Realizing an Efficient IoMT-Assisted Patient Diet Recommendation System Through Machine Learning Model

CELESTINE IWENDI¹, (Senior Member, IEEE), SULEMAN KHAN², JOSEPH HENRY ANAJEMBA³, (Member, IEEE), ALI KASHIF BASHIR⁴, (Senior Member, IEEE), AND FAZAL NOOR⁵

¹Department of Electronics, Bangor College China, Central South University of Forestry and Technology, Changsha 410004, China
²Department of Computer Science, Air University Islamabad, Islamabad 44000, Pakistan
³Department of Communication Engineering, College of Internet of Things, Hohai University, Changzhou Campus, Changzhou 213000, China
⁴Department of Computing and Mathematics, Manchester Metropolitan University, Manchester M15 6H, U.K.
⁵Faculty of Computer Science and Information Systems, Islamic University of Madinah, Medina 42351, Saudi Arabia

Corresponding author: Joseph Henry Anajemba (herinopallazo@ieee.org)

ABSTRACT Recent studies have shown that robust diets recommended to patients by Dietician or an Artificial Intelligent automated medical diet based cloud system can increase longevity, protect against further disease, and improve the overall quality of life. However, medical personnel are yet to fully understand patient-dietician’s rationale of recommender system. This paper proposes a deep learning solution for health base medical dataset that automatically detects which food should be given to which patient base on the disease and other features like age, gender, weight, calories, protein, fat, sodium, fiber, cholesterol. This research framework is focused on implementing both machine and deep learning algorithms like, logistic regression, naive bayes, Recurrent Neural Network (RNN), Multilayer Perceptron (MLP), Gated Recurrent Units (GRU), and Long Short-Term Memory (LSTM). The medical dataset collected through the internet and hospitals consists of 30 patient’s data with 13 features of different diseases and 1000 products. Product section has 8 features set. The features of these IoMT data were analyzed and further encoded before applying deep and machine and learning-based protocols. The performance of various machine learning and deep learning techniques was carried and the result proves that LSTM technique performs better than other scheme with respect to forecasting accuracy, recall, precision, and $F_1$-measures. We achieved 97.74% accuracy using LSTM deep learning model. Similarly 98% precision, 99% recall and 99% $F_1$-measure for allowed class is achieved, and for not-allowed class precision is 89%, recall score is 73% and $F_1$ Measure score is 80%.

INDEX TERMS Recommendation system, RNN, GRU, LSTM, IoMT, Naive Bayes logistic regression.

I. INTRODUCTION

Recommendation system for patients/dieticians is a system that monitors a user (patient/dietician) in a tailored approach towards remarkable or suitable diets or food intake in large varieties of likely selections and that results in such selections as desired output [1]. A recommendation system for patients/dieticians is cautiously implemented for the purpose of encouraging the patients to take nutritional supplements; diets and food which are considered better to meet the patients’ health needs, taste and dietary preferences. Lately, in terms of life saving healthy living, recommendation systems are now believed to be a probable solution that will facilitate patients’ choice of food intake considering the enormous amount of accessible data interrelated to foods/recipes [2]. Diverse methods towards achieving tailored and efficient recommendations have been proposed by different authors, and we will be highlighting some of these recent researches in the related works section of this paper.

Researchers [3]–[5], have proved that robust diets indeed function as preventative medicine to many patients with diseases. In Patient-Dietician based product information, following a healthy diet recommended by the dietician or an AI automated medical diet system can increase longevity, protect
against further disease, and improve the overall quality of life for the patient [6]. While nutritious foods boast vitamins, minerals, antioxidants, fiber, protein, and fat, all of which stimulates better healthcare and are key to ideal physical function, it can also affect the patient whose body are not tolerant to the nutritious intake due to the kind of diseases they are suffering. Furthermore, nutritional information modeling from cloud system and implementation in the diet recommendation system concerning the patients’ nutritional condition, patient health assessment of food items, creates conflicting nutritional theories with the current practice. Therefore, various springs of nutritional errors need to be addressed in future food/diet-based recommendation system [7]. This research motivation is to achieve and integrate a wide-ranging of nutritional theory into the internet of things (IoT) system along with creating information system of patient/user-specific nutritional measurement and methods for estimating the effectiveness of a specific nutritional model. Meanwhile, diet recommendation system and knowledge-based menu recommendation have been found to be helpful in health management and disease prevention [8].

Real time selection of healthy diet based on patients’ nutritional need has been a serious issue according to researchers [3], [5], and [9]. The authors [9] noted that insufficient and wrong food consumption is acknowledged to be the leading source of several health challenges and ailment. According to their study, patients rely on medicines instead of resorting to precautionary nutritional measures in food/diet intake. This is due mainly to diversity of products information about healthy diets. In order to address this issue, the authors [9] created a cloud-based recommendation model that uses ant colony algorithm similar to author [10] to create an ideal list of food that refers appropriate diets based on their pathological records and values. This method plays an important part in controlling various diseases. However, the authors failed to address the timing fragmentation of the recommendation system for diverse food consumption timing like, breakfast, lunch or dinner in a day. The study also failed to model the nutritional composition in the singular food items with peculiar reference to timing and daily nutritional requirements of users. In the present study, this problem has been taking care of by implementing the Recurrent Neural Network, Naive Bayes and Long Term Short Memory that is suitable for precision, recall and all measures for allowed and not allowed classes of products anytime of the day.

A mobile recommender application system was developed by [11]. The authors combined artificial intelligence methods via a knowledge base to manage diabetic patients’ nutrition according to the strategies of American Diabetes Association (ADA). In their study, a food recommendation system was developed and evaluated which reminds diabetic patients to choose healthy snacks according to their diet. Patients’/users’ physical activity was among key factors considered in designing and modeling of the application. The authors calculated users’ energy expenditure on the basis of physical activity level using Harries Benedict equation in order to recommend best snacks match for users based on their calorie requirement. Unfortunately, this system was designed with a focus on patients’ interests and BMI rather than the patients’ conditions. Other limitations of the study by [11] include the small sample size in the estimation phase and failure to include main meals. With more exact algorithms, the quality of the recommendations can be increased.

Generally, the motivation of this research is to achieve and integrate a wide-ranging nutritional theory into the IoT system in addition to creating information system of patient/user specific nutritional measurement and methods for estimating the effectiveness of a specific nutritional model.

In summary, the contributions of our research are as outlined:

- Investigation of the inner workings of our proposed model applying the single and ensemble machine learning algorithms like naive byes and logistic regression, and deep learning classifiers like RNN, GRU and LSTM.
- Providing a comprehensive insight about how our model works under the products and patient disease specifications.
- Analyzing the behavior of our AI and deep learning mechanisms to allow a better understanding of the nature of the problem of the patients and what food they should take in at appropriate time.
- Through analysis of our machine Learning and deep learning, we showcased that different patient diseases have different recommender evidence, which might require different treatment and special care.

The rest of this paper is arranged as follows: Section II describes related works, Section III, introduce the system’s materials and methods including implementation using AI, Section IV: Summaries the findings. Section V concludes the work.

II. RELATED WORKS

A personalized diet recommendation system was developed using artificial bee colony algorithm [12] for the required daily nutrition. The authors proposed a system that uses rule based reasoning and fuzzy ontology to make food and nutrition recommendations efficiently while a genetic algorithm was proposed for menu generation. Unfortunately, the system relied on Google fit Application Programming Interface (API) of the user for information regarding daily activities and energy requirement of the user. The system also relied on past disease record of the patient to make personalized diet recommendation for users implying that this system may not be suitable for users without available disease record. The foregoing poses tremendous limitations on the number of users that can benefit from the system. Clustering analysis used for diabetic patients was used in presenting a food recommendation system by the authors in [13]. They proposed that food and nutrition is a key to a healthy living. However, the authors [14] instead of using long-term information for menu recommendation computed
daily nutritional requirement using only the physical user information. The study also failed to present an approach that handle nutritional and preference management simultaneously. In our approach we have used both user information and product information for a short and long term scenario in making sure patients with diseases are protected. A study was performed by the authors in [15] evaluated several medicines reporting systems which is targeted at reporting medicine shortages. Their system also incorporated different registries for batch recall, and manufacturers homepages. The research concluded a high desirability to incorporate dietetic and nutritional that are clinically used in registries to keep medical data. In the present study, we have used python to gather data and performed Machine Learning on the products. We have also addressed the peculiar dietary/nutritional needs of an individual patient via a registry base alerting system by an AI automatic system notification.

A new approach for recommending healthy diet using predictive data mining algorithm was proposed by [16]. The study developed a data mining model that propose healthy food habits and eating patterns for users to know the number of calories burned, the intake of macronutrients and so on. The patient diet recommendation system models users’ peculiar diet/nutritional preferences based on individual eating habits and body statistics. Although this study is effective in predicting healthy diets for patients and nutritionists/doctors, however, the drawback is that it is void of a flexible model and achieves minimal designing solutions per patient’s need. In our model, we address this issue with a better LSTM method that delivers patient needs with accurate precision.

In another study, a nutrition assistance system was developed by [17], the system gives feedback on a patient’s dietary behavior and accommodates behavior change through diverse persuasive elements such as self-monitoring, personalization, and reflection implementation, recommendations or tracking. Whereas an automated food/diet recommendation system could provide great benefits when compared to human nutritionists, it also faces a number of limitations ranging from usability, efficiency, efficacy to satisfaction. The results notwithstanding, there is a need to integrate contextual and social information as well as enhance the accuracy of the received input data. The system developed by [17] need be improved according to the given feedback so as to achieve desired effect in the long term as a mobile platform application for daily use. In the present study, we have good satisfaction rate of our proposal. The authors in [18] have a system that cannot be applied in food/diet recommendation. However, the delinearization of their system to fire alerts early and make possible dietary/food recommendations to patients would add additional realism as well as bridge a research gap. This is one of the contributions of the present paper. This is also similar to [19] where the authors proposed a Diet Organizer System. They created a profile using a real-time dynamic survey which the medical doctors prepared and which was users-compiled. The system which is referred as DIETOS is capable of recommending not just specific foods in the same category and which has similar health grade, but also can provide nutritional related suggestions to some category of health issues. Our system was far better because we cover more health conditions than they did while the authors in [20] collected data from individuals and predicted their health statutes using a deep neural network model known as DeepFog but failed to remodel their system for specific application, development and possible deployment in diet/food recommender system for patients with health challenges.

Recently, the technology of deep learning has been incorporated in several systems of recommendations. The authors in [21], [22] describes basic vocabularies of recommender systems and deep learning technology and a different approach in coming up with recommendation which to them is the most efficient and direct way of finding and evaluating content recommendation. Meanwhile, lack of Health knowledge makes it difficult for Patients to recover demanded information about their health, product to choose from a well-known Online Health Communities (OHC) which the authors in [23] designed and proves to be a good approach and real in determining patients interest during online conversations. In the present system, automating our model advanced this proposer. There are other Recommender models which make use of different algorithms in providing both products or services to users as proposed by [24] without proper data analysis. The same complained by authors [25], [26], who argued that medical sector still lag behind in using big data analytic. They went ahead to proposed five approaches for healthcare establishments which considers implementing the big data analytic technologies. While a hardware device proposed and implemented by [27] has the capacity to assemble huge quantity of data for processed product and further analysis assimilate them into the cloud base which would eventually benefit users in obtaining diet/food recommendations. Furthermore, several techniques for projecting a social media for healthcare data as a heterogeneous healthcare information network were also proposed by [28]. Their experiment shows operational approaches outperform the approaches that are based on contents for dynamic users.

Alian et al. [29], clarifies that a system should be intelligent enough to be able to predict a physical health condition of patients, their social activities and records. They used Restricted Boltzmann Machine (RBM)-Convolutional Neural Network (CNN) deep learning approach, to provide an understanding of the big data analytics application towards the execution of an active engine of health recommender system. While Fidan et al. [30] integrated the user-based ontological AI profile with a wide-ranging scientific experimental diabetes for personalized recommendations based on geographical status, cultural, distinct socioeconomic, and predominantly to AI-based patients. This is quite different from our own AI model. Meanwhile, the patients’ attitude is also important according to [31] but the most important is Transparency and Traceability in food supply chain as to determine which product is suitable for the patient and
choice of food to prevent poisoning [32], [33], [35], [35]. Certainly, the resultant effect of busy life styled-patients may assume unhealthy diets. Intelligent Nutrition in Healthcare, Nourishment recommendation framework for children and diet recommendation based on user information were also discussed [36]–[38].

In summary, we have reviewed various existing papers and found out the lacunas in the existing systems. In our proposed system, an efficient recommendation system for patient-dietician based product information, where an artificial intelligence based solution using a medical dataset will automatically detect which food should be given to which patient base on the patient disease and other features are also considered like age, gender, weight, calories, protein, fat, sodium, fiber, and cholesterol. Also, previous results classically contain voracious hard-coded heuristics and algorithms. Intrinsically, the drawback of recent techniques is that their models lack flexibility and minimal results. Different single and ensemble machine learning algorithms and deep learning models which includes RNN, LSTM, GRU, MLP, naive bayes and logistic regression classifiers are used in this study. The proposed model consists of six phases. First phase is data reading, second phase is preprocessing, and third phase is optimal features visualization. Training and testing are fourth and fifth phases respectively. Last phase is evaluation phase. Lastly, review of the most recent related works shows that even though a good number of investigations are targeted at emerging tools of computation for food/diet consumption recommendation, nearly all of such systems failed to handle both the preferences and nutritional information of users, directly. In the future, we shall concentrate more on automating this system and adopting it with other eHealth functionalities [39]. Internet of Things nodes, Robotic navigation and Wireless sensor networks will serve as future tools for distant patients on a large scale recommendation [40]–[45], [51] and [52].

III. SYSTEM MATERIALS AND METHODS
The section describes the methodology used in this research. Let us remember that the aim of this study is to recommend diet to different patient using deep and machine learning classifiers for health base medical dataset which will automatically detect which food should be given to which patient base on the disease and other features like age, gender, weight, calories, protein, fat, sodium, fiber, and cholesterol. For this purpose, we have used different deep learning classifiers like RNN, GRU and LSTM and machine learning classifiers naive bayes and logistic regression. In order to know which feature has more impact in the dataset, random forest classifier was used for this purpose. The proposed model which is illustrated in Figure 1 consists of six phases. First phase is data reading, the preprocessing of collected data is established in the second phase, while the third phase is analysis the optimal features visualization. While training and testing are fourth and fifth phases respectively and finally, evaluation phase which is the last phase.

![Figure 1. Work flow of proposed technique.](image)

### TABLE 1. Number of features in product.

| S/No | Product Features       | Feature Type |
|------|------------------------|--------------|
| 1    | Product Barcode        | Numeric      |
| 2    | Product Calories       | Numeric      |
| 3    | Product Proteins       | Numeric      |
| 4    | Product Fat            | Numeric      |
| 5    | Product Sodium         | Numeric      |
| 6    | Product Carbohydrate   | Numeric      |
| 7    | Product Fiber          | Numeric      |
| 8    | Product Cholesterol    | Numeric      |

A. DATASET
The dataset used in this research consists of around 1000 products and 30 patients collected by using the IoT and cloud method. 1000 products were tested on different disease patients. The dataset has 21 features and 16933 records in it. Products features are listed in Table 1 and patient’s features are listed in Table 2.

B. DATA PROCESSING
1) DATA NORMALIZATION
After selection of dataset, data cleaning operations are performed on datasets to remove noise from dataset and normalize the features. The purpose of normalization is to scale the dataset in one range. The reason for doing this is that dataset has different scale values some are single digit values, some features has two digit values and some features has...
TABLE 2. Features of patients.

| S/No | Patient Features | Feature Type |
|------|------------------|--------------|
| 1    | Patient Number   | Numeric      |
| 2    | Patient Age      | Numeric      |
| 3    | Patient Gender   | Categorical  |
| 4    | Patient Weight   | Numeric      |
| 5    | Patient Disease  | Categorical  |
| 6    | Patient Calories | Numeric      |
| 7    | Patient Protein  | Numeric      |
| 8    | Patient Fat      | Numeric      |
| 9    | Patient Sodium   | Numeric      |
| 10   | Patient Carbohydrate | Numeric  |
| 11   | Patient Fiber    | Numeric      |
| 12   | Patient Cholesterol | Numeric     |
| 13   | Target Class     | Categorical  |

three-digit values so we bring all the values in to single scale to make the performance of machine learning models better, and for this purpose we performed min-max normalization.

Min-max scaling normalizes values in the range of [0, 1] in this research. Equation (1) states the min-max normalization.

\[ Z_i = \frac{F_i - \min(F)}{\max(F) - \min(F)} \]  (1)

where \( y = (F_1, F_2, \ldots, F_n) \) are the number of features while \( F_i \) is the feature which we want to normalize and \( Z_i \) represents the normalized features. By doing this now all features have same weights and all features are in one scope.

2) DATA ENCODING

During the cause of this research, inconsistent and duplicate values are removed from dataset before performing data encoding. After that, the nominal features are converted to numeric values. The purpose of doing this is because backend operations inside machine learning models are done on numeric values before implementing them using machine learning model. In this research, non-numeric data was converted to numeric data before data encoding was performed. ML algorithms backend calculations were also performed on numeric values not nominal values before passing data to the proposed model.

3) OPTIMAL FEATURE VISUALIZATION

Figure 2 indicates that product calories have 48% importance in the dataset. Product fat has 12% importance. Product carbohydrate and protein have 8% importance respectively. Product sodium has 6% importance. User no has 5% importance in the dataset. Similarly, user fat, user protein and product fiber have 2% importance respectively. Disease, age, product barcode, user calories, user weight and user carbohydrate have 1% importance inside the dataset.

Random Forest is a mix of decision trees. In order to get prediction right random forest combine all the decision trees and gives more accurate results. Random forest not only used for classification and regression but also applied to best features from the dataset. We can perform classification and regression by using random forest; this is the best thing about random forest. In case of classifying random forest, the majority vote was used to predict the target but for regression analysis, random forest takes mean value of all the decision trees and then predict as threshold is set for each node. Splitting is then performed base on that threshold [46].

Threshold is set by calculating entropy and gain-index. Equations for entropy and gain-index are given below.

\[ Entropy : K(x_1, x_2, \ldots, x_s) = \sum_{i=1}^{s} x_i \log(1/x_i) \]  (2)

\[ Gain(D, S) = K(D) \sum_{i=1}^{s} x_i K(D_i) \]  (3)

C. DEEP LEARNING CLASSIFIERS

1) MULTILAYER PERCEPTRON (MLP)

There are different types of neural networks that are constantly being developed. However, all ANNs may be characterized by their processing unit (PE) transfer functions. Their learning methods and by the connection equations, PE, is a fundamental component of ANN and it receives many weighted signals from other processing units [46]. Figure 3 shows the Biological Neuron structure [47] while Figure 4 shows the working flow of neural network.

Forward propagation is most widely used ANN architecture trained with backpropagation error developed by
Agatonovic-Kustrin and Beresford [48]. The architecture of forward ANN is on 1st layer it have input units, in the middle it have hidden layers and last layer consist of output units Figure 5 [49]. The job of input unit is to provide data from external source. Then this data is moved to hidden layers where it is multiplied with weights and then it pass to output layer to generate final signals [50]. The classification ability of ANN totally base on hidden layers, hidden layers are further connected by the synapses with neighbor’s layers. If we have \( m \) input data points \((x_1, x_2, \ldots, x_m)\), then we name it as \( m \) number of features inside the data. In ANN architecture every feature is multiplied with weight \((w_1, w_2, \ldots, w_m)\) and then add them as shown in (4) below.

\[
W.X = w_1x_1 + w_2x_2 + \ldots + w_mx_m = \sum_{i=1}^{m} w_ix_i \tag{4}
\]

\( m \) represents total number of features in the dataset given as input \( X \) to input layer, \( w \) represents weights every feature multiplied with its weight. It is also known as dot product.

Bias function is added inside the dot product function and it will give following (5).

\[
z = \sum_{i=1}^{m} w_i x_i + \text{bias} \tag{5}
\]

In (5), \( z \) represents activation function \( f(z) \) in this way we will get output for 1st neuron and for 1st hidden layer. We will repeat this whole process until last weight and for last input as shown in Figure 6.

2) RECURRENT NEURAL NETWORK (RNN)

RNN represents one of the classes of artificial neural networks (ANN) where node-to-node connections produce a graph directed along a temporal order which give way for the exhibition of dynamic behavior. It is also a kind of cutting-edge ANN that contains directed memory cycles.

3) LONG SHORT TERM MEMORY (LSTM)

LSTM is an architecture or model which performs a memory extension for the RNN. In this study 3 layers LSTM with batch size 32 and sigmoid function is used for activation. For optimization adam function is used. Function loss is calculated with binary cross entropy.

4) GATED RECURRENT UNITS (GRU)

The concept of the Gated Recurrent Units (GRU) is more recent that the LSTM. Generally, it performs more efficiently and unlike the LSTM, it trains models faster. The model is can be easily manipulated and modifications are easily done on the model. However, in a case longer memory is required, LSTM outperforms the GRU. Eventually, performance comparisons is basically dependent on the type of dataset in use. Although the LSTM and GRU also share some similarities, there are some vital variances that should be mentioned and recalled:

- The GRU is consisting of two gates, while the LSTM consists of three gates.
- GRUs are void of internal memory that are contrarily to the visible hidden state, and the output gate which is incorporated in LSTMs is not present in the GRUs.
- When computing GRU output, second nonlinearity is not applied unlike the LSTMs.

D. MACHINE LEARNING CLASSIFIERS

1) LOGISTIC REGRESSION

Logistic Regression is also well known classification algorithm used in machine learning. Generally a dichotomous result is obtained with logistic regression. The algorithm’s aim is to look for a correlation between the likelihood of specific outcome and characteristics. A logit function or the log odds function is used in logistic regression. In (6), we describe logistic regression as follows:

\[
\log \left( \frac{P(X)}{1-P(X)} \right) = \beta_0 + B_1X \tag{6}
\]

In above equation logit function is \( \log \left( \frac{P(X)}{1-P(X)} \right) \) and odd function is \( \frac{P(X)}{1-P(X)} \). The odds reflect the probability ratio of inclusion of the feature to the possibility of failure or
absence of feature. Usually only one is in this algorithm after mapping inputs to log odds in a linear combination. Now, if we find the opposite of the previously mentioned function;

\[ P(X) = \frac{e^{\beta_a + \beta_1 x}}{1 + e^{\beta_a + \beta_1 x}} \]  

(7)

This (7) is known as a sigmoid function and it creates curve like S shaped. The probability value is generated within the scope of 0 < P < 1. Therefore, we picked the parameters in the logarithm in a way to maximize the possibilities of observing sample values.

2) NAIVE BAYES

Naive Bayes is a compilation of algorithms that share a mutual rule in which all pairs of features are independent. Two premises are taken into consideration in the algorithm;

1) every function is separate and
2) we need to translate the texts into numeric values in the case of attributes in text format.

We know, in Bayes’ Theorem which is stated in (8);

\[ P_A \frac{P(A / B) P(A)}{P(B)} \]  

(8)

where, A and B events, P(A) = prior probability (event’s probability before evidence), P(A / B) = B’s posterior probability (event’s probability after evidence). Now, we can implement Bayes’ theorem by (9);

\[ P_y = \frac{P(X / y) P(y)}{P(X)} \]  

(9)

where, X = dependent feature vector and y = class variable. X is of size n such that X = (X₁, X₂, X₃ . . . , Xₙ) To split evidence into independent segments for events A and B; P(A, B) = P(A)P(B) Now results becomes

\[ P \left( \frac{y}{X_{1...n}} \right) = \frac{P \left( X_1 / y \right) P \left( X_2 / y \right) \ldots \ldots \ldots P \left( X_n / y \right)}{P(X_1) P(X_2) \ldots \ldots \ldots P(X_n)} \]  

(10)

It can be expressed as (11);

\[ P \left( \frac{y}{X_{1...n}} \right) = \frac{P(y) \Pi^n_{i=1} P \left( X_i / y \right)}{P(X_1) P(X_2) \ldots \ldots \ldots P(X_n)} \]  

(11)

Denominator is constant for input, so in (12);

\[ P \left( \frac{y}{X_{1...n}} \right) = \infty P(y) \Pi^n_{i=1} P \left( X_i / y \right) \]  

(12)

To produce a classifier model, we have to determine input probabilities for of y and take the output having highest probability. Hence, in (13);

\[ y = \text{argmax} P(y) \Pi^n_{i=1} P \left( X_i / y \right) \]  

(13)

In the end, we are only left with calculating P(X/y) and P(y).

### TABLE 3. Training accuracies of models.

| Model Name   | Average Accuracy % |
|--------------|--------------------|
| MLP          | 92.91              |
| RNN          | 94.5               |
| GRU          | 95.29              |
| LSTM         | 96.5               |
| Naive Bayes  | 92.81              |
| Logistic Regression | 92.79            |

## E. EVALUATION METRICS

Different metrics are used to evaluate the performance of our proposed model. These are mentioned below.

\[ \text{Accuracy} = \frac{T_p + T_n}{T_p + F_p + T_n + F_n} \]  

(14)

Precision’s objective is to evaluate the True Positive (TP) entities in relation to False Positive (FP) entities.

\[ \text{Precision} = \frac{T_p}{T_p + F_p} \]  

(15)

The purpose of recall is to evaluate True Positive (TP) entities in relation to (FN) False Negative entities that are not at all categorized. Mathematical form of recall is mentioned in (16);

\[ \text{Recall} = \frac{T_p}{T_p + F_n} \]  

(16)

Sometimes performance assessment may not be good with accuracy and recall. For instance, if one mining algorithm has low recall but high precision that another algorithm is needed. Then there is the question of which algorithm is better. This problem is solved by using F1-measure that gives an Average recall and precision. F1 measure can be calculated as follows

\[ \text{Measure} = \frac{2 * \text{Precision} * \text{Recall}}{\text{Precision} + \text{Recall}} \]  

(17)

### IV. RESULTS

Experiments are performed on Core–I3 system using colab with 8GB Ram of computer and 13GB from google colab laboratory is used. 4 CPU’s 1.7 GHz processor is used for experiments. Data Set is divided in to three sections training set, cross validation set and testing set. KFold Cross validation was used. 70% dataset is used as training set and remaining 30% dataset is used for testing purpose. Cross validation is used for both training and testing set. Table 3 represents the training Accuracies of deep learning and machine learning classifiers used in this study. From Table 3 and Figure 7 we can conclude that LSTM has highest training accuracy among all the classifiers listed in Table 3 which is 96.5%. 3 layer LSTM with 32 batch size is used along sigmoid activation function. MLP, naive bayes and logistic regression has 92.82%, 92.91% and 92.79% training accuracies respectively. RNN and GRU training accuracies are 95.29% and 94.5% respectively.

In Figures 8, 9 and 10 red line represents the training curve and green curve is cross validation curve. In Figure 8 we can see that naive bayes training and validation score is same around 92.91%. For logistic regression training score
increases in start and goes to 93% and then it came back to 92.8% along validation score. Figure 10 represents the training and validation score for multilayer perceptron (MLP). MLP training scores increases in start and eventually it goes down and came to 92.83%.

From Figure 11 and Table 4 we can see that deep learning classifiers outclass machine learning classifiers in terms of accuracy. LSTM achieved 97.74% testing accuracy. GRU testing accuracy is also closer to LSTM accuracy which is 96.10%. Testing accuracy for RNN model is 95.24% while MLP has 93.82% testing accuracy respectively. Naive bayes and logistic regression has 93.96%, 93.80% testing accuracies respectively.

In Figure 12 we can see that naive bayes testing and validation score are around 93.96%. For logistic regression testing score increases in start from 92% and goes to 93.80%. The interesting thing for logistic regression in 13 is that cross validation curve remained same throughout this study. Figure 14 represents the testing and validation score for multilayer perceptron (MLP). MLP testing score increases from 92% and goes to 93.82%.

Figure 15 represents training and testing scores for GRU. Blue curve represents training curve and green curve represents testing curve. Blue curve which is training curve starts...
from 93.7% and after 50 epoch it goes to 95%. Similarly for testing curve it starts from 94% and goes to 97.5% and then it comeback to 96%.

Figure 16 represents training and testing loss for GRU. Blue curve represents training loss and green curve represents testing loss. Blue curve which represents training loss it starts from 0.28 and reduces to 0.125. Similarly testing loss starts from 0.22 and comedown to 0.075.

Figure 17 represents training and testing scores for LSTM while Figure 18 represents training and testing loss for LSTM respectively. From Figure 15 we can see that blue curve which is training curve starts from 93% and goes up to 97%, similarly green curve which represents testing score for LSTM starts from 94% and goes to 97%. From Figure 16 we can see that training loss starts from 0.3 and decreases after...
50 epoch and it come down to 0.1. Testing curve also starts from 0.2 and comedown to 0.05.

Figure 19 represents training and testing scores for RNN. Blue curve represents training curve and green curve represents testing curve. Blue curve which is training curve starts from 93% and after 50 epoch it goes to 95%. Similarly for testing curve it starts from 94% and goes to 96%.

Table 5 represents that LSTM model out class other models in terms of precision, recall and F1 Measure. For allowed class LSTM classifier has 98% precision, 99% recall and F1 measure scores respectively. For not allowed class it has 89% precision 73% recall and 80% F1 measure respectively. Other models mention in Table 5 performs well for allowed class but did not perform well for not allowed class but LSTM outclass all other models mention in this research and produced good results for allowed and not allowed classes. Finally, we have used Figure 21 to show the classification report for Machine learning and deep learning models.

V. CONCLUSION AND FUTURE WORK

Recent studies have shown that robust diets recommended to patients by Dietician or an Artificial Intelligent automated medical diet based cloud system can increase longevity, protect against further disease, and improve the overall quality of life. However, medical personnel are yet to fully understand patient-dietician’s rationale of recommender system. Therefore, this paper proposes a deep learning based solution for
health base medical dataset that automatically detects which food should be given to which patient base on the disease and other features like age, gender, weight, calories, protein, fat, sodium, fiber, cholesterol. This research framework uses deep learning and machine learning different algorithms such as naive byyes, logistic regression Multilayer Perceptron (MLP), Recurrent Neural Network (RNN), Long Short Term Memory (LSTM) and Gated Recurrent Units (GRU). Finally, looking at Tables 5 and Figure 19 we can conclude that LSTM and GRU performs very well in terms of precision, recall and $F_1$ measures for allowed and not allowed classes. For allowed class LSTM classifier has 98% precision, 99% recall and $F_1$ measure scores respectively. For not allowed class it has 89% precision, recall and all other models mention in this research in terms of accuracy, models mention in Table 5 performs well for allowed class but did not perform well for not allowed class but LSTM outclass all other models mention in this research in terms of accuracy, precision, recall and $F_1$ Measure and produced good results for allowed and not allowed classes.

REFERENCES

[1] T. N. Trang Tran, M. Atas, A. Felfernig, and M. Stettinger, “An overview of recommender systems in the healthy food domain,” J. Intell. Inf. Syst., vol. 50, no. 3, pp. 501–526, Jun. 2018.

[2] C. Chen, L. Feng, T. Hai, S. Deshou, S. Wenjie, L. Weizhong, Z. Tingming, B. Xiaoqian, and X. Zhi, “Deep learning and its applications in biomedicine,” Genomics Proteomics Bioinf., vol. 16, no. 1, pp. 17–32, 2018.

[3] S. Saini and S. K. Dubey, “Recommendation of diet to jaundice patient on the basis of nutrients using AHP and fuzzy AHP technique,” Int. J. Intell. Eng. Syst., vol. 10, no. 4, pp. 91–99, Jul. 2017. doi: 10.22260/ijies.2017.083116.

[4] L. Yang, C.-K. Hsieh, H. Yang, J. P. Pollak, N. Dell, S. Belongie, C. Cole, and D. Estrin, “Yum-Me: A personalized nutrition-based meal recommender system,” ACM Trans. Inf. Syst., vol. 36, no. 1, pp. 1–31, Jul. 2017.

[5] J. Mariapun, C.-W. Ng, and N. N. Hairi, “The gradual shift of overweight, obesity, and abdominal obesity towards the poor in a multi-ethnic developing country: Findings from the Malaysian National health and morbidity surveys,” J. Epidemiol., vol. 28, no. 6, pp. 279–286, Jun. 2018.

[6] A. Kale and N. Auti, “Automated menu planning algorithm for children: Food recommendation by dietary management system using ID3 for Indian food database,” Procedia Comput. Sci., vol. 50, pp. 197–202, Jan. 2015.

[7] H. Schäfer, M. Elahi, D. Elsweiler, G. Groh, M. Harvey, B. Ludwig, F. Ricci, and A. Said, “User nutrition modelling and recommendation: Balancing simplicity and complexity,” in Proc. Adjunct Publication 25th Conf. User Modeling, Adapt. Pers. (UMAP), 2017, pp. 9–12.

[8] H. Dingr, S. Yüksel, and L. Martínez, “Balanced scorecard-based analysis about European energy investment policies: A hybrid hesitant fuzzy decision-making approach with Quality Function Deployment,” Expert Syst. Appl., vol. 115, pp. 152–171, Jan. 2019.

[9] F. Rehman, O. Khalid, N. Haq, A. R. Khan, and K. B. Sajjad, “Diet-right: A mobile application for personalized diet recommendation system using fuzzy ontology,” in Proc. IEEE Int. Conf. Ind. Technol.(ICIT), Lyon, France, Feb. 2018, pp. 1935–1939. doi: 10.1109/ICIT.2018.8532482.

[10] S. Norouzi, A. K. Ghalsabie, and S. Sistani, “A mobile application for managing diabetic patients’ nutrition: A food recommender system,” Arch. Iranian Med., vol. 21, no. 10, pp. 466–472, 2018.

[11] M. Raut, K. Prabhu, R. Fatehpuria, S. Bangar, and S. Sahu, “A personalized diet recommendation system using fuzzy ontology,” Int. J. Eng. Sci. Invention, vol. 7, no. 3, pp. 51–55, 2018.

[12] P. Maiyaporn, P. Phathrajarjjan, and P. Suphakant, “Food recommendation system using clustering analysis for diabetic patients,” in Proc. Int. Conf. Inf. Syst. Appl., vol. 6, no. 2, 2010, pp. 5–14.

[13] R. Yera Toledo, A. A. Alzahrani, and L. Martinez, “A food recommender system considering nutritional information and user preferences,” IEEE Access, vol. 7, pp. 96695–96711, 2019.

[14] C. Iwendi, Z. Zhang, and X. Du, “ACO based key management routing mechanism for WSN security and data collection,” in Proc. IEEE Int. Conf. Wireless Mobile Comput., Netw. Commun. (Wmob), New York, NY, USA, Oct. 2016, pp. 1–8. doi: 10.1109/wiMob.2016.7763190.

[15] R. Priyadarshini, R. Barik, and H. Dubey, “DeepFog: Fog computing-based deep neural architecture for prediction of stress types, diabetes and hypertension attacks,” Computation, vol. 6, no. 4, p. 62, Dec. 2018.

[16] H. Kaur, N. Kumar, and S. Batra, “An efficient multi-party scheme for privacy preserving collaborative filtering for healthcare recommender system,” Future Gener. Comput. Syst., vol. 86, pp. 297–307, Sep. 2018.

[17] C. C. Yang and L. Jiang, “Enriching user experience in online health communities through thread recommendations and heterogeneous information network mining,” IEEE Trans. Comput. Soc. Syst., vol. 5, no. 4, pp. 1049–1060, Dec. 2018. doi: 10.1109/tcsys.2018.2879044.

[18] N. Wang, L. Kung, and T. A. Byrd, “Big data analytics: Understanding its capabilities and potential benefits for healthcare organizations,” Technol. Forecasting Social Change, vol. 126, pp. 3–13, Jan. 2018.

[19] S. K. Panda, A. Blome, L. Wisniewski, and A. Meyer, “IoT retrofitting approach for the food industry,” in Proc. 24th IEEE Int. Conf. Emerg. Technol. Factory Autom. (ETFA), Zaragoza, Spain, Sep. 2019, pp. 1639–1642. doi: 10.1109/etfa.2019.8869095.

[20] R. Priyadarshini, R. Barik, and H. Dubey, “DeepReco: Deep learning based health recommender system: An enable study,” in Proc. Adjunct Publication 25th Conf. User Modeling, Adapt. Pers. (UMAP), 2017, pp. 9–12.

[21] H. Dincer, S. Yüksel, and L. Martínez, “Balanced scorecard-based analysis about European energy investment policies: A hybrid hesitant fuzzy decision-making approach with Quality Function Deployment,” Expert Syst. Appl., vol. 115, pp. 152–171, Jan. 2019.

[22] H. Schäfer, M. Elahi, D. Elsweiler, G. Groh, M. Harvey, B. Ludwig, F. Ricci, and A. Said, “User nutrition modelling and recommendation: Balancing simplicity and complexity,” in Proc. Adjunct Publication 25th Conf. User Modeling, Adapt. Pers. (UMAP), 2017, pp. 9–12.

[23] H. Dincer, S. Yüksel, and L. Martínez, “Balanced scorecard-based analysis about European energy investment policies: A hybrid hesitant fuzzy decision-making approach with Quality Function Deployment,” Expert Syst. Appl., vol. 115, pp. 152–171, Jan. 2019.

[24] H. Schäfer, M. Elahi, D. Elsweiler, G. Groh, M. Harvey, B. Ludwig, F. Ricci, and A. Said, “User nutrition modelling and recommendation: Balancing simplicity and complexity,” in Proc. Adjunct Publication 25th Conf. User Modeling, Adapt. Pers. (UMAP), 2017, pp. 9–12.
CELESTINE IWENDI (Senior Member, IEEE) received the second master’s degree in communication hardware and microsystem engineering from Uppsala University, Sweden, in 2008, ranked under 100 in the World University ranking, and the Ph.D. degree in electronics from the University of Aberdeen, U.K., in 2013. He is currently an Associate Professor in Sweden. He is also a Highly Motivated Researcher with a wireless sensor network security book, and over 100 publications. He is also a Senior Lecturer with Bangor College China and has strong teaching emphasis on communication, hands-on experience, willing-to-learn, and 18 years technical expertise, where he currently teaches Engineering Team Project, Circuit Theory, Data Networks and Distributed Systems, and Control Systems. He is also the Wireless Sensor Network Chief Evangelist, a Researcher, and a Designer. He has developed operational, maintenance, and testing procedures for electronic products, components, equipment, and systems; and provided technical support and instruction to staff and customers. His researches focus on wireless sensor networks, Security of Things (SoT), machine learning, AI, communication controls, the Internet of Things (IoT), electromagnetic machines, 5G networks, and low-power communication protocols.

Dr. Iwendi has been a Board Member of the IEEE Sweden Section, since 2017. He is also a Fellow of The Higher Education Academy, U.K., to add to his teaching and professional experiences. He is also the Co-Chair of the special session on Wireless Sensor Networks: Hardware/Software Design Aspects for Industry at the Prestigious International Conference of Industrial Technology ICT. He was an Editor of the International Journal of Engineering and Allied Disciplines, in 2015, the Newsletter Editor of the IEEE Sweden Section, from 2016 to 2018, and the Editor-in-Chief of the Wireless Sensor Network Magazine, in 2009, a Committee Member of the International Advisory Panel, International Conference on Marine, Ocean and Environmental Sciences and Technologies (MAROCENET), from 2014 to 2016, the Editor-in-Chief of the Journal of Wireless Sensor Network, in 2009. He is also on the Advisory Board of the International Journal of Innovative Computer Science and Engineering (IJICSE), in 2013.

SULEMAN KHAN received the master’s degree from the Department of Computer Science, Air University Islamabad, in 2019. He is currently a Research Associate with Air University, Pakistan. His research interests include network security, machine learning, and data science.

JOSEPH HENRY ANAJEMBA (Member, IEEE) graduated in computer science from the Federal Polytechnic Oko, Nigeria. He received the master’s degree in information communication technology from the National Open University of Nigeria (NOUN), in 2016. He is currently pursuing the Ph.D. degree in information and communication engineering with the Department of Communication Engineering, College of Internet of Things, Hohai University, China (under the Chinese University PULL Scholarship).

He has to his credit several articles and conference papers. His current research interests include cellular wireless communications, antenna and V2V technology, and 5G cellular networks and security, and the several other IoT related areas.
ALI KASHIF BASHIR (Senior Member, IEEE) received the B.S. degree from the University of Management and Technology, Pakistan, the M.S. degree from Ajou University, South Korea, and the Ph.D. degree in computer science and engineering from Korea University, South Korea.

He is currently a Senior Lecturer with the School of Computing, Mathematics, and Digital Technology, Manchester Metropolitan University, U.K. He is also a Distinguished Speaker of ACM. His past assignments include an Associate Professor of information and communication technologies with the Faculty of Science and Technology, University of the Faroe Islands, Denmark; Osaka University, Japan; the Nara National College of Technology, Japan; the National Fusion Research Institute, South Korea; Southern Power Company Ltd., South Korea; and the Seoul Metropolitan Government, South Korea. He is the author of over 80 peer-reviewed articles. He is supervising/co-supervising several graduate (M.S. and Ph.D.) students. His research interests include the Internet of Things, wireless networks, distributed systems, network/cyber security, and cloud/network function virtualization.

Dr. Bashir has served as the Program Chair, the Publicity Chair, and the Track Chair on several conferences and workshops. He has delivered several invited and keynote talks, and reviewed the technology leading articles for journals like the IEEE Transactions on Industrial Informatics, the IEEE Communication Magazine, the IEEE Communication Letters, the IEEE Internet of Things, and the IEICE Journals, and conferences, such as the IEEE Infocom, the IEEE ICC, the IEEE Globecom, and the IEEE Cloud of Things. He is also serving as the Editor-in-Chief for the IEEE Future Directions Newsletter. He is also an Editor of several journals and also has served/serving as a Guest Editor on several special issues in journals of IEEE, Elsevier, and Springer.

FAZAL NOOR received the B.Eng. and M.Eng. degrees from Concordia University, in 1984 and 1986, respectively, and the Ph.D. degree in engineering from McGill University, Canada, in 1993. He is currently working as an Associate Professor with the Faculty of Computer Science and Information Systems, Islamic University of Madison. He has numerous publications in International conferences and journals to his credit. His current research interests are in image recognition, parallel and distributed computing, embedded systems, the IoT, robotics, and computer vision.