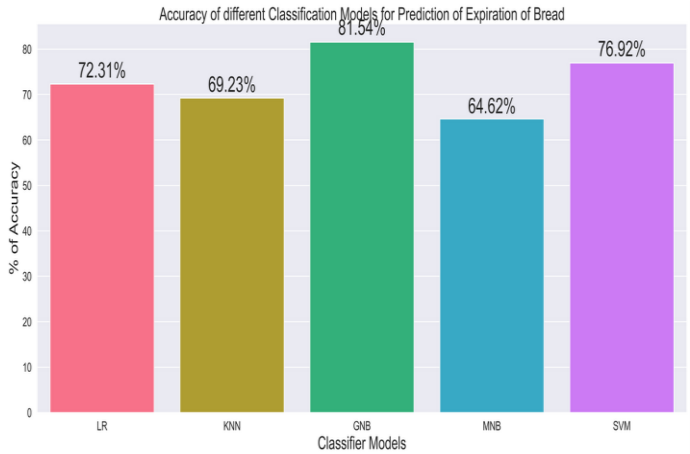

Figure 23. Comparative analysis of different linear machine learning models

4.2. Comparative Analysis

Due to changes in data, the accuracy of each classifier fluctuates while using balancing techniques on a dataset. The outcomes and comparisons of all approaches utilised in this study are shown in the table below.

Table 4. Comparative Analysis

Classifier/Algorithm	Balancing Techniques	Accuracy %
Logistic regression	SMOTE-TOMEC Links	72.31%
SVM	SMOTE-TOMEC Links	76.92%
KNN	SMOTE-TOMEC Links	69.23%
Multi Nomial Naive Bayes	SMOTE-TOMEC Links	64.62%
Gaussian Naïve Bayes	SMOTE-TOMEC Links	81.54%

Above tables shows that Gaussian Naïve Bayes has shown good accuracy after balancing techniques as 81.54%.

4. Conclusions

Consumers have expressed an interest in a range of breads, with wheat bread being one of the more popular options available. Quality wheat bread must be made by bakers who are well-liked by the general public in order to be considered a success. Sales will increase significantly if there is a major improvement in the overall quality of the bread. Fungi must feed on the organic matter that they are growing on in order to survive, such as bread or other grains of wheat, in order to survive. Due to the way mushrooms reproduce, they form colonies of spores, which are visible on bread as a result of their reproductive mechanism. Molds such as Aspergillus and Penicillium, as well as Mucor and Rhizopus, can be seen growing on bread and other baked items, and they include a variety of species. To make due in a dim, crisp climate with little air dissemination, a contaminated spore should initially distinguish bread and afterward embed its "hyphae" into the bread's surface, a cycle known as hyphal development. In the environment, a mold colony, also known as microbial mycelium, forms as a result of spores from mold rapidly spreading across the environment. First and foremost, in order for organoleptic evaluation to be recognized as a legitimate scientific profession, it is necessary to standardize, rationalize, and link the approach to objective assessment to the method to objective assessment. Organoleptic tests are frequently used in the food industry and other agricultural products to determine the quality of the products being evaluated. With this method of evaluating information, it is feasible to obtain results that are unusually accurate in their accuracy. In some cases, assessment outperforms even the most sensitive of instruments in terms of specific performance. In the food logistics sector, the expiration of a loaf of bread is a very common challenge to deal with. Consumers may become unwell as a result of consuming fungus bread for a variety of reasons, including the following: Patients may have nausea, diarrhoea, and a range of other medical problems as a result of this condition. Consequently, an intelligent method for determining the current condition of bread is necessary, which will benefit both retailers and consumers. A prototype consisting of an Arduino Nano microcontroller, MQ series sensors for carbon monoxide and carbon dioxide detection, and shopper bags of bread to collect data has been developed as a consequence of this research. In order to determine the current status of the bread in these companies, a number of machine learning algorithms are used to analyze the information collected. One-sided information was acquired by these sensors, resulting in distorted results. The information gathered from sensors is then balanced with the assistance of SMOTE and TOMEC Links, respectively (data balancing techniques). To improve the efficiency of IoT-based datasets, data preparation and feature engineering have been used to them as well. Linear models have been employed to forecast the current condition of the loaf of bread, respectively. Results show that among linear models, the Gaussian Nave Bayes has the highest accuracy with 81.54 percent accuracy, which is the highest accuracy among linear models.

When a dataset is imbalanced, predictive models struggle. Therefore, data balancing techniques (Tomek and SMOTE) have been used to verify that all data points in the dataset are equal in size and weight. Outliers have been removed from the data so that it can be used and interpreted in a more flexible manner. This study also revealed the comparison of several machine learning algorithm-based categorization models to forecast the bread condition at the earliest possible stage. Findings that aren't included here: Classifiers can now be compared in terms of accuracy following the data balancing process. This approach, along with Logistic Regression and Support Vector Machine, as well as K-nearest neighbors, was shown to be 81.54% accurate after a series of comparisons. Bread is a high-carbohydrate food that is widely consumed by members of the general population. To establish the quality of the products being tested, organoleptic tests were often employed in the food sector and other agricultural products. It is possible to acquire exceptionally accurate results by employing this approach of evaluating information. Occasionally, assessment outperforms even the most sensitive of tools in certain respects. Furthermore, this work can be expanded to determine how likely people are to develop diseases associated with fungal infections on food products in the next few years based on factors such as their lifestyle and level of physical activity.

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