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Prediction Of Type-Ii Diabetes Using Machine Learning Techniques

K. Kowsalya[1], S. Vimal[2]
Research Scholar[1], Assistant Professor[2], Department of Computational Intelligence[1,2]
SRM Institute of Science and Technology, Kattankulathur Campus, India[1,2]
kk8917@srmist.edu.in[1], vimals@srmist.edu.in[2]

Abstract-In the world, 70% of the death rate is due to the non-communicable Diabetes disease. Due to unhealthy lifestyle, the majority 90 to 95% diabetes cases are Type 2 diabetes which can be determined by the examination of diabetes-related parameters. The main propose of this study to developing a fuzzy expert technique to diagnosis of diabetes mellitus very efficiently. The implementation of this techniques is involved four main steps like (a) Fuzzification (b) Rules Evaluation (c) Output aggregation and (d)Defuzzification. The two comparative studies are done in this work. First, the proposed techniques are compared with regression method and several classification techniques such as Native Bayes, Support Vector Machine and Multilayer Perception. Second, use Mamdani fuzzy interference method to diagnosis the type II diabetics mellitus effectively. The fuzzy expert techniques were developed and validated with original data using data mining algorithm. The Pima Indian dataset, includes 768 records and 9 attributes were used in this research work. The pre-processing method are used two different techniques (1) Multiple Imputation method (2) Listwise deletion method to handled missing data in the given dataset. Finally, the different evaluation metrices are calculated and compared with results.

1. INTRODUCTION

Machine Learning (ML) is becoming familiar day by day because of its working capacity with heterogeneous data set. The data is directly learned by the ML algorithms, will be producing hidden insights and could do prediction or forecasting the future outcomes on its learning basis [1]. By the approaches of classification or regression prediction can be done. The data quality is factor which is used for the classification accuracy of the predictions. The features values, inconsistent, voluminous and noisy and class imbalanced might be missing in the data generated from different sources [2]. So, the data which is imperfect needs the stage of data preparation for cleaning and preparing the data [3] for more analysis. For getting more quality data, the pre-processing is the step that is provided by the machine learning. A significant amount of time [4] is taken by this step which must be carefully implemented for improving the overall performance of the model.

The method which is proposed does the feature analyses and does accurate categorization by the missing data patterns variety to find the correlation between the features with missing values and also with definitions that is specific. The proposed HIMP does the imputation of missing data with MNAR patterns and the result is stored, and then does the results decomposition into two datasets DMCAR and DMAR also the data which is missing with MCAR and MAR patterns. Then, using single imputation methods like K-nearest neighbour (KNN) [5] and hot-deck [6], the DMCAR is imputed; then by using three multiple imputation methods like, Multivariate Imputation by Chained Equations (MICE) [7], expectation maximization (Em) and Markov Chain Monte Carlo (MCMC). The step involves estimating the imputed values by each method are assessed by using various classifiers for determining winner imputed methods with its DMCAR and DMAR datasets. At last, for forming the imputed datasets, HIMP got merged to the winner datasets. The HIMP which is proposed was subjected to evaluation and done comparison with any other methods of imputation using various classifiers under various factors like recall, precision, accuracy and F1-score.

2. RELATED WORKS

The investigation of missing pattern gives relationship and connection descriptive measures between present values and missing values [8]. After knowing the missing patterns, it is useful as an exploratory step before imputation to select the methods of proper data imputation. The categorization of missing patterns is done into three types, missing at random (MAR), missing not at random (MNAR) and missing completely at random (MCAR). All patterns of MAR, MNAR and MCAR in the real-world datasets that are classified in the multi-pattern missing values.

Missing completely at random (MCAR) pattern is the one where randomly throughout the dataset, the MCAR pattern occurs completely. In this missingness type, the observed [9,10]values are similar to the distributions which are present in the missing observations of random subset. If the Y feature value is missing, the values which are missing on Y feature will have an occurrence of MCAR pattern that are independent to the features that are observed and Y values. The same observed and missing Y distributions will be assigned as 1st equation (eq. (1)). By using various methodologies like single imputation, pairwise deletion and complete case analysis (CCA) the correction can be done for MCAR pattern.

The Missing at random (MAR) pattern is the one where the MAR pattern occurs randomly throughout the dataset. In MAR, the probability that a record with missing values belongs to a feature does not depend on the value of the missing value but can be dependent on the observed data [11]. Due to this, the Y feature missing and observed distributions will be same and equally dependent on observed values of X [12].

The Missing not at random (MNAR) pattern is the data pattern which will be occurred in an non-random manner because of intentional reasons in the whole dataset. In the initial stage, the missingness feature could be initialized logically; also, the dataset doesn't contain dataset which is conceptually associated. The other fact is that, the feature initialization can't be done conceptually and logically. Then by using the features of one or multiple, the specification of missingness cause can be done in the dataset [13,14,15]. By the 3rd equation (eq. (3)), the feature Y observed and missing values are not same as under some specifications in the pattern of MNAR [16]. The values that are missing can be sorted out by imputation and simple methods.

3. PROPOSED TECHNIQUE

The proposed method to develop and implemented the fuzzy expert system, it includes the Mamdani fuzzy inference techniques. This research work implanted in Matlab. The main purpose of this study involves four stages (a) To generated each attribute for fuzzy sets along with their membership functions (b) Based on the membership function the fuzzy rules and defined and evaluated (c) The output function is aggregated in order to achieved a single fuzzy set (d) Finally, we used centroid defuzzification techniques.

In this framework, we compared different components to be compared and executed as shown in figure 3.1 described as follows:

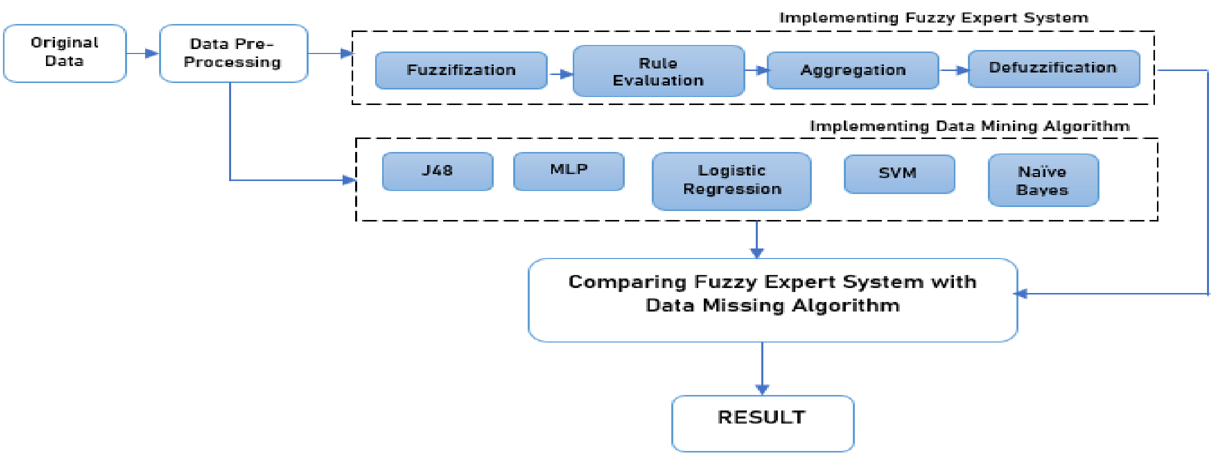

Figure 1: Proposed Framework

3.1. Dataset

In order to compare and validate the findings, the system is tested on the most commonly used Pima Indian diabetes dataset [9], which belongs to the National Institute of Diabetes and Digestive and Kidney Diseases. It is part of the UCI machine learning dataset available to researchers. This dataset contains 768 instances and 9 attributes. The input attributes are age, glucose concentration in blood 2 hours after having breakfast (Glucose), serum insulin in blood 2 hours after having breakfast (Insulin), body mass index (BMI), number of pregnancies (NP), triceps skin fold thickness (TSFT), diabetes pedigree function (DPF), and diastolic blood pressure (BP). The output of the system is either 0 or 1. 0 is interpreted as "no diabetes mellitus" and 1 is interpreted as "diabetes mellitus".

3.2. Data Pre-processing

This step is one of the most important phases in the data mining process. It prepares and transforms the initial dataset. Raw data is generally incomplete, inconsistent, and noisy. Analysing data that has such problems can produce misleading results. Thus, some data pre-processing methods can be applied to raw data before running an analysis. Data pre-processing methods involve replacing missing values, normalisation, data discretisation, data transformation, data integration, feature extraction, etc. In this study, two comparative studies were conducted using the Pima Indian Diabetes Dataset, which has missing values for some of the attributes. In the first comparative study, the fuzzy expert system was compared with classification models and regression model. In this study, all attributes and instances of the original dataset were used. In the second study, the fuzzy expert system was compared with the fuzzy expert system presented in [10]. In this study, 192 cases from the lower age range (25 to 30 years old) were extracted from the original dataset (PIDD). Figure 4.1 and Figure 4.2 give summaries of the missing values in the original dataset and the dataset including 192 instances.

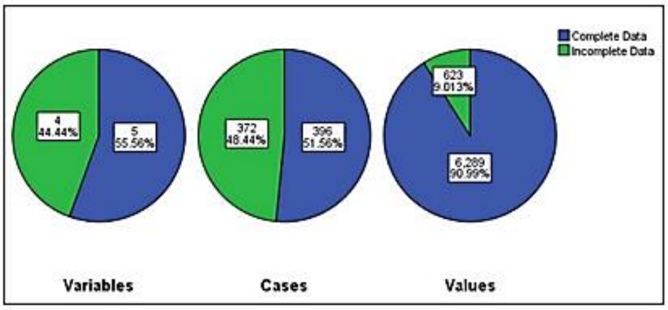

Figure 2: Summary of Missing Values in the Original Dataset

In the above figure, the first pie chart displays the number and the percentage of missing variables. It demonstrates that four of the nine variables (attributes), namely insulin, body mass index, triceps skin fold thickness, and diastolic blood pressure, have missing values. The second pie chart shows the number of cases (instances) that are missing some values. The number of cases that have at least one missing value is 372, while 396 cases are complete. The last pie chart illustrates that 9% of all values are missing, whereas approximately 91% of the values are present.

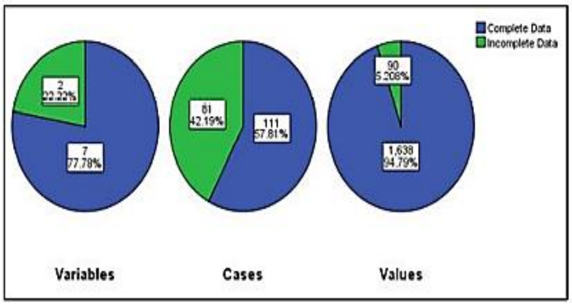

Figure 3: Summary of Missing Values in the Dataset including 192 instances

As we can see in the above figure, the first pie chart shows that two of the nine variables, which are insulin and body mass index, have missing values. The second pie chart displays that the number of cases that have at least one missing value is 81, while 111 cases are complete. The third pie chart presents the percentage of the missing values in the dataset which is 5%, while around 95% of the values are present. In this thesis, two different methods are used to handle the missing values in the original dataset and the dataset that includes 192 instances which are:

(i) Multiple Imputation Method

It is important to select a method to that is capable of replacing these missing values with plausible values. In this study, the multiple imputation technique [14] was selected based on the percentage and pattern of the missing values. Multiple imputation is an approach that replaces each deficient or missing value with more than one acceptable value representing a distribution of possibilities. It looks at the pattern of the available data, and based on probability judgment, attempts to find the best matches, replacing the missing values with imputed values. Replacement is performed repeatedly in order to find the perfect fit. IBM SPSS Statistics version 22 was used to perform the multiple imputation process. The missing values of the original dataset were replaced using the multiple imputation method, with the exception of four records. These four records were deleted from the dataset because of a lack of sufficient data. Also, all missing values of the dataset that includes 192 instances were replaced using the multiple imputation method. Table 4.1 and 4.2 give summaries of cases in the original dataset and the dataset including 192 instances after the application of the multiple imputation method. These datasets are named dataset 1 and dataset 2.

Table 3.1: Cases in the Original Dataset after the application of the Multiple Imputation Method (Dataset 1)

Class	Number of Cases	Total Number of Cases
Diabetic	**269**	**764**
Non-diabetic	**495**	

Table 3.2: Cases in the Dataset including 192 Cases after the application of the Multiple Imputation Method (Dataset 2)

Class	Number of Cases	Total Number of Cases
Diabetic	**56**	**192**
Non-diabetic	**136**	

(ii) Listwise Deletion

In this method, an entire case (instance) is excluded from the dataset if any single value is missing [20]. Based on the analysis of the original dataset that is represented in Figure 4.1, 372 cases have at least one missing value. These cases were deleted using IBM SPSS Statistics version 22. Also, the dataset that contains 192 has 81 incomplete cases, so these cases were removed from the dataset. Summaries of the instances in both datasets after the application of the listwise method are provided in Table 4.3 and Table 4.4. The datasets are named dataset 3 and dataset 4.

Table 3.3: Summary of the Cases in the Original Dataset after the application of the Listwise Method (Dataset3)

Class	Number of Cases	Total Number of Cases
Diabetic	**130**	**396**
Non-diabetic	**266**	

3.3. Fuzzy Inference System

In Proposed, the Mamdani fuzzy inference system step by step.

(a) Fuzzification

This is the first step of the Mamdani fuzzy inference system. In the fuzzification step, the fuzzy sets for the input attributes and the output, along with the membership functions are defined. The attributes of the Pima Indian Diabetes Dataset are used. The Datasets are:

- Age: {Young, Middle Aged, Old, Very Old}.
- Glucose: {Low, Normal, Medium, High, Very High}.
- Insulin: {Low, Medium, High}.
- Body Mass Index: {Normal, Medium, High}.
- Number of Pregnancies: {Absent, Average, High}.
- Triceps Skin Fold Thickness: {Normal, Medium, High}.

- Diabetes Pedigree Function: {Low, Medium, High, Very High}.
- Diastolic Blood Pressure: {Low, Medium, High, Very High}.
- Output: {Low, Medium, High}.

Table 3.4: Ranges of the Output of Fuzzy Expert System

Output	**Range**	**Fuzzy set**
Result	< 0.5	Low
	0.4 – 0.6	Medium
	0.5 – 1	High

This research considered low as "non-Diabetic", while medium and high are treated as "Diabetic".

(b) Rule Evaluation

In this step, the fuzzy rules were generated and evaluated. In this system, some of the rules have a single antecedent and a single consequent, whereas other rules have multiple antecedents and a single consequent. These rules are defined by physicians (domain experts) and presented in the following table.

Table 3.5: Fuzzy Rules of Fuzzy Expert System

1	If (Glucose is Low) Then (DM is Low)
2	If (Glucose is Very High) Then (DM is High)
3	If (Glucose is High) Then (DM is High)
4	If (Glucose is Medium) Then (DM is Medium)
5	If (Glucose is Medium) & (BMI is High) & (TSFT is High) Then (DM is High)
6	If (Glucose is Medium) & (BMI is Medium) & (DPF is High) Then (DM is High)
7	If (Glucose is Medium) & (BMI is Medium) & (DPF is Very High) Then (DM is High)
8	If (Glucose is Medium) & (INS is Medium) & (BMI is Low) & (Age is Young) & (NP is Absent) Then (DM is Low)
9	If (Glucose is Medium) & (INS is Medium) & (BMI is Low) & (Age is Young) & (NP is Average) Then (DM is Low)
10	If (Glucose is Medium) & (INS is Medium) & (BMI is Medium) & (Age is Middle) & (NP is Absent) Then (DM is Low)
11	If (Glucose is Medium) & (INS is Medium) & (BMI is Medium) & (Age is Middle) & (NP is Average) Then (DM is Low)
12	If (Glucose is Medium) & (INS is High) & (BMI is Medium) & (TSFT is High) Then (DM is High)
13	If (Glucose is Medium) & (INS is High) & (BMI is High) & (TSFT is High) Then (DM is High)
14	If (Glucose is Medium)& (BMI is Medium) & (TSFT is High) & (NP is High) Then (DM is High)
15	If (Glucose is Medium)&(BMI is Medium)&(TSFT is High)&(NP is Average) Then (DM is High)
16	If (Glucose is Medium) & (Age is Very Old) & (BP is High) Then (DM is High)
17	If (Glucose is Medium) & (Age is Very Old) & (BP is Very High) Then (DM is High)
18	If (Glucose is Normal) & (BMI is Normal) Then (DM is Low)
19	If (Glucose is Normal) & (INS is Low) Then (DM is Low)
20	If (Glucose is Normal) & (BMI is Medium) & (Age is Young) Then (DM is Low)
21	If (Glucose is Normal)&(INS is High)&(BMI is Medium)&(TSFT is High) Then (DM is Medium)
22	If (Glucose is Normal) & (INS is High) & (BMI is High) & (TSFT is High) Then (DM is Medium)
23	If (Glucose is Normal)&(INS is Medium)&(BMI is Medium)&(TSFT is High)Then(DM is Medium)
24	If (Glucose is Normal) &(INS is High) & (BMI is Medium) & (TSFT is High) Then (DM

	is Medium)
25	If (Glucose is Normal)&(INS is Medium)&(BMI is Medium)&(TSFT is High)Then(DM is Medium)
26	If (Glucose is Normal) & (BMI is Medium) & (Age is Young) Then (DM is Low)

(c) Aggregation of Rules

After defining and evaluating the rules, the clipped consequent membership functions were aggregated to obtain a single fuzzy set output. Max operation was used to aggregate the outputs of the fuzzy expert system. For example, we applied Max operation to the example of the patient discussed in Section 3.2.1. We took the maximum of the medium fuzzy sets (0.57) and the maximum of the high fuzzy sets (0.57).

(d) Defuzzification

This step is the last step in the Mamdani fuzzy inference system. It is used to obtain a single crisp number from the single aggregated fuzzy set. The centroid defuzzification method was used in this study. The equation of this method is provided in Section 2.6. The centre point of the aggregated fuzzy set(s) is found by using the equation of the defuzzification method. The final crisp number of the fuzzy expert system was 0.72, thus indicating that the patient in question has diabetes. Since our fuzzy expert system is built based on human knowledge (i.e. domain experts), changing the membership functions and the fuzzy rules will change the performance of the fuzzy system.

3.4. Implementing the Data mining Algorithms

Weka was used to build J48, MLP, logistic regression, SVM, and Naïve Bayes. There are two test methods which are percentage split and cross validation. Both methods were used to test each model. A simple way to use one dataset for both training and estimation the performance of an algorithm on unseen data is to split the dataset. This method splits the dataset into a training dataset and a test dataset. In this study, a supervised (resample) filter [14] was applied to the instances using Weka. This filter produces a random subsample of a dataset using sampling with replacement. It also maintains the class distribution in the subsample. In order to use this filter, the dataset must have a nominal class attribute. The number of instances in the generated training and testing datasets can be specified. As such, we selected 70% of the cases for training and used the remaining 30% as the testing dataset. After dividing the dataset into training and testing, the algorithm was run on the training dataset and a model was implemented and assessed on the testing dataset, following which a classification accuracy was obtained. In k-fold cross validation, k is the number of splits to make in the dataset. k=10 is selected in this study. This splits the dataset into 10 parts, and the algorithm is run 10 times. Every time the algorithm is run, it is trained on 90% of the data and tested on 10% of the data; for each run of the algorithm, a change is made in terms of which 10% of the data the algorithm is tested on.

4. PERFORMANCE MEASURE

Comparing the Fuzzy Expert System with the Data Mining algorithms Several performance metrics were used to evaluate the performance of our fuzzy expert system and the other data mining models for the incidence of diabetes, which are confusion matrix, accuracy, specificity, sensitivity, precision, and F-Measure.

$$Accuracy = \frac{TP + TN}{TP + FP + TN + FN} \times 100$$

$$Specificity = \frac{TN}{FP + TN} \times 100$$

$$Sensitivity = \frac{TP}{TP + FN} \times 100$$

$$Precision = \frac{TP}{TP + FP} \times 100$$

$$F-measure = \frac{Precision \times Recall}{Precision + Recall} \times 100$$

where TP, TN, FP, and FN denote true positives, true negatives, false positives and false negatives, respectively.

5. EXPERIMENTAL RESULT

We applied MLP, logistic regression, SVM, and Naïve Bayes to the pre-processed dataset that we applied the multiple imputation method to (dataset 1) and used 10-fold cross validation. Also, we applied the fuzzy expert system to dataset 1

Table 5.1: Confusion Matrix of the Classifiers Using 10-Fold Cross Validation

Classifier	Desired Results	Prediction	
		Diabetic	Non-Diabetic
Fuzzy Expert System	Diabetic	241	28
	Non-diabetic	29	466
MLP	Diabetic	161	108
	Non-diabetic	82	413
Logistic regression	Diabetic	176	93
	Non-diabetic	78	417
SVM	Diabetic	154	115
	Non-diabetic	63	432
Naïve Bayes	Diabetic	143	126
	Non-diabetic	53	442
J48	Diabetic	161	108
	Non-diabetic	82	413

Table 5.2: Prediction Accuracy of the Classifiers Using 10-Fold Cross Validation

Classifier	Accuracy
Fuzzy Expert System	92.5%
MLP	77.6%
Logistic Regression	76.7%
SVM	76.5%
Naïve Bayes	74%
J48	75%

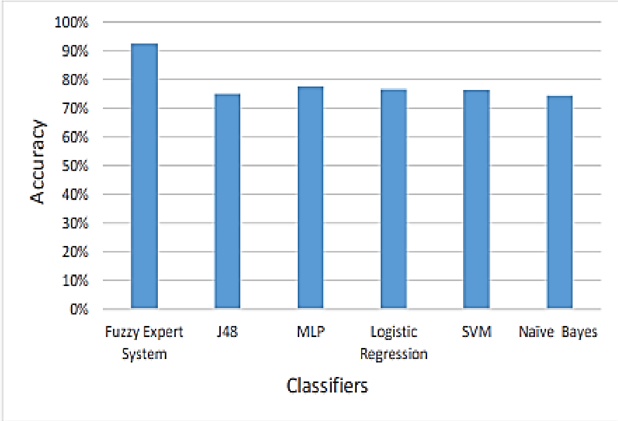

Figure 4: Accuracy of Each Classifier Using 10 Cross Validation

As we can clearly see, the fuzzy expert system has the highest accuracy with the lowest number of false positives and negatives. This figure also illustrates that logistic regression and SVM classifiers perform at nearly the same rate of accuracy. Lastly, Naïve Bayes has the lowest prediction accuracy with the highest sum of false positives and negatives cases.

Table 5.3: Results of the Classifiers (10-fold cross validation)

Classifier	Specificity	Sensitivity	Precision	F-Measure
Fuzzy Expert System	**94.7 %**	**92%**	**89.7 %**	**91%**
J48	80%	71.8 %	64%	68%
MLP	82.6%	65.6 %	65%	65%
Logistic Regression	88.7%	57%	71%	63.6 %
SVM	89%	55%	72%	62%
Naïve Bayes	82%	62.6 %	63%	62.8 %

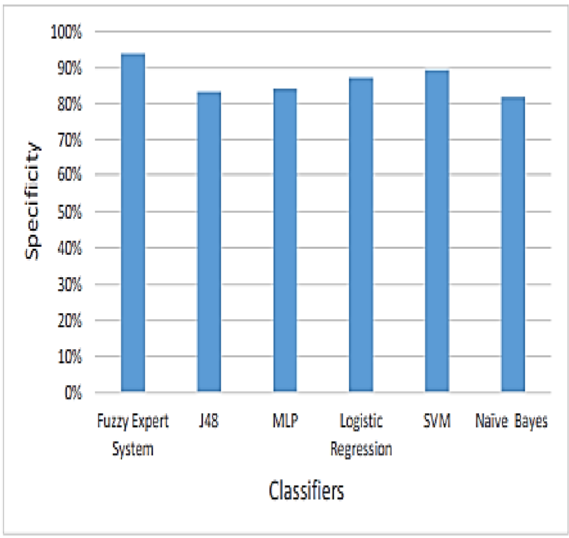

Figure 5: Specificity of Each Classifier Using 10-Fold Cross Validation

As we can see in the above figure, the fuzzy expert system has the highest number of true negative cases followed by SVM. On the other hand, Naïve Bayes has the lowest true negative rate.

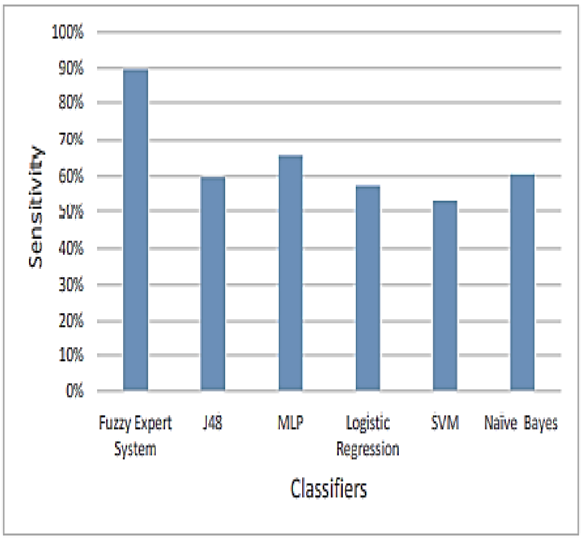

Figure 6: Sensitivity of Each Classifier Using 10-Fold Cross Validation

Figure 6 shows that the fuzzy expert system has the highest number of true positive cases. MLP has a higher true positive rate compared to logistic regression, SVM, J48, and Naïve Bayes. However, SVM has the highest number of false negative cases and the lowest number of true positive cases.

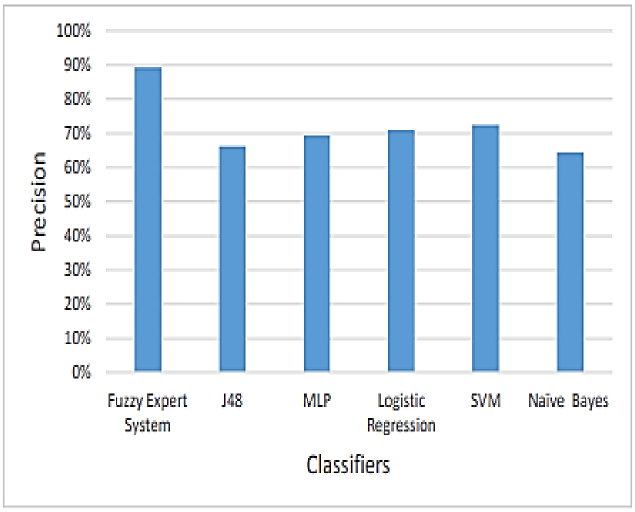

Figure 7: Precision of Each Classifier Using 10-Fold Cross Validation

The bar graph above illustrates that the fuzzy expert system has the highest precision value i.e. the lowest number of false positive errors committed by this classifier. By comparison, Naïve Bayes has the lowest precision value, with the large number of false positive cases compared to the other classifiers.

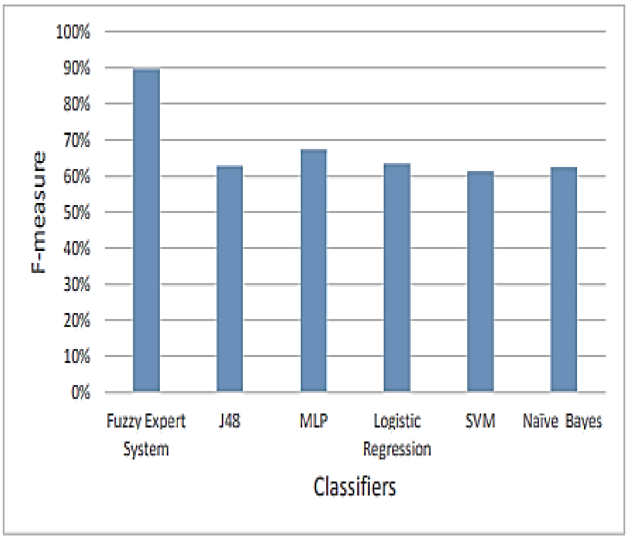

Figure 8: F-measure of Each Classifier Using 10-Fold Cross Validation

As we can clearly see, that the fuzzy expert system has the highest F-measure value, which ensures that both precision and recall are reasonably high. Also, we can see that J48 and Naïve Bayes have the same F-measure values. The F-measure value for SVM is slightly lower than these.

6. CONCLUSIONS

The main research studies were developed a fuzzy expert technique to diagnosis for Type II diabetes mellitus. The proposed techniques were included four main steps like using Mamdani fuzzy inference method, fuzzification, rule evaluation, output aggregation and defuzzification. We also compared a proposed method and various machine learning algorithms in weka tool and validated to our proposed system and other methods using real dataset from Pima Indian Diabetes dataset. In pre-processing, we used two different methods like Multiple Imputation (MI) and Listwise deletion to handle the missing data. we applied the algorithm fuzzy expert technique, logistic regression and other machine learning techniques to the pre-processed data to predict the better outcome of the work. Based on the research outcome, we performed five different metrics such as accuracy, sensitivity, specificity, precision, confusion matrix and F-measures. We found that the fuzzy expert techniques performed a better accuracy rate compared with other classifiers. the proposed technique fuzzy expert system achieved a accuracy rate 93.5%, specificity rate 95%, precision rate 90% and F-measure rate 91%. The proposed method fuzzy expert techniques was successfully implemented successfully to diagnose and predict the Type II diabetes to overcome many critical issues in existing related studies, to help specialists to reduce human mistakes when diagnosing the disease.

REFERENCE

1. World Health Organization, "Global report on diabetes," World Health Organization 2016, pp. 1-88, 2016.
2. C. D. Mathers and D. Loncar, "Projections of Global Mortality and Burden of Disease from 2002 to 2030," PLOS Med, vol. 3, no. 11, pp. 442-462, 2006.
3. World Health Organization, "Definition, diagnosis and classification of diabetes mellitus and its complications. Part 1: Diagnosis and classification of diabetes mellitus," World Health Organization, pp. 1-66, 1999.
4. National Institute of Diabetes and Digestive and Kidney Diseases, "Causes of Diabetes," National Institute of Diabetes and Digestive and Kidney Diseases, pp. 1-16, 2014.
5. M. Truglio-Londrigan and S. B. Lewenson, Public Health Nursing, 2nd ed. Jones & Bartlett Publishers, 2012.
6. S. Smyth and A. Heron, "Diabetes and obesity: the twin epidemics," Nature Medicine, vol. 12, no. 1, pp. 75–80, 2006.
7. T. Vos, R. Barber, B. Bell, S. Biryukov, A. Bertozzi-Villa, I. Bolliger, and L. Duan, "Global, regional, and national incidence, prevalence, and years lived with disability for 301 acute and chronic diseases and injuries in 188 countries" The Lancet, vol. 386, no. 9995, pp. 743–800, 2015.
8. M. Kalpana and A. Kumar, "Fuzzy Expert System for Diagnosis of Diabetes Using Fuzzy Determination Mechanism," International Journal of Advanced Research in Computer Science, vol. 3, no. 1, pp. 244–250, 2012.
9. H. Chen and C. Tan, "Prediction of Type-2 Diabetes Based on Several Element Levels in Blood and Chemometrics," Biological Trace Element Research, vol. 147, no. 1–3, pp. 67–74, 2011.
10. M. Thirugnanam, P. Kumar, S. V. Srivatsan, and C. R. Nerlesh, "Improving the Prediction Rate of Diabetes Diagnosis Using Fuzzy, Neural Network, Case Based (FNC) Approach," in International Conference on Modeling Optimization and Computing, 2012, vol. 38, pp. 1709–1718.
11. S. Kumari and A. Singh, "A data mining approach for the diagnosis of diabetes mellitus," in 2013 7th International Conference on Intelligent Systems and Control (ISCO), 2013, pp. 373–375.
12. J. Lukasiewicz, "Philosophical remarks on many-valued systems of propositional logic," in Polish Logic 1920-1939, Oxford University Press, 1967, pp. 153–179.
13. L. A. Zadeh, "Fuzzy sets," Information and Control, vol. 8, no. 3, pp. 338–353, 1965.
14. L. A. Zadeh, "Outline of a New Approach to the Analysis of Complex and Decision Process," in IEEE Transactions on Systems, Man, and Cybernetics, 1973, vol. 1, pp. 28–44.

15. M. Negnevitsky, Artificial intelligence: a guide to intelligent systems. 2 nd ed. AddisonWesley, 2001.
16. G. José, Handbook of Research on Fuzzy Information Processing in Databases. IGI Global, 2008.
17. L. A. Zadeh, “Fuzzy Sets and Systems,” International Journal of General Systems, vol. 17, pp. 129–138, 1990.
18. G. Chen and T. Tat Pham, Introduction to Fuzzy Sets, Fuzzy Logic, and Fuzzy Control Systems. CRC Press, 2001.
19. R. A. Aliev, “Fuzzy Sets and Fuzzy Logic,” in Fundamentals of the Fuzzy Logic-Based Generalized Theory of Decisions, Springer Berlin Heidelberg, 2013, pp. 1–64.
20. A. K. Nandi, “GA-Fuzzy Approaches: Application to Modeling of Manufacturing Process,” Statistical and Computational Techniques in Manufacturing, pp. 145–185, 2013.