International Journal of Recent Technology and Engineering (IJRTE)
ISSN: 2277-3878, Volume-8 Issue-3, September 2019

A Fuzzy Knowledge Based System for Financial Credit Classification

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***Abstract:** Fuzzy knowledge-based systems are successfully applied in several areas to classify and modelling the knowledge base using fuzzy If then rules. In recent era, taking the loan from banking system is highly practiced and the finding the eligible person to grant the credit is challenging task. In this context, this article designed a fuzzy knowledge base system and defined eight rules for credit allocation system and implemented on two different dataset German credit allocation system and Australian credit allocation system. These data downloaded from well-known machine learning repository UCI. To classify the credit allocation data, fuzzy decision tree and Wang and Mendel model has been used. To estimate the performance of the proposed method for credit allocation system the accuracy and the interpretability is used. The experimental analysis highlight that the Wand and Mendel model gives higher accuracy i.e. 99.9% and the interpretability of the proposed model is very less or negligible.*

***Index Terms:** Fuzzy Classifier; Fuzzy rules; Knowledge Base; Financial credit classification, etc.*

I. INTRODUCTION

In recent era, there are many areas such as classification [1], controlling [2] and modeling [3] related work has been done with the help of either the fuzzy knowledge base system or fuzzy rule base system, because the nature of the data is fuzzy. The fuzzy rule base system is designed with the help of human expert knowledge and the fuzzy IF – THEN rules [4-5]. The structure of the fuzzy knowledge system is shown in fig 1. This figure illustrates the fuzzy knowledge base system. The prime component of the fuzzy knowledge base system is input of data, knowledge base and the output unit. The knowledge base of the fuzzy system contains two different component databases and the rule base. The database contains the membership functions, linguistic variables and the scaling function and the rule base contains the set of rules that has been implement in classification of data viz. IF THEN rules. The fuzzy knowledge base system has been successfully implemented in several fields such as intrusion detection on network traffic data [6] smart base isolation system [7], tool wear monitoring [8] and many more. This system has also implemented in medical diagnosis, bioinformatics, antimissile system, water treatment, home appliances and many more and demonstrate how the proposed system examine the knowledge base and function. This is known as

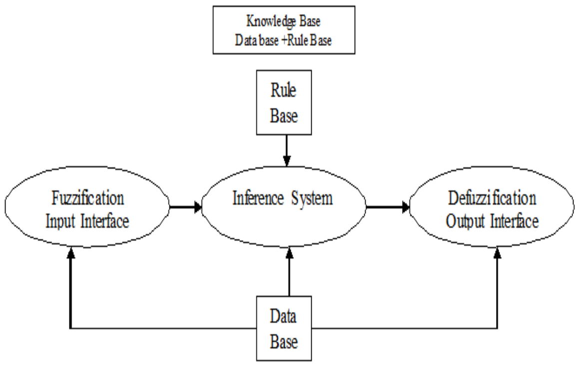

Fig 1: A block diagram of fuzzy knowledge base system

the interpretability in terms of fuzzy system [9]. The interpretability measures in which extent the proposed model behaves like original product. Another measure that is required to gauge the functional behavior of proposed model the accuracy has been used [10]. The accuracy and interpretability are opposite in nature, if any model achieve higher accuracy that paid the cost of interpretability or if try to gain high interpretability paid on cost of accuracy. So, it is required to make a balance between accuracy and interpretability [11-14]. This article designs a fuzzy knowledge base system for financial credit allocation system. This article used fuzzy decision tree and Wang and Mendel model for financial credit allocation system. The proposed method is deployed on two different set of financial data such as German credit allocation and Australian credit allocation data and estimate the proposed method in terms of accuracy and interpretability. The experimental analysis highlights that the Wand and Mendel model gives high accuracy for both of the dataset at the cost of very lower or negligible interpretability. In this article, first we have discussed the methodology that has been used for classification and estimation of proposed method in section 2. Section 3 discussed the proposed method for credit allocation system and section 4 deals with the experimental analysis of proposed model on both of the datasets. Finally, section 5 conclude the article and outlined the future research.

Manuscript published on 30 September 2019
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II. METHODOLOGY

In this section, we have discussed the methodologies that have been used for designing and estimation of financial credit system. To classify the financial credit classification system, the fuzzy decision tree and Wang and Mendel model and to estimate the fuzzy knowledge base system the accuracy and interpretability has been used. To know the interpretability the Nauck's index has been used.

A. Fuzzy decision tree: As we know that the decision tree has been widely used for data classification technique and help for understanding the representation of data. In this context, several researches have been conducted to generate the decision tree. The one of the most frequently used algorithms is ID3 and C5.0. But above algorithm works efficiently for discrete data. To cover the importance of fuzzy data, the fuzzy decision tree has been designed [15-16]. It is the generalized version of crisp set [17-18] and has been proposed by Chang and Pavlidis 1977 [19]

B. Wang and Mendel model: To improve the performance fuzzy data classification, the rule base generation has been proposed by Wang and Mendel 1992 [20]. It has been widely accepted and implemented due to its simplicity and performance. Several study highlights that this model gives higher accuracy and interpretability over the decision tree-based classification. It is working on input-output mechanism of data set E= {e1, ……….en) where ek={ek1, ………… ekm }, represents the functional behaviour of the problem set. The one of the main limitations of this model is the selection of rule. If the selected rule is not related or valid for given data then it does not give appropriate result [21].

C. Nauck's index: In order to estimate the performance of the fuzzy rule-based classification section, the Nauck index has been proposed by the Nauck in 2003 [22]. It is the product of complexity, coverage degree and the partition index. Mathematically, it is defined as:

$$Nauck - Index = comp \times \overline{cov} \times \overline{part}$$

Where comp represents the complexity, cov represents the coverage degree and part is the partition index. The complexity of the fuzzy rule base system is the ratio of number of membership function of output variables and the number of input variables. The cov is the coverage degree of the partition index and is the ration of the total number of membership function of the ith variable and the total number of continuous domains. The part represents the partition index and is the inverse of the number of membership function minus one from each variable [23-25].

III. DATASET DESCRIPTION

The proposed fuzzy knowledge base system for financial credit decision has been implemented with the help of GUAJE tool on the two different financial credit allocation system such as German and Australian financial credit system. Such data set are downloaded from machine learning repository (http://archive.ics.uci.edu/ml). The description of the German and Australian financial credit system is shown in Table 1 and Table 4 respectively.

Table 1: Dataset description of German Financial Credit System

SN	Characteristic	Value
1	Type	Classification
2	Number of Attributes	20 (7 Numerical, 13 Categorical)
3	Number of Instances	1000
4	Attribute Characteristic	Integer

Statlog (German Credit Approval) data set (available from http://archive.ics.uci.edu/ml) belongs to well-known financial benchmark data. It addresses the problem of the credit applicant classification into one of two groups labelled as "good credit risk" (Class 1) and "bad credit risk" (Class 2). The data contains 1000 instances (700 representing Class 1 and 300 - Class 2). The German credit approval data is characterized by 20 attributes including 7 numerical and 13 categorical/qualitative (Shown in Table 2) and the description of the attribute is given in Table 3.

Table 2: Attribute categorization of German Credit Approval Data

Numerical Attribute	Categorical Attribute
Credit duration	Status of existing account
Credit amount	Credit purpose
Instalment rate (% of income)	Savings
Present residence	Present Employment
Age	Personal status and sex
Number of credits	Other debtors/guarantors
Number of people liable to provide maintenance for	Property
	Other installment plans
	Housing
	Job
	Telephone
	Foreign worker
	Credit history

Table 3: Description of the attribute given in the German financial credit data.

Sl. No	Attribute Name	Description
1	Status of existing account	It has four different values: A11: Indicates new account A12: indicates up to 200 months old account A13: Indicates more than 200months old or Salary assignment for last 1 year A14: No Checking Account
2	Duration in month	It indicated how old account.
3	Credit History	It has five different value: A30: No credit taken or all credit paid A31: All credits at this bank paid back A32:Existing credit paid back till now A33: Delay in paying off in the past A34: Critical account/ other credit exists

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DOI:10.35940/ijrte.C6234.098319
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4	Credit purpose	It has 11 different value: A40: Car (New) A41: Car (Old) A42: Furniture/ Equipment A43: Radio/ Television A44: Domestic Appliances A45: Repairs A46: Education A47: Vacation A48: Retraining A49: Business A410: Others
5	Credit Amount	It indicates how much credit has been granted.
6	Savings Account/Bonds	It has five different value indicates the account A61: Indicates up-to 100 months old A62: Indicates account is old between 100 and 500 months. A63: Indicates account is old between 500 and 1000 months. A64: Indicates account is more than 1000 months old. A65: Indicates unknown account.
7	Present employment since	It has five different value indicates the employment history of person. A71: Indicates the person is unemployed. A72: Indicates the person has less than one year employment. A73: Indicates person employment between 1 and 4 years. A74: Indicates person employment between 4 and 7 years. A75: Indicated more than 7-year employment
8	Installment rate in percentage of disposable income	Its indices the total installment rate to pay.
9	Personal status and sex	It indicates the person personal status and has five value: A91: Male-divorced/ separated A92: Female-divorced/ separated/married A93: Male- single A94: Male-married/ widowed A95: Female-single
10	Other debtors / guarantors	It indicates the person credit guarantor related information and have three different value: A101: It indicates person has not be the guarantor of any credit. A102: It indicates person is co-applicant. A103: It indicates the person is guarantor of other credit.
11	Present residence since	It indicates the person present residence status.
12	Property	It indicates the types of property for credit. It has four different value: A121: It indicates real estate property A122: It indicates society saving agreement or life insurance. A123: It indicates car or other type of vehicles. A124: It indicates unknown type of property.
13	Age in Years	It indicates the age of the person in the year
14	Other instalment plans	It indicates the instalment plans of credit and have three different value. A141: Bank A142: Stores A143: None
15	Housing	It indicates type of housing of person and have three different value. A151: It indicates the person have rented house. A152: It indicates the person have their own house. A153: It indicate person have rented house but it is free of cost.
16	Number of existing credits at this bank	It indicates the total number of credit account at the present bank.
17	Job	It indicates the current employment status of the person and have four different value. A171: Unemployed/ unskilled -non-resident A172: Unskilled – resident A173: Skilled employee / official A174: management/ self-employed/highly qualified employee/officer
18	Number of people being liable to provide maintenance for	It indicates the number of people being liable to provide maintenance.
19	Telephone	It has two value either the person has telephone or not. 191: It indicates person do not have any telephone. 192: It indicates person have telephone under the own registration.
20	Foreign Worker	It indicates either the person is working in foreign or not. 201: It indicates person is working in foreign country 202: It indicates non-Foreign working person.

Table 4: Dataset description of Australian Financial Credit System

SN	Characteristic	Value
1	Type	Classification
	Number of Attributes	14 (6 Numerical, 8 Categorical)
3	Number of Instances	690
4	Attribute Characteristic	Integer

Statlog (Australian Credit Approval) data set (available from http://archive.ics.uci.edu/ml) belongs to well-known financial benchmark data. It addresses the problem of the credit applicant classification into one of two groups labelled as "good credit risk" (Class 1) and "bad credit risk" (Class 2). The data contains 690 instances (307 representing Class 1 and 383 - Class 2). The Australian credit approval data is characterized by 14 attributes including 6 numerical and 8 categorical/qualitative.

IV. OUR PROPOSED METHOD

In this section, we have designed a fuzzy knowledge-based system for financial credit system. Here we have considered two different financial credit system viz. German and Australian financial credit data that are downloaded from UCI repository of machine learning dataset (http://archive.ics.uci.edu/ml). The proposed model is shown in Figure 2.

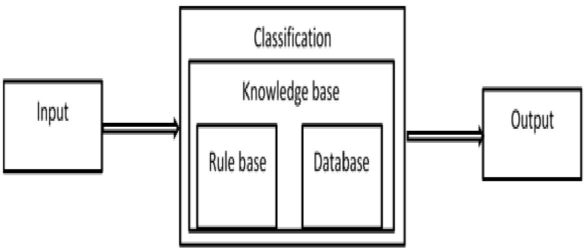


Fig 1: Fuzzy knowledge-based system for financial credit system

The proposed classification method has three different sections, form the input section we have given the financial credit system data as input which is classified in two different class Good credit and Bad credit. The classification section contains two different parameters rule base and database. The rule base contains the number of rules and parameters that has been used for classification. Whereas the database contains the information related to inputted data, membership function, partitioning methods, scaling factor, interpretability measurement index and so on. The proposed classification technique has following rules:

1. IF Status of existing account is A14 THEN class 1.
2. IF credit history is A31 THEN class 2
3. IF the credit purpose is A140 THEN class 2
4. IF Savings Account/Bonds is A65 THEN class 2
5. IF Present employment since is A74 and A75 THEN class 1
6. IF other debtors / guarantors is a101 THEN class 1
7. IF Property is A124 THEN class 2
8. IF Job is A173 and A174 THEN class 1

Finally, the proposed method is implemented on the both of the data with the consideration of above rules and the result of the proposed method is discussed in next section.

V. EXPERIMENTAL RESULTS AND ANALYSIS

In this section, we have implemented the proposed fuzzy knowledge base classification system by considering the above defined rule for classification of financial credit allocation data of German and Australian data. The data sets are prepared with the help of test cases that has been given by the customers for taking loan from bank. The detailed description of the data is given in the Table1 to Table 4. The proposed method has been implemented on the well-known open access fuzzy classification tool “Guaje”. The proposed mechanism is the type-1 fuzzy classification system. The classification of financial data follows the following steps:

1. First create a knowledge-base with the given datasets.
2. Select the hierarchal fuzzy partition method to partition the data.
3. Select the rules fuzzy decision tree and Wang and Mendel model for data classification respectively. In fuzzy decision tree, we select the depth of the tree is 18.
4. Finally compute the accuracy and interpretability of proposed method for both fuzzy decision tree and Wang and Mendel model.
5. To know the interpretability, the Nauck Index has been computed and fined that the proposed method accuracy is high but the interpretability is relatively very low or negligible.

The parameter has been used for classification using fuzzy decision tree and wang and Mendel model for both datasets is given in Table 5 and Table 6.

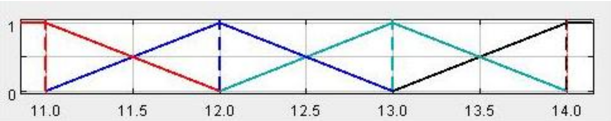
Table 5: Database Parameter used for fuzzy classification of financial credit system

Database Parameter	Value (German Credit Allocation System)	Value (Australian Credit Allocation System)
Number of MFs	20	14
Number of Variables	21 (20 input, 1 Output)	15 (14 input, 1 Output)
Fuzzy Partition	Hierarchal fuzzy partition	Hierarchal fuzzy partition
Scaling factor	0.6	0.6
Coverage of MFs	0.9	0.97
Interpretability measures	Nauck Index	Nauck Index
Linguistic Modifiers	185	200

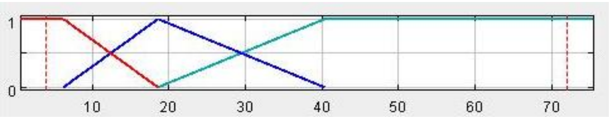
Table 6: Rule base Parameter used for fuzzy classification of financial credit system

Rule base Parameter	Value (German Credit Allocation System)	Value (Australian Credit Allocation System)
Number of rules	8	8
Rule consistency	High	High
Rule selection	Fuzzy Decision Tree and Wang and Mendel	Fuzzy Decision Tree and Wang and Mendel
Rule learning	Supervised	Supervised

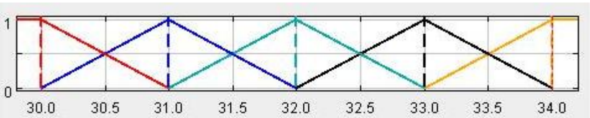
The membership functions of all inputs (a-u) based on hierarchal fuzzy partition (hfp) for German financial credit system is shown in figure 3. The graph a to u represents the membership function of each attribute (input and output) defined in Table 3.



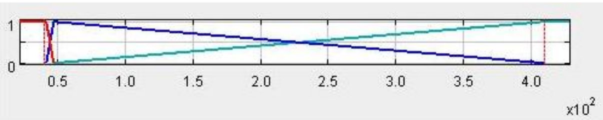
a. **Membership function of the input variable 'Status of existing account'**



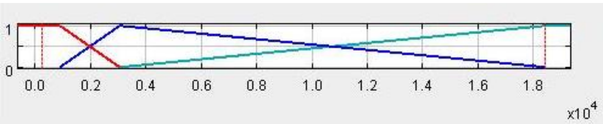
b . Membership function of the input variable 'Duration in Months'



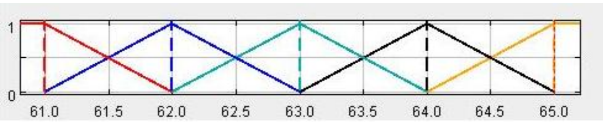
c. Membership function of the input variable 'Credit History'



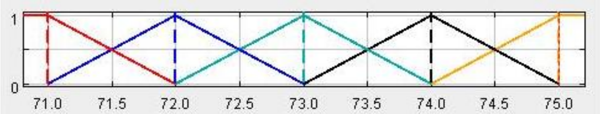
d. Membership function of the input variable 'Credit Purpose'



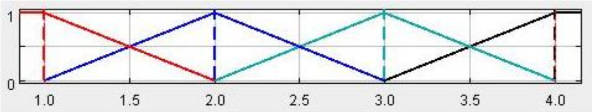
e. Membership function of the input variable 'Credit Amount'



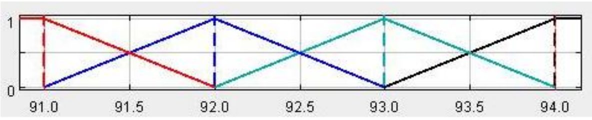
f. Membership function of the input variable 'Credit account and Bonds'



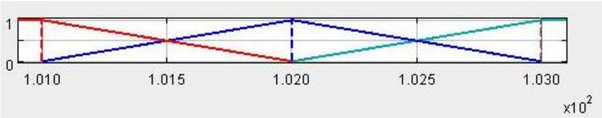
g. Membership function of the input variable 'Present Employment Since'



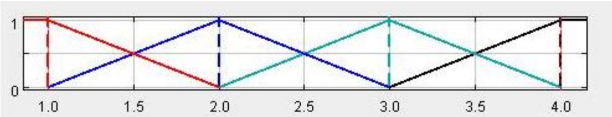
h. Membership function of the input variable 'Instalment rate in percentage of disposable income'



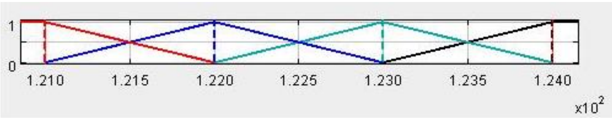
h. Membership function of the input variable 'Personal status and sex'



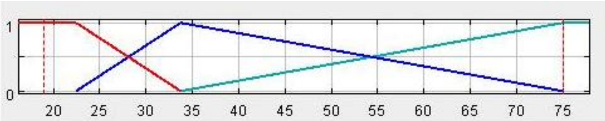
i. Membership function of the input variable 'Other debtores/Gurantors'



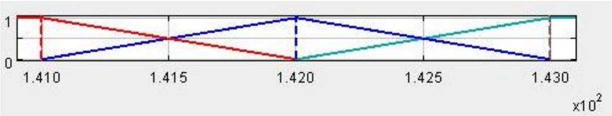
j. Membership function of the input variable 'Present Residence Since'



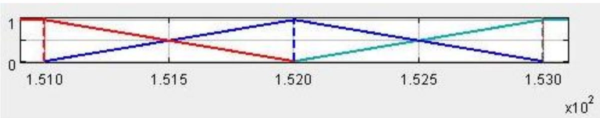
k. Membership function of the input variable 'Property'



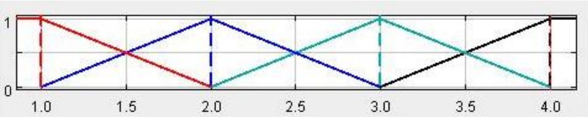
l. Membership function of the input variable 'Age in Year'



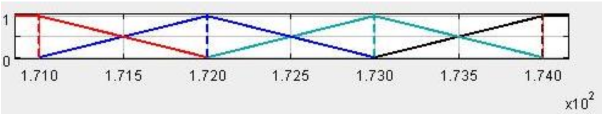
m. Membership function of the input variable 'Other Installment Plan'



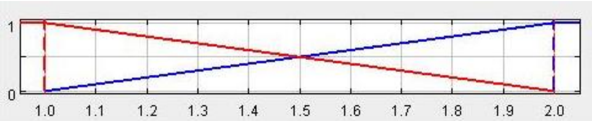
n. Membership function of the input variable 'Housing'



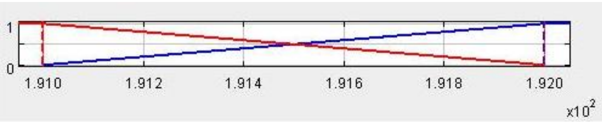
o. Membership function of the input variable 'No. of existing credit account at this bank'



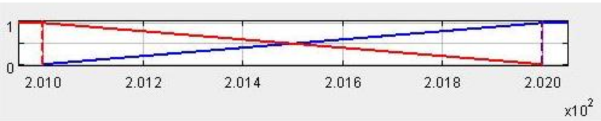
p. Membership function of the input variable 'Job'



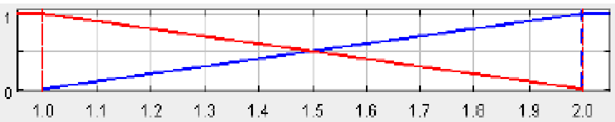
q. Membership function of the input variable 'Number of people being liable to provide maintenance for'



r. Membership function of the input variable 'Telephone'



s. Membership function of the input variable 'Foreign Worker'



u. Membership function of the output variable 'Class'

Figure 2: Membership function used for German financial credit allocation system

Figure 3 show the different membership function and their functional output for financial credit allocation classification system. One can clearly see that the different membership function takes different levels and produces different output for fuzzy knowledge base system for credit allocation system.After that we have compute the accuracy and interpretability of both fuzzy decision tree and Wang and Mendel model for German credit allocation dataset. Result of fuzzy decision tree model is shown in Table 7.

Table 7: Classification result of Fuzzy Decision Tree on German financial credit system (Total Instance =1000)

	Class 1	Class 2
TP	638	221
FP	79	62
TN	221	638
FN	62	79
Error cases	62	78

From the Table 7, it can be clearly seen that the total 62 instances are reported as misclassified for class 1 and 78 instances for class 2. Performance of the fuzzy decision tree is shown in Table 8.

Table 8: Performance of fuzzy decision tree model on German financial credit system.

Measures	**Value**
Accuracy	85.9%
Precision	0.857
Recall	0.879
F-measures	0.858
Mean Square Classification Error	0.014

The result of the Wang and Mendel model is shown in Table 9.

Table 9: Classification result of Wang and Mendel Model on German financial credit system (Total Instance =1000)

	Class 1	Class 2
TP	699	300
FP	0	1
TN	300	699
FN	1	0
Error cases	1	0

From the Table 9, it can be clearly seen that only 1 instance is reported as misclassified for class 1 and none of the instances for class 2. Performance of the Wang and Mendel is shown in Table 10.

Table 10: Performance of Wang and Mendel model on German financial credit system

Measures	**Value**
Accuracy	99.9%
Precision	0.999
Recall	0.999
F-measures	0.999
Mean Square Classification Error	0.072

From the above analysis we can conclude that the Wang and Mendel model perform better on German financial credit allocation data. The Wang and Mendel produces 99.9% accuracy and reported only one instance for error case. However, the fuzzy decision tree model accuracy is 85.9% and reported total 140 instances for error case. Finally, we can conclude that the Wang and Mendel is more suited for German credit approval system. But in fuzzy knowledge base system, the one of the main important issue is to find the interpretability of the fuzzy system. Generally, it seems that the higher accuracy leads to the lower interpretability. To find the interpretability of every measure, we have used Nuack-Index. The Interpretability of the fuzzy decision tree and Wang and Mendel is shown in Table 11 and Table 12.

Table 11: Interpretability measures for Fuzzy decision tree based model.

Interpretability Parameter	**Fuzzy Decision Tree**
Interpretability Index	0.001 **Very Low**
Nauck's Index	0
Number of Rules	1097
Total Rule Length	20391
Average Rule Length	18.588
Accumulated Rule Complexity	1145.853

Retrieval Number: C6234078219/2019©BEIESP
DOI:10.35940/ijrte.C6234.098319
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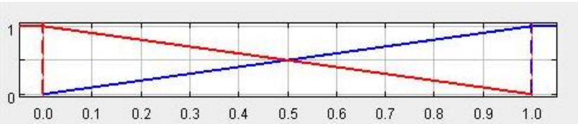
Table 12: Interpretability measures for Wang and Mendel based model

Interpretability Parameter	Wang and Mendel
Interpretability Index	o.oo1 (very low)
Nauck's Index	0
Number of Rules	1371
Total Rule Length	25871
Average Rule Length	18.87
Accumulated Rule Complexity	1433.189

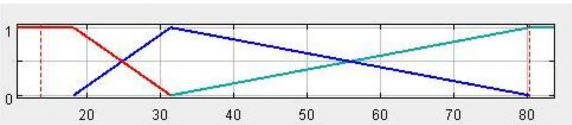
From the Table 11 and 12, it can be clearly seen that the interpretability of the both measures is equal 0.001, that is considered as very low or negligible. But the number of rules generation and total rule length is higher in Wang and Mendel model. So, we can conclude that the Wang and Mendel model can be used for financial credit allocation system.

Apart from the German credit allocation system, we have also used Australian credit allocation system for designing the fuzzy knowledge base system for credit allocation. This has also followed the above discussed process.

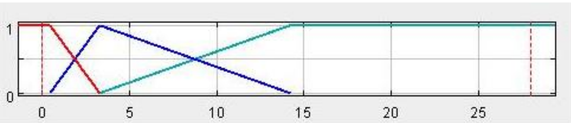
The membership functions (MFs) of all inputs (a-n) based on hierarchal fuzzy partition (hfp) for Australian financial credit system is shown in figure 4(a-n).



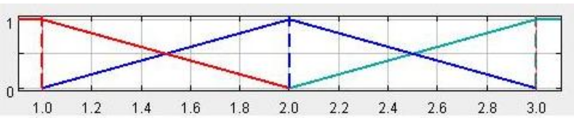
a. MFs of the input variable 'Attribute 1'



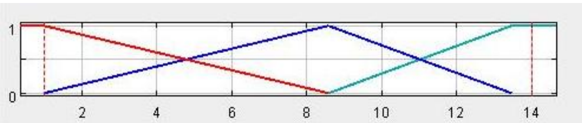
b. MFsof the input variable 'Attribute 2'



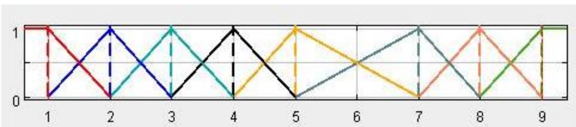
c. MFsof the input variable 'Attribute 3'



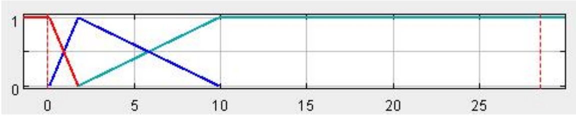
d. MFs of the input variable 'Attribute 4'



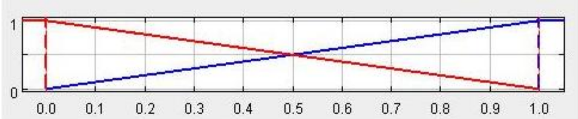
e. MFs of the input variable 'Attribute 5'



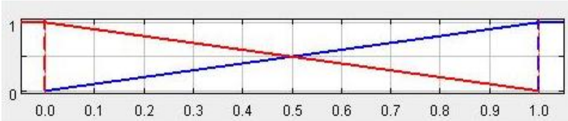
f. MFs of the input variable 'Attribute 6'



g. MFs of the input variable 'Attribute 7'

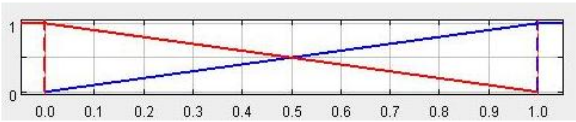


h. MFs of the input variable 'Attribute 8

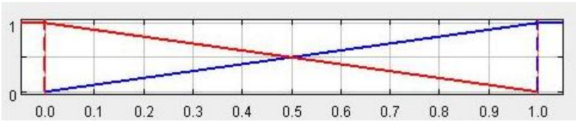


i. MFs of the input variable 'Attribute 9'

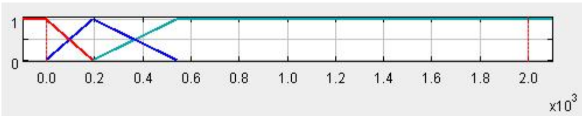
j. MFs of the input variable 'Attribute 10'



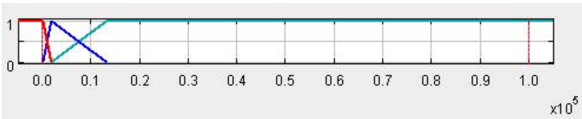
k. MFs of the input variable 'Attribute 11'



l. MFs of the input variable 'Attribute 12'



m. MFs of the input variable 'Attribute 13'



n. MFs of the input variable 'Attribute 14'

Figure 3: Membership function used for Australian financial credit allocation system

After that we have compute the accuracy and interpretability of both fuzzy decision tree and Wang and Mendel model for Australian credit allocation system dataset. Result of fuzzy decision tree model is shown in Table 13.

Table 13: Classification result of Fuzzy Decision Tree on Australian financial credit system (Total Instance =690)

	Class 1	Class 2
TP	355	260
FP	47	28
TN	260	355
FN	28	47
Error cases	28	46

From the Table 13, it can be clearly seen that the total 28 instances are reported as misclassified for class 1 and 46 instances for class 2. Performance of the fuzzy decision tree is shown in Table 14.

Table 14: Performance of fuzzy decision tree model on Australian financial credit system

Measures	Value
Accuracy	89.1%
Precision	0.892
Recall	0.891
F-measures	0.891
Mean Square Classification Error	0.028

From Table 14, it can be clearly seen that the accuracy, precision and recall value for fuzzy decision tree is good and gives higher accuracy, precision and recall value than German financial credit system but the mean square classification error in increase in Australian financial credit allocation system. The result of the Wang and Mendel model is shown in Table 15.

Table 15: Classification result of Wang and Mendel on Australian financial credit system (Total Instance =690)

	Class 1	Class 2
TP	354	288
FP	19	29
TN	288	354
FN	29	19
Error cases	24	18

From the Table 15, it can be clearly seen that the total 24 instances are reported as misclassified for class 1 and 18 instances for class 2. And the classification error is reduced in Wang and Mendel model. Performance of the Wang and Mendel model is shown in Table 16.

Table 16: Performance of Wang and Mendel model on Australian financial credit system

Measures	Value
Accuracy	92.9%
Precision	0.931
Recall	0.93
F-measures	0.931
Mean Square Classification Error	0.087

From the above analysis, it can be seen that the accuracy, precision, recall and f-measure value of the Wang and Mendel is increased over the fuzzy decision tree, but the mean squared error is also increased. It also decreases the error case of classification. So, we can conclude that the Wang and Mendel model can be used for Australian financial credit allocation system. But it can be seen that the accuracy is high at the cost of interpretability. To know the interpretability of the both models, we have the computed the interpretability with the help of Nauck-Index. The interpretability of the both model is shown in Table 17 and Table 18.

Table 17: Interpretability measures for Fuzzy Decision Tree based model of Australian Financial Credit Analysis.

Interpretability Parameter	Fuzzy Decision Tree
Interpretability Index	0 Very Low
Nauck's Index	0
Number of Rules	932
Total Rule Length	12647
Average Rule Length	13.57
Accumulated Rule Complexity	989.217

Table 18: Interpretability measures for Wang and Mendel based model of Australian Financial Credit Analysis.

Interpretability Parameter	Wang and Mendel
Interpretability Index	o.o38 (very low)
Nauck's Index	0
Number of Rules	868
Total Rule Length	12152
Average Rule Length	14
Accumulated Rule Complexity	922.982

From the Table 17 and 18, it can be clearly seen that the interpretability of the both measures less than 1, i.e. 0 and 0.038 that is considered as very low or negligible. But the number of rules generation and total rule length is higher in Fuzzy decision tree-based model. The accuracy and interpretability of the Wang and Mendel model is higher than fuzzy decision tree-based model. So, we can conclude that the Wang and Mendel model can be used for financial credit allocation system. Further we have made a comparative analysis to validate the result with other similar research work reported in different journal. The result of comparative analysis is given in Table 19 and 20 respectively for German and Australian credit data.

Table 19: Comparative result of the classification accuracy using German financial dataset.

Sl.No.	Reference	Model	Accuracy
1.	[26]	Naive Bayes	75.6%
2.	[27]	DT (Entropy Reduction)	80.3%
3.	[29]	Random Forests	76.20%
4.	[30]	LDA	76.5%
5.	[31]	ELM	96.33%
6.	**Proposed Method**	**Wang and Mendel**	**99.9%**
7.	Proposed Method	Fuzzy Decision Tree	85.9%

Table 20: Comparative result of the of the classification accuracy using Australian financial dataset.

Sl.No.	Reference	Model	Accuracy
1.	[26]	Linear Logistic	86.23%
2.	[28]	PNN (Pruned Neural Network)	85.64%
3.	[29]	Random Forest	89.40%
4.	[30]	LDA	85.50%
5.	**Proposed Method**	**Wang and Mendel**	**92.9%**
6.	Proposed Method	Fuzzy Decision Tree	89.1%

From Table 19 and 20, it may be concluded that our proposed method gives better results than other previous research but still the interpretability of the proposed method is negligible. Future research will address the issue and try to make a balance between accuracy and interpretability.

V. CONCLUSION AND FUTURE SCOPE

This research article discussed the different fuzzy classification technique such as fuzzy decision tree and Wang and Mendel model and designs an approach for credit allocation system. In this article, we have defined eight different rules for credit allocation system. The proposed method has been implemented on two different dataset such as German credit allocation system and Australian credit allocation system. The Wang and Mendel classification technique gives better results than the fuzzy decision tree on both of the datasets. So, we can conclude that the Wang and Mendel model can be used as a classification technique for financial credit allocation system. As we know that the higher accuracy in fuzzy knowledge base system lead to very low or negligible interpretability and vice versa. The discussed experimental result also has similar behaviour. So, it is required multi-objective evolutionary technique to make a balance between accuracy and interpretability. Further research will address the above discussed issue.

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