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Diet Recommendation System based on Different Machine Learners

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ABSTRACT

In today's culture, many people suffer from a range of ailments and illnesses. It's not always simple to recommend a diet right away. The majority of individuals are frantically trying to reduce weight, gain weight, or keep their health in check. Time has also become a potential stumbling block. The study relies on a database that has the exact amounts of a variety of nutrients. As a result of the circumstance, we set out to create a program that would encourage individuals to eat healthier. Only three sorts of goods are recommended: weight loss, weight gain, and staying healthy. The Diet Recommendation System leverages user inputs such as medical data and the option of vegetarian or non-vegetarian meals from the two categories above to predict food items. We'll discuss about food classification, parameters, and machine learning in this post. This research includes different machine learner K-nearest neighbor, Support vector machine, Decision Tree, Navier buyers, Random Forest and Extra tree classifier comparative analysis for future diet plan prediction."

Keywords :— Diet Recommendation, Machine Learning, Clustering, Health Factors, vegetarian and non-vegetariana

I. INTRODUCTION

A significant component in human existence is the state of one's health. People are neglecting their physical and mental health as a result of their hectic schedules and heavy workloads. Physical inactivity is the most serious concern facing today's age, The World Health Organization says so. People who desire to live a healthy lifestyle should follow their normal eating and exercise routines. In order to be healthy and preserve their health, humans need a certain quantity of nourishment. According to [1, 2], dietary factors are a major contributing factor to the rapid rise in the prevalence of obesity and diabetes. Dietary variables are also a significant contribution to levels of malnutrition, obesity, and overweight, according to the Global Burden of Disease Study, and unreasonably restrictive diets are responsible for 11 million preventable early deaths each year [3]. Food recommendation is a vital job in food computing since it aims to locate acceptable food products for users based on their individual requirements. As a result, it plays an essential part in human dietary decision- making.

When compared to other types of suggestion, food advice has its unique set of qualities. In the case of food preference learning, this is a key phase in the process of making meal recommendations. Food choice, on the other hand, is influenced by a variety of variables, including taste preferences, perceptual differences, cognitive restraints, cultural familiarity, and even hereditary influence1. As a result, proper food preference learning is more difficult to achieve in this situation.

The paper review diet recommender method was developed in order to encourage a healthy lifestyle in Mauritius. The remaining sections of the paper are organised as follows: Section II describes the associated works of the present paper diet guidance system and the significance of these studies. Section III describes the work done in the area of methodology. A study of deep learning approaches for recommendation systems is presented in Section IV, which compares machine learning classifiers with deep learning methods for recommendation systems. Finally, Section V provides a rough outline of the flow and considers potential future developments.

Table 1. Diet Recommendations According To Nutrition Knowledge Score [12]

		Nutrition knowledge score quintile[a] Mean (SD)						
Food Group	Recommended daily servings in DASH diet	Lowest (≤55) n = 175, 21.1%	Second (56–64) n = 160, 19.3	Third (65–71) n = 160, 19.3%	Fourth (72–79) n = 182, 22%	Highest (80+) n = 151, 18.2%	p trend[b]	p trend[c]
Whole grains	3	1.54 (1.4)	1.59 (1.3)	2.01 (1.8)	1.73 (1.3)	2.19 (1.5)	<0.001	<0.001
Fruit	4–6	1.50 (1.4)	1.57 (1.3)	1.76 (1.3)	1.88 (1.6)	2.23 (1.5)	<0.001	<0.001
Vegetables	4–6	3.13 (2.4)	2.99 (2.1)	3.75 (2.4)	3.83 (2.5)	4.82 (2.9)	<0.001	<0.001
Legumes	0.64 (3–6/week)	0.33 (0.3)	0.42 (0.4)	0.37 (0.4)	0.50 (0.5)	0.62 (1.0)	<0.001	<0.001
Low-fat dairy foods	2–4	0.21 (0.3)	0.19 (0.3)	0.23 (0.3)	0.26 (0.4)	0.30 (0.4)	0.046	0.123
Red processed meat	Limited	1.38 (0.9)	1.15 (0.7)	1.01 (0.7)	1.00 (0.7)	0.88 (0.5)	<0.001	<0.001
Sweetened snacks and beverages	Limited	2.86 (2.8)	2.32 (1.9)	2.99 (2.8)	2.36 (2.4)	2.13 (1.9)	0.004	0.001
Salty snacks	Limited	0.58 (0.6)	0.63 (0.7)	0.52 (0.5)	0.50 (0.4)	0.46 (0.4)	0.027	0.019
Na consumption	2300 mg	3099.60 (1410.7)	3007.77 (1145.4)	3057.26 (1279.8)	3013.43 (1169.0)	3110.51 (1082.1)	0.912	0.558
Overall DASH score		21.87 (4.2)	22.63 (4.6)	23.89 (4.3)	24.45 (4.4)	25.83 (4.1)	<0.001	<0.001

Abbreviations: DASH, Dietary Approaches to Stop Hypertension.

[a] Figures are unadjusted.

[b] p for trend unadjusted.

[c] p for trend adjusted for age, gender and energy intake.

II. Related Works

Thi Ngoc Trang et al [1] demonstrate how their technique may be utilised to give a complete evaluation of current research on healthcare recommender systems: Nonetheless, our research varies from previous related overview studies in that it provides insight into recommended scenarios and approaches. This type of proposal includes food suggestions, medication recommendations, health status predictions, healthcare service recommendations, and healthcare professional recommendations. They also present real-world examples to assist students gain a full understanding of recommendation systems. Based on their most current reports and personal health facts, they feel their System may be fundamentally advantageous for physicians to recommend diet and exercise, which they believe is a huge breakthrough. To do this, they have divided the system into two modules: 1. Health monitoring; 2. Recommendations for diet and physical activity. The system would suggest that the reports be restored to normal during follow-up sessions in the Health Monitoring module.

Wenbin Yue et al [3] declare that the goal of this work is to provide a comprehensive examination of traditional recommendation methodologies and applications in the healthcare field. Content-based recommendation (also known as CF recommendation), collaborative filtering (CF recommendation), and hybrid recommendation are three major recommendation methodologies discussed. Following that, we offer a high-level overview of five health-related application scenarios, including dietary advice, lifestyle advice, training advice, patient and physician decision-making, and illness prediction, among others. Finally, some of the most critical challenges confronting this new and developing profession are recognised, along with compelling reasons.

Celestine Iwendi et al [4] explore how their system may be utilised to gather data. This research framework aims to implement both machine and deep learning algorithms such logistic regression, naive bayes, Recurrent Neural Network (RNN), Multilayer Perceptron (MLP), Gated Recurrent Units (GRU), and Long Short-Term Memory (LSTM) (LSTM). For inclusion in the medical dataset, 30 individuals' data with 13 features of various ailments, as well as 1000 items, were gathered via the internet and hospitals. There are eight features in the product area. Before being submitted to deep learning and machine learning-based techniques, the properties of this IoMT data were analysed and further encoded. The results reveal that the LSTM approach beats the competition in terms of forecasting accuracy, recall, precision, and other F1-measures, among other things, when compared to competing machine learning and deep learning methodologies. We were able to get 97.74 percent accuracy using the LSTM deep learning model. Similarly, permitted classes get accuracy, recall, and F1-measure scores of 98 percent, 99 percent, and 99 percent, respectively, but not-allowed classes achieve precision, recall, and F1-measure scores of 89 percent, 73 percent, and 80 percent, respectively.

Firstyani Imannisa Rahma et al [5] how a system may use data from the COVID-19 Task Force in this province, as well as the Indonesian Dietary Recommendations, to help decide which nutrition is necessary by recovered patients after discharge. The following criteria were used to calculate body mass for the prototype of this system: Weight of the Age Group 3, Vegetable Consumption 4, Fat Consumption 4, Salt & Sugar Consumption 2, and Sports Body Mass Pattern 1 = 0.34980639174099 and Pattern 2 = 0.65019360825901 are the Pattern Preference values obtained after cranking the two patterns used: Pattern 1 = 0.34980639174099 and Pattern 2 = 0.65019360825901. Pattern 2 has the highest preference value that can be used as a recommendation: 0.65019360825901.

Romeshwar Sookrah et al [6]. It consists of a recommendation engine that uses content-based filtering and machine learning algorithms to recommend hypertensive patients personalised diet plans based on factors like age, food preferences, allergies, smoking and alcohol consumption, blood pressure, and dietary intake, among others. The system is based on a smartphone application that is simple to use and carry about. The application has aided users in regulating and reducing their blood pressure, according to the findings of a survey.

Weiqing Min et al [7] present an uniform paradigm for meal advice. The primary concerns that impact food recommendation are identified in the article, including the inclusion of varied context and domain information, the creation of a personal model, the study of unique food attributes, and the application of machine learning. Following that, we'll go through some of the present solutions to these issues, as well as some of the research challenges and future potential in this field. According to our knowledge, this is the first survey to focus on food suggestion in the multimedia industry and to create a collection of research papers and technologies that will be valuable to academics in the subject.

Berkeley N. Limketkai et al [8] talk on how to utilise the system. As computing technology has evolved throughout time, it has made it easier to integrate digital technology into the medical industry, which is now being followed by similar applications in clinical nutrition. This paper discusses a variety of uses of such technologies for nutrition, including the use of mobile apps and wearable technology, as well as the development of decision support systems for parenteral feeding and the use of telehealth for remote nutritional evaluation.

Junkang Zhao et al [9] Dietary pattern analysis is one way of inquiry that might be used to better understand the complex relationship between nutrition and health. Although there are various statistical methodologies available, the literature favours more conventional methods such as dietary quality ratings, principal component analysis, factor analysis, clustering analysis, and reduced rank regression, among others. Several innovative techniques have been assessed and explored in depth very infrequently, if at all.

Wickramasinghe et al [10], the strategy that may be employed in this study is to treat the sickness by following a suitable diet plan and then using classification algorithms to discover the most appropriate diet plan. The suggested work agreements correspond to the recommendation of various dietary programmes for CKD patients based on their blood potassium levels, as predicted by the potassium zone for CKD patients. Multiclass Decision Jungle, Multiclass Decision Forest, Multiclass Neural Network, Multiclass Logistic Regression, and Multiclass Logistic Regression are among the algorithms employed in the experiment. The results show that the Multiclass Decision Forest approach exceeds the other classification methods in terms of accuracy, with a score of 99.17 percent.

Anonnya Banerjee et al [12] proposed the Nourishment Recommendation Framework (NRF), in which we receive user input from children, assess the data, and provide an output that provides a better diet plan as a final result. Its purpose is to provide nutritional meals matched to the age, development, gender, and health records of children aged 8 to 13.

During the training phase of the prototype system, Zhidong Shen and colleagues present a neural network that classifies food into defined categories, as described in [14]. The major purpose of the proposed technique is to improve the accuracy of the pre-training model. The author of the essay offers a client-server architecture for a prototype system. The client submits an image detection request, which is subsequently processed by the server. There are three key software components in the prototype system: a pre-trained CNN model training module for classification, a text data training module for attribute estimation, and a pre-trained CNN model training module for attribute estimation.

Samuel Manoharanand et al [15] introduced a k-clique embedded deep learning classifier recommendation system for suggesting diets to patients in paper, and it has been effectively implemented. The K-clique was added to the recommendation system in order to improve the precision and accuracy of the deep learning classifier, which had previously failed (gated recurrent units).

To establish a dataset for empirical study of the proposed system, patient information was obtained from multiple sources, including the internet and hospitals. A total of 50 patients were studied, with thirteen features of various illnesses, and a total of 1,000 goods were studied, with eight feature sets. Before being given to the deep learning classifiers for categorization, all of these features were encoded and organised into many groups. The improved precision and accuracy observed for the developed system experimentally are compared with machine learning techniques such as logistic regression and Nave Bayes, as well as other deep learning classifiers such as the MLP and RNN, to demonstrate the proficiency of the K-clique deep learning classifier-based recommendation system (K-DLRS).

Iigo Orue Saiz et al [16] attempt to determine what research have been conducted and what recommendation systems have been used for this goal during the previous five years in the major databases. One observation that can be made from the results obtained is that the existing works place a strong emphasis on the recommendation system (which is usually collaborative filtering) and less emphasis on data description or the sample under investigation; the indices used for the calculation of calories or nutrients are not specified. Consequently, it is vital to work with open data or well-described data, which enables the experience to be replicated by other parties, or at the very least to be similar, in order to be successful. Our society has placed a high importance on the development of healthy habits, particularly diet-oriented behaviours, in recent years, and this has become one of its most important priorities.

M. Geetha et al [17] employ a machine learning technique to analyse the body of a person with a pre-medical history and forecast the future health status over the course of a calendar year. It gives diet advice systems that take into account present and prior food consumption records, and it recommends correct diet reports in a more dependable way than before.

III. Proposed System

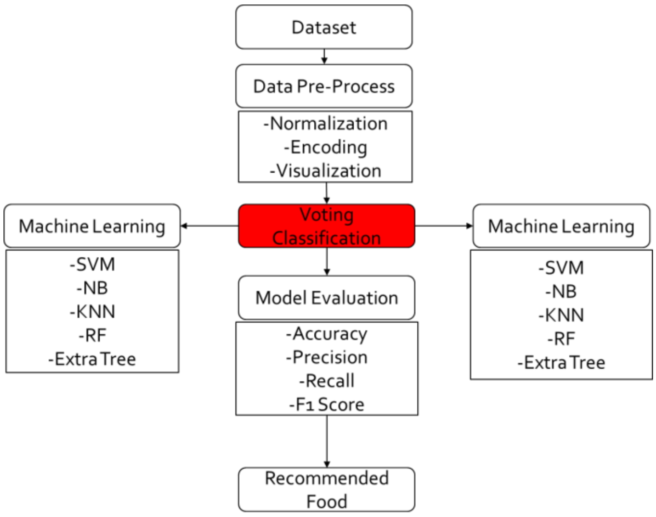

Figure 1. Tentative System Flow

As shown in figure 1 proposed system flow which will work for future direction for making diet recommendation system. Here as shown in the figure at pre-processing task we can use Normalization to remove big value for easy calculation of big digit data. In Encoding process will encode the data as labelling. Here main thing is use voting classifier which will act as heart of system. Two ML voting system gives batter results as compare to one classifier.

Datasets:

In [3] example of a formalised the dataset that was utilised to perform this project consists of a collection of different food products as well as the time period during which the food must be eaten, i.e., dinner, breakfast, and lunch, among other things. In addition, the collection provides information about whether a certain food item is vegetarian or not. Food.csv may be found at https://github.com/vishalverma116/ML project/blob/master/food.csv.

Pre-Process

Normalization [4,12] normalisation is the process of reducing a dataset to a single range of values. We did this because the dataset has a variety of scale values; some are single digit values, some features have two digest values, and some features have three-digit values; we wanted to bring all of the values into a single scale in order to improve the performance of machine learning models, so we used min-max normalisation to accomplish that. In this study, min-max scaling is used to normalise data that fall between 0 and 1 on the scale."

Data "encoding [4,16,17] is performed after inconsistent and duplicate values have been eliminated from the dataset, in accordance with the findings of this study. Following that, the nominal characteristics are translated to numerical values. The reason for this is because backend operations in machine learning models are performed on numeric values before they are implemented using a machine learning model, hence doing so will improve performance. The non-numeric data used in this study was transformed to numeric data before being used in the data encoding process. Before providing input to the proposed model, backend computations were conducted on numeric values rather than nominal values using machine learning" methods.

Features Selection:

"It is possible to pick features by using the recursive feature elimination (RFE) approach, which fits a model and eliminates the weakest feature (or features) until the desired number of features is obtained. Features are ranked according to the model's coef_ or feature importance's_ attributes, and by recursively eliminating a small number of features per loop, RFE attempts to eliminate any dependencies or collinearity that may exist in the model. RFE is a type of dependency and collinearity elimination algorithm. When submitting an RFE, a certain number of features must be retained; however, the exact number of features that must be retained" is not always known in advance. [14].

In [14,16] technique selects attributes based on a decision tree, which is used for the selection process. It creates a structure that looks like a flow chart, with nodes signifying tests on different attributes. Each branch corresponds to the result of a test, and each leaf node represents a prediction about a class. The property that does not form a component of the tree is deemed irrelevant and is thus thrown away.

Content-based filtering [2] is a method that is often used in the development of features. In a content-based recommendation system, new products will be offered to a user based on their content characteristics that are comparable to the items on which the user has taken action. The most common method of determining whether or not a user loves an item is to look at both his explicit feedback (rating) and implicit feedback (browsing and purchase history).

Machine Learning

The Support Vector Machine (SVM) "may be used to solve both classification and regression problems. The Support Vector Machine (SVM) is a widely used Supervised Learning tool for solving classification and regression issues. The goal of the SVM technique is to find the best line or decision boundary for categorising n-dimensional space into classes, such that subsequent data points may be easily placed in the correct category after the first. A hyperplane is a boundary that indicates the best possible choice. The extreme points/vectors that will help in the creation of the hyperplane are chosen using SVM. The mechanism utilised is a Support Vector Machine, and support vectors are the most severe examples of this approach. SVMs may be classified into two groups." [2,4,8]

The Naive "Bayes approach, which is based on the Bayes theorem, is an efficient supervised learning strategy for classification tasks. The Naive Bayes Classifier is a basic and effective classification approach that assists in the building of fast machine learning models that produce accurate predictions. It has a wide range of uses. It's a probabilistic classifier, which means it generates predictions based on the chances of something existing. Spam filtering, sentiment analysis, and article categorization are just a few of the uses for the Naive Bayes Algorithm. It's typically utilised for text classification assignments that require a lot of data to" train with. [3,6,9]

The "Decision Tree is a supervised learning strategy that may be used to tackle classification and regression problems. However, it is most commonly used to solve categorization issues. The core nodes in this tree-structured classifier contain dataset properties, branches represent decision rules, and leaf nodes offer the conclusion. A decision tree is made up of two nodes: the Decision Node and the Leaf Node. Choice nodes are used to make any kind of decision and have a lot of branches, whereas Leaf nodes are the consequence of such decisions and have no more branches. The evaluations or tests are carried out in line with the features of the dataset given. The components described in the issue or decision are used to create a visual representation of all possible solutions to a problem or" option. [1,12,15]

Extra "Trees Classifier (Extra Trees Classifier) is an ensemble learning strategy that generates a classification result by integrating the results of numerous de-correlated decision trees gathered in a "forest" into a single classification result. Despite the fact that it uses a simpler technique to build the decision trees that make up the ensemble, it may often produce results that are on par with, if not better than, those achieved using the random forest algorithm. It's also straightforward to use, since it just has a few key hyperparameters to adjust, as well as clear instructions on how to change their" values.

The "K-Nearest Neighbor technique is based on the Supervised Learning methodology and is one of the most often used Machine Learning algorithms. The K-NN approach assumes that the new case/data and past cases are comparable, and it places the new example in the category that is closest to the existing categories. The K-NN algorithm stores all of the existing data and classifies incoming data points depending on how similar they are to previous data. This means that new data may be swiftly sorted into a well-defined category using the K-NN approach, saving time and effort. Although the K-NN technique may be used for both regression and classification, classification is the most common use. The K-NN approach makes no assumptions about the data it is given because it is a non-parametric algorithm. The KNN approach only saves data during the training phase, and when new data is received, it is classified into a category that is extremely similar to the data it recorded during the training" phase. [1,6,14,16]

Random "Forest is a well-known machine learning approach for learning new things that use the supervised learning technique. Depending on the scenario, machine learning may be applied to both classification and regression problems. It is based on ensemble learning, which is a method for combining several classifiers to solve a complex problem and improve the model's performance. Random Forest is a classification technique that combines the results of many decision trees on different subsets of a dataset and averages the results in order to improve the dataset's projected accuracy. The random forest collects predictions from each tree and forecasts the ultimate conclusion based on the majority of votes collected, rather than relying on a single decision tree. The more trees in the forest, the more accurate the model gets, and the risk of" overfitting is reduced. [2,4,5,9,10]

IV. Results and Analysis

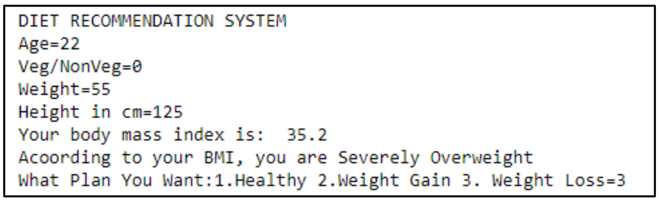

Figure 2. BMI Calculation

```
K-Nearest Neighbors
              precision    recall  f1-score   support

           0       1.00      0.95      0.98       165
           1       0.53      1.00      0.69        10
           2       1.00      0.97      0.98        30

    accuracy                           0.96       205
   macro avg       0.84      0.97      0.88       205
weighted avg       0.98      0.96      0.96       205

[[157   8   0]
 [  0  10   0]
 [  0   1  29]]
------------------------------------------------------------
```

Figure 3. KNN Classifier

```
Liner SVM
              precision    recall  f1-score   support

           0       1.00      0.95      0.98       165
           1       0.53      1.00      0.69        10
           2       1.00      0.97      0.98        30

    accuracy                           0.96       205
   macro avg       0.84      0.97      0.88       205
weighted avg       0.98      0.96      0.96       205

[[157   8   0]
 [  0  10   0]
 [  0   1  29]]
```

Figure 4. Liner SVM Classifier

```
Decision Tree
              precision    recall  f1-score   support

           0       1.00      0.95      0.98       165
           1       0.53      1.00      0.69        10
           2       1.00      0.97      0.98        30

    accuracy                           0.96       205
   macro avg       0.84      0.97      0.88       205
weighted avg       0.98      0.96      0.96       205

[[157   8   0]
 [  0  10   0]
 [  0   1  29]]
```

Figure 5. Decision Tree Classifier

```
Random Forest
              precision    recall  f1-score   support

           0       1.00      0.95      0.98       165
           1       0.53      1.00      0.69        10
           2       1.00      0.97      0.98        30

    accuracy                           0.96       205
   macro avg       0.84      0.97      0.88       205
weighted avg       0.98      0.96      0.96       205

[[157   8   0]
 [  0  10   0]
 [  0   1  29]]
```

Figure 6. Random Forest Classifier

```
Naive Bayes
              precision    recall  f1-score   support

           0       1.00      0.89      0.94       165
           1       0.53      1.00      0.69        10
           2       0.74      0.97      0.84        30

    accuracy                           0.91       205
   macro avg       0.76      0.95      0.82       205
weighted avg       0.94      0.91      0.92       205

[[147   8  10]
 [  0  10   0]
 [  0   1  29]]
```

Figure 7. Navier Bayer's Classifier

```
ExtraTreesClassifier
              precision    recall  f1-score   support

           0       1.00      0.99      0.99       165
           1       0.83      1.00      0.91        10
           2       1.00      1.00      1.00        30

    accuracy                           0.99       205
   macro avg       0.94      1.00      0.97       205
weighted avg       0.99      0.99      0.99       205

[[163   2   0]
 [  0  10   0]
 [  0   0  30]]
```

Figure 8. Extra tree Classifier

```
SUGGESTED FOOD ITEMS ::
Pumpkin

 Thank You for taking our recommendations. :)
```

Figure 9. Weight Loss Plan

```
SUGGESTED FOOD ITEMS ::
Bagels made in wheat
Cauliflower
Coffee
Grapes
Milk
Onions
Peas
Pumpkin
Chicken Sandwich
Sugar Doughnuts
Pop Corn
Chappati
Tomato
Yogurt
Brownie
Noodles
Uttapam
Bhaji Pav
```

Figure 10. Healthy Plan

```
------------------------------------------------------------
SUGGESTED FOOD ITEMS ::
Coffee
Pop Corn

 Thank You for taking our recommendations. :)
```

Figure 11. Weight Gain Plan

TABLE I. ANALYSIS OF RESULT

Model	*Precision*	*Recall*	*Accuracy*	*F1-Score*
KNN	84%	97%	96%	88%

NB	76%	95%	91%	82%
SVM	84%	97%	96%	88%
DT	84%	97%	96%	88%
RF	84%	97%	96%	88%
ET	94%	100%	99%	97%

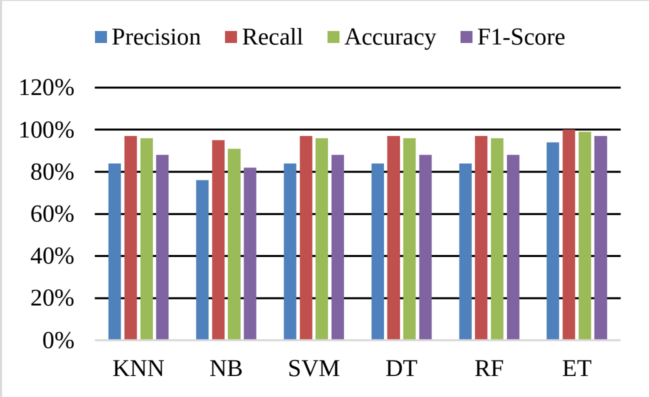

Figure 12. Analysis Graph

V. CONCLUSION

Patients who follow a well-balanced diet advised by a dietician or who utilise a machine-assisted medical diet-based system live longer, are less likely to develop new illnesses, and have a greater overall quality of life, according to recent research. Medical personnel, on the other hand, are still learning about the patient reasons for utilising the recommender system from dieticians. As a consequence, this review research examined all methods, approaches, features, and classifiers in depth to determine their benefits. There are also some drawbacks. As a result, it can be stated that in order to design a better diet advising system, one must first define the recipe, followed by medical-related aspects. After all, the final phase is to select a better classification algorithm that will work efficiently and rapidly in order to provide a strategy based on Veg and non-Veg metricians. The system implements a Modified attributes selection method in conjunction with a Voting based method of Machine Learning classifier, it will be more effective for classifying plans and retrieving choices of food that are either vegetarian or non-vegetarian in nature. Using food suggestion methodologies will surely be beneficial to the healthcare business in the future.

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