Credit Risk Prediction and Classifier Comparison Using Enhanced Fuzzy Based Genetic Approach

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Abstract:
Credit risk assessment is important for financial institutions, which helps them to decide whether or not to accept loan applications from customers. DNN's are used to establish multiple layer network structure evaluation model in credit risk assessment field, in which can directly obtain feature information to improve accuracy of classification from a large number of customer credit data. In this paper proposed Enhanced Fuzzy Based Genetic Approach used genetic approach reminiscence to do not forget suitable B cells in the course of the cloning system and designed two types of reminiscence: easy reminiscence and layer memory. Accomplish such combination; two noteworthy GA-Fuzzy half breed approaches have been investigated: Fuzzy Logic helped evolutionary algorithm and Genetic-Fuzzy Systems. The performance of the proposed scheme is evaluated using various metrics such as: Acquisition Cost, Cost Per Promotion, Life Time, Time to Process, Accuracy, Precision and Recall.

Keywords: Credit Prediction, Genetic Approach, Precision, Recall, Fuzzy Logic.

1. INTRODUCTION

Banks and monetary organizations utilize credit scoring models widely to decide great and awful credits. Advances are typically the most huge reason for hazard in banks. Utilizing credit scoring will decrease the season of advance endorsement methodology and spare expense per advance and upgrade credit choices. This improvement causes loan specialists to ensure that they are applying similar criteria to same gatherings of borrowers. In these circumstances banks can oversee the current credits a lot simpler than previously. Due to the quick development of car financing over the most recent two decades, the utilization of information digging for credit chance prediction increments rapidly.

The main examination concerning credit scoring was begun by Olson and Wu in 2010 to group credit applications as fortunate or unfortunate payers. Reasonable and Isaac exhibited a credit scoring model in the mid 60s. From that point forward, different models have been created utilizing conventional measurable techniques, for example, discriminant investigation strategy. Customary straight relapse has additionally been utilized as another conventional measurement technique for credit scoring. Ongoing methods of credit hazard appraisal treat loaning choice issue as a paired characterization issue. The exhibition of bio-propelled algorithms, as artificial neural systems and developmental calculation, for different information mining issues has been shown by numerous examinations already. Numerous bio-enlivened algorithms have been proposed for credit scoring. as of late artificial genetic approach systems (AIS) have been effectively utilized in a wide assortment of use regions.

Artificial genetic approach systems are computational systems motivated by the procedures of the natural genetic approach framework. This meta heuristic developed during the 90s as another computational model in AI. Chase and Cooke apply AIS to design acknowledgment issues in 1996. Timmis and Knight characterize AIS as "versatile systems motivated by hypothetical immunology and watched genetic approach capacities, standards and models, which are connected to critical thinking". There are different sorts of AIS, and specialists worked for the most part on the speculations of genetic approach systems, clonal determination, and negative choice. In this part, we have proposed an AIS-based characterization framework with another clonal choice algorithm. Inside the proposed AIS, fuzzy rationale has been connected to separate interpretable fuzzy principles. The primary reason that urged us to utilize the AIS metaheuristic for credit hazard prediction issue is that AIS has a nature which we can utilize it for our concern successfully. This nature is that AIS will in general investigate the pursuit space of the issue all around productively. This capacity is related with the hyper mutation administrator of AIS. We have chosen AIS for credit scoring prediction issue on the grounds that past examinations demonstrate that the purported arrangement issue has an extremely explorative pursuit space. We have encountered this nature of credit scoring characterization issue in our investigations distinctively. The primary perception which demonstrates the explorative idea of this issue is that the wellness capacity yields changes radically for fundamentally the same as data sources. In addition, AIS has demonstrated its superior for two-class arrangement issues in past examinations.

The new proposed characterization framework in this part is an improved form of fuzzy based credit prediction genetic approach and comprehensible credit scoring-FAIS (CCS-FAIS) classifiers as the two past adaptations of AIS-based arrangement framework for credit chance prediction. In our proposed model, we have utilized genetic approach memory to recollect great B-cells during the cloning procedure. We have planned two types of memory: straightforward memory and - layer memory. Results show that our new meaning of memory for AIS-based fuzzy guideline extraction builds the last characterization pace of credit scoring process extensively. The Weka Data Mining instrument has been utilized to contrast our classifier and a few surely understood classifiers. The table 1 shows the Advantages and Limitations of Principle Constituents of SC.

Table 1: Advantages and Limitations of Principle Constituents of SC

Constituents of SC	**Advantages**	**Limitations**
GA	Natural evolution and optimization	Inability of storing and handling imprecision
FL	Approximate reasoning imprecision	Inability of learning
NN	Learning and implicit knowledge representation	Inability for optimization
PR	Uncertainty	Inability of learning

The evolutionary fuzzy displaying centers around four noteworthy approaches of Genetic-Fuzzy model, for example the Michigan, the Pittsburg, the Iterative Rule Learning (IRL) and Genetic Cooperative-Competitive Learning (GCCL). The qualities of every one of these approaches have been talked about. The part obliges an exchange on the sub segments of real cross breed approaches alongside their constraints and correlations among each other. In the territory of clever choice emotionally supportive network, real application areas are taking favorable circumstances of AI strategies, particularly Genetic-Fuzzy hybridization. A study during examination in the territory of different planned applications is recorded. This examination covers a few significant applications areas where the machine insight is required to be constructed. The genuine uses of fluctuated areas, for example, arrangement, drug, control systems, mechanical autonomy, travel industry, stock and offer, organizing, and so forth utilize crossover structures of GFS so as to accomplish advanced rule learning. The part at long last makes determinations from the present best in class in the use of rule learning from Genetic-Fuzzy hybridization. Subject to the end made, the part legitimizes the extent of the examination did and revealed in this postulation. Because of broad research audit on Genetic-Fuzzy hybridization, it has been seen that no summed up structure utilizing evolutionary fuzzy approach has been created in the field of training to take care of the issues which need numerical plan.

GA gives a way to encode and to develop rule precursor conglomeration administrators, distinctive rule semantics, rule-based total administrators and de-fuzzification techniques. In this manner, GAs remain today as one of the least information securing plans accessible to structure and in some sense, streamline Fuzzy Rule Based Systems (FRBSs) as for the plan choices, enabling chiefs to choose what parts are fixed and which ones advance as indicated by the exhibition measures. Such qualities lead to the plan of a canny system with GA fuzzy hybridization which is a promising exploration field of current computational insight worried about the improvement of the up and coming age of wise systems.

2. LITERATURE SURVEY

Krunal M. Surti, Mr. Ashish Patel (2017): suggested linear regression with principle-based grouping and logistic regression is employed. Preprocessing is used to investigate, analyze, and determine the factors that play a crucial role in identifying credit default. A transforming model converts each entry into a vector. Each value in the vector represents a probability value; that is, each feature of each credit is converted to a corresponding value through statistical methods or Naive Bayes. They propose a technique to handle URI without any queries. It divides the URI path string into tokens, thus applying Naive Bayes to obtain their probability value. The analysis of three algorithms is provided by scaled conjugate angle back propagation, Levenberg Marquardt, and One-step secant back propagation (SCG, LM, and OSS). Different parameters have been utilized for analysis to attempt to do the comparison; training time, gradient, MSE, and R. The efficient algorithm is OSS; the algorithm with the highest gradient is SCG. The best algorithm is LM since it has the highest R, making it the most suitable for this dataset. The feature selection method also employs random forest strategy and emphasizes that the selected social and economic factors should also include those commonly used by banks.

Simon Lohmüller, Fabian Rabe, Andrea Fendt, Bernhard Bauer, Lars Christoph Schmelz[2018]: Proposed enhancements of SON Management models using psychological Machine Learning (ML) techniques. Consequently, the simulated behavior of three different SON Functions is studied and characterized by a Linear Regression (LR) Model. In a subsequent step, performance data from network cells are analyzed for similarities using k-Means Clustering. The findings from these two steps are then integrated by fitting the models onto smaller groups of cells. Finally, the utility of these models for predicting network performance is assessed, and the various refinement stages are compared with each other. Cells are classified based on mobile network context data. However, in this approach, the MNO must perform the classification manually through analysis. Q3 now addresses whether it is possible to automatically segment the group of 35 cells into logical groupings of similarly behaving cells. The assumption will be that these smaller groups may demonstrate a more homogeneous behavior concerning the relationship between capacity, step-size, and the specific KPI. Furthermore, groups could assist an MNO in discovering significant features of cells and thereby configure newly deployed cells appropriately. On a technical level, Clustering should categorize cells based on their average KPI under different SCV sets and group cells with similar characteristics into the same category, allowing for more tailored LR Models per group. The cells are divided into two groups for each SON Function: a group of default cells and one for exception cells.

M. Ozgur Cingiz, Ahmet Unudulmaz, Oya Kalıpsız[2013]: Suggested predicting task issue impacts that can lead to loss in software projects concerning their characteristics on risk factors, and we also need to rank our risk components to ascertain how they can provide insight into project issue impacts individually. For this purpose, five classification methods for predicting issue impact and two filtering feature selection techniques for ranking the significance of risk factors are utilized. Some software risks can be forecasted before initiating the software project, but some cannot be defined. Software risk management aims to identify unusual risks prior to the commencement of the software project. Software risk factors can have varying impacts on the success rate of software projects. Some risk factors can significantly influence the project's success rate while others may not. In software management, key risk factors are identified and efforts are made to prevent the occurrence of these risk factors. Severity values of the informational index refer to classes, and risk factors refer to features. The relationship between each component and classes can be obtained by utilizing filtering feature selection techniques. Two of these techniques employed are Chi-Squared Statistics and Information Gain methods. The relationship estimates of risk factors and severity values indicate which risk factor is more indicative for forecasting severity (class) values.

Wei Pang, Xiaofang Xie, Pengfei Fan, Jiaqi Liu[2016]: Proposed a flexible work refinement and collocation points strategy by breaking down the optimization problem into various grids, employing the

Lagrange interpolation method to estimate the optimization problem in each task, and subsequently calculating the discrete errors. Based on the discrete errors, divide the maximum error of the task into two equal grids and increase the collocation points for the remaining grids, which do not meet the tolerance, to enhance the accuracy of the solution. When the state factors and control factors are non-smooth, employ the global collocation directs insertion polynomial to tackle the problem, which can greatly impact the accuracy. To ensure solution precision, it is necessary to partition the sectioned. A series of initial grids will use the maximum error as the judgment standard to refine the task; simultaneously, identify the grids whose errors exceed the tolerable errors, then split the task into two identical grids whose errors are larger than others. When the task and the collocation points are refined, the results of the final iteration are used as the initial estimate for the next, which will improve the convergence speed.

Irit Nowik[2016]: Proposed two models; S model and T-model. In each model to characterize risk measures for the row-player (PI) and the column player (PII). The S-model characterizes another diversion in which players veer off at all perilous heading. The risk characterized in the T-model can fill in as a refinement for the idea of "trembling hand immaculate equilibrium". To create explanatory techniques for figuring the risks and the procedures that help it for every player in every one of the S-and T-models. The risk estimates characterized here empowers testing and assessing predictions on the conduct of players. The primary model relates to the vital and cognizant deviation the model "the Strategic model" (or "S-model"). The second model identifies with the incidental trembling-hand deviations and in this manner is named "the Trembling hand-model" (or "T-model"). S The more numerically testing model among the two is the S-model. In the S-model the row player (PI) and the column player (PII) each picks the bearing of deviation and then PI and PII both get the (distinction in) payoffs, which results from the deviations from the NE. In this way the S-model can be seen as another lose-lose situation, characterized over the first diversion. In the S-model the players control the bearing of their deviations.

3. PROPOSED WORK

3.1 Fuzzy Based Credit Prediction Using Genetic Approach

The reminiscence cells in natural genetic method system are used for casting off similar overseas materials. In this bankruptcy, we have employed genetic method reminiscence at some point of the cloning system for decided on B cells. Consistent with the cloning technique, a B mobile is changed randomly. Randomness of the change is a manner of exploring inside the search area. The balance of exploration and exploitation is a main hassle in heuristic seeks algorithms. So that you can make the most the preceding expertise of cloning, the memory statistics the modifications of B cells, which permits the set of rules to provide higher quality B cells. The cloning method with this sort of reminiscence will increase the possibility of modifications, which have been recorded in memory in former iterations of set of rules. We called this kind of reminiscence simple reminiscence. In every generation, the contents of memory degrade slightly. The effectiveness of reminiscence decreases regularly the usage of the proliferation method. Whilst the generation of excessive satisfactory B cells using the memory is stopped, the range of biased memory-primarily based adjustments decreases for this reason. The proposed algorithm was given here.

```
(1) procedure Proposed Classifier
(2) do
(3)  Set current learning class as c;
(4) While Termination Test
(5)    Generate initial B-cell repertoire from class c antigens;
(6)    While cycle < Max_Iterations {
(7)    Perform Clonal Selection Procedure;
(8)      // Use three selection procedures as:
(9)     //(1) Roulette Wheel Selection,
(10)   //(2) Tournament Selection,
(11)    //(3) Uniform Selection.
(12)   Use memory (Simple and k-layered to clone selected B-Cells;
(13)   Perform Hyper-mutation;
```

(14) }
(15) Perform Rule Learning Procedure;
(16) //(1) Select the best B cell
(17) //(2) Add rule of the best B cell to the current rule set
(18) If classification rate is not increased, then the current loop exits.
(19) }
(20) Until All classes have been learned

Algorithm 1: Genetic Approach

(1) Initialization: in this stage, a population of B cells is generated. the quantity of initial population is normal. This variety is a parameter that's referred to as initial populace length. To generate a B cellular, an instance of current-day magnificence from facts set is selected randomly and fuzzy terms for antecedent a part of the guideline of thumb (B cell) are computed in step with every attribute cost of the chosen schooling instance. Consequent part of the generated rule turns into the magnificence of determined on example. Preliminary age of B mobile is another parameter denoted through default Age. After generation of initial population, health is computed for each B cellular independently.

(2) Rule Generation: A population of B cells searches for optimized rule iteratively. At the first step of GENETIC approach, a few B cells are decided on to be cloned. this option is primarily based on roulette-wheel selection set of rules. B cells with better fitness have extra hazard to be decided on. The number of decided on B cells is steady (selection size). Now it is time to proliferate the selected B cells. Hypermutation occurred during the cloning process. A B cell includes a rule and the guideline has antecedents. Hypermutation considers a trade to those antecedents which causes a alternate to the corresponding B cellular. most number of simultaneous adjustments in antecedents of a B cellular might be determined by way of a parameter which is called max term changes wide variety.
We need to limit the variety of modifications because growing the wide variety of modified antecedents of a rule will increase the opportunity of corruption of that rule notably. Now a random range is generated to determine the range of adjustments to the selected B cell (max price is max term modifications quantity), after that the set of rules determines which antecedents ought to be changed the use of genetic method reminiscence. on this set of rules, simple reminiscence is offered by means of a matrix. Rows are fuzzy terms, columns are attributes, and entry (i,j) is the value of changingjth attribute to ith fuzzy term, so the opportunity of choosing jth characteristic is sum of jth column entries divided by using sum of all entries and the probability of changing to a fuzzy term is proportional to the value of every fuzzy term.
The determination of accurate aspect which could be able to reveal the development of a alternate is vital. in this set of rules, we use relative affinity (distinction of new affinity and old affinity) as fee of a exchange to a fuzzy term. If the set of rules uses k-layer memory, we should note that ok is similar to max term adjustments number. The k-layer reminiscence carries ok matrices. size of 1-matrix is like simple reminiscence. p-matrix is used whilst p simultaneous adjustments happened; consequently, the number of columns would be equal to the variety of attributes or C (attributes, p) and the range of rows could be the same as num of fuzzy terms^p . If we do now not use memory, the probability of changing an attribute price to do not care is a parameter this is known as don't Care alternative charge.

The effect of reminiscence controls by means of weight approach of default chance and memory possibility. This weight is a parameter that's referred to as memory Weight. Range of clones produced for each B cell is every other parameter which is called clone number. The age of generated B cells is calculated using (5). This equation controls the population length. Keep in mind

$$\mathrm{Age}^{\mathrm{new}} = \mathrm{Age}^{\mathrm{old}} + \mathrm{Age}^{\mathrm{default}} \times \mathrm{affinity\ if\ affinity}^{\mathrm{new}} > \mathrm{affinity}^{\mathrm{new}}$$

After cloning, B cells of preceding generations have become older. A few B cells would be deleted from the main populace because their age reaches 0.

(3) Rule Learning: Whilst AIS set of rules is completed, the fittest B mobile is chosen. The guideline which is represented by way of this B mobile is delivered to the very last resulted rule set. Then, the category price of present day rule set is in comparison to the antique rule set which does not include the brand new rule. Category rate is calculated the usage of (6). If the distinction is higher than a threshold (accuracy Threshold), the addition is prevalent. Take into account

$$classification\, rate = \frac{NCP}{number\ of\ patterns}$$

(4) Termination Test: If a stopping condition is satisfied, the mastering of contemporary class is finished, and the algorithm goes to analyze the next class. If the situation isn't pleased, the algorithm tries to research any other rule by way of initializing a new population for the following execution of AIS. We will use any stopping situation for terminating the loop. We limit the wide variety of learned policies for every elegance. That is finished with the aid of a parameter that is called max Rule Set length.

3.2 Classifier Comparison On Enhanced Fuzzy Based Genetic Approach

A GFS is fundamentally a fuzzy system increased by a learning procedure based on evolutionary calculation, which incorporates any technique for EC family, for example, Genetic Algorithms, genetic programming, and evolutionary methodologies. The most broad GFS type is the Genetic Fuzzy Rule Based System (GFRBS), where GA is utilized to learn or tune (enhancing parameter) various parts of a Fuzzy Rule Based System (FRBS). In the structure of GFS, a GA is utilized to look into the exhibition of Fuzzy Logic controller (FLC) yet the presentation of FLC relies upon its Knowledgebase (KB) comprising Database (DB) and Rulebase (RB). So as to achive plan of FRBS, errands, for example, structuring derivation instrument just as age of fuzzy rule set (KB or FRB) are required to be fulfilled. FRBSs are not ready to learn themselves, however require the KB to be gotten from master information. So as to evacuate such impediment, evolutionary learning procedure ends up basic to utilize to mechanize FRBS structure. By using this sort of learning process FRBS can be characterized naturally. The expressed sort of configuration can be considered as an advancement or search issue. So as to take care of advancement issues, GAs are chosen because of real capacities, for example, Being worldwide hunt technique, GAs can investigate enormous a pursuit space; Able to discover close ideal arrangements in complex inquiry spaces; and Able to give conventional code structure and free execution. The overall architecture is given in figure 1.

1. Interface Layer

The base layer of the Genetic-Fuzzy Rule Based System is named as interface layer. It is made out of three noteworthy segments: Environment, FRBS and Output Interface. This layer is fundamentally organized utilizing input interface, examination with fuzzy system and handled yield of FRBS. Here, the information interface characterizes the individuals from an application space and collaborate with FL layer which is in charge of structuring and executing the fuzzy system. The FL layer is clarified as under.

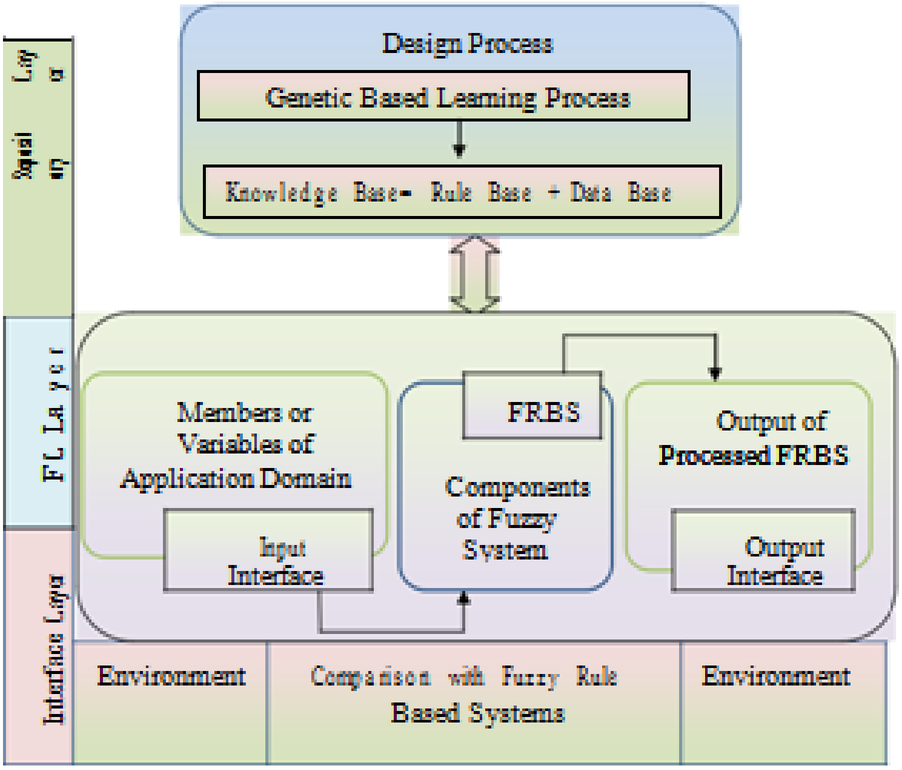

Figure 1: General Structure of Genetic Fuzzy Rule Based System

2. FL Layer

The center layer of the Genetic Fuzzy Rule Based System is named as FL layer. It associates with the interface layer to have input factors. This layer comprises of different parts, for example, Fuzzification Interface, Inference Mechanism and Defuzzification Interface. This layer is capable to plan the procedures which are identified with fuzzy system execution. The information interface chooses the individuals or the factors of the application space so as to produce fuzzification. The induction instrument is planned utilizing the individuals which are chosen in the information interface and will be engaged with the way toward producing the FRBS. The yield interface is in charge of defuzzification of information factors. It gives the outcomes created by Fuzzy System (FS).

3. Repository Layer

The top most layer of the Genetic Fuzzy Rule Based System is named as vault layer. This layer is in charge of planning of GFRBS. So as to structure, GFRBS, evolutionary systems are required to be consolidated so as to accomplish programmed age or adjustment of whole piece of the Knowledge Base (KB). KB is a blend of Data Base (DB) and Rule Base (RB). The parameters of knowledgebase incorporate fuzzy rules and participation capacities. Both the constituents associate with derivation system of the center layer. So as to accomplish advancement, it is required to locate a proper KB.

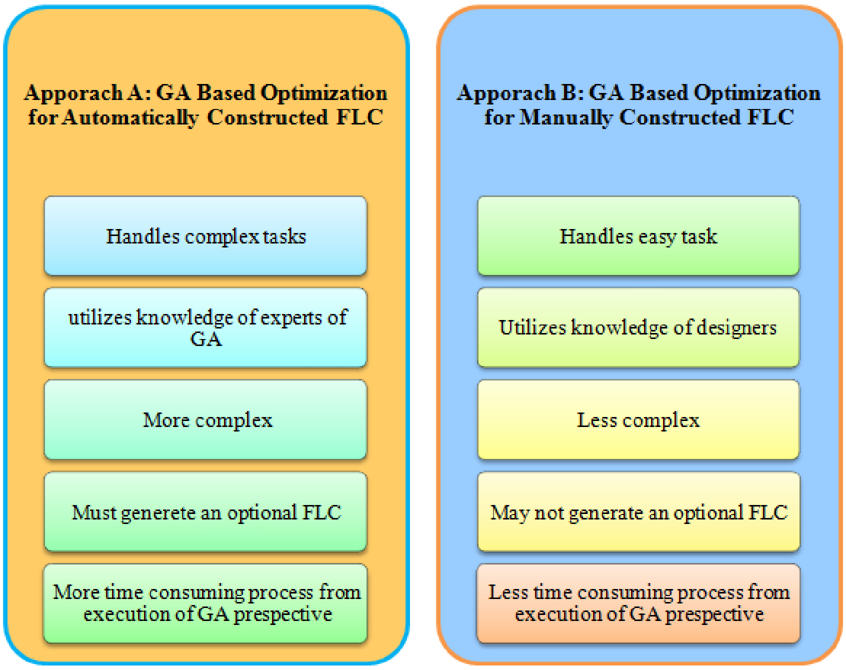

Figure 2: Approaches for GA based Optimization for FLC

Approach A: GA based optimization for automatic constructed FLC

The approach "A" is basically reasonable for fathoming complex undertakings. For a mind boggling task, it is extremely hard to plan KB physically in light of the fact that in such cases execution of GFS can't be accomplished according to desires. Programmed plan of FLC through GA progresses toward becoming answer for complex errands. GA uses data of DB, RB and resulting some portion of each rule of the FLC. The predefined preparing set is used by GA strings to improve FLC whicg is given in figure 2. Therefore, ideal FLC can be advanced through cycles. To plan system based on such approach is a basic assignment.

Approach B: GA based optimization of manually constructed FLC

The working normal for the approach "B" is based on designer‟s information of the procedure to be controlled. So as to process etymological information portrayal, scopes of factors are chosen and distinctive semantic terms are planned according to prerequisites of the issue. The quantity of information blends for the structure of FLC relies upon the quantity of info factors and their semantic terms. So as to propose the DB of the FLC physically, it is needed dispersion of participation capacities and factors by fashioner and proper structure of RB is made conceivable, later. This kind of structure of FLC might be adaptable however it isn't ideal also. In this approach, a GA is utilized to tune the DB and additionally RB of the FLC with the assistance of preparing situations. After the GA-based tuning is finished, the FLC will most likely decide the yield for a lot of contributions inside a sensibly precision limit. Figure 7.2 speaks to parallel approaches to be specific "An" and "B" alongside their attributes for creating Genetic-Fuzzy systems.

4. EXPERIMENTAL RESULTS

4.1 Fuzzy Based Credit Prediction Using Genetic Approach

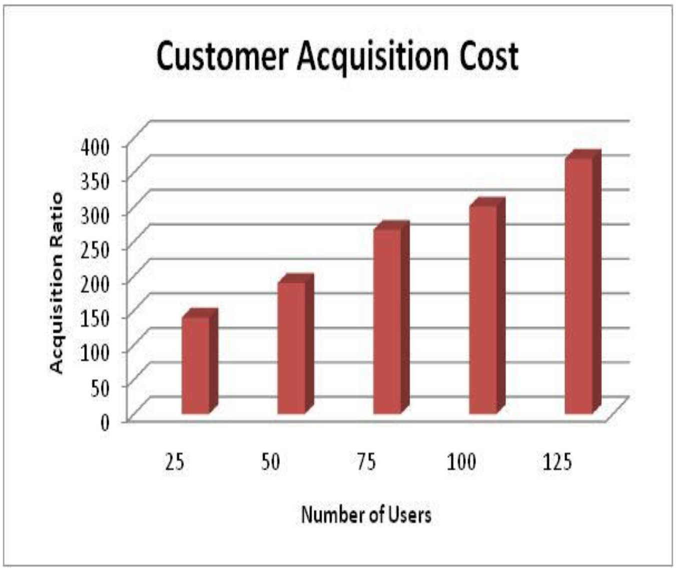

Figure 3: Chart of Customer Acquisition Cost

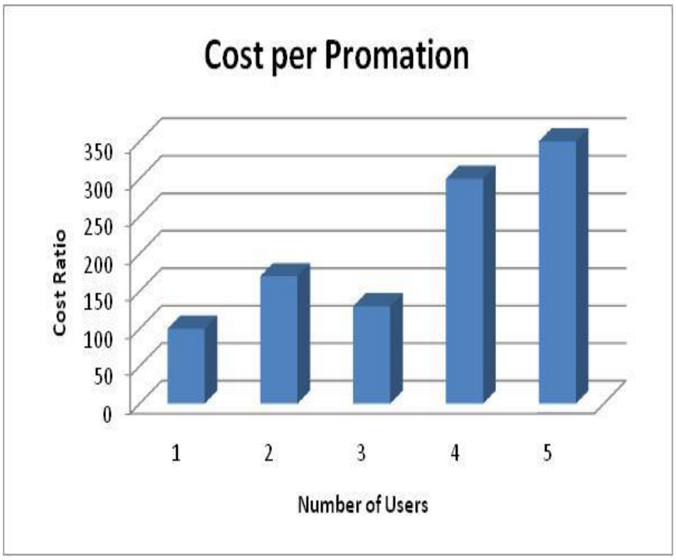

Figure 4: Chart of Cost per Promotion

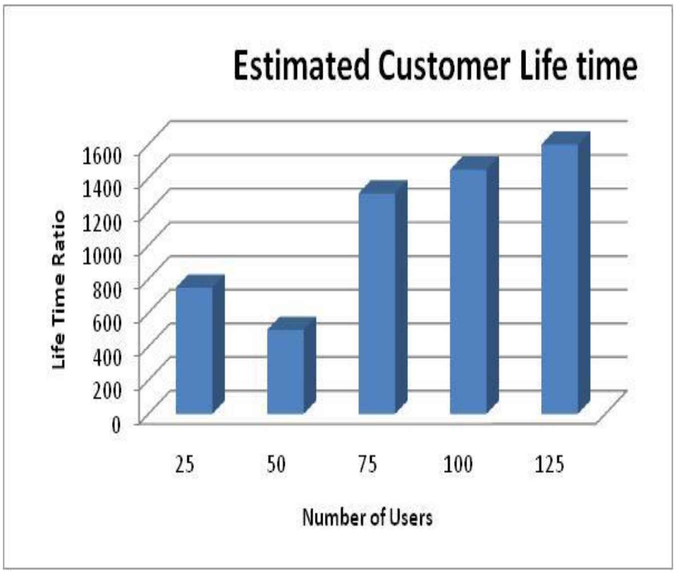

Figure 5: Chart of Estimated Customer Life time

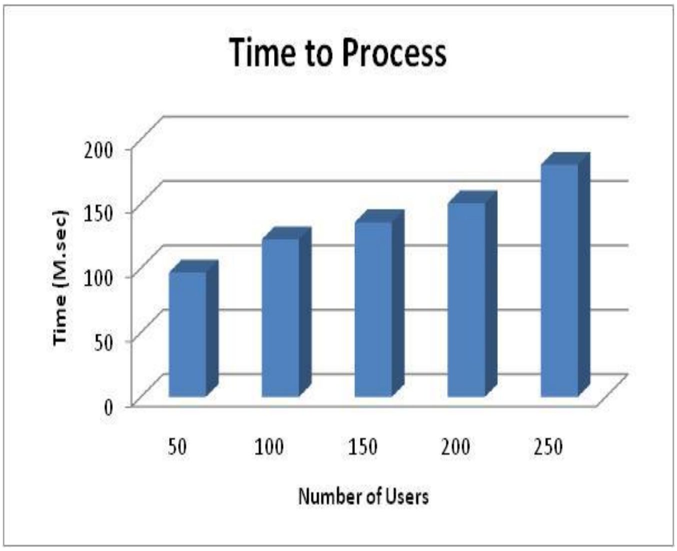

Figure 6: Chart of Time to Process

The Figure 3 Customer Acquisition Cost shows the different values of number of users and the acquisition ratio. Number of Users in x axis and the acquisition ratio in y axis. If the no of users is 25 then the Acquisition ratio becomes 140.Also, if the no of users is 50 then the acquisition ratio becomes 190.Until the no of users 125 then the acquisition ratio becomes 370. Therefore, the customer acquisition cost is varied depending upon the no of users and the acquisition ratio.

The Figure 4 Cost per promotion shows the different values of number of users and cost ratio. Number of users in x axis and the cost ratio in y axis. If the number of users is 30 then the Cost ratio becomes 100. Also, if the number of users is 60 then the cost ratio becomes 170. Until the number of users 150 then the cost ratio becomes 350. Therefore, the cost per promotion is varied depending upon the number of users and cost ratio.

The Figure 5 Estimated Customer Life time shows the different values of number of users and Life time ratio. Number of users in x axis and the Life Time ratio in y axis. . If the number of users is 25 then the estimated customer life time value becomes 750. Also, if the number of users is 50 then the estimated customer life time value becomes 499. Until the number of users 125 then the estimated customer life time value becomes 1600. Therefore, the Estimated Customer life time is varied depending upon the number of users and the estimated customer life time values.

The Figure 6 Time to process shows the different values of number of users and Time. Number of users in x axis and Time in y axis. If the number of users is 50 then the Time ton process becomes 96.5. Also, if the number of users is 100 then the time to process becomes 122.3. Until the number of users 250 then the Time to process becomes 180.2. Therefore, Time to process is varied depending upon the number of users and time to process.

4.2 Classifier Comparison On Enhanced Fuzzy Based Genetic Approach

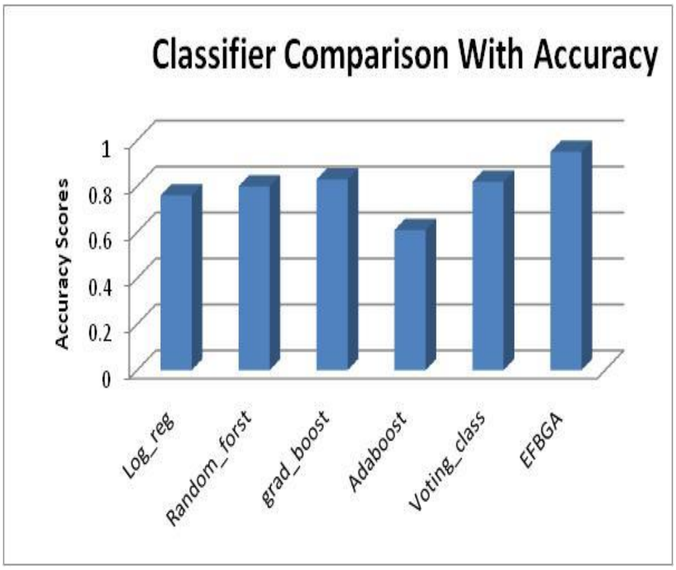

Figure 7: C omparison with Accuracy

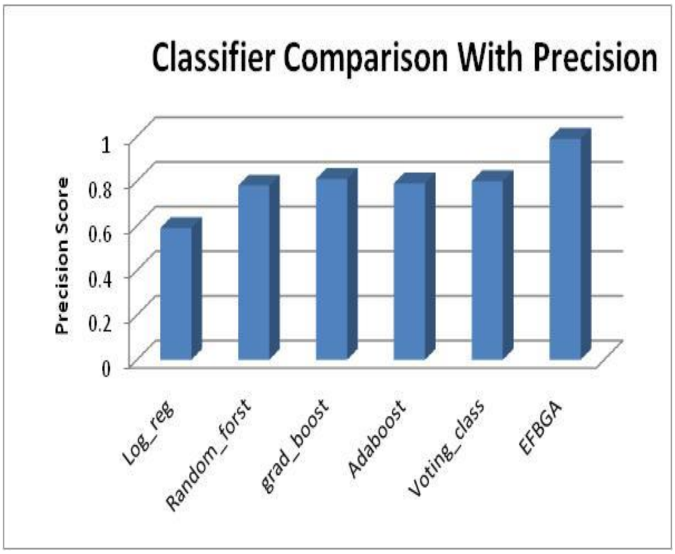

Figure 8: Comparison with precision

The figure 7 shows in classifier comparison with accuracy explains the values of log reg, random forst, grad boost, adaboost, voting class and EFBGA. While comparing these values grad boost value is higher than the other. Log reg, random forest, grad boost, adaboost, voting class, EFBGA values in X axis and accuracy scores in Y axis.

The figure 8 shows in classifier comparison with precision explains the values of log reg, random forst, grad boost, adaboost, voting class and EFBGA. While comparing these values grad boost value is higher than the other. Log reg, random forst, grad boost, adaboost, voting class and EFBGA values in X axis and precision scores in Y axis.

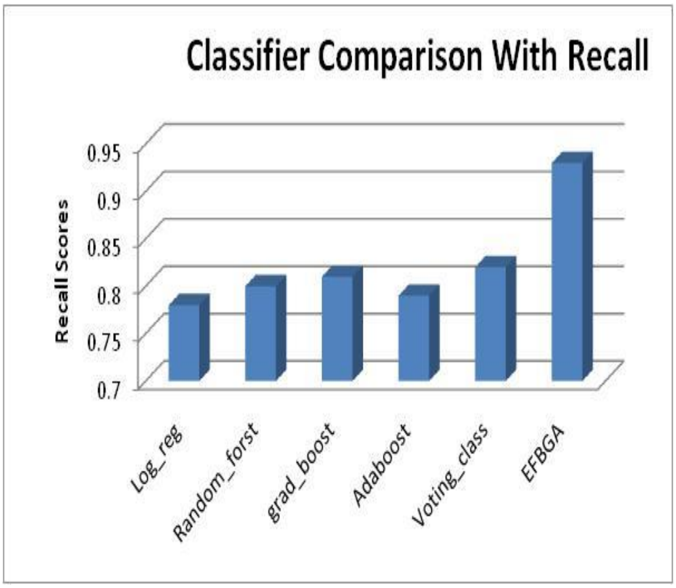

Figure 9: Comparison with Recall

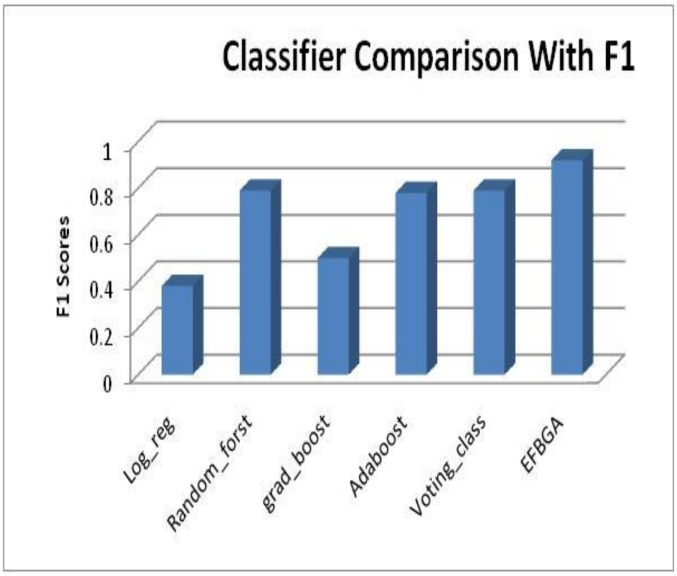

Figure 10: Comparison with f1

The figure 9 shows in classifier comparison with recall explains the values of log reg, random forst, grad boost, adaboost, voting class and EFBGA. While comparing these values grad boost value is higher than the other. Log reg, random forst, grad boost, adaboost, voting class and EFBGA values in X axis and recall scores in Y axis.

The figure 10 shows in classifier comparison with f1explains the values of log reg, random forst, grad boost, adaboost, voting class and EFBGA. While comparing these values grad boost value is higher than the other. Log reg, random forst, grad boost, adaboost, voting class and EFBGA values in X axis and f1 scores in Y axis.

CONCLUSION

Proposed a fuzzy classification device for credit scoring called the GENETIC approach, which utilizes genetic memory to retain suitable B cells during the cloning process. We developed two forms of memory: simple memory and layered memory. Results demonstrated that our new definition of memory for the genetic approach-based fuzzy rule extraction significantly enhances the final classification rate of credit risk prediction. Proposed the necessity of combining GA with FS is explained. To achieve such integration, two significant GA-Fuzzy hybrid methods have been examined: Evolutionary Algorithm aided by Fuzzy Logic and Genetic-Fuzzy Systems. This section elaborates on GFS in broad ranges of methodologies for genetic rule learning. The overall structure of GFS has been presented along with two significant methods for improved rule learning utilizing GA for both automatically generated FLC and manually designed FLC. The mechanisms of Genetic-Fuzzy hybridization are organized using two popular styles of encoding: "Chromosome is rule" approach and "Chromosome is set of rule" approach. Genetic-Fuzzy hybridization methods are devised using either of the two aforementioned styles. GFS hybridization is categorized into three major approaches: the Michigan, the Pittsburgh, and The IRL.

REFERENCES:

1. Krunal M. Surti , Mr. Ashish Patel, “Effective Credit Default Scoring using Anomaly Detection”, IJSTE - International Journal of Science Technology & Engineering | Volume 3 | Issue 11 | May 2017 ISSN (online): 2349-784X.
2. Simon Lohm¨uller, Fabian Rabe, Andrea Fendt, Bernhard Bauer, Lars Christoph Schmelz**,** “SON Function Performance Prediction in a Cognitive SON Management System”, 2018 IEEE Wireless Communications and Networking Conference Workshops (WCNCW): 7th International Workshop on Self-Organizing Networks (IWSON).
3. M.Ozgur Cingiz, Ahmet Unudulmaz, Oya Kalıpsız, “Prediction of Project Problem Effects on Software Risk Factors”, 12th IEEE International Conference on Intelligent Software Methodologies, Tools and Techniques.
4. Wei Pang, Xiaofang Xie, Pengfei Fan, Jiaqi Liu**,** “An Adaptive Collocation Method and Mesh Refinement for Solving Non-smooth Trajectory Optimization problems”, 2016 8th International Conference on Intelligent Human-Machine Systems and Cybernetics.
5. Irit Nowik**,** “The Game on the Risk in Deviating from Nash Equilibrium”, Second International Symposium on Stochastic Models in Reliability Engineering, Life Science and Operations Management.
6. Joshua T. Cook, Laura E. Ray and James H. Lever, “Dynamics Model for Mobility Optimization and Control of Off-Road Tractor Convoys”, 2016 American Control Conference (ACC) Boston Marriott Copley Place.
7. Yahya Choua, Laurent Santandréa, Yann Le Bihan, and Claude Marchand, “Mesh Refinement in Eddy Current Testing With Separated T-R Probes”, IEEE TRANSACTIONS ON MAGNETICS, VOL. 46, NO. 8, AUGUST 2010.
8. Jihoon Seo, Juyul Lee, and Keunyoung Kim “Decoding of Polar Code by Using Deep Feed-Forward Neural Networks” IEEE2018,2018 workshop on computing,Networking and Communications.
9. Ghulam Mohi Ud Din, Angelos K. Marnerides**,** “Short Term Power Load Forecasting Using Deep Neural Networks”IEEE2017, 2017.International Conference on Computing, Networking and Communications (ICNC): Green Computing, Networking, and Communications.

10. Carlos Bentes, Domenico Velotto, Susanne Lehner**,** "TARGET CLASSIFICATION IN OCEANOGRAPHIC SAR IMAGES WITH DEEP NEURAL NETWORKS: ARCHITECTURE AND INITIAL RESULTS"IEEE2015.
11. Nimish Shah, Paragkumar Chaudhari, and Kuruvilla Varghese, " Runtime Programmable and Memory Bandwidth Optimized FPGA-Based Coprocessor for Deep Convolutional Neural Network"IEEE2018. IEEE TRANSACTIONS ON NEURAL NETWORKS AND LEARNING SYSTEMS
12. Nima Amini, Seyyed Ali Seyyedsalehi, " Manipulation of attractors in feed-forward autoassociative neural networks for robust learning"IEEE2017.
13. Paul M. Baggenstoss " On the Duality Between Belief Networks and Feed-Forward Neural Networks"IEEE2018.
14. Yiming Tian, Xitai Wang "SVM ensemble method based on improved iteration process of Adaboost algorithm"IEEE2017.
15. Mücahid Barstugan, Rahime CEYLAN "A Discriminative Dictionary Learning-AdaBoostSVM Classification Method on Imbalanced Datasets"IEEE2017.