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Classification and Prediction Evaluation of a Fuzzy Rule-Based Model for Diabetes Diagnosis, Level of Care and Pima Indians Diabetes Datasets

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Abstract— Classification and prediction of diseases is crucial in decision-making for the healthcare sectors, especially diabetes, a chronic disease. The availability and accessibility of diabetes datasets assists medical practitioners in the diagnosis process as well as researchers in various fields and these datasets are valuable sources. However, diabetes datasets are exposed to vagueness and uncertainty issues. This research work improved an interrelated decision-making model for diabetes by proposing a fuzzy rule-based model to handle the vagueness and uncertainty issues. The research methodology starts with pre-processing of the simulated diabetes diagnosis and level of care datasets that were validated by medical experts, as well as the Pima Indians Diabetes Dataset (PIDD). This is followed by the design of the fuzzy model and the construction of the fuzzy rules. Next, the testing of the fuzzy model using six supervised machine learning algorithms namely J48, Logistic, Naive Bayes Updateable, Random Tree, Bayes Net and AdaBoostM1. Lastly, the evaluation of the fuzzy model in terms of the accuracy, precision, recall, F1-Score and confusion matrix. Experimental results show 100% accuracy for the diabetes diagnosis fuzzy model, for all the five machine learning algorithms mentioned except AdaBoostM1 with 79.8165% accuracy. In addition, for the level of care fuzzy model, the highest accuracy produced is 97.1098% for J48 algorithm and the lowest accuracy is 93.1049% for Naive Bayes Updateable and Bayes Net algorithms. Furthermore, for the PIDD fuzzy model, the highest accuracy obtained is 74.8698% for J48 and AdaBoostM1 algorithms and the lowest accuracy is 70.1823% for Random Tree algorithm. Overall, the proposed fuzzy model produced a good accuracy and working as expected associated to the previous interrelated decision-making model.

Keywords-decision-making; fuzzy rule-based model; supervised machine learning; classification; prediction.

I. INTRODUCTION

Diabetes is a chronic disease identified by, an increased levels of glucose in the blood. Diabetes can cause further complications such as heart disease, kidney failure, nerve damage, blurred vision, infections, and even mental health. Therefore, early detection is crucial to save life.

Diabetes consists of four types namely type 1, type 2, gestational diabetes, and autosomal inherited type of diabetes mellitus [1, 2]. Diabetes type 2 is the most common type of diabetes amounting 90% of 537 million cases of diabetes worldwide [3] and is the focus of this research work.

Diabetes is diagnosed based on a set of signs and symptoms, present in diabetes datasets. Diabetes datasets are valuable sources that, facilitates the diagnosis process and research in various fields such as Artificial Intelligence (AI), diabetes management, education, engineering, etc. However, vagueness and uncertainties issues exist, which is represented by the values in these datasets. Fuzzy logic is like human thinking and reasoning and can handle these issues and improve the decision-making process. Fuzzy logic has been utilized in diabetes diagnosis and current research in AI is on-going to improve the models [4, 5, 6, 7, 8].

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Machine learning (ML) and data mining techniques provide substantial capability to support medical decision-making and computerizing numerous tedious tasks. These techniques provide classification, clustering, association, and regression algorithms that have been extensively used. Moreover, machine learning is not restricted to any comprehensive framework which allows researchers to extend and improve the models [9]. Research in ML and data mining has contributed to medical diagnosis [10, 11, 12].

This research work is motivated due to the importance of classification and prediction for diabetes diagnosis. Furthermore, the capability of fuzzy logic technique that supports human understanding can improve diabetes diagnosis for an effective decision-making. Diabetes data are subject to vagueness, the numeric values are uncertain and lack interpretable facts. The objective of this paper is to improve the interrelated decision-making model proposed by Normadiah et al. [13] to handle the vagueness and uncertainty issues utilizing fuzzy logic. The datasets that are used in this model is the simulated diabetes diagnosis and level of care datasets that were validated by medical experts [14]. The proposed fuzzy rule-based model is built based on these datasets [14] and the Pima Indians Diabetes Dataset (PIDD), a widely used dataset in previous research [8, 15, 16, 17, 18].

This paper is organized into five sections. Section II explains about the previous research works which is related to our research work. Section III illustrates the methodology of our research work. Section IV describes the produced results and discussion. Finally, section V concludes the paper and suggest future works.

II. RELATED RESEARCH

This section clarifies about the diabetes datasets, supervised ML algorithms utilized and medical models that are built for decision-making which are related to our research work.

A. *Diabetes Datasets*

Patients' datasets are important and beneficial sources in research of various fields. The content of diabetes datasets consists of predictor attributes that represent the signs and symptoms of diabetes, and the target attribute that specify the classification of diabetes for example, whether the patient have diabetes or not. The Pima Indians Diabetes Dataset (PIDD) is one of the datasets available at Kaggle [19] which consists of 8 predictor attributes, 1 target attribute and 768 records. Pregnancies, glucose, blood pressure, skin thickness, insulin, BMI, diabetes pedigree function and age are the predictor attributes in PIDD. The outcome to determine whether the patient has diabetes, or not is the target attribute in PIDD. Other publicly available diabetes datasets at Kaggle [19] besides PIDD are Diabetes Dataset, Diabetic Retinopathy and Diabetes Health Indicators datasets. Moreover, University of California Irvine (UCI) machine learning repository provides Diabetes dataset [27], which can be accessed publicly.

This research work is based on a simulated diabetes datasets that were validated by medical experts [13]. Detailed description on the datasets will be explained in section III *A*. Some of the predictor attributes for these datasets are Acanthosis Nigricans (Acan. Nig.), A1c, FPG, RPG, OGTT, HDL, TG and History of Cardiovascular Disease (CVD). Table I presents the simulated diabetes datasets example consisting of the diabetes diagnosis and level of care datasets from medical experts.

TABLE I. EXAMPLE OF DIABETES DIAGNOSIS AND LEVEL OF CARE DATASETS FROM MEDICAL EXPERTS

Physical Exam	Lab Report									
Acan. Nig.	A1c (mmol/mol)	FPG	RPG	OGTT	HDL	TG	History of CVD	Diagnosis		Level of Care
Y	36	5.2	8.7	Nil	1.4	1.2	T	Healthy	Prediabetes	Primary Care
Y	40	6.1	10	6.3 (FPG)	1.3	2.8	T	IFG	Diabetes	Primary Care
Y	48	7.3	12.3	Nil	0.9	2.8	T	T2DM	Diabetes	Primary Care
T	60	8.8	16	Nil	0.9	3	Y	T2DM	Diabetes	Secondary Care
T	55	7.5	13	Nil	1	2.8	Y	T2DM	Diabetes	Secondary Care
Y	43	6.4	9.8	9.8 (2-hr PPG)	1.2	2	T	IGT	Prediabetes	Primary Care

Several recent datasets were also developed to assist research in AI. Among the datasets are Saudi Arabian dataset [9] that classify and predict three types of diabetes: pre-diabetes, type 1 diabetes, and type 2 diabetes [9]; the ShanghaiT1DM and ShanghaiT2DM which contribute to the development of data-driven algorithms/models and diabetes monitoring/managing technologies [20]; and secondary dataset from medical database record review that were used to classify and predict type-2 diabetes in public hospitals in Afar regional state, Ethiopia [21].

B. *Supervised Machine Learning Algorithms*

Supervised machine learning is an algorithm used to learn the mapping function from the input (1) to the output (O), where O = *f*(1), with the purpose to determine the mapping function accurately for the output (O) to be predicted when a new data (1) occurs [29]. Supervised learning consists of two types: classification and regression. This research work focuses on classification because predicting a patient for diabetes is a classification problem.

Classification is a kind of data analysis that can effectively be used to segregate data models for predictions to allow the recognition of trends in datasets [30]. Classification is a vital technique used in a wide area of applications. Classification is a machine learning algorithm that, identify and predict classes among data points; classes are then assigned to match groupings to enable greater prediction accuracy. The supervised machine learning algorithms applied in this research work is based on six standard algorithms which are used by Normadiah et al. [13]:

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the J48, Logistic, Naive Bayes Updateable, Random Tree, Bayes Net and AdaBoostM1 standard algorithms.

C. Medical Models for Decision-Making

Medical models have been constructed to support the decision-making process. However, the models constructed are based on specific stages of healthcare only and therefore the decision model is static. The nature of healthcare process is dynamic, complex, consists of various stages from primary to palliative that are closely related to each other, and the decision-making process is different depending on the type of disease [13]. For these reasons, an interrelated decision-making model for an intelligent decision support system in healthcare is proposed by Normadiah et al. [13]. Fig. 1 shows the interrelated decision-making model proposed by Normadiah et al. [13] that can be applied for various stages of diagnosis, consisting of five level of care: Primary, Secondary, Tertiary, Quaternary and Palliative Care.

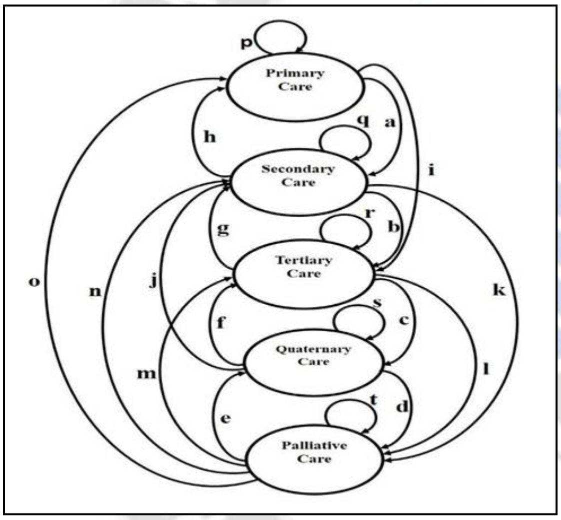

Figure 1. Interrelated Decision-Making Model in Healthcare [13]

To provide more comprehensive decision-making in a way of human thinking and reasoning, the model proposed by Normadiah et al. [13] is improved by utilizing the fuzzy technique. This is because diabetes datasets are exposed to vagueness and uncertainty.

Table II in Appendix summarizes the recent medical models for decision-making in terms of references; year of references; datasets used; algorithms/techniques proposed; whether the model comprise various stages and provides iterative decision-making in healthcare; whether the model is a dynamic decision-making model; and whether the model caters for vagueness and uncertainty issues.

Based on Table II, several of the research works applied publicly available datasets [10, 11, 22, 23, 24, 25, 27, 28], whereas the remaining research works used collected dataset from implemented research [13, 21, 9, 12, 20, 34]. This indicates the significance of developing and validating datasets by medical experts to provide acceptance and usable models to improve decision-making. The dataset used in our research work is based on a thorough research work by Normadiah [14] which produced the simulated diabetes treatment dataset validated by medical expert [13] that provides predictor and target attributes for diabetes diagnosis and level of care.

In Table II, AI, ML, and data mining algorithms have been proposed for the decision-making models. Majority of the research focus on a single algorithm [9, 10, 12, 20, 21, 22, 23, 24, 25, 26, 27]. Several algorithms have also been combined in the model [13, 11, 28].

Analysis of these models in Table II is made based on three criteria as follows:

- Does the model comprise various stages and provides iterative decision-making in healthcare? Various stages mean that the model covers the Primary, Secondary, Tertiary, Quaternary and Palliative Care. Iterative decision-making denote that the model provides recursive data flows within its own stage and iterative data flows with other stages. From the models in Table II, only the model proposed by Normadiah et al. [13], provides this feature that represents the decision-making process in real world, which is illustrated in Fig. 1.
- Is the model a dynamic decision-making model? A dynamic decision-making model connects all stages in healthcare, not only a specific stage. All the models in Table II do not connect the stages in healthcare and the stages are stand-alone except for the model proposed by Normadiah et al. [13].
- Does the model cater for vagueness and uncertainty issues? For this feature, the fuzzy technique has been proved to cater the vagueness and uncertainty issues as shown in Table II [11, 12, 25, 26, 28]. Most of the research work [9, 10, 13, 20, 21, 22, 23, 24, 27] in Table II does not provide this feature.

Therefore, the model proposed in this research work aims to improve the model proposed by Normadiah et al. [13] by adding a new feature to cater the vagueness and uncertainty issues utilizing the fuzzy technique.

III. METHODOLOGY

A fuzzy rule-based model for diabetes diagnosis is proposed, as shown in Fig. 2. The first step is preprocessing of the three datasets: diabetes diagnosis, level of care and Pima Indians Diabetes datasets. The second step is the design of the fuzzy model by initializing the fuzzy sets that represents the linguistic modifiers. The third step is the construction of the fuzzy rules based on the linguistic modifiers. The fourth step is modeling of the fuzzy diabetes diagnosis, level of care and Pima Indians using ML algorithms. The final step is the evaluation of the fuzzy model using accuracy, precision, recall, F1-Score and confusion matrix measures for classification and prediction.

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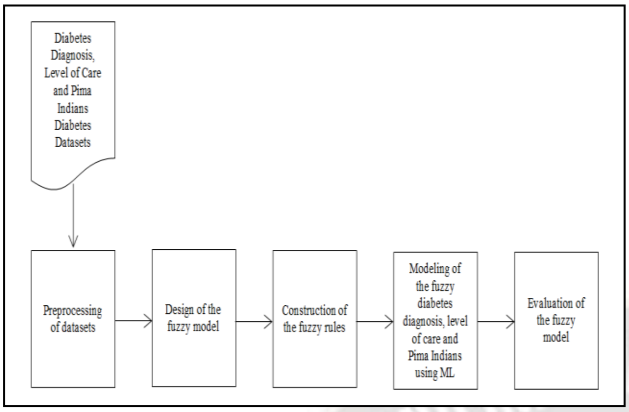

Figure 2. Proposed Fuzzy Rule-Based Model for Diabetes Diagnosis

A. Datasets Description and Pre-Processing

This research work is based on the simulated diabetes datasets that were validated by medical experts [13], which consists of diabetes diagnosis dataset and the level of care dataset. The diabetes diagnosis dataset contains 5000 records and 37 attributes. The level of care dataset contains 5000 records and 37 attributes. There are 36 predictor attributes and 1 target attribute for each of the dataset. Among the 36 predictor attributes, 10 predictor attributes are selected to be evaluated. The datasets were cleaned by removing the missing values due to the large number of missing values that exists in these datasets. The cleaned diabetes diagnosis dataset contains 2616 records, while the level of care dataset contains 2422 records.

In addition to the diabetes diagnosis and level of care datasets, the PIDD is also used in this research work. PIDD contains 768 records and 9 attributes with no missing values. There are 8 predictor attributes and 1 target attribute in PIDD.

B. Design of the Fuzzy Model

The first step to design the fuzzy model is the initialization of input and output variables. The crisp input variables (predictor attributes) and output variable (target attribute) are initialized. Then, these variables are transformed to fuzzy linguistic modifiers and the membership functions are created for each fuzzy variable. Table III in Appendix shows the fuzzy representation, where the number of membership functions is mapped to each of the linguistic labels for some of the predictor attributes and target attribute for diabetes diagnosis, level of care datasets and PIDD.

Fig. 3 shows example of the variables for Age, Sex and OGTT which are chosen to indicate the fuzzy partitions with 3, 2 and 6 linguistic labels respectively. The fuzzy diabetes diagnosis, level of care and PIDD model was designed using the MATLAB R2022b Fuzzy Logic Designer application.

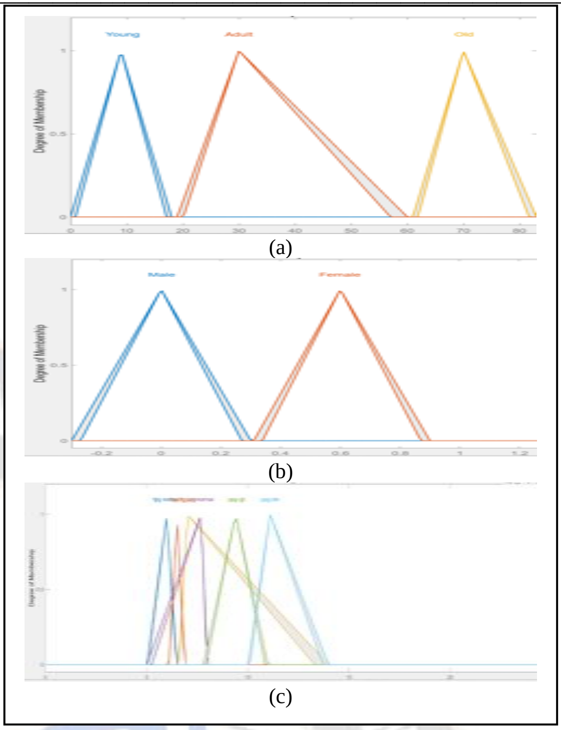

Figure 3. Fuzzy Linguistic Variables for (a) Age (b) Sex (c) OGTT

C. Construction of the Fuzzy Rules

Fuzzy rules are constructed to deduce an output based on the input variables. The fuzzy rule is based on the implication [29]-[30]:

IF x is A THEN y is B

Where, the basis of *x* is *A*, and the resultant of *y* is *B* can be true to a level, instead of true or false. The linguistic modifiers A and B are represented using fuzzy sets. The lists of linguistic labels shown in Table III are the fuzzy sets.

The design of the fuzzy model and fuzzy rules are performed by referring to academic research work [13, 14] and Ministry of Health Malaysia sources [1]. The operator OR is used as the fuzzy rule evaluation. Table IV shows some of the proposed fuzzy rules. For example, the fuzzy rule for the last row in Table IV is:

IF (age is Old) OR (sex is Female) OR (acanthosis nigricans is No) OR (A1c is Prediabetesl) OR (FPG is IFG) OR (RPG is OGTT) OR (OGTT is PPGIGTl) OR (HDL is High) OR (TG is High) OR (CVD is No) THEN (Diabetes Diagnosis is IFGIGTPrediabetes)

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TABLE IV. FUZZY RULES

Age	Sex	Acanthosis Nigricans	A1c	FPG	RPG	OGTT	HDL	TG	CVD	Diabetes Diagnosis	Level of Care
Adult	Male	Yes	Normal	Normal	OGTT	Nil	High	Optimal	No	Healthy Prediabetes	Primary Care
Adult	Female	Yes	Normal	IFG	Second RPG	FPG Normal	High	High	No	IFGIGT Prediabetes	Primary Care
Adult	Female	Yes	Diabetes	DM	Second RPG	Nil	Low	High	No	T2DM Diabetes	Primary Care
Old	Male	No	Diabetes	DM	Second RPG	Nil	Low	High	Yes	T2DM Diabetes	Secondary Care
Old	Male	No	Diabetes	DM	Second RPG	Nil	Borderline	High	Yes	T2DM Diabetes	Secondary Care
Old	Female	No	Prediabetes	IFG	OGTT	PPGIGT	High	High	No	IFGIGT Prediabetes	Primary Care

D. Testing of the Fuzzy Model

The constructed fuzzy model is tested based on six ML algorithms, which is applied in the research work by Normadiah et al. [13]. The six ML are J48, Logistic, NaiveBayes Updateable, RandomTree, BayesNet and AdaBoostM1. The experiments were implemented using WEKA version 3.8.6 running on the 11th Gen Intel Core i7 processor with the speed of 2.80 GHz and RAM memory of 16 GB.

E. Evaluation of the Fuzzy Model

The validity of the fuzzy model is evaluated using the accuracy, precision, recall, F1-Score and confusion matrix measures. Accuracy is the percentage of data points which are correctly identified, that indicates the overall accuracy of the model. Precision determines the fraction of predictions as a positive class were positive. Recall denotes the fraction of all positive samples that were correctly predicted as positive by the classifier. F1-Score is the combination of precision and recall into a single measure. The accuracy precision, recall and F1-Score are calculated as follows:

$$\text{Accuracy}=(TN+TP)/(TP+FN+FP+TN) \quad (1)$$

$$\text{Precision}=TP/(TP+FP) \quad (2)$$

$$\text{Recall}=TP/(TP+FN) \quad (3)$$

$$\text{F1-Score}=2TP/(2TP+FP+FN) \quad (4)$$

A confusion matrix defines the predicted class and the actual class, displaying the number of predictions which are correct and incorrect for each class. Confusion matrix comprises of binary classification with only two classes and multiclass classification with more than two classes. This research work produced two class classification confusion matrixes for the level of treatment dataset and PIDD, and three class classification confusion matrixes for the diabetes diagnosis dataset. Fig. 4 shows the confusion matrix for two class classification and Fig. 5 shows the confusion matrix for three class classification.

		Predicted Class: Positive	Predicted Class: Negative
Actual Class	Positive	True Positive (TP)	False Negative (FN)
	Negative	False Positive (FP)	True Negative (TN)

Figure 4. Confusion Matrix for Binary Classification

		Predicted Class: A	B	C
Actual Class	A	1	2	3
	B	4	5	6
	C	7	8	9

TP = 1
FN = 2 + 3 = 5
FP = 4 + 7 = 11
TN = 5 + 6 + 8 + 9 = 28

Figure 5. Confusion Matrix for Three Class Classification

IV. RESULTS AND DISCUSSION

The diabetes diagnosis dataset comprises of 2616 records or instances. The accuracy result for the five algorithms: J48, Logistic, Naïve Bayes Updateable, Random Tree, Bayes Net, are 100%, except for AdaBoostM1 with 79.8165% accuracy. This proved the effectiveness of the fuzzy rule-based model which is executed using the machine learning algorithms. The confusion matrix for AdaBoostM1 is presented in Fig. 6. The actual and predicted classes in Fig. 6 consist of the classifications of diabetes, which are “Healthy Prediabetes” (HP), “IFGIGT Prediabetes” (IFGIGTP) and “T2DM Diabetes” (T2DMD).

		Predicted Class: IFGIGTP	T2DMD	HP
Actual Class	IFGIGTP	0	0	528
	T2DMD	0	312	0
	HP	0	0	1776

Figure 6. Confusion Matrix for AdaBoostM1 Algorithm Diabetes Diagnosis Fuzzy Rule-Based Model

Fig. 6 shows that the classifier correctly predicts 312 of the T2DMD class and 1776 of the HealthyPrediabetes class based on the actual class. However, the classifier incorrectly predicts all 528 of the IFGIGTP class based on the actual class. Therefore, this decreases the percentage of the accuracy.

The level of care dataset comprises of 2422 records or instances. The accuracy, precision, recall and F1-Score result for the all the six machine learning algorithm tested is illustrated in Table V. The level of care fuzzy rule-based model produced the highest accuracy of 97.1098% for J48 algorithm and the lowest accuracy of 93.1049% for Naïve Bayes Updateable and Bayes Net algorithms.

TABLE V. RESULT FOR LEVEL OF CARE FUZZY RULE-BASED MODEL

ML Algorithm	Accuracy (%)	Precision	Recall	F1-Score
J48	97.1098	0.975	0.971	0.972
Logistic	96.3254	0.967	0.963	0.965

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NaiveBayes Updateable	93.1049	0.937	0.931	0.934
RandomTree	97.0685	0.975	0.971	0.972
BayesNet	93.1049	0.937	0.931	0.934
AdaBoostM1	95.3757	0.956	0.954	0.955

Fig. 7 shows the bar chart of the six ML algorithms for level of care fuzzy rule-based model, with good accuracy of 90% above. Fig. 8 shows the bar chart of the six ML algorithms for level of care fuzzy rule-based model, in terms of precision, recall and F1-Score.

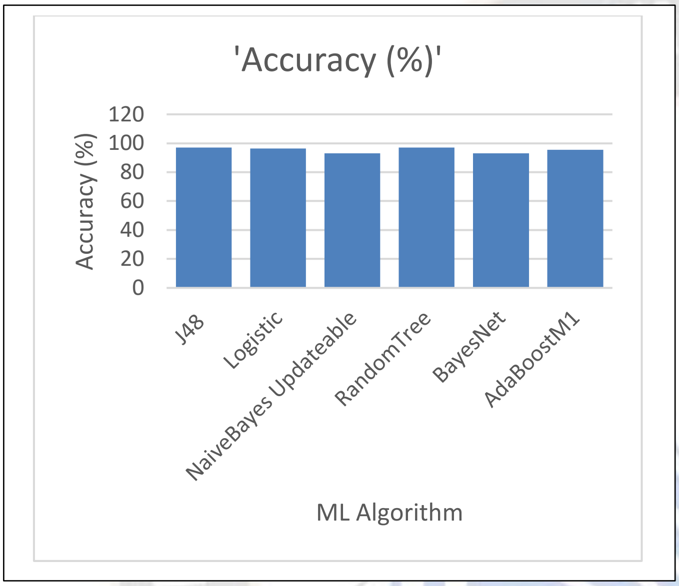

Figure 7. Accuracy for Level of Care Fuzzy Rule-Based Model

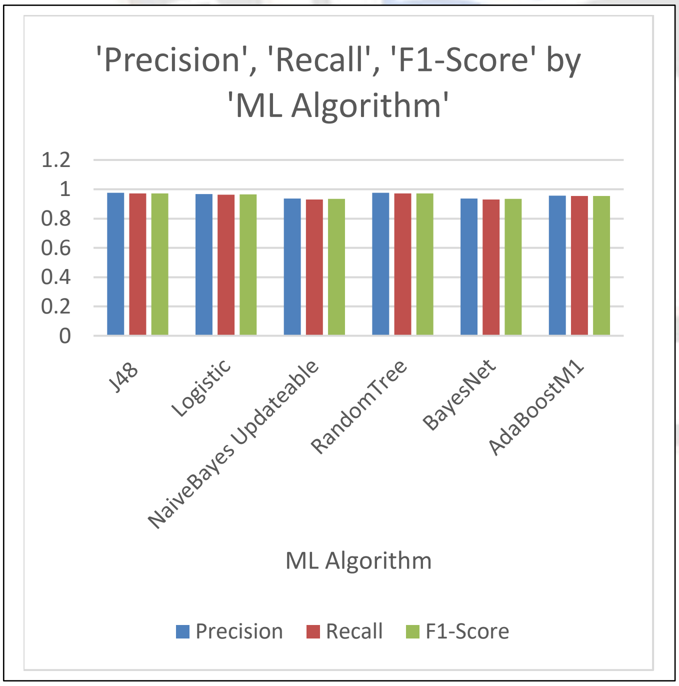

Figure 8. Precision, Recall and F1-Score for Level of Care Fuzzy Rule-Based Model

Fig. 9 shows the confusion matrix for the J48 algorithms with the highest accuracy of 97.1098% and Fig. 10 shows the confusion matrix for Naïve Bayes Updateable and Bayes Net algorithms with the lowest accuracy of 93.1049%. From Fig. 9, a number of 70 items are incorrectly classified as "Secondary Care" and "Primary Care", which is 15+55 highlighted from the J48 algorithm. For the Naïve Bayes Updateable and Bayes Net algorithm, a larger number of 167 items are incorrectly classified as "Secondary Care" and "Primary Care", which is 64+103 highlighted in Fig. 10. As the result, the accuracy percentage of these two algorithms decreases.

		Predicted Class	
		SecondaryCare	PrimaryCare
Actual Class	SecondaryCare	187	15
	PrimaryCare	55	2165

Figure 9. Confusion Matrix for J48 Algorithm Level of Care Fuzzy Rule-Based Model

		Predicted Class	
		SecondaryCare	PrimaryCare
Actual Class	SecondaryCare	138	64
	PrimaryCare	103	2117

Figure 10. Confusion Matrix for Naïve Bayes Updateable and Bayes Net Algorithms Level of Care Fuzzy Rule-Based Model

The PIDD dataset comprises of 768 records or instances. The accuracy, precision, recall and F1-Score result for the all the six machine learning algorithm tested is illustrated in Table VI. The PIDD fuzzy rule-based model produced the highest accuracy of 74.8698% for J48 and AdaBoostM1 algorithms and the lowest accuracy of 70.1823% for Random Tree algorithm.

TABLE VI. RESULT FOR PIDD FUZZY RULE-BASED MODEL

ML Algorithm	Accuracy (%)	Precision	Recall	F1-Score
J48	74.8698	0.747	0.749	0.728
Logistic	73.6979	0.729	0.737	0.727
NaiveBayes Updateable	73.1771	0.724	0.732	0.725
RandomTree	70.1823	0.692	0.702	0.654
BayesNet	73.0469	0.722	0.730	0.723
AdaBoostM1	74.8698	0.742	0.749	0.736

Fig. 11 shows the bar chart of the six ML algorithms for PIDD fuzzy rule-based model, with average accuracy of 70% above. Fig. 12 shows the bar chart of the six ML algorithms for PIDD fuzzy rule-based model, in terms of precision, recall and F1-Score.

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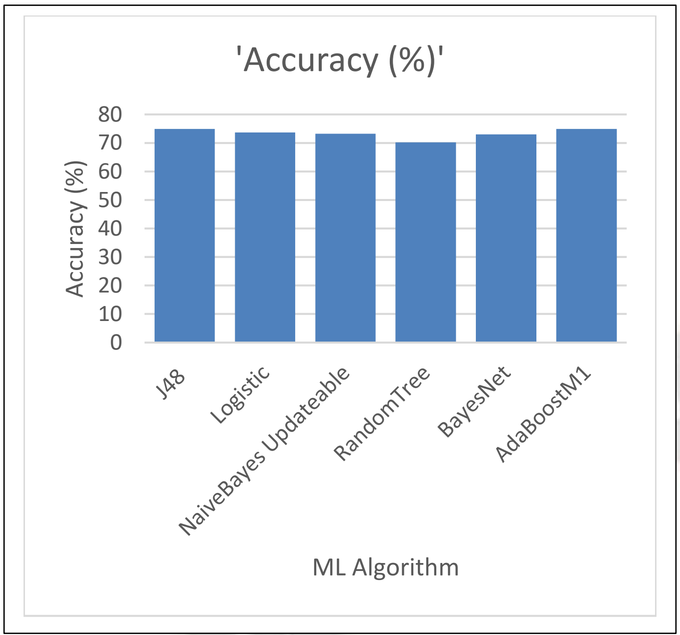

Figure 11. Accuracy for PIDD Fuzzy Rule-Based Model

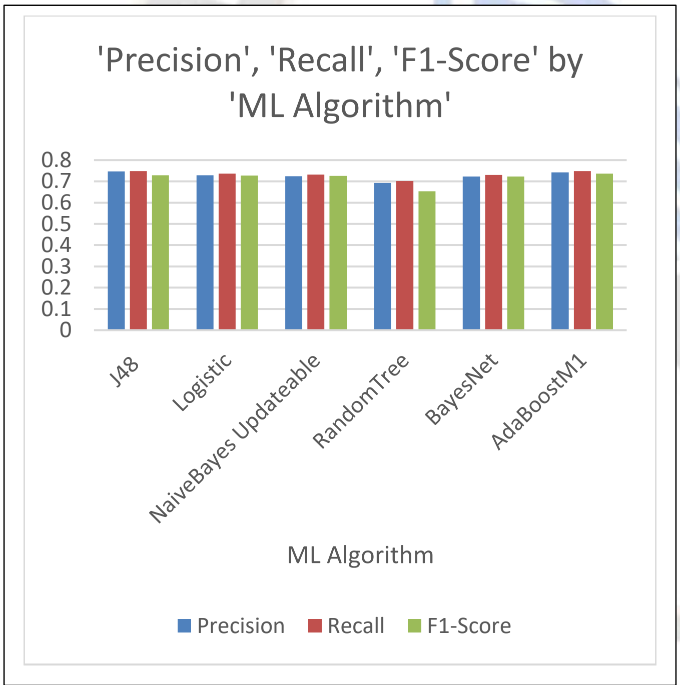

Figure 12. Precision, Recall and F1-Score for PIDD Fuzzy Rule-Based Model

Fig. 13 and Fig. 14 shows the confusion matrix for the J48 and AdaBoostM1 algorithms with the highest accuracy of 74.8698% and Fig. 15 shows the confusion matrix for the Random Tree algorithm with the lowest accuracy of 70.1823%. From Fig. 13 and Fig. 14, a number of 193 items are incorrectly classified as “Diabetes” and “NonDiabetes” (152+41 from J48 algorithm and 136+57 from AdaBoostM1 algorithm) which is highlighted. For the Random Tree algorithm, a larger number of 229 items (139+90) are incorrectly classified highlighted in Fig. 15.

		Predicted Class	
		Diabetes	NonDiabetes
Actual Class	Diabetes	116	152
	NonDiabetes	41	459

Figure 13. Confusion Matrix for J48 Algorithm PIDD Fuzzy Rule-Based Model

		Predicted Class	
		Diabetes	NonDiabetes
Actual Class	Diabetes	132	136
	NonDiabetes	57	443

Figure 14. Confusion Matrix for AdaBoostM1 Algorithm PIDD Fuzzy Rule-Based Model

		Predicted Class	
		Diabetes	NonDiabetes
Actual Class	Diabetes	129	139
	NonDiabetes	90	410

Figure 15. Confusion Matrix for Random Tree Algorithm PIDD Fuzzy Rule-Based Model

Table VII compares the accuracy of the diabetes diagnosis (DD Fuzzy Model), level of care (LOC Fuzzy Model) and PIDD (PIDD Fuzzy Model) fuzzy rule-based models for each ML algorithms. Fig. 16 shows the bar chart comparison for the three models.

TABLE VII. RESULT FOR PIDD FUZZY RULE-BASED MODEL

ML Algorithm	DD Fuzzy Model	LOC Fuzzy Model	PIDD Fuzzy Model
J48	100	97.1098	74.8698
Logistic	100	96.3254	73.6979
NaiveBayes Updateable	100	93.1049	73.1771
RandomTree	100	97.0685	70.1823
BayesNet	100	93.1049	73.0469
AdaBoostM1	79.8165	95.3757	74.8698

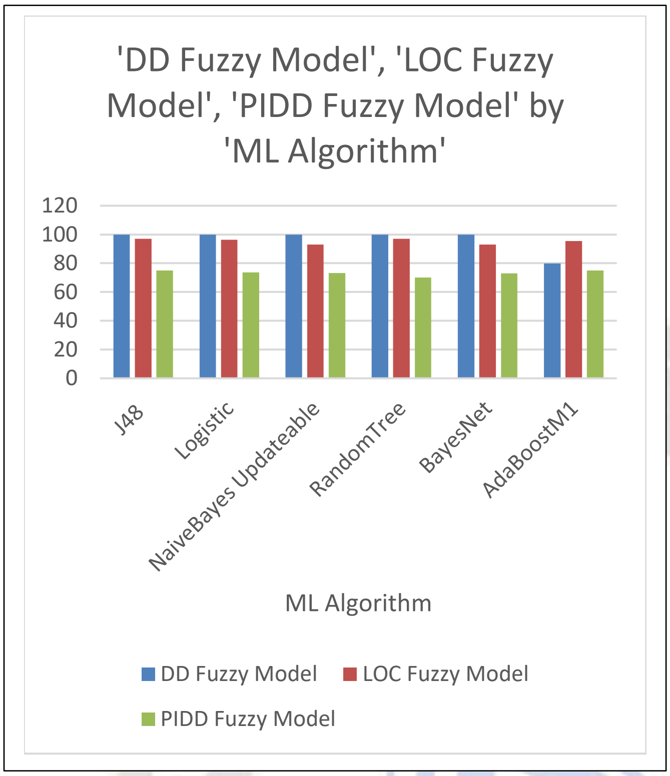

Figure 16. Accuracy of the Three Fuzzy Rule-Based Models

From the results, it shows that the diabetes diagnosis fuzzy model with three classes produced better results compared to the level of care and PIDD fuzzy model with two classes in terms of accuracy, precision, recall and F1-Score. Generally, the proposed fuzzy rule-based model produced better accuracy based on the simulated diabetes diagnosis and level of care datasets that were validated by medical experts applied in the research work by Normadiah [13] compared to the PIDD which are utilised in most of the research works. Furthermore, the proposed fuzzy rule-based model which is improved from the interrelated decision-making model for diabetes diagnosis is [13, 14] is working as expected.

V. CONCLUSION AND FUTURE WORKS

As a conclusion, the proposed fuzzy rule-based model tested with the six machine learning algorithms mentioned provides a good performance. The vagueness and uncertainty issues are handled by the proposed fuzzy rule-based model with the design and implementation of linguistic labels for a comprehensive and reliable decision-making, which is valuable to the healthcare sector.

For future works, further investigation of the performance improvement is required to analyze the AdaBoostM1 algorithm for the diabetes diagnosis fuzzy model with three classes; the Naïve Bayes Updateable and Bayes Net algorithms for the level of care fuzzy model with two classes; and Random Tree algorithm for the PIDD fuzzy model with two classes. In addition, it is suggested that the fuzzy rule-based model is tested with various machine learning algorithms to determine the robustness of the model. Furthermore, the speed of the machine learning algorithms executed to the proposed fuzzy rule-based model, can also be further explored to produce a more efficient model.

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APPENDIX

TABLE II. MEDICAL MODELS FOR DECISION-MAKING

References	Year	Datasets	Algorithms/Techniques	Comprise Various Stages and Provides Iterative Decision-Making in Healthcare	Dynamic Decision-Making Model	Cater Vagueness and Uncertainty Issues
[10]	2021	Cleveland, CombinedHunVa	ML: NN, Support Vector Machine (SVM), K-NN, Naïve Bayes (NB), Random Forest (RF)	No	No	No
[11]	2021	PIDD	Fuzzy + cosine amplitude method	No	No	Yes
[22]	2021	PIDD	ML: J48, K-NN, Feed Forward Neural Network, RB-Bayes, NB, NN, Proposed	No	No	No

			Long Short-Term Memory (LSTM)			
[23]	2021	PIDD	ML: Decision Tree (DT), KNN, RF, NB, AdaBoost, LR, SVM	No	No	No
[13]	2022	Simulated diabetes treatments	Multi-agent + ML: J48, Logistic, Naivebayes Updateable, RandomTree, BayesNet, AdaBoost	Yes	Yes	No
[9]	2022	Saudi Arabian hospital	ML: SVM, RF, K-NN, DT, Bagging and Stacking	No	No	No
[12]	2022	Homogeneous patients underwent prostate surgery	Expert fuzzy model	No	No	Yes
[24]	2022	PIDD and Laboratory of the Medical City Hospital (LMCH) diabetes	Proposed twice-growth deep neural network (2GDNN)	No	No	No
[21]	2023	Secondary dataset from the medical dataset record review in Afar, Northeastern Ethiopia	ML: DT, J48, NN, K-NN, SVM, Binary Logistic Regression, RF, NB	No	No	No
[25]	2023	Publicly available datasets: Appendicitis, Australian, Banana, Bands, Diabetes, Haberman, Ionosphere, Liver, Ring, Letter Recognition	Fuzzy Similarity Phrases (FSPs)	No	No	Yes
[20]	2023	ShanghaiT1DM and ShanghaiT2DM	Preparation of datasets for future research in data-driven machine learning classification techniques	No	No	No
[26]	2023	Insulin-dependent patients	Fuzzy non-linear delay controller	No	No	Yes
[27]	2023	PIDD	Optimal Decision Tree, M-ANFIS, K-NN	No	No	No
[28]	2023	Cleveland	Proposed EGA + FWSVM	No	No	Yes

TABLE III. FUZZY REPRESENTATION

Datasets	Attributes		Number of Linguistic Labels	Lists of Linguistic Labels
Simulated Diabetes Datasets: Diabetes Diagnosis and Level of Care [13, 14]	Predictor Attributes	Age	3	[Young, Adult, Old]
		Sex	2	[Male, Female]
		Acanthiosis Nigricans	2	[No, Yes]
		A1c	3	[Normal, Prediabetes, Diabetes]
		FPG	3	[Normal, IFG, DM]
		RPG	3	[Normal, OGTT, SecondRPG]
		OGTT	6	[FPGNormal, IPGIFG, FPFDM, PPGNormal, PPGIGT, PPGDM]
		HDL	3	[Low, Borderline, High]
		TG	3	[Optimal, Elevated, High]
		CVD	2	[No, Yes].

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	Target Attribute	Diabetes Diagnosis	3	[HealthyPrediabetes, IFGIGTPrediabetes, T2DMDiabetes]
		Level of Care	2	[PrimaryCare, SecondaryCare]
PIDD [19]	Predictor Attributes	Pregnancies	3	[Average, Seldom, Frequent]
		Glucose	2	[Prediabetes, Normal]
		Blood Pressure	4	[Normal, Stage 1, Stage 2, Crisis]
		Skin Thickness	3	[Thick, Average, Standard]
		Insulin	2	[Nondiabetic, Diabetic]
		BMI	5	[Obese, Overweight, Normal, ExtremelyObese, Underweight]
		Diabetes Pedigree Function	2	[Minimum, Maximum]
		Age	3	[Young, Adult, Old]
	Target Atttributes	Outcome	2	[Diabetes, Nondiabetes]