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A Rule-Based Expert Advisory System for Restaurants Using Machine Learning and Knowledge-Based Systems Techniques

Khalid M. O. Nahar, Yarmouk University, Jordan*

Mustafa Banikhalaf, Yarmouk University, Jordan

https://orcid.org/0000-0002-1861-7805

Firas Ibrahim, The World Islamic Sciences and Education University, Jordan

https://orcid.org/0000-0002-0960-4543

Mohammed Abual-Rub, King Faisal University, Saudi Arabia

https://orcid.org/0009-0001-0982-0211

Ammar Almomani, School of Computing, Skyline University College, Sharjah, UAE & Al-Balqa Applied University, Jordan

https://orcid.org/0000-0002-8808-6114

Brij B. Gupta, Department of Computer Science and Information Engineering, Asia University, Taichung, Taiwan & Symbiosis Centre for Information Technology (SCIT), Symbiosis International University, Pune, India & Lebanese American University, Beirut, Lebanon & Center for Interdisciplinary Research, University of Petroleum and Energy Studies (UPES), Dehradun, India*

ABSTRACT

A healthy diet and daily physical activity are a cornerstone in preventing serious diseases and conditions such as heart disease, diabetes, high blood pressure, and hypertension. They also play an important role in the healthy growth and cognitive development for young and old people. Thus, this paper presents a new restaurant advisory system (RAS) using artificial intelligence (AI) techniques such as machine learning, decision tree, and rule-based methods. The proposed system makes a smart decision based on the user's input information to generate a list of appropriate meals that fit his/her health condition. For accuracy and efficiency measurement procedure in the decision-making process, a dataset from 1100 participants suffering from several diseases such as allergy, age, and body has been created and validated. The performance of the RAS was tested using Visual Basic.net Framework and prolog language. The RAS achieves an accuracy of 100% by testing 30 different live cases.

KEYWORDS

Advisory System, Decision Tree, Knowledge Base Systems, Machine Learning, Restaurant System, Rule-Based Expert System

1. INTRODUCTION

Community health promotion and disease prevention are two essential concepts that form a golden rule for improving people's quality of life. A good nutrition program when accompanied by suitable

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*Corresponding Author

diets, empowers people, especially patients, to take control of their health care. Numerous non-communicable diseases and chronic diseases such as obesity, diabetes, cancer, and cardiovascular diseases can be diet-related diseases caused by the consumption of foods and drinks high in fat, salt, and sugars (Neuhouser, 2019). According to World Health Organization (WHO), 2018 reports about non-communicable diseases (NCDs), cardiovascular diseases and diabetes have the highest prevalence that is associated with mortality and morbidity (Organization, 2018). Nyberg et al. conducted a multi-cohort study to find the relationship between Body Mass Index (BMI) and the development of NCDs such as diabetes and hypertension (Nyberg et al., 2018). The obtained results show that obesity is one of the dangerous risk factors for the development of NCDs. In Jordan, obesity rates are increasing yearly, as it scored a high percentage in 2018 about 40% of females and 27% of males from the total population in Jordan (Organization, 2018). Therefore, several dietary expert systems based on AI techniques have been proposed to assist patients and as well as normal people of different ages to choose meals that suit their health condition. For instance, a decision support tool, namely SCHOOLTHY, is presented in (Segredo et al., 2020), to automatically produce healthy and balanced meal plans in school canteens. In another instance, a personalized expert recommendation system is introduced in (Chen et al., 2017), for optimized nutrition (PERSON) with direct recommendations of products based on individual genes.

Restaurant meals are considered a favorable choice for most people around the world. However, they are not suitable for everyone, especially those who adhere to a specific diet or suffer from chronic diseases. Therefore, having guidelines based on medical recommendations to prepare appropriate meals according to the client's health is an essential need. Recently, the fields of food science and nutrition research have benefited from the development of artificial intelligence (AI) technologies (Miyazawa et al., 2022).

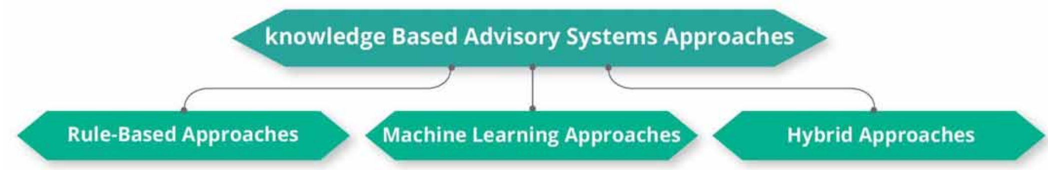
In this context, advances in AI presented by Knowledge-based Systems (KBSs) and Expert Systems facilitate the development of end-to-end solutions to meet client requirements carefully. Basically, KBSs can imitate the human capabilities of thinking and have decision-making abilities in a particular field of interest, by storing knowledge extracted from human expertise. It has several real-life applications that can extend into different domains, such as advice, diagnosis, repairing, forecasting, designing, and controlling. Furthermore, it can support the medical, military, manufacturing, educational, and training sectors (Tan et al., 2016). In general, advisory applications based on KBSs can provide people with useful advice and suggestions about a particular problem to find the best choice among several alternatives. Hence, this paper presents RAS, which can take input live data from a client such as weight, height, and age as well as his health status, to offer him a wide variety of meals that suit his taste and health conditions. The RAS fires matched rules, by collecting facts generated by nutrition specialists and building a rule-based system accordingly. Then, the training dataset is used to build a decision tree model and validate the dataset in order to decide on the appropriate rule for the RAS.

The rest of the paper is organized as follows: the most related works to this research interest are reviewed in section 2. The building stages are clarified in section 3. Results and evaluation, discussions, and conclusions are demonstrated in sections 4 and 5, respectively.

2. RELATED WORK

In general, providing general eating advice and nutrition counseling in the health and disease field by expert systems requires modeling human knowledge in a way that a computer can process. Due to its health promotion importance and disease prevention reinforcement, several approaches have been suggested to present efficient and effective nutrition solutions. These approaches have been classified into three categories, as seen in Figure 1: Rule-Based Approaches, Machine Learning Approaches, and Hybrid Approaches.

Figure 1. Knowledge-based advisory systems approaches



2.1. Rule-Based Approaches

It is the simplest form of expert systems which can be considered a modest form of AI representation. In order to represent knowledge extracted from the expert, it utilizes rules to code this knowledge for the reasoning process as in the human expert to solve intensive problems. Instead of expressing knowledge in a declarative and static manner, the Rule-Based system represents knowledge in terms of a set of rules that advises the user what to choose according to different alternatives.

With the aid of AI and Rule-Based expert systems, (Chen et al., 2012) have constructed a nutrient diagnosis system called Nutritional Care Process and Model (NCPM). The model facilitates the diagnosis process for some diseases based on nutrient information and special calculations depending on the patient's case. It also gathers rules from literature and human experts' interviews with 50 rules and achieves faster results than human experts.

Al-Dhuhli et al. (2013) constructed a Rule-Based expert system by providing a wide range of nutrient advice to the users, such as proteins and vitamin quantities to be supplied. The system uses a user-friendly interface to acquire the necessary data to help users also in increasing or decreasing their weight. The rules were generated by nutrient experts and specialized websites and converted to if-then statements to provide the user with the proper advice with an accuracy of 86.66%.

A diabetic patient's diet is considered as part of the therapy procedure besides medications to maintain blood sugar in normal ranges. (Arwan et al., 2013) have developed a food recommendation system that provides patients with nutrient tips and guidelines based on rules from an expert system. The system was built using ontology and semantic matching techniques (OWL and SWRL). It depends on the patient's age, diabetes type, body mass index (BMI), activities, and the number of calories with an accuracy of 73%.

The fear of chronic diseases, such as diabetes, hypertension, and cholesterol formed a nightmare for patients due to having the wrong diet plan. Hence, (Chen et al., 2013) have provided a solution by developing a diet recommendation expert system based on the JENA inference engine, fuzzy logic, and knapsack problem algorithm to find the optimal diet. The accuracy of the system was verified by nutrient experts, and it scored 100% with 13 rule numbers. The user can select between 6 to 10 food alternatives.

Basically, patients require a lot of attention and observation, especially in controlling their dietary intake, to maintain good health levels for chronic diseases. Chi et al. have proposed a dietary monitoring KBS for Chronic Kidney Disease (CKD) patients based on Web Ontology Language (OWL) and Semantic Web Rule Language (SWRL) (Chi et al., 2015). KBS engineers, specialized physicians in CKD, and dietitians were consulted to build up the system with 29 semantic rules. The system achieved better accuracy and faster response time than human experts.

Indeed, having a balanced diet involves both the number of intake calories and the quality of intake food is very important. Therefore, (Lee et al., 2014) have applied Type-2 Fuzzy Sets and Genetic Fuzzy Markup Language with 237 fuzzy rules, to build a personalized diet linguistic recommendation rule-based system. The system experimental results recorded better results than previous work based on type-1 fuzzy logic systems.

In order to promote children's health, (Hazman & Idrees, 2015) have proposed a prototype expert system to produce healthy meals according to the child's growth stage, gender, and health status. The web-based prototype was allocated into three layers, the knowledge base layer, inference knowledge layer, and task knowledge layer. It gives a child some nutrient-healthy variant meals with explanations.

Espín et al. (2016) have proposed an expert system devoted to caring for elderly people by creating a nutritional recommender (NutElCare) that takes into consideration not only building healthy plans but also considering the taste preferences of the user. The system was based on guidelines from nutrient experts and implemented using semantic web technologies that depended on extracting new technology from existing applications and agents.

The Food Frequency Questionnaire (FFQ) is used to assess a person's healthiness of a diet by filling in intake data for small periods of time, such as 4 days. After filling in data in a web-based application from 163 participants, the system can monitor, evaluate, and advise the user with scores for the diet and modifications to be added (Zenun Franco, 2017).

Healthcare systems tended to overcome the nutrient problems that happened to elderlies because of their decreased abilities in tasting, smelling, dental health, …etc. (Cioara et al., 2018) have personalized an expert system for elderly nutrition care which depended on ontology and semantic reasoning to evaluate the rules of diet for elderlies depending on BMI and other parameters. The system was evaluated by experts from a sample of 210 elderly people with sound time results.

Maintaining a healthy lifestyle by having a balanced diet and adequate physical activities was the main concern of (Dragoni et al., 2018). A rule-based system based on Semantic Web technologies was built with the aid of experts in the domain by generating 126 Mediterranean Diet rules. The system was examined by experts who evaluated live examples generated randomly. The time and throughput depended on the number of checked rules, since 400 ms and 350 user/minute approximately for 10 rules, 1300 ms and 100 user/minute approximately for 100 rules.

Bruevich et al. (2019) have employed mobile applications to produce and analyze the diet of individual healthy nutrients. The system depended on rules generated by experts based on data provided by the user, like age, height, width, food allergy, and some daily activities.

Lőrincz et al. (2017) have designed a rule-based system of 29 rules. The system focused on enhancing both diet and physically oriented lifestyle, by providing expert advice for the users. It was tested by using outlet cases by monitoring the results for 7 days.

2.2. Machine Learning Approaches

Learning is considered a powerful tool for automation and analysis of many alternatives when massive quantities of knowledge are presented. It also can make the system more effective and faster in the data analysis process and inference of decisions. Several contributions have gained the advantage of machine learning approaches in building advisory expert systems.

Murino et al. (2015) have developed a dietary assessment system for food recognition by using deep convolutional neural networks. The system focused on classifying food images to manage diet plans using 6-layer deep convolutional neural networks and using the majority vote for image recognition. They have used a manually annotated dataset with 573 food items and the overall accuracy reached 84.9%.

Yang et al. (2017) have constructed a nutrient-based meal recommender (FoodDist), that considers people's food preferences combined with the prevention of many diseases such as diabetes and hypertension. A deep convolutional neural network has been used based on multitask learning and with live examples for a dataset of 227 users with an accuracy of 83.09%.

Sookrah et al. (2019) tackle preventing and minimizing Hypertension health problems by recommending a diet recommender using machine learning algorithms and multilayer Neural Networks with an accuracy of 99%. The system includes the most important leading factors such as age, user preferences about food, allergies, smoking level, alcohol level, blood pressure level, and dietary intake.

2.3. Hybrid Approaches

(Chen et al., 2015) have focused on providing healthy diet recommendations for chronic disease patients based on information generated by experts. They have used three basic techniques, decision trees, ontology, and JENA to build the recommendation system. A dataset based on the user's diet records of the previous seven days was constructed and used as input to the decision tree to generate user nutrient information. The system has 9 types of rules, three for each disease namely, diabetes, hypertension, and cholesterol. Based on that information, the ontology rules and JENA Java interface and inference engine generated the rules and achieved an accuracy of 100%. (Marinchev & Agre, 2016) have developed an expert system for healthful and dietary nutrition, with different physical activity categories to help adults with ages under 60 years. The system generates information about the nutrient components of any product. Drools system was used in implementing the production rules with proper attributes, conditions, and actions. In addition to this, the k-nearest neighbor algorithm is used with some modifications, to predict the category of unknown foods. Table 1 displays the summary of the literature.

Table 1. Literature summary

Reference	Method	Dataset	Number of Rules	Test Results
(Nyberg et al., 2018)	Rule-based method	No dataset, just using live examples	50 rules	Faster time than human experts
(Segredo et al., 2020)	Rule-based method	No dataset, just using live examples	NA	Accuracy 86.66%
(Chen et al., 2017)	OWL and SWRL methods	No dataset, just using live examples	NA	Accuracy 73%
(Tan et al., 2016)	JENA inference engine, fuzzy logic, and knapsack problem algorithm	No dataset, just using live examples	13 rules	Accuracy 100%
(Chen et al., 2012)	Web Ontology Language (OWL) and Semantic Web Rule Language (SWRL)	No dataset, just using live examples	29 semantic rules	Faster time and better results than human experts
(Al-Dhuhli et al., 2013)	Rule-based based on Type-2 Fuzzy Sets and Genetic Fuzzy Markup Language	No dataset, just using live examples	237 rules	Better results than type-1 fuzzy logic
(Lőrincz et al., 2017)	Decision trees, Ontology, and JENA	The dataset is composed every 7 days based on the user's diet records	9 types of rules	Accuracy 100%
(Arwan et al., 2013)	Rule-based method	No dataset, just using live examples	N.A	Providing children with healthy meals choices
(Chen et al., 2013)	Rule-based System depending on Semantic Web technologies	No dataset, just using live examples	N.A	Providing elderlies with healthy meals choices and alarming options in case of deficiencies
(Murino et al., 2015)	Rule-based System depending on Drools system	No dataset, just using live examples	N.A	N.A
(Lee et al., 2014)	Rule-based System depending on Ontology and Semantic Reasoning	No dataset, just using live examples	N.A	Evaluated by 210 elderlies
(Hazman & Idrees, 2015)	Rule-based System depending on Semantic Web technologies	No dataset, just using live examples	126 Mediterranean Diet rules	The time between 400-1300 ms Throughput between 100-350 user/minute

3. RESTAURANT ADVISORY SYSTEM BUILDING STAGES

3.1. General Structure

Building an advisory system requires facts, rules, and knowledge extracted from an expert in the nutrient field, and stored in the knowledge base unit, to become the foundation of the system. Hence, we propose an advisory rule-based system with the aid of machine learning for generating appropriate meals according to the customer's health status, food allergy problems, and overall body structure the proposed system starts working by collecting input from users using a user-friendly interface, allowing them to insert complete and correct data. The system takes this knowledge and passes it to the inference engine which depends on the KBS and the working memory to generate the appropriate set of meals. The user may require an explanation facility to clarify the reason for choosing one meal instead of another. Figure 2 shows the structure of the restaurant advisory system with the previously mentioned units.

3.2. Building Stages

To achieve better rules' extraction and implementation, a dataset is built using questionnaires distributed among target people inside Jordan, and each tuple is labeled using a suitable class. The rule extraction process depends on machine learning techniques, and decision trees, to have more accurate rules for a variety of classes. To obtain data for the system, a simple interactive graphical interface is designed to collect complete data with minimum questions. Finally, the rules are implemented to generate the best collection of suggested meals based on the user's health status, measurements, and according to breakfast and lunch times of meals. Figure 3 shows the building stages of the proposed system.

3.2.1 Stage (1): Knowledge Extraction From Nutrient Expert

The main and most important stage in any expert system is knowledge acquisition to formulate facts and rules for developing the rest of the stages. In our model, we conducted a nutrient expert, Hala Gameel Ailabouni, with a master's degree in nutrients from Jordan University of Science and Technology, who provided us with the properties and quantities for each meal according to the user's features, such as age, weight, diseases, allergy, and others.

Each meal was designed according to Arabian recipes with detailed ingredients, such as the number of rice cups, the weight of meat, the presence or absence of some components, and so on. All this knowledge was converted to appropriate electronic facts and rules.

Figure 2. Restaurant advisory system structure

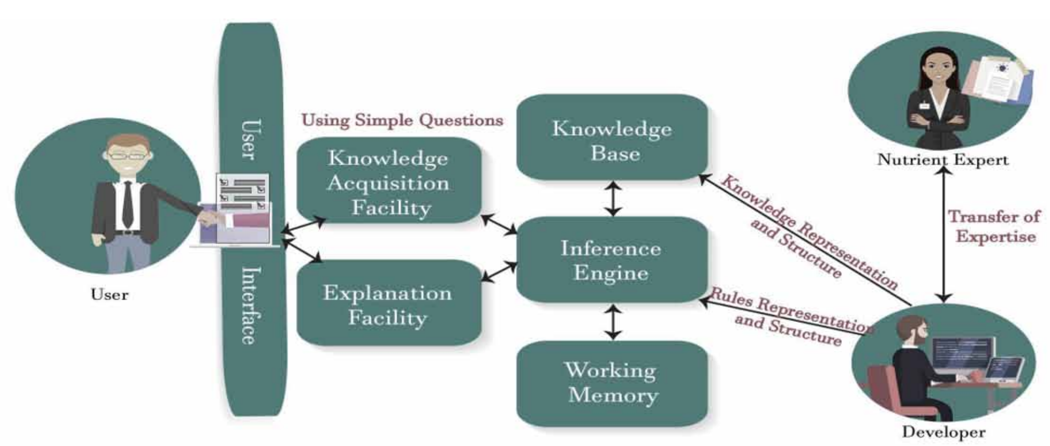
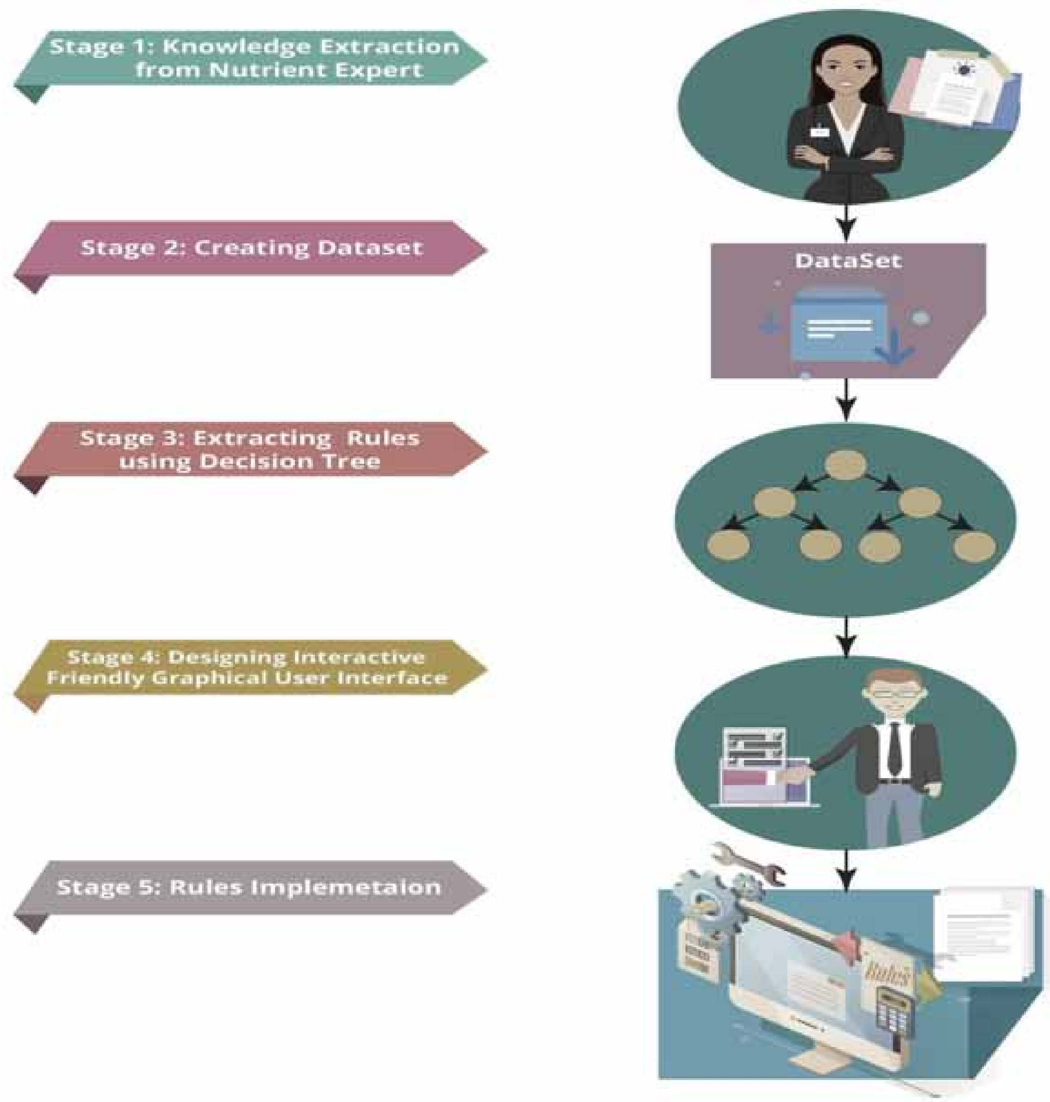


Figure 3. Restaurant advisory system building stages



3.2.2 Stage (2): Creating the Dataset

In this paper, the dataset is created by using a proper questionnaire. The sample is taken from the Jordanian population randomly using multistage sampling techniques that depend on clustering and simple random sampling techniques. The questionnaire covers approximately the main cities in Jordan such as Amman, Irbid, Madaba, and Aqaba. It is distributed online using social media applications, Google Forms, and handed over as paper copies for elderlies who do not use social media applications. The following listed features in Table 2 are used to construct a well-defined advisory system.

The questionnaire form focuses on obtaining the age of the participant, the number of calories in the diet (if existed), food allergies (specifically milk and eggs), diseases (specifically diabetes and hypertension), if the participant is an athlete, and the weight and height to calculate the BMI to determine the category of the body fatness. The size of the sample is 1100 participants with

Table 2. Features and values for advisory system dataset

Feature	Values
Age Category:	Under 15, Above 15
Calories:	1200 or less, between 1300 and 1500, between 1600 and 2000, or None
Diet Type:	Keto, Vegetarian, Sleeve gastrectomy, or None
BMI:	Underweight, Normal, Overweight, or Obese
Athlete:	TRUE or FALSE
Allergy:	Cowmilk, Eggs, Peanuts, Nuts, Wheat Bread, Fish, Grain, Garlic, or None
Diseases:	Cholesterol, Diabetes, Hypertension, Heart Diseases, Ulcer, or None

different random values to guarantee including every case. The collected questionnaires needed some processing steps in order to have a structured and well-defined dataset that facilitates the mission for a decision tree classifier or any other machine learning process. The processing steps are listed in Figure 4. The first step is converting paper questionnaires into electronic forms by filling data into an Excel sheet. The second step is to combine both the web-based questionnaire and the electronic form into a single Excel sheet. The third step focuses on cleaning the dataset of any missing values. For instance, the most frequent items to fill in are used for the categorical values such as true or false, while for the numerical values, the mean of the remaining items is used. After data cleaning, we discrete numerical values into discrete categories for easier use and classification. The discretization method involves converting weight and height into BMI values and then categorizing each value to its corresponding group, such as Overweight, Underweight, or Normal. The last step is data labeling to classes corresponding to each case in the system.

The data labeling step depends on generating a probability tree diagram as shown in Figure 5. However, the tree generated a big number of 112 classes. To minimize the number of classes, we have contacted the nutrient expert and have done some data studying in order to merge some classes if possible.

The number of classes is reduced to 32 classes, by studying the probability tree and excluding redundant classes in their internal properties. The reduction does not affect the quality or accuracy of the classes according to the expert's opinion and the study of data. The 32 classes are presented

Figure 4. Dataset processing

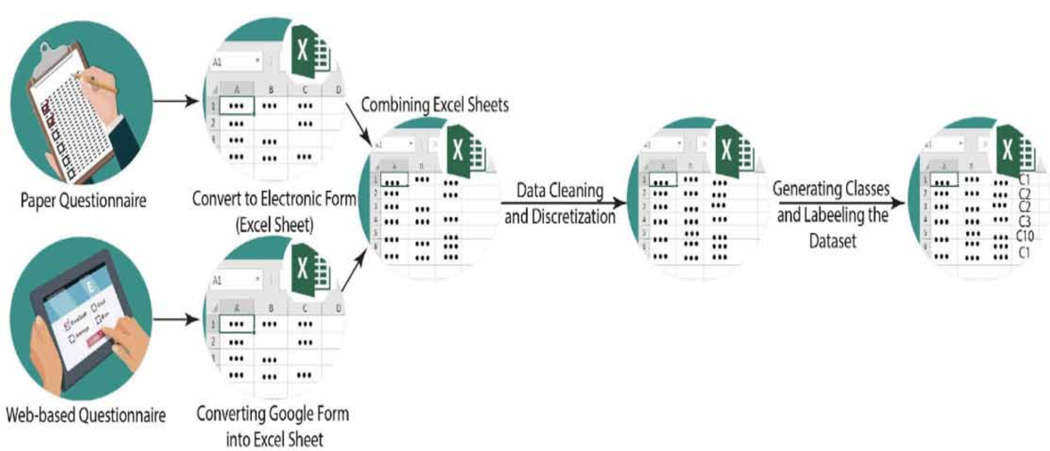
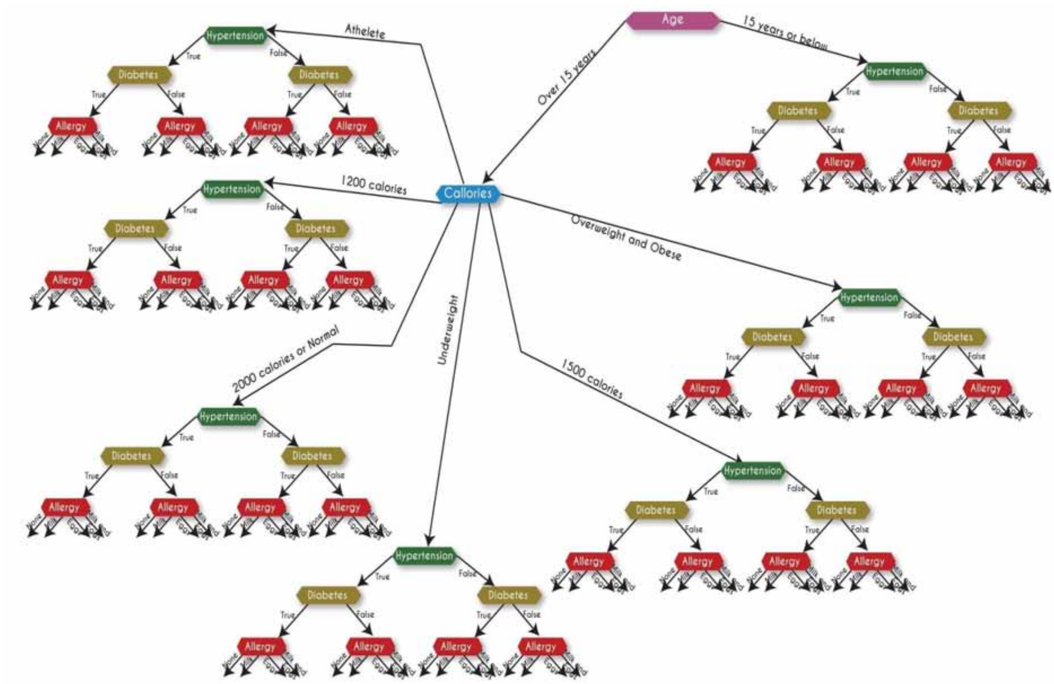


Figure 5. Probability tree diagram for the classes



in Figure 6. Furthermore, the hypertension feature is included in the implementation of the rules, as it affects the quantity of salt and pepper only, and it has no effects on the suggested meals and their components. On the other hand, if a customer has diabetes and a special kind of diet, such as 1200 calories, the categories are similar to normal people. For children, the meals are the same as the normal category but with half the quantity. Figure 7 displays a sample of the labeled dataset.

3.2.1 Stage (3): Extracting Rules Using Decision Tree

A rule-based advisory system relies on extracting experience from experts to build a set of cases managed by rules such as if-then statements. Providing the system with a huge number of rules can slow down its searching capabilities. Machine learning techniques such as classification algorithms and decision trees are employed, to minimize search time and have the right checking order of rules. The dataset for this research was used to guarantee the optimal tree with minimum branches, which contains certain features about the customer's preferences, based on his/her body requirements according to weight, height, number of calories, having certain diseases, and food allergy.

The decision tree is used with the aid of KNIME Analytics Platform software to generate the rules based on the labeled dataset. In decision analysis and rules extraction, decision trees can be used as a classifier to represent decision-making visually and explicitly. It is the most relevant classification type that matches our problem's requirements, and, in the end, it can generate the rules in Prolog language.

The dataset was partitioned into two groups, 75% for training and 25% for testing. For the validation process, we used 10 outlet random cases. The decision tree achieved an overall accuracy of 0.9927. In Figure 8 below, the decision tree structure for the dataset can be seen.

3.2.2 Stage (4): Designing Interactive Friendly Graphical User Interface

The KBS relies on information extracted from the user. Consequently, it is necessary to design an interface that combines ease of use, an attractive layout, and as few inputs as possible. This makes

Figure 6. Modified probability tree diagram with class labelling

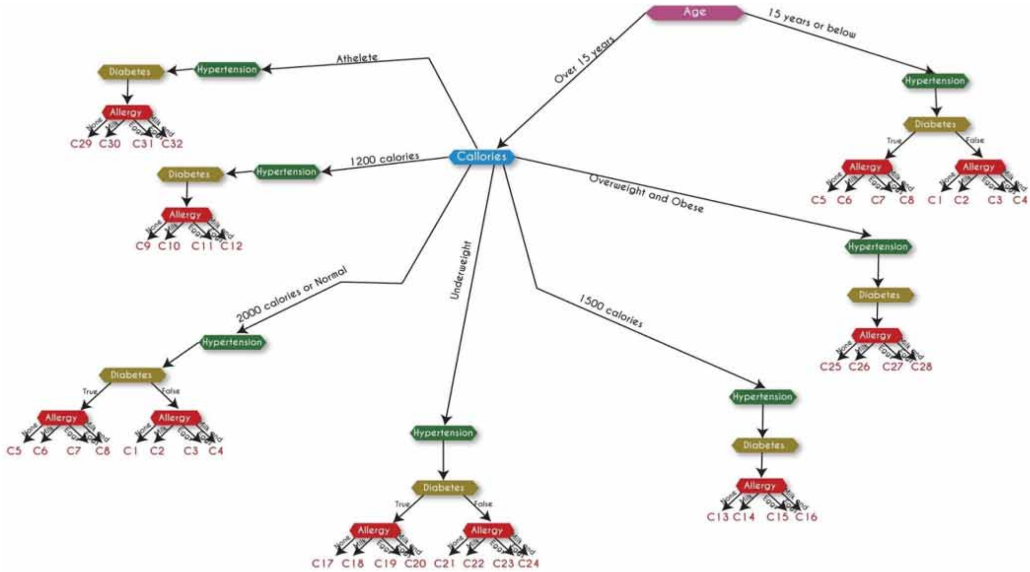
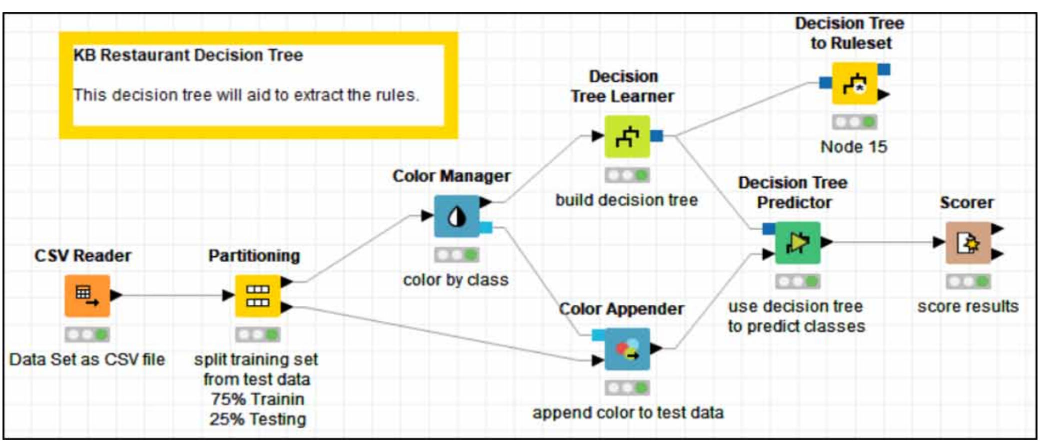


Figure 7. Sample of the labeled dataset

	A	B	C	D	E	F	G	H	I
1	ID	Diet_Type	Diabetes	Hypertesion	Allergy	Athlete	BMI_Category	Age_Group	Class
2	1	None	FALSE	FALSE	None	FALSE	Overweight	Over15	C25
3	2	D2000	TRUE	FALSE	None	FALSE	None	Over15	C5
4	3	None	FALSE	FALSE	None	TRUE	None	Over15	C29
5	4	D1500	FALSE	FALSE	None	FALSE	None	Over15	C13
6	5	None	TRUE	TRUE	None	FALSE	Normal	Over15	C5
7	6	None	FALSE	FALSE	None	FALSE	Normal	UnderOrEqual15	C1
8	7	None	TRUE	FALSE	None	FALSE	Overweight	Over15	C25
9	8	None	FALSE	FALSE	None	FALSE	Normal	UnderOrEqual15	C1
10	9	None	FALSE	FALSE	None	FALSE	Overweight	Over15	C25
11	10	None	FALSE	FALSE	Cow_Milk	TRUE	None	Over15	C30
12	11	D2000	FALSE	FALSE	None	FALSE	None	Over15	C1
13	12	None	FALSE	FALSE	Cow_Milk_Eggs	FALSE	Normal	UnderOrEqual15	C4
14	13	None	FALSE	FALSE	None	FALSE	Overweight	Over15	C25
15	14	None	FALSE	TRUE	None	FALSE	Normal	UnderOrEqual15	C1
16	15	D1200	FALSE	TRUE	None	FALSE	None	Over15	C9

Figure 8. Decision tree learners and predictor for the dataset



the user not feel bored and gives the system complete and accurate data. The interface is designed to have simple screens as few as possible with radio and checkboxes to minimize data entry from the user. Figure 9 shows some screenshots of the interface.

3.2.3 Stage (5): Rules Implementation

The output of stage (4) is a decision tree model which has been converted into a ruleset using the KNIME decision tree to create ruleset nodes that generated written rules in prolog language. After the rules are extracted, they have been converted into if-then statements implemented by Visual Basic .net. Table 3 displays the object-attribute-value triplets for the used predicates in the system. The set of facts is listed in Table 4. Table 5-Appendix A shows the 41 rules that are written in both English language and in Clips form.

Figure 9. Screenshots of the interface

Table 3. Object-attribute-value triplets

Object	Attribute	Values
BMI_Category	Human body's fat distribution	- Underweight - Normal - Overweight and Obese
Diet_Type	Intake number of calories	- 1200 Calories or Less - 1200-1500 Calories - 1500-2000 Calories - No Diet
Age	The age of the user	- Under 15 years - 15 years or more
Athlete	User's frequent playing sport	- True - False
Hypertension	Human high blood pressure	- True - False
Diabetes	Human's high sugar blood levels	- True - False
Milk	Human allergy to milk products	- True - False
Eggs	Human allergy to eggs products	- True - False

Table 4. Facts

Underweight BMI	BMI<18.5
Normal BMI	18.5 <=BMI<= 25
Overweight BMI	BMI> 25
Above 15	Age >=15
Below 15	Age<15

4. RESULTS AND EVALUATION

For testing and evaluation purposes, the system was run by different users 30 times and the results were monitored by the developer and the nutrient expert. Each test case was different in terms of age, diseases, playing sports, or allergies. The flow of the run is shown in Figure 10.

Figure 11.a represents the user's information acquisition based on his/her health status and body measures. Figure 11.b represents the user's choice of one meal from a list of suitable meals with respect to diseases and allergies. The user can also choose to have a breakfast, or lunch list of meals.

Figure 11.c represents ingredients and quantities which the system will choose depending on all the input information from the user. Figure 11.d represents simple explanatory statements about the suggested choice.

Figure 10. Flow of running

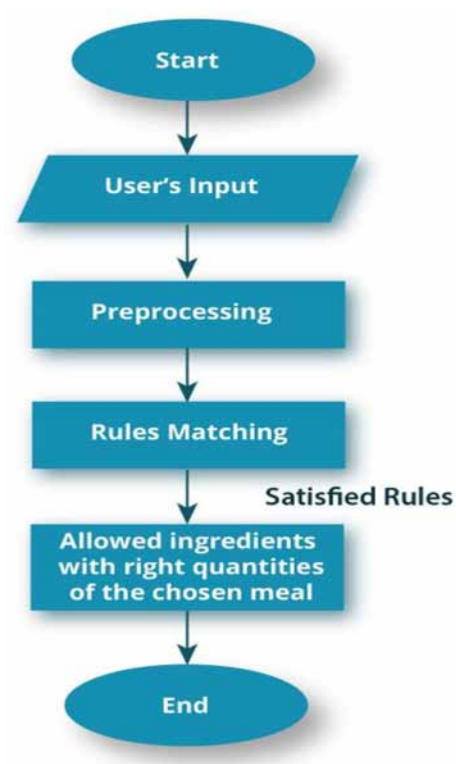


Figure 11. (a) User personal information, (b) the user chooses the meal, (c) the system chooses the appropriate meal, (d) explanation

4.1 Accuracy Measurement

For the evaluation part, we calculated the accuracy for the tested cases using accuracy and the overall accuracy of the RAS. The assessment was made by the expert for each case by comparing the results with the proposed cases. Accuracy is used to show how precise the model is by finding how many meals were predicted correctly.

$$Accuracy = \frac{Number\ \ of\ \ correctly\ \ predicted\ \ meals}{Number\ \ of\ \ total\ \ meals} \tag{1}$$

The accuracy of our system was 100% by the assessment of the expert for the 30 different cases.

5. CONCLUSION AND FUTURE WORK

This paper develops an advisory expert system for restaurants in order to improve and promote the health level in the community by providing healthy meals depending on the health state of the user. The adopted approach is based on acquiring knowledge, facts, and rules from a nutrient expert, using decision trees and rule-based methods. The Dataset was built using questionnaires distributed in Jordan to collect information about users' health and fat distribution. Experimental results show that the proposed RAS can help people to have their meals in a healthy style. They also show that the expert system is able to generate the right kinds of meals based on users' features, like health status. It can also provide benefits for people who want to have healthy meals outside their homes while considering the health status and body measures of the customer.

The accuracy of the proposed system was 100% by the assessment of the expert for the 30 different cases.

As future work, this system can be expanded to cover more diseases and food allergy cases and to add more options in every meal to empower the user to build the meal from scratch.

CONFLICT-OF-INTEREST STATEMENT

This to confirm that the article entitled "A Rule-Based Expert Advisory System for Restaurants Using Machine Learning and Knowledge-Based Systems Techniques" is authored by an editor of this journal, who left the responsibility of editing this work to another Managing Editor.

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APPENDIX A

Table 5. Set of extracted rules

Rule #	Rule in English Text	Rules from KNIME Ruleset Node	Formal Rule in Clips
Rule #1	If there is no Diabetes disease And no Allergy And Diet_Type is 2000 Calories and there is no BMI_Category Then Food_Class is “C1”	$Diabetes$ = “FALSE” AND $Allergy$ = “None” AND $Diet_Type$ = “D2000” AND $BMI_ Category$ = “None” => “C1”	(defrule R1 (value1 ? Diabetes) (value2 ? Allergy) (value2 ? Diet_Type) (value3 ? BMI_Category) => (if (eq ? Diabetes FALSE) and (eq ? Allergy None) and (eq ? Diet_Type D2000) and (eq ? BMI_Category None) then (assert (C1 ?Food_class))
Rule #2	If there is no Diabetes Disease And no Allergy And BMI_Category is Normal Then Food_Class is “C1”	$Diabetes$ = “FALSE” AND $Allergy$ = “None” AND $BMI_Category$ = “Normal” => “C1”	(defrule R2 (value1 ? Diabetes) (value2 ? Allergy) (value3 ? BMI_Category) => (if (eq ? Diabetes FALSE) and (eq ? Allergy None)and (eq ? BMI_Category Normal) then (assert (C1 ?Food_class))
Rule #3	If there is Milk_Allergy And Diet_Type is 2000 Calories and there is no BMI_Category Then Food_Class is “C2”	$Allergy$ = “Cow_Milk” AND $Diet_Type$ = “D2000” AND $BMI_ Category$ = “None” => “C2”	(defrule R3 (value1 ? Allergy) (value2 ? Diet_Type) (value3 ? BMI_Category) => (if (eq ? Allergy Cow_Milk) and (eq ? Diet_ Type D2000) and (eq ? BMI_Category None) then (assert (C2 ?Food_class))
Rule #4	If there is no Diabetes Disease And Milk_ Allergy And BMI_ Category is Normal Then Food_Class is “C2”	$Diabetes$ = “FALSE” AND $Allergy$ = “Cow_Milk” AND $BMI_ Category$ = “Normal” => “C2”	(defrule R4 (value1 ? Diabetes) (value2 ? Allergy) (value3 ? BMI_Category) => (if (eq ? Diabetes FALSE) and (eq ? Allergy Cow_Milk) and (eq ? BMI_Category Normal) then (assert (C2 ?Food_class))
Rule #5	If there is no Diabetes disease And Eggs_ Allergy And Diet_Type is 2000 Calories and there is no BMI_Category Then Food_Class is “C3”	$Diabetes$ = “FALSE” AND $Allergy$ = “Eggs” AND $Diet_Type$ = “D2000” AND $BMI_ Category$ = “None” => “C3”	(defrule R5 (value1 ? Diabetes) (value2 ? Allergy) (value3 ? Diet_Type) (value4 ? BMI_Category) => (if (eq ? Diabetes FALSE) and (eq ? Allergy Eggs) and (eq ? Diet_Type D2000) and (eq ? BMI_Category None) then (assert (C3 ?Food_class))
Rule #6	If there is no Diabetes Disease And Eggs_ Allergy And BMI_ Category is Normal Then Food_Class is “C3”	$Diabetes$ = “FALSE” AND $Allergy$ = “Eggs” AND $BMI_Category$ = “Normal” => “C3”	(defrule R6 (value1 ? Diabetes) (value2 ? Allergy) (value3 ? BMI_Category) => (if (eq ? Diabetes FALSE) and (eq ? Allergy Eggs) and (eq ? BMI_Category Normal) then (assert (C3 ?Food_class))

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Table 5. Continued

Rule #	Rule in English Text	Rules from KNIME Ruleset Node	Formal Rule in Clips
Rule #7	If there is no Diabetes Disease And Eggs_ Allergy And Milk_ Allergy And Diet_type is 2000 calories And there is no BMI_Category Then Food_Class is “C4”	$Diabetes$ = “FALSE” AND $Allergy$ = “Cow_Milk_Eggs” AND $Diet_Type$ = “D2000” AND $BMI_Category$ = “None” => “C4”	(defrule R7 (value1 ? Diabetes) (value2 ? Allergy) (value3 ? Diet_Type) (value4 ? BMI_Category) => (if (eq ? Diabetes FALSE) and (eq ? Allergy Cow_Milk_Eggs) and (eq ? Diet_Type D2000) and (eq ? BMI_Category None) then (assert (C4 ?Food_class))
Rule #8	If there is no Diabetes Disease And Eggs_ Allergy And Milk_ Allergy And BMI_ Category is Normal Then Food_Class is “C4”	$Diabetes$ = “FALSE” AND $Allergy$ = “Cow_ Milk_Eggs” AND $BMI_ Category$ = “Normal” => “C4”	(defrule R8 (value1 ? Diabetes) (value2 ? Allergy) (value3 ? BMI_Category) => (if (eq ? Diabetes FALSE) and (eq ? Allergy Cow_Milk_Eggs) and (eq ? BMI_Category Normal) then (assert (C4 ?Food_class))
Rule #9	If there is Diabetes Disease And there is no Allergy And Diet_type is 2000 calories And there is no BMI_Category Then Food_Class is “C5”	$Diabetes$ = “TRUE” AND $Allergy$ = “None” AND $Diet_Type$ = “D2000” AND $BMI_ Category$ = “None” => “C5”	(defrule R9 (value1 ? Diabetes) (value2 ? Allergy) (value3 ? Diet_Type) (value4 ? BMI_Category) => (if (eq ? Diabetes TRUE) and (eq ? Allergy None) and (eq ? Diet_Type D2000) and (eq ? BMI_Category None) then (assert (C5 ?Food_class))
Rule #10	If there is Diabetes Disease And there is no Allergy And BMI_ Category is Normal Then Food_Class is “C5”	$Diabetes$ = “TRUE” AND $Allergy$ = “None” AND $BMI_Category$ = “Normal” => “C5”	(defrule R10 (value1 ? Diabetes) (value2 ? Allergy) (value3 ? BMI_Category) => (if (eq ? Diabetes TRUE) and (eq ? Allergy None) and (eq ? BMI_Category Normal) then (assert (C5 ?Food_class))
Rule #11	If there is Diabetes Disease And there is Milk_Allergy And BMI_ Category is Normal Then Food_Class is “C6”	$Diabetes$ = “TRUE” AND $Allergy$ = “Cow_Milk” AND $BMI_ Category$ = “Normal” => “C6”	(defrule R11 (value1 ? Diabetes) (value2 ? Allergy) (value3 ? BMI_Category) => (if (eq ? Diabetes TRUE) and (eq ? Allergy Cow_Milk) and (eq ? BMI_Category Normal) then (assert (C6 ?Food_class))
Rule #12	If there is Diabetes Disease And there is Eggs_Allergy And BMI_ Category is Normal Then Food_Class is “C7”	$Diabetes$ = “TRUE” AND $Allergy$ = “Eggs” AND $BMI_Category$ = “Normal” => “C7”	(defrule R12 (value1 ? Diabetes) (value2 ? Allergy) (value3 ? BMI_Category) => (if (eq ? Diabetes TRUE) and (eq ? Allergy Eggs) and (eq ? BMI_Category Normal) then (assert (C7 ?Food_class))

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Table 5. Continued

Rule #	Rule in English Text	Rules from KNIME Ruleset Node	Formal Rule in Clips
Rule #13	If there is Diabetes Disease And there is Eggs_Allergy And Diet_Type is 2000 calories And there is no BMI_Category Then Food_Class is "C7"	$Diabetes$ = "TRUE" AND $Allergy$ = "Eggs" AND $Diet_Type$ = "D2000" AND $BMI_Category$ = "None" => "C7"	(defrule R13 (value1 ? Diabetes) (value2 ? Allergy) (value3 ? Diet_Type) (value4 ? BMI_Category) => (if (eq ? Diabetes TRUE) and (eq ? Allergy Eggs) and (eq ? Diet_Type D2000) and (eq ? BMI_Category None) then (assert (C7 ?Food_class))
Rule #14	If there is Diabetes Disease And there is Milk_ Allergy And Eggs_Allergy And BMI_Category is Normal Then Food_Class is "C8"	$Diabetes$ = "TRUE" AND $Allergy$ = "Cow_Milk_Eggs" AND $BMI_Category$ = "Normal" => "C8"	(defrule R14 (value1 ? Diabetes) (value2 ? Allergy) (value3 ? BMI_Category) => (if (eq ? Diabetes TRUE) and (eq ? Allergy Cow_Milk_Eggs) and (eq ? BMI_Category Normal) then (assert (C8 ?Food_class))
Rule #15	If there is Diabetes Disease And there is Milk_ Allergy And Eggs_Allergy And Diet_type is 2000 calories And there is no BMI_Category is Then Food_Class is "C8"	$Diabetes$ = "TRUE" AND $Allergy$ = "Cow_Milk_Eggs" AND $Diet_Type$ = "D2000" AND $BMI_Category$ = "None" => "C8"	(defrule R15 (value1 ? Diabetes) (value2 ? Allergy) (value3 ? Diet_Type) (value4 ? BMI_Category) => (if (eq ? Diabetes TRUE) and (eq ? Allergy Cow_Milk_Eggs) and (eq ? Diet_Type D2000) and (eq ? BMI_Category None) then (assert (C8 ?Food_class))
Rule #16	If there is no Allergy And Diet_type is 1200 calories And there is no BMI_Category is Then Food_Class is "C9"	$Allergy$ = "None" AND $Diet_Type$ = "D1200" AND $BMI_Category$ = "None" => "C9"	(defrule R16 (value1 ? Allergy) (value2 ? Diet_Type) (value3 ? BMI_Category) => (if (eq ? Allergy None) and (eq ? Diet_Type D1200) and (eq ? BMI_Category None) then (assert (C9 ?Food_class))
Rule #17	If there is Milk_Allergy And Diet_type is 1200 calories And there is no BMI_Category is Then Food_Class is "C10"	$Allergy$ = "Cow_Milk" AND $Diet_Type$ = "D1200" AND $BMI_Category$ = "None" => "C10"	(defrule R17 (value1 ? Allergy) (value2 ? Diet_Type) (value3 ? BMI_Category) => (if (eq ? Allergy Cow_Milk) and (eq ? Diet_Type D1200) and (eq ? BMI_Category None) then (assert (C10 ?Food_class))
Rule #18	If there is Eggs_Allergy And Diet_type is 1200 calories And there is no BMI_Category is Then Food_Class is "C11"	$Allergy$ = "Eggs" AND $Diet_Type$ = "D1200" AND $BMI_Category$ = "None" => "C11"	(defrule R18 (value1 ? Allergy) (value2 ? Diet_Type) (value3 ? BMI_Category) => (if (eq ? Allergy Eggs) and (eq ? Diet_Type D1200) and (eq ? BMI_Category None) then (assert (C11 ?Food_class))

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Table 5. Continued

Rule #	Rule in English Text	Rules from KNIME Ruleset Node	Formal Rule in Clips
Rule #19	If there is Milk_Allergy And Eggs_Allergy And Diet_type is 1200 calories And there is no BMI_Category is Then Food_Class is “C12”	$Allergy$ = “Cow_Milk_Eggs” AND $Diet_Type$ = “D1200” AND $BMI_Category$ = “None” => “C12”	(defrule R19 (value1 ? Allergy) (value2 ? Diet_Type) (value3 ? BMI_Category) => (if (eq ? Allergy Cow_Milk_Eggs) and (eq ? Diet_Type D1200) and (eq ? BMI_Category None) then (assert (C12 ?Food_class))
Rule #20	If there is no Allergy And Diet_type is 1500 calories And there is no BMI_Category is Then Food_Class is “C13”	$Allergy$ = “None” AND $Diet_Type$ = “D1500” AND $BMI_Category$ = “None” => “C13”	(defrule R20 (value1 ? Allergy) (value2 ? Diet_Type) (value3 ? BMI_Category) => (if (eq ? Allergy None) and (eq ? Diet_Type D1500) and (eq ? BMI_Category None) then (assert (C13 ?Food_class))
Rule #21	If there is Milk_Allergy And Diet_type is 1500 calories And there is no BMI_Category is Then Food_Class is “C14”	$Allergy$ = “Cow_Milk” AND $Diet_Type$ = “D1500” AND $BMI_Category$ = “None” => “C14”	(defrule R21 (value1 ? Allergy) (value2 ? Diet_Type) (value3 ? BMI_Category) => (if (eq ? Allergy Cow_Milk) and (eq ? Diet_Type D1500) and (eq ? BMI_Category None) then (assert (C14 ?Food_class))
Rule #22	If there is Eggs_Allergy And Diet_type is 1500 calories And there is no BMI_Category is Then Food_Class is “C15”	$Allergy$ = “Eggs” AND $Diet_Type$ = “D1500” AND $BMI_Category$ = “None” => “C15”	(defrule R22 (value1 ? Allergy) (value2 ? Diet_Type) (value3 ? BMI_Category) => (if (eq ? Allergy Eggs) and (eq ? Diet_Type D1500) and (eq ? BMI_Category None) then (assert (C15 ?Food_class))
Rule #23	If there is Milk_Allergy And Eggs_Allergy And Diet_type is 1500 calories And there is no BMI_Category is Then Food_Class is “C16”	$Allergy$ = “Cow_Milk_Eggs” AND $Diet_Type$ = “D1500” AND $BMI_Category$ = “None” => “C16”	(defrule R23 (value1 ? Allergy) (value2 ? Diet_Type) (value3 ? BMI_Category) => (if (eq ? Allergy Cow_Milk_Eggs) and (eq ? Diet_Type D1500) and (eq ? BMI_Category None) then (assert (C16 ?Food_class))
Rule #24	If there is Diabetes Disease And no Allergy And BMI_Category is Underweight Then Food_Class is “C17”	$Diabetes$ = “TRUE” AND $Allergy$ = “None” AND $BMI_Category$ = “Underweight” => “C17”	(defrule R24 (value1 ? Diabetes) (value2 ? Allergy) (value3 ? BMI_Category) => (if (eq ? Diabetes TRUE) and (eq ? Allergy None) and (eq ? BMI_Category Underweight) then (assert (C17 ?Food_class))

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Table 5. Continued

Rule #	Rule in English Text	Rules from KNIME Ruleset Node	Formal Rule in Clips
Rule #25	If there is Diabetes Disease And Milk_ Allergy And BMI_ Category is Underweight Then Food_Class is "C18"	$Diabetes$ = "TRUE" AND $Allergy$ = "Cow_Milk" AND $BMI_Category$ = "Underweight" => "C18"	(defrule R25 (value1 ? Diabetes) (value2 ? Allergy) (value3 ? BMI_Category) => (if (eq ? Diabetes TRUE) and (eq ? Allergy Cow_Milk) and (eq ? BMI_Category Underweight) then (assert (C18 ?Food_class))
Rule #26	If there is Diabetes Disease And Eggs_ Allergy And BMI_ Category is Underweight Then Food_Class is "C19"	$Diabetes$ = "TRUE" AND $Allergy$ = "Eggs" AND $BMI_Category$ = "Underweight" => "C19"	(defrule R26 (value1 ? Diabetes) (value2 ? Allergy) (value3 ? BMI_Category) => (if (eq ? Diabetes TRUE) and (eq ? Allergy Eggs) and (eq ? BMI_Category Underweight) then (assert (C19 ?Food_class))
Rule #27	If there is Diabetes Disease And Milk_Allergy And Eggs_Allergy And BMI_ Category is Underweight Then Food_Class is "C20"	$Diabetes$ = "TRUE" AND $Allergy$ = "Cow_Milk_Eggs" AND $BMI_Category$ = "Underweight" => "C20"	(defrule R27 (value1 ? Diabetes) (value2 ? Allergy) (value3 ? BMI_Category) => (if (eq ? Diabetes TRUE) and (eq ? Allergy Cow_Milk_Eggs) and (eq ? BMI_Category Underweight) then (assert (C20 ?Food_class))
Rule #28	If there is no Diabetes Disease And no Allergy And BMI_Category is Underweight Then Food_ Class is "C21"	$Diabetes$ = "FALSE" AND $Allergy$ = "None" AND $BMI_Category$ = "Underweight" => "C21"	(defrule R28 (value1 ? Diabetes) (value2 ? Allergy) (value3 ? BMI_Category) => (if (eq ? Diabetes FALSE) and (eq ? Allergy None) and (eq ? BMI_Category Underweight) then (assert (C21 ?Food_class))
Rule #29	If there is no Diabetes Disease And Milk_ Allergy And BMI_ Category is Underweight Then Food_Class is "C22"	$Diabetes$ = "FALSE" AND $Allergy$ = "Cow_Milk" AND $BMI_Category$ = "Underweight" => "C22"	(defrule R29 (value1 ? Diabetes) (value2 ? Allergy) (value3 ? BMI_Category) => (if (eq ? Diabetes FALSE) and (eq ? Allergy Cow_Milk) and (eq ? BMI_Category Underweight) then (assert (C22 ?Food_class))
Rule #30	If there is no Diabetes Disease And Eggs_ Allergy And BMI_ Category is Underweight Then Food_Class is "C23"	$Diabetes$ = "FALSE" AND $Allergy$ = "Eggs" AND $BMI_Category$ = "Underweight" => "C23"	(defrule R30 (value1 ? Diabetes) (value2 ? Allergy) (value3 ? BMI_Category) => (if (eq ? Diabetes FALSE) and (eq ? Allergy Eggs) and (eq ? BMI_Category Underweight) then (assert (C23 ?Food_class))

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Table 5. Continued

Rule #	Rule in English Text	Rules from KNIME Ruleset Node	Formal Rule in Clips
Rule #31	If there is no Diabetes Disease And Milk_Allergy And Eggs_Allergy And BMI_Category is Underweight Then Food_Class is "C24"	$Diabetes$ = "FALSE" AND $Allergy$ = "Cow_Milk_Eggs" AND $BMI_Category$ = "Underweight" => "C24"	(defrule R31 (value1 ? Diabetes) (value2 ? Allergy) (value3 ? BMI_Category) => (if (eq ? Diabetes FALSE) and (eq ? Allergy Cow_Milk_Eggs) and (eq ? BMI_Category Underweight) then (assert (C24 ?Food_class))
Rule #32	If there is no Milk_Allergy And no Eggs_Allergy And BMI_Category is "Overweight" Then Food_Class is "C25"	$Allergy$ = "None" AND $BMI_Category$ = "Overweight" => "C25"	(defrule R32 (value1 ? Allergy) (value2 ? BMI_Category) => (if (eq ? Allergy None) and (eq ? BMI_Category Overweight) then (assert (C25 ?Food_class))
Rule #33	If there is Milk_Allergy And BMI_Category is "Overweight" Then Food_Class is "C26"	$Allergy$ = "Cow_Milk" AND $BMI_Category$ = "Overweight" => "C26"	(defrule R33 (value1 ? Allergy) (value2 ? BMI_Category) => (if (eq ? Allergy Cow_Milk) and (eq ? BMI_Category Overweight) then (assert (C26 ?Food_class))
Rule #34	If there is Eggs_Allergy And BMI_Category is "Overweight" Then Food_Class is "C27"	$Allergy$ = "Eggs" AND $BMI_Category$ = "Overweight" => "C27"	(defrule R34 (value1 ? Allergy) (value2 ? BMI_Category) => (if (eq ? Allergy Eggs) and (eq ? BMI_Category Overweight) then (assert (C27 ?Food_class))
Rule #35	If there is Milk_Allergy And Eggs_Allergy And BMI_Category is "Overweight" Then Food_Class is "C28"	$Allergy$ = "Cow_Milk_Eggs" AND $BMI_Category$ = "Overweight" => "C28"	(defrule R35 (value1 ? Allergy) (value2 ? BMI_Category) => (if (eq ? Allergy Cow_Milk_Eggs) and (eq ? BMI_Category Overweight) then (assert (C28 ?Food_class))
Rule #36	If there is no Allergy And no diet type is selected And there is no BMI_Category Then Food_Class is "C29"	$Allergy$ = "None" AND $Diet_Type$ = "None" AND $BMI_Category$ = "None" => "C29"	(defrule R36 (value1 ? Allergy) (value2 ? Diet_Type) (value3 ? BMI_Category) => (if (eq ? Allergy None) and (eq ? Diet_Type None) and (eq ? BMI_Category None) then (assert (C29 ?Food_class))
Rule #37	If there is Milk_Allergy And no diet type is selected And there is no BMI_Category Then Food_Class is "C30"	$Allergy$ = "Cow_Milk" AND $Diet_Type$ = "None" AND $BMI_Category$ = "None" => "C30"	(defrule R37 (value1 ? Allergy) (value2 ? Diet_Type) (value3 ? BMI_Category) => (if (eq ? Allergy Cow_Milk) and (eq ? Diet_Type None) and (eq ? BMI_Category None) then (assert (C30 ?Food_class))

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Table 5. Continued

Rule #	Rule in English Text	Rules from KNIME Ruleset Node	Formal Rule in Clips
Rule #38	If there is Eggs_Allergy And no diet type is selected And there is no BMI_Category Then Food_Class is "C31"	$Allergy$ = "Eggs" AND $Diet_Type$ = "None" AND $BMI_Category$ = "None" => "C31"	(defrule R38 (value1 ? Allergy) (value2 ? Diet_Type) (value3 ? BMI_Category) => (if (eq ? Allergy Eggs) and (eq ? Diet_Type None) and (eq ? BMI_Category None) then (assert (C31 ?Food_class))
Rule #39	If there is Milk_Allergy And Eggs_Allergy And no diet type is selected And there is no BMI_Category Then Food_Class is "C32"	$Allergy$ = "Cow_Milk_Eggs" AND $Diet_Type$ = "None" AND $BMI_Category$ = "None" => "C32"	(defrule R39 (value1 ? Allergy) (value2 ? Diet_Type) (value3 ? BMI_Category) => (if (eq ? Allergy Cow_Milk_Eggs) and (eq ? Diet_Type None) and (eq ? BMI_Category None) then (assert (C32 ?Food_class))
Rule #40	If the Age is less than 15 Then Food_Quantity is "Half_Normal_Adult"	N.A	(defrule R40 (value1 ? Age) => (if (< ? Age 15) then (assert (Half_Normal_Adult ? Food_Quantity))
Rule #41	If there is Hypertension Then Salt_Pepper_Quantity is "Minimum"	N.A	(defrule R41 (value1 ? Hypertension) => (if (eq ? Hypertension TRUE) then (assert (Minimum ? Salt_Pepper_Quantity))

Khalid M. O. Nahar is an associate professor in the Department of Computer Sciences-Faculty of IT, Yarmouk University, Irbid-Jordan. He received his BS and MS degrees in computer sciences from Yarmouk University in Jordan, in 1992 and 2005 respectively. He was awarded a full scholarship to continue his PhD in Computer Sciences and Engineering from King Fahd University of Petroleum and Minerals (KFUPM), KSA. In 2013 he completed his PhD and started his job as an assistant professor at Tabuk University, KSA for 2 years. In 2015 he backs to Yarmouk University, and for now he is the assistant dean for quality control. His research interests include: continuous speech recognition, Arabic computing, natural language processing, multimedia computing, content-based retrieval, Artificial Intelligence (AI), Machine Learning, IOT, and Data Science.

Mustafa Banikhalaf is a renowned scholar with a Ph.D. in Computer Science from Edinburgh Napier University, UK. His groundbreaking research encompasses the Internet of Things (IoT), Vehicular Ad hoc Networks (VANETs), wireless networking, and blockchain technology. With an emphasis on innovation and application, his work in these cutting-edge fields has paved the way for enhanced connectivity, security, and performance. Striving to stay ahead in these rapidly evolving disciplines, Dr. Banikhalaf is committed to educating and inspiring future computer scientists with his profound knowledge and expertise.

Firas Ibrahim Alzobi is an associate professor in Computer Networks Security, chair of Information System and Networks Department in the World Islamic Sciences and Education University W.I.S.E/Jordan since 2022. He received his Ph.D in Computer Networks from the Technical University of Sofia/Bulgaria in 2005. He then joined Jerash private university/Jordan in 2005. He became chair of Computer science department in 2006. He then moved to King Saud University/KSA in 2007 until 2009. He then joined Tabuk University/KSA in 2009 until 2017. Finaly he joined the WISE University. Dr. Firas research interests include Networks, Sybersecurity, Cloud Computing, IoT, and Artificial Intelligence. He has published more than 20 journal papers and conference papers.

Dr Ammar Almomani Received PhD degree from Universiti Sains Malaysia (USM) in 2013. , he has published 100 + articles most of them Scopus Q1, Q2, and WOS, Included six German and 2 India patents. Currently he is an a Professor and Head of the research and innovation department and an academic staff Member of IT school at Skyline University College-Sharjah-UAE, with many international awards, supervisor on many Ph.D. students.

Brij B. Gupta received the PhD degree from Indian Institute of Technology (IIT) Roorkee, India. In more than 17 years of his professional experience, he published over 450 papers in journals/conferences including 30 books and 10 Patents with over 15000 citations. He has received numerous national and international awards including Canadian Commonwealth Scholarship (2009), Best Faculty Award (2018 & 2019), etc. He is also selected in the 2021 and 2020 Stanford University's ranking of the world's top 2% scientists. He is also a visiting/adjunct professor with several universities worldwide. He is also an IEEE Senior Member (2017) and also selected as 2021 Distinguished Lecturer in IEEE CTSoc. Dr Gupta is also serving as Member-in-Large, Board of Governors, IEEE Consumer Technology Society (2022-2024). At present, Prof. Gupta is working as Director, International Center for AI and Cyber Security Research and Innovations, and Professor with the Department of Computer Science and Information Engineering (CSIE), Asia University, Taiwan. His research interests include cyber security, cloud computing, artificial intelligence, blockchain technologies, social media and networking.