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An extension of complex fuzzy inference system for alert earlier credit risk at business banks

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Abstract: The purpose of this study is to suggest a novel integrated model for assessing credit risk at commercial banks that is based on a complex fuzzy transfer learning framework. Research Design and Methodology: We used transfer learning on a complex fuzzy inference system, complex fuzzy set theory, and a complex fuzzy inference system to build a credit risk prediction model. Parallel to this, we compared the proposed model with the previously used credit risk prediction method known as the Mamdani CFIS model. Results: The study has validated the complex fuzzy inference model's capacity to accurately predict credit risk. When compared to the Mamdani CFIS model, the suggested model exhibits superior time performance. In particular, the time needed to construct the intricate fuzzy inference system and to carry out inference in the suggested model is much reduced when compared to the Mamdani CFIS. Conclusion: In addition to elucidating the role and possibilities of complex fuzzy inference systems, this work shows that the transfer learning model on complex fuzzy inference systems may significantly accelerate the prediction of credit risk. This is especially important in the context of early warning, which enables commercial banks to implement more efficient risk prevention and management strategies.

Keywords: *Complex fuzzy inference system, Complex fuzzy transfer learning, Credit risk, Fuzzy inferecne system.*

1. Introduction

Bank risks rise in tandem with the economy's demand for capital, putting significant strain on credit risk management. Credit risk mitigation has gained importance since the 2007–2008 financial crisis, which compelled financial institutions to gather all the data they needed to make the right choices. When it comes to precisely determining a customer's capacity to repay loans, risk analysts are crucial. Early warning of credit risks is therefore regarded as a useful remedy, assisting commercial banks in identifying and reducing the percentage of clients with past-due loans or bad debts while preserving credit quality. Regularly re- viewing and assessing investment portfolios can help achieve this. Predictive models for banking financial crises are becoming a vital tool for spotting early warning signs in the banking sector.

Banking risk issues have been examined using a variety of methodologies, from traditional techniques to state-of-the-art AI and machine learning technology. Examples include neural networks, swarm intelligence, fuzzy logic, genetic algorithms, and artificial neural networks (ANN).

Fuzzy logic and fuzzy set theory, introduced initially by Zadeh [1] have drawn the interest of several academics. Since then, fuzzy inference models have been used in various fields, including commercially significant ones. Seyfi-Shishavan, et al. [2] have sought to investigate the significant impacts of the COVID-19 pandemic on the financial industry. The weights of the important components are estimated using a novel and extended intuitionistic fuzzy best-worst method (IFBWM), and the performance index of the banking sector is calculated using a fuzzy inference system (FIS). The

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proposed method looked at how the banking sector finances supply chains and pinpointed the main dangers this sector confronts in times of emergency, such as pandemics.

Karbassi, et al. [3] describes the usage of a three-stage hybrid FIS for credit scoring as a statistical method for assessing credit ratings in ambiguous situations. Turkey's national banks tested this model. The authors in research in Fonseca, et al. [4] developed a novel two-stage procedure that uses soft computing techniques (FIS and neural net- works) and analyzes and assesses the usage of soft computing systems for clients' credit risk assessment in a Brazilian private credit card issuer. Shariatmadari, et al. [5] proposed a Fuzzy Inference System (FIS) model that applies Gaussian membership functions to credit scoring for corporate customers in the banking industry. The model is validated through an extreme condition test, showing its high practical applicability in credit risk assessment by Shariatmadari, et al. [5]. Mehdi, et al. [6] studied Adaptive Neural Network-Based Fuzzy Inference System (ANFIS), which combines neural networks and fuzzy logic, to assess the impact of risks on financial performance.

A comprehensive risk index that takes into account all banking risk categories and characteristics was developed using a fuzzy inference system based on adaptive neural networks by Ahmed, et al. [7]. This approach determines the most important risk factors, the general risk trend, and the relative significance of a bank's risk ratios in influencing its financial health. The Self-Evolving Recurrent Neuro- Fuzzy Inference System (SERNFIS) and modified differential harmony search were used by Dash and Dash [8] to test a model for stock price prediction. They used data from a time series of the stock market over several time ranges. The fuzzy IF-THEN rules and Takagi-Sugeno-Kang (TSK) model were also applied. To evaluate performance and analyze the likelihood of going bankrupt, Kin, et al. [9] built an easy bankruptcy prediction model utilizing the FIS for individuals and businesses.

According to the reviewed literature, there has been a great deal of research on the use of FIS for corporate and bank insolvency prediction. However, imprecision pervades our daily lives, and the uncertainty of real-life data increases as variations in the data's processes (periodicity) become more pronounced. None of the current theories can fully explain situations where data are only partially known. They fall short in their capability to take responsibility for periodic information that contains uncertain components, which causes information loss.

Ramot, et al. [10] 's addition of the complex term to the phase term to capture temporal and periodic occurrences helped deal with occasional factors in data, which helped conceptualize the complex fuzzy set (CFS). For financial trend prediction modeling with uncertain data, the ANCFIS (Adaptive Neuro Complex Fuzzy Inference System) model by Chen, et al. [11] is advised. Furthermore, the Mamdani Com- plex Fuzzy Inference System (Mamdani-CFIS) in Selvachandran, et al. [12] has been introduced recently and is appropriate for decision support problems due to its unique inference structure. The training and testing processes in Mamdani-CFIS have since been enhanced by three extensions: the Complex Fuzzy Transfer Learning model in Huong, et al. [13], MCFIS with Rule Reduction in Tuan, et al. [14] and MCFIS with Fuzzy Knowledge Graph by Lan, et al. [15].

The aforementioned poll makes it evident that many academics are interested in studying early warning signs of credit hazards. The results of several studies have been published, and all of these have helped to lower banks' risk ratios. New tactics that enable the organization's goals to be achieved more rapidly and precisely are also essential as competition heats up and bank demands and targets increase daily. Therefore, in order to assess and empirically determine the degree of financial risk that consumers face and to give early warning of a customer's bad debt position, the research team used complex fuzzy theory, more especially the complex fuzzy inference model.

This work introduces a version of CFTL to assess a customer's credit standing and give credit institutions recommendations and alerts based on customer data. Our suggested model is evaluated against analogous approaches on the Credit ScoreCard dataset in terms of accuracy, computation time, and number of rules. The benefits and applicability of the suggested model were confirmed by the experimental findings.

This article's remaining portion is organized as follows: The preliminary information is presented in Section 2, which includes the basic definitions of the CFTL and the Mamdani-CFIS model. The novel Mamdani CFIS extensions that com- bine CFTL and Mamdani-CFIS are investigated in Section 3. On Credit ScoreCard datasets, Section 4 contrasts our suggested model's performance with that of the existing Mamdani-CFIS approaches on Credit ScoreCard datasets in terms of predicted time, accuracy, and number of rules. The final section must summarize the work that will be done after this one.

2. Preliminaries

2.1. The Mandani Complex Fuzzy Inference System's Operation (MCFIS)

For processing data with periodic and ambiguous occurrences, the MCFIS in Selvachandran, et al. [12] is a promising fuzzy system due to its ease of use and adaptability in simulating nonlinear dynamic systems. The following steps make up the MCFIS process:

a) Fuzzification: The fuzzification procedure involves fuzzifying the input data with each linguistic label's complex fuzzy membership functions.

b) Aggregation: Calculate each rule's firing strength from the membership values.

c) Consequence: Use the rule firing strength to find the consequent values for each complex fuzzy rule.

d) Defuzzification: This phase involves transforming the complex fuzzy results from the previous step into precise values.

2.2. Complex Fuzzy Transfer Learning (CFTL)

The CFTL model was introduced by Huong, et al. [13] to enhance the quality of the existing inference process concerning periodic events. When reference or forecast information is scarce, the model facilitates knowledge transmission. The model accomplishes knowledge transfer in the absence of reference or predictive information. This model combines FIS and machine learning methods—transfer learning—to solve the shortage of knowledge. Using a previously learned model to train a new model has the advantage of transfer learning.

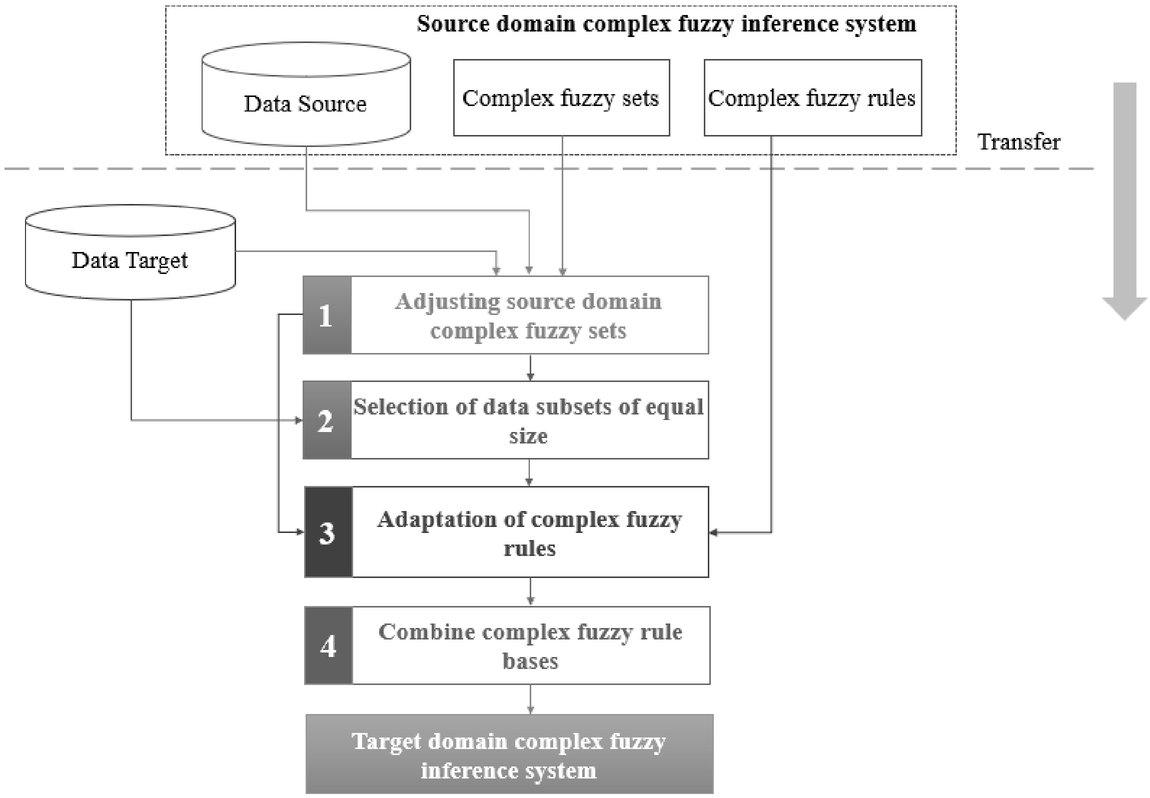

Figure 1.
Complex Fuzzy Transfer Learning Framework by Huong, et al. [13].

There are four primary stages in the CFTL design. The source domain com- plicated fuzzy set is first modified to fit the destination domain. The next step involves choosing equal-sized data subsets at random using the target's attribute fields and data labels. Each data record within the subset will generate adaptation rules, and a data subset will generate a set of adaptive complex fuzzy rules (CFRs). The final adaptive rules, which serve as the foundation for inference in the target domain, are created by combining adaptive CFRs.

The use of the CFTL models enables the early development of learning models based on limited data sizes. This is particularly beneficial in improving the initialization performance of complex fuzzy inference models, which are designed to enhance accuracy by incorporating complex factors. However, these factors often result in prolonged model initialization times. By leveraging transfer learning, CFTL can utilize knowledge from previously trained models, reducing initialization time while maintaining high efficiency and accuracy.

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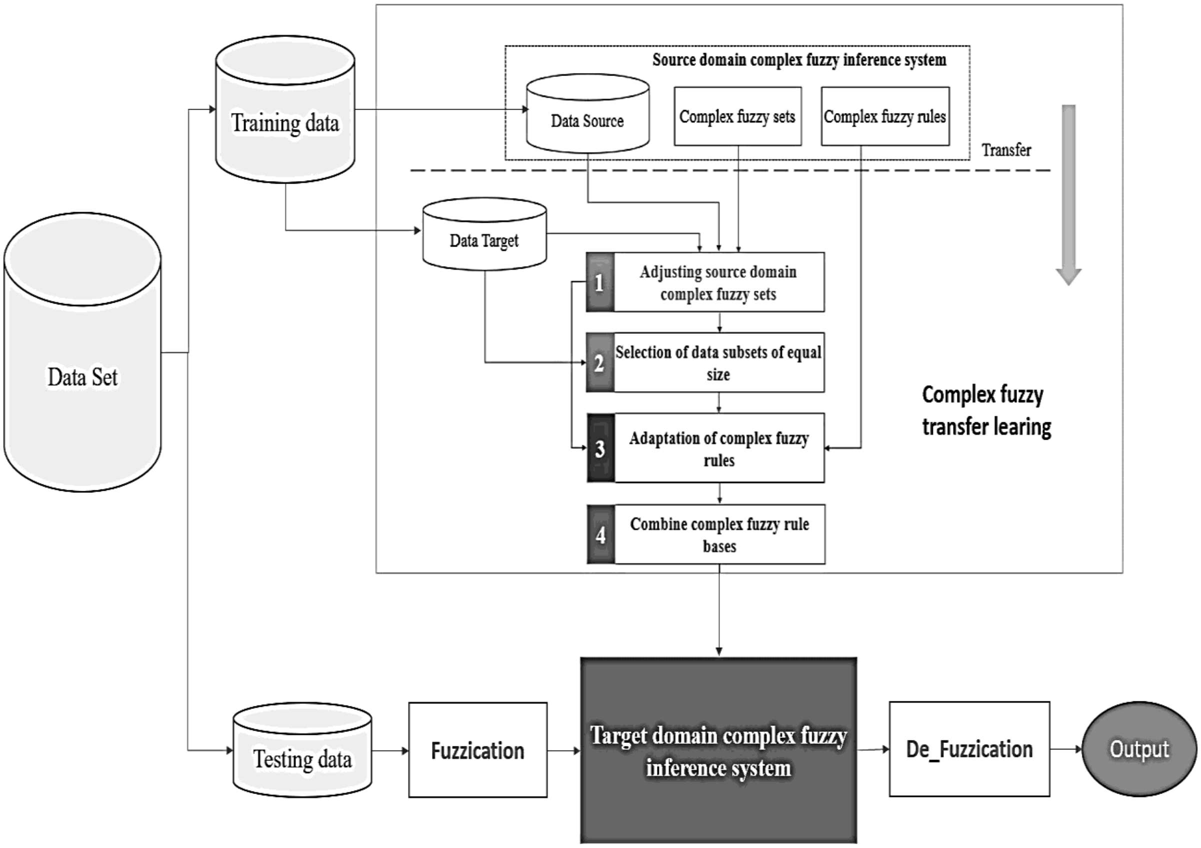

Figure 2.
Mamdani CFTL Model for Alert Earlier Credit Risk.

3. An Enhanced Mamdani Complex Fuzzy Inference System for Alert Earlier Credit Risk

This section introduces the Mamdani CFIS extension (Mamdani-CFTL), which combines Mamdani-CFIS with Complex Fuzzy Transfer Learning for Alert Earlier Credit Risk. Figure 2 illustrates this. In addition to an adaptive complex fuzzy rule base in the form of IF-THEN statements, this model is composed of three parts: fuzzification, fuzzy inference, and defuzzification. Complex fuzzy transfer learning is the process of employing adaptive complex fuzzy rules to translate complex fuzzy inputs into complex fuzzy outputs. Any vector aggregation procedure can be used to combine the results of various rules to form a single complicated fuzzy output set. The complex fuzzy output set from the second stage is subsequently transformed into clear results using the defuzzification approach.

There are six stages in the Mamdani CFTL's general framework.

Stage 1: Establish an adaptive complex fuzzy rule-base using complex Fuzzy transfer Learning.

Stage 2: Fuzzification of the inputs

The choice of the complex fuzzy inputs is the classical complex membership function in the form:

$$\phi(x)= \varphi(x).e^{j\mu(x)} \quad (1)$$

where $\mu(x) \in (0, 2\pi]$, $\varphi(x) \in [0, 1]$ and $\varphi(x)$ and $\mu(x)$ represent the amplitude and phase terms of the elements, respectively.

Stage 3: Determine the firing strength of the complex fuzzy rule.

The firing strengths ω_u for each complex fuzzy rule are calculated in this step. The following function can be used to estimate the value ω_u:

$$\omega_u = \tau_u.e^{j\psi u} \quad (2)$$

Stage 4: Determine the outcome of the complex fuzzy rules.

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The Mamdani implication rule is used in Mamdani CFIS to determine the value of the consequence of the complex fuzzy rules.

$$\phi_{A\rightarrow B}(x,y) = (\varphi_A(x).\varphi_B(y)).e^{j2\pi\left(\frac{\mu_A(x)}{2\pi}.\frac{\mu_B(y)}{2\pi}\right)} \quad (3)$$

Choose a function $U_0 : [0, 1]^2 \rightarrow [0, 1]$, with $U_0(1, 1) = 1$, and a function g_0: $(0, 2\pi]^2 \rightarrow (0, 2\pi]$, with $g_0(2\pi, 2\pi) = 2\pi$. We form the consequent of CFRu for each u:

$$\Gamma_u(y) = U_0(\tau_u, r_{Cu}(y))e^{jg_0(\psi_u, \mu_{Cu}(y))} = \omega_u.\phi_{Cu}(y)$$

(4)

where "." denotes the complex dot product.

Stage 5: Aggregation for the output distribution In this stage, the output distribution is calculated as follows:

$$D(y) = \Gamma_1(y) + \Gamma_2(y) + \ldots + \Gamma_k(y) \quad (5)$$

- Stage 6: Defuzzification and obtaining the outputs.

4. The Experiments

This section evaluates the proposed CFTL's effectiveness for alerting earlier credit risk in the commercial bank when the rule base is minimal or incomplete compared to the most recent data.

4.1. Experimental Dataset and Environment

We used a Lenovo laptop with a Core i7 processor to run the models for Python operation. Credit ScoreCard data is used to calculate the proposed Mamdani- CFTL and compare it with the related approach, Mamdani-CFIS. To ascertain Mamdani-CFTL's learning capacity to enhance the rule base in the event of knowledge leverage in the target domain of the current approach in the CFS environment, the evaluation results on three validity indicators—computational time, accuracy, and number of rules—were examined.

The experimental scenario aims to verify the Mamdani-CFTL's capacity for reasoning in circumstances of knowledge leverage and to compare it to the relevant approach, the Mamdani-CFIS. Additionally, we have designed two experimentation strategies to contrast them with the appropriate method, Mamdani-CFIS. To gauge the effectiveness of the MCFIS, scenario 1 is employed. In Scenario 2, knowledge leverage is used to test the Mamdani-CFTL's capacity for reasoning. In our trials, Hold-out cross-validation divides the datasets into two parts: training (80%) and testing (20%). We experiment based on a Credit ScoreCard dataset from Kaggle in Orange90 [16] with 120269 examples. The following Table 1 gives a summary of this dataset.

Table 1.
Credit ScoreCard data summary.

No.	Feature name	Value Range
1	Revolving Utilization of Unsecured Lines	0-9340
2	Age	21-103
3	Number Of Time 30-59 Days Past Due Not Worse	0-98
4	Debt Ratio	0-11311
5	Monthly Income	0-629000
6	Number Of Open Credit Lines and Loans	0-58
7	Number Of Times 90 Days Late	0-98
8	Number of Real Estate Loans or Lines	0-54
9	Number Of Time 60-9 Days Past Due Not Worse	0-98
10	Number Of Dependents	0-20
11	Serious Dlq in 2yrs	0-1

4.2. Experimental Results and Discussion

Figures 3, 4 and 5 show the values of the criteria that were derived by using Mamdani-CFIS and Mamdani-CFTL on the Credit ScoreCard dataset.

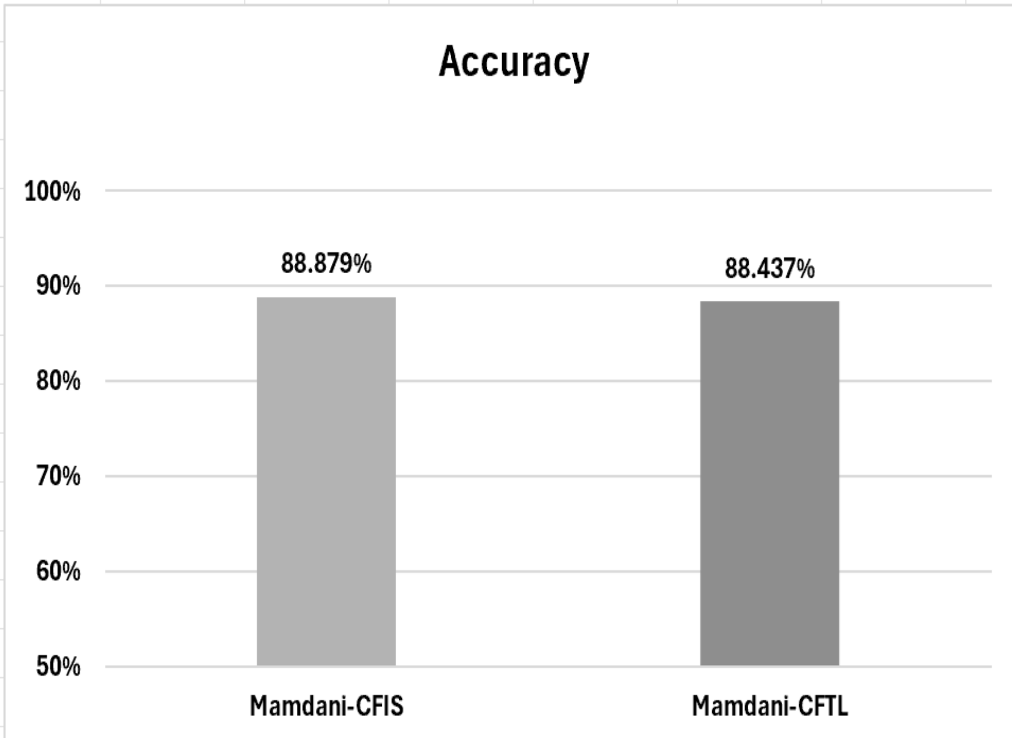

Figure 3.
The compare result on accuracy criteria.

Mamdani-CFIS's accuracy results are marginally better than Mamdani-CFTL's, as seen in Figure 3. The Mamdani-CFTL model only shows this number as 88.879%, while the Mamdani-CFIS model shows it at 88.437%. As a result, it is reasonable to conclude that the two models have equal accuracy. However, Figure 4's average number of Mamdani-CFTL rules is 2926, which is 292 fewer than Mamdani-CFIS's result. As a result, Mamdani-CFTL's rule base has fewer rules than Mamdani-CFIS'

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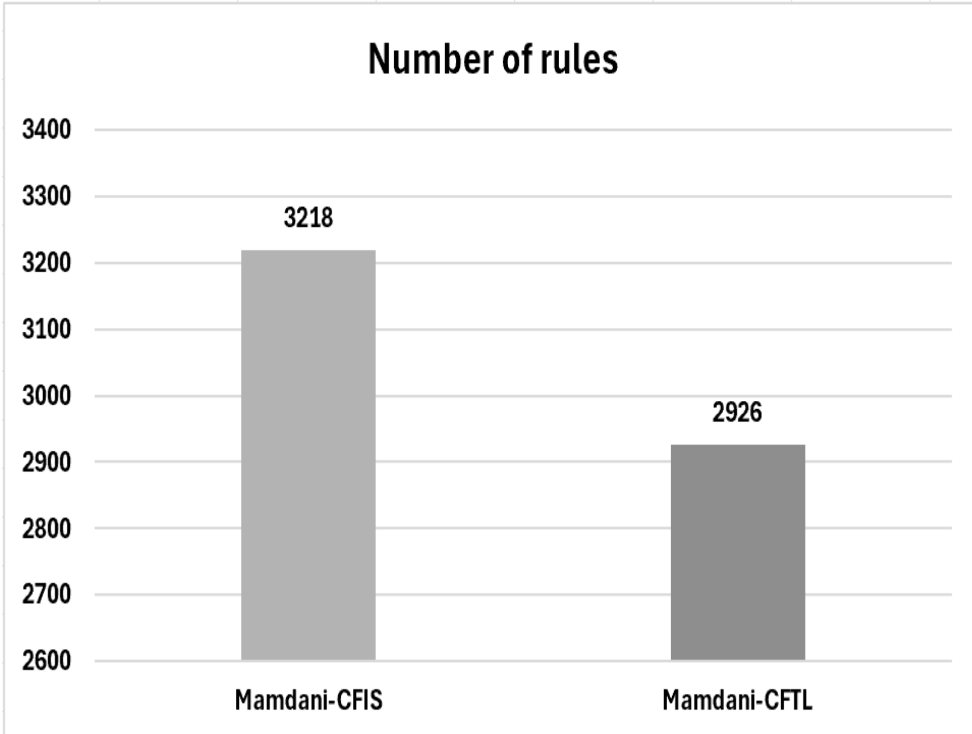

Figure 4.
The compare result on the number of rules.

Figure 5.
The comparison results on the time-consuming criteria.

Furthermore, as Figure 5 illustrates, Mamdani-CFTL takes less time than Mamdani-CFIS. For Mamdani-CFTL and Mamdani-CFIS, the average total du- ration of rule generation is 1570.24 and 14238.69, respectively, with the same ac- curacy value. These findings demonstrate how much superior the experimental outcomes with Mamdani-CFTL are. For datasets with a large number of records, the Mamdani-CFTL model has clearly shown its superiority in terms of execution time. The computation time for each performed time is almost always much shorter than that of MCFIS and has nearly the same accuracy. Furthermore, the experimental periods when Mamdani-CFTL runs longer than MCFIS correlate to periods when there are more rules and Mamdani-CFTL's accuracy is higher than Mamdani-CFIS during such periods.

5. Conclusion

Credit risk is a critical issue that can negatively impact various aspects of social economic life. For banks, credit risk not only poses the potential for severe and unforeseen losses but also undermines profitability and compromises operational security. The Complex Fuzzy Transfer Learning (CFTL) system is introduced to address the performance limitations of previous complex fuzzy inference methods in identifying credit risk. By applying this system, early credit risk prediction becomes more effective, particularly in scenarios where data is limited or incrementally updated over time.

Experimental results on the Credit Score dataset have demonstrated the proposed model's superior performance in terms of rule generation, computation time, and accuracy. These outcomes highlight the model as a reliable solution, supporting commercial banks in identifying and providing early warnings about credit risks. This, in turn, helps minimize losses and enhances operational safety in financial activities.

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Transparency:

The authors confirm that the manuscript is an honest, accurate, and transparent account of the study; that no vital features of the study have been omitted; and that any discrepancies from the study as planned have been explained. This study followed all ethical practices during writing.

Competing Interests:

The authors declare that they have no competing interests.

Authors' Contributions:

All authors contributed equally to the conception and design of the study. All authors have read and agreed to the published version of the manuscript.

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