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A Mamdani FIS to Monitor Programmer Performance on GitHub

Susi Eva Maria Purba[1], Retantyo Wardoyo*[2]
[1,2]Department of Computer Science and Electronics, FMIPA UGM, Yogyakarta, Indonesia
e-mail: *susi.eva1597@mail.ugm.ac.id, [2*]rw@ugm.ac.id

Abstrak

Bekerja dalam sebuah tim merupakan kegiatan kolaboratif yang digunakan untuk mencapai tujuan bersama. Dalam praktiknya, perlu diperhatikan bagaimana kontribusi yang tidak seimbang dapat mendemotivasi kesempatan yang mungkin dimiliki oleh anggota tim dalam berkontribusi maksimal untuk mencapai tujuan tersebut. Pengelolaan sumber daya akan sangat dibutuhkan dalam praktik kolaboratif. Salah satu cara yang dapat dilakukan adalah melakukan pemantauan terhadap kinerja setiap individu dalam tim. Pada penelitian sebelumnya, pengukuran kinerja dirancang menggunakan Prometer memanfaatkan beberapa parameter dengan memanfaatkan himpunan crisp pada setiap tahapan. Metode tersebut dikembangkan dalam penelitian ini dengan penambahan variabel dan memanfaatkan logika fuzzy yang mampu mempertimbangkan nilai keanggotaan untuk setiap nilai yang terlibat. Nilai keanggotaan yang dipertimbangkan untuk setiap variabel diharapkan dapat memberikan penilaian yang cukup signifikan terhadap setiap tim yang menjadi objek penelitian, yaitu tim yang bekerja dalam mengembangkan proyek perangkat lunak menggunakan platform GitHub. Hasil kolaborasi akan dipantau berdasarkan keterlibatan setiap kolaborator terhadap pengerjaan proyek melalui data yang terekam pada variabel pull requests, issues, commits, additions code dan deletions code. Hasil yang diperoleh dengan memanfaatkan variabel dan beberapa rule yang telah dirancang menggunakan fungsi implikasi Mamdani kemudian dibandingkan dengan hasil yang diperoleh Project Manager sehingga diperoleh nilai akurasi sebesar 86.67% untuk penggunaan rule inklusif dan eksklusif (operand AND).
Kata kunci*—Mamdani, pemantauan, pengembangan perangkat lunak, GitHub*

Abstract

A collaborative activity used to accomplish shared objectives is teamwork. It is essential to know how unequal contributions can inhibit team members' chances to give their all in achieving these objectives. It will be necessary to manage resources in this joint approach. Monitoring each team member's performance in one technique to do this. In previous research, performance measurement was designed using Prometer with several parameters, utilizing the crisp set at each stage. This study developed the method by adding variables and utilizing fuzzy logic, which can consider the membership value for each value involved. The membership value considered for each variable is expected to provide a significant assessment of each team working on developing software projects using the GitHub platform. The results will be monitored based on the involvement of each collaborator in project work through the data recorded in the pull requests, issues, commits, additions code, and deletion code variables. The results obtained by utilizing the variables and several rules that have been designed with the Mamdani implication function are then compared with the observations obtained by the Project Manager so that an accuracy value of 86.67% is accepted for the use of inclusive and exclusive rules (operand AND).
Keywords—*Mamdani, monitoring software development, GitHub*

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1. INTRODUCTION

People widely implement collaboration activities in social life to complete household chores, school assignments, community projects, and other endeavors. During implementation, individuals as human resources become a crucial aspect to consider for achieving collective success. Even though teams are assigned specific tasks, the context of collaborative work demands that all team members make significant contributions. If the group becomes unequal or if specific individuals monopolize tasks, the outcome can demotivate and deprive other team members of opportunities they might otherwise have. The project manager plays a role in balancing these opportunities by overseeing every visible detail of activities. This monitoring practice allows teamwork practice serves as a means for self-evaluation through feedback, which becomes apparent during collaborative efforts.

A version control system (VCS) like Git stands are widely used in software projects, notably for tracking individual performance. Measuring productivity proves to be complex and intricate [1]. Numerous approaches have emerged because none of these broader observations are genuinely disputable. We should consider adopting a unidimensional approach to measuring productivity [2]. Prometer [3] exemplifies a research category that attempted to assess individual activity in software development via VCS. The researchers measured individual performance by utilizing four input variables: pull requests, issues, commits, and lines of codes. They then processed these variables using a specific formula to calculate a total score, which served as the output variable. Managing these specified variables involved implementing a calculation method to determine individual scores. Despite this, the outcomes of productivity performance measurements based on the variable used still represent ambiguous information, necessitating alternative methods to aid in monitoring individual performance. Fuzzy logic comes into play to bridge the gap between machines' precise language and humans' inherently imprecise language. Fuzzy logic enables the swift and efficient implementation of human expert systems in machine language [4]. The input variable values lack definitive boundaries, which each variable's value tending to fluctuate over time within each project. In our comparison, we will delve into the application of fuzzy logic, utilizing these dynamic input variables to generate an output capable of monitoring individual performance on assigned projects.

Typically, a scale from 0 to 100 assigns scores. Furthermore, the evaluation range often remains consistent for each observable instance. The research [5] utilized two input variables: student tests and behavior scores. The output comprises recommendations regarding how teachers should grade students. Researchers used the Mamdani method as a fuzzy inference system to control every variable integrated into this evaluation to maximize it. Simultaneously, a questionnaire with predetermined inquiries and responses from the domain contributed to some of the study data. Applying the Mamdani approach, the researcher conducted a study to ascertain the extent of student satisfaction with the professors' performance at the STTIND [6]. Survey participant responses will undergo processing using a fuzzy set that employs a specified universe of ratings, explicitly ranging from 1 to 5. The input variables encompass tangibility, reliability, responsiveness, assurance, and empathy. Evaluating the output is carried out by studying the responses provided by the participants. The outcome maintains the same range, whether from the original data or results from fuzzy calculations.

Assessment activities frequently involve utilizing the Mamdani method, also recognized as the Min-Max method. Ebrahim Mamdani introduce this technique in 1975. On each rule in implication, the conjugate form (AND) exhibit value membership in the shape of a minimum (MIN), while the consequent combination takes the form of a maximum (MAX) [7].

Various types of membership functions can be applied. The research assumes that the modeling employed yields a small impact. The MAPE value of 29.37% achieved through membership function Triangle, Phi, and Trapezium, was demonstrated through a case study involving medical records of patients at Jombang Hospital [8].

This study will implement fuzzy logic using two membership functions for each variable, with an output variable rating scale ranging from 0-100. The rules designed for implementation using Mamdani's inference will support the Project Manager in monitoring.

2. METHODS

In chronological order, the study unfolded with the implementation of the ensuing steps: data collection, knowledge acquisition, design of fuzzy inference system and implementation, and evaluation.

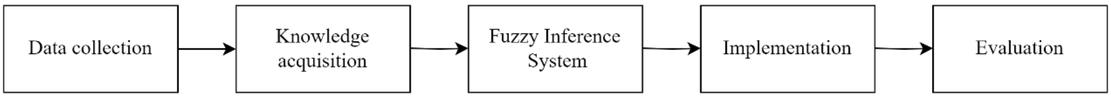


Figure 1 Stage of research

Figure 1 depicts the steps defining data collection through literature review and questionnaire methods. The literature review involved reading scientific literature, journals, and related materials. After identifying potentially impactful variables,the subsequent step involved distributing questionnaires to aid researchers in selecting the variables influencing the research objective. Understanding existing data characteristics was followed by executing knowledge acquisition. This step involved defining characteristics of linguistic variables like variable names, sets of linguistic variables, domain names, and semantic rules. These relate to fuzzy sets in the available universe. Proceeding, fuzzy operators, and implication methods were applied using designated rules. Finally, the last implementation stage involved defuzzification, displaying results in the original dataset's format. Acquiring the output prompted the subsequent action of evaluating the implemented fuzzy system.

3. RESULTS AND DISCUSSION

3.1 Data Collection

In this study, researchers employed several metrics for monitoring programmer productivity. Some of the metrics adhered to the following criteria:

1) The chosen metrics needed to be connected to activity on GitHub.
2) The selected metrics must directly correlate with the programmer's contribution.
3) The metric had to be retrievable from GitHub REST API.

Based on the aforementioned metrics criteria, the researchers utilize four fundamental metrics from prior studies [3] to monitor the programmer performance. Beyond these four metrics, the researcher used a survey approach to gather additional data, enhancing the metrics' validity. A total of 44 respondents participated in this research. The subsequent recapitulation is based on the distributed questionnaire and responses received from the participants.

Table 1 Questionnaire Recapitulation

Respondent	Answering item					Skor
	Q1	Q2	Q3	Q4	Q5	
1	5	5	4	4	4	22
2	3	3	4	4	4	18
3	5	4	5	5	4	23
4	4	4	4	5	5	22
5	5	5	5	5	5	25
…	…	…	…	…	…	…
44	4	4	4	4	4	20
Correlation Value $r_{computed}$	0.63923	0.682485	0.653236	0.789321	0.6902	

With a confidence level of 95% (0.297), the researchers established the validity of the quantitative data, affirming the data's usability for research purposes. Following the quantitative data validity assessment, the researcher conducted a descriptive qualitative data analysis. The following list outlines respondents' provided variables that could potentially augment the research data: time, commit, score efficiency code, score impact code, graph contributor, branch, merge request, code reuse, meta base, Jira card, collaborator, star, capacity code changes, code review, contribution activity, changelog, and Azure DevOps. The descriptive data analysis, which aligns with the metrics criteria requirement, concludes that the additional feature to include in this study is time. Figure 2 illustrates a representation of the collected sample data in this study.

	User	Commit_Count	File_Changes_Count	Deletion_Count	Addition_Count	Issue_Count	Pull_Count	Duration (Days)
0	lucacasonato	1937.0	1937.0	8070.0	27282.0	205	252.0	78.06
1	hashrock	125.0	125.0	875.0	2437.0	38	30.0	12.74
2	iuioiua	111.0	111.0	542.0	404.0	32	18.0	4.67
3	crowlKats	107.0	107.0	466.0	1351.0	24	23.0	313.48
4	sylc	79.0	79.0	303.0	1267.0	19	14.0	49.20
...	...	...	...	...	...	...	...	...

Figure 2 Sample Data

The researcher must configure settings on the developer settings page to obtain a personal access token for authenticating API requests to GitHub.

```
# set token
token = "set_token"

# set repository
owner = "set owner from repository"
repo = "set name of repository"

# set header
headers = {"Authorization": f"Token {token}"}
```

Figure 3 Set Token and Header

Researchers require the requests library, JSON, pandas, and datetime to access the data. The requests library requests facilitate interaction with the API using HTTP requests like POST and GET, allowing information retrieval and storage in objects. Yet, researchers must refrain from directly utilizing the acquired information in Python and must parse it using the JSON library. The result, obtained via the JSON module, assumes the data type of a dictionary. Converting this data type into a DataFrame using Panda's module is essential. DataFrame's structured nature offers indexed access to columns and rows, along with methods for data analysis like statistics, aggregation, and procedures for stage analysis, visualization, and modeling. For manipulation of date and time, the datetime module proves crucial. Its classes and functions enable effective manipulation of dates and times, including formatting, parsing, and arithmetic operations. Additionally, the timedelta class calculates differences between datetime objects based on time units like seconds, minutes, hours, or days through arithmetic procedures, allowing time-based calculations.

3.2 Knowledge Acquisition

The research entails executing several stages to enhance the study's quality:

3.2.1 Exploratory Data Analysis (EDA)

Conducting EDA provides insights, facilitates understanding of data characteristics, and identifies various analysis variable variations [9], enabling the identification of necessary steps. The research data here needs to include duplicate data within each column.

3.2.2 Normalization

Statistics data will influence the analysis of the data. If there are outliers to the research data, it is necessary to do pre-processing to handle these cases. Normalization is one of the pre-processing approaches to contribute equally to each feature [10]. To ensure this feasibility, the researchers follow these steps and employ the interquartile range method or IQR:

a) Calculates the first (Q1) and third (Q3) quartiles.
b) Calculates the interquartile range.

$$IQR = Q3 - Q1 \quad (1)$$

c) Specifies the lower limit and upper limit. The standard formula used to calculate the lower bound is:

$$Lower\ bound = Q1 - (1.5 * IQR) \quad (2)$$

and the standard formula used to calculate the upper bound is:

$$Upper\ bound = Q3 + (1.5 * IQR) \quad (3)$$

d) Identify values that are outside the lower and upper limits as outliers. Identifying and dealing with outliers can be challenging, but it is essential to data analytics. Handling these conditions is done by using normalization.

3.2.3 Feature Selection

Feature selection is selecting the relevant features and removing the irrelevant ones. In this research, the data does not have a clear label to train the model, so the feature selection is capable of the unsupervised learning method. Utilizing the implemented correlation calculations on each data train, we can derive the following analysis:

a) Pearson Correlation:
In the 1st and 3rd data train, the feature with the lowest correlation is the duration (days). In the 2nd data train, features that correlate > 0.5 are: the commit count - issue count (0.84), commit count – pull count (1), and deletion count – addition count (0.95). In the 4th data train, features that correlate > 0.5 are: the commit count – deletion count (0.73), commit count – addition count (0.98), commit count – pull count (0.86), and deletion count - addition count (0.84).
b) Kendall Correlation:
In the 1st, 2nd, and 4th data train, the feature with the lowest correlation is the duration (days). In the 3rd data train, features that correlate < 0.5 are the issue count and duration (days).
c) Spearman Correlation:
We know that in the 1st, 2nd, and 4th data train, the feature with the lowest correlation is duration (days). In the 3rd data train, features that correlate < 0.5 are the issue count and duration (days).

Based on the analysis above, the feature that has the lowest correlation to all features is duration (days) feature, followed by the issue count. In this research, the elimination feature is the duration (days).

3.3 Variable Linguistic Definitions

Linguistics uses natural language to name a group representing something, specific circumstances, or conditions. In this case, the method used to define fuzzy sets with variables in the form of predetermined words or sentences is defining linguistic variables. Linguistic variables consist of X, T, U, and M where:

X: linguistic variable name

T: term or set of linguistic values where X is

U: the domain where the linguistic variable X has a quantitative value

M: semantic rules that relate to the linguistic value of T of a fuzzy set in U

The result variable from the knowledge acquisition stage will serve as the input variable. Apply linguistic values - a few, normal, lots – to the input variable. The domain selection for each linguistic variable relies on availability, as each variable possesses a dynamic range of data. Determine the scope of each variable by considering its minimum and maximum values.

$$Range_{variabel(x)} = Max_{variabel\,(x)} - Min_{variabel\,(x)} \tag{4}$$

By knowing the $Range_{variabel(x)}$ using Equation (4) then, the membership function for each variable input is:

$$\mu_{few}(x)\ \begin{cases} 1 & ; \quad x \le \frac{1}{4} range \\ \frac{\left(\frac{1}{2} range - x\right)}{\frac{1}{4} range} & ; \quad \frac{1}{4} range \le x \le \frac{1}{2} range \\ 0 & ; \quad x \ge \frac{1}{2} range \end{cases} \tag{5}$$

$$\mu_{normal}(x)\ \begin{cases} 0 & ; \quad x \le \frac{1}{4} range\ or\ x \ge max \\ \frac{\left(x - \frac{1}{4} range\right)}{\left(\frac{1}{2} range\right)} & ; \quad \frac{1}{4} range \le x \le \frac{1}{2} range \\ 1 & ; \quad \frac{1}{2} range \le x \le \frac{3}{4} range \\ \frac{\left(\frac{1}{4} range\ -\ x\right)}{\left(\frac{1}{4} range\right)} & ; \quad \frac{3}{4} range \le x \le max \end{cases} \tag{6}$$

$$\mu_{lots}(x) = \begin{cases} 0 & ; \quad x \le \frac{1}{2} range \\ \frac{\left(x - \frac{1}{2} range\right)}{\frac{1}{4} range} & ; \quad \frac{1}{2} range \le x \le \frac{3}{4} range \\ 1 & ; \quad \frac{3}{4} range \le x \le max \end{cases} \tag{7}$$

The fuzzification applied to each input variable is triangular and trapezoidal.

The primary objective of this research is to support software project managers in effectively supervising software project development by closely monitoring the performance of each team member engaged in the project. The output variable’s range is set within [0, 100], and it will be categorized into three sets: Low, Normal, and High, as follows. This categorization is visually represented in Figure 4, where the membership graph for the output variable is depicted:

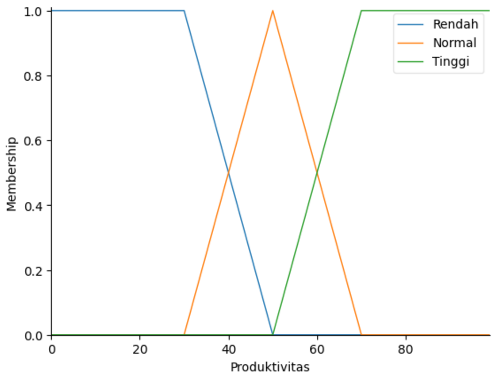


Figure 4 Membership Function for Productivity

3.4 Fuzzy Inference System

The cornerstone of this research is the Fuzzy Inference System (FIS), a widely embraced computational framework grounded in fuzzy theory's concept, mainly centered around Fuzzy IF-THEN rules and fuzzy reasoning. Inference, which entails synthesizing numerous rules while harnessing available data, is pivotal in this context. This process serves to establish coherent, logical correlation that underpin effective decision-making. We actively consider all relevant rules within the knowledge base during the inference process. This study has crafted three distinct rule types: exclusive rule (operand AND), exclusive rule (combination of operand AND & OR), and inclusive rule. To enhance the ease of variable utilization, each variable is associated with a shorthand acronym: p1 (pull request), p2 (issue), p3 (commit), p4 (addition), p5 (deletion), and consequent (productivity). The ensuing elaboration delves into the particulars of each rule type:

1) *Exclusive rule (operand AND):*

The FIS method used in this study is the Mamdani implication function using the fuzzy rules "IF-THEN: with the operator used for input variables is the "AND" operator. The following are the examples of exclusive rules (operand AND) used:

$$IF\ (p_1\ is\ normal) \cap (p_2\ is\ normal) \cap (p_3 is\ normal)\ \cap (p_4\ is\ normal) \\ \cap (p_5\ is\ normal)\ THEN\ (consequent\ is\ high)$$

We are still considering using operators in this rule during the implementation and testing.

2) *Exclusive rule (combination of operand AND – OR):*

We will consider the role played when the user executes addition and deletion actions in the monitoring process. The "OR" operator is exclusively applied to addition and deletion variables in this case.

$$IF\ (p_1\ is\ normal) \cap (p_2\ is\ normal) \cap (p_3 is\ normal) \\ \cap (p_4\ is\ few) \cup (p_5\ is\ normal)\ THEN\ (consequent\ is\ high)$$

3) *Inclusive rule:*

If we employ the earlier rules, applying each rule at a given time is contingent upon specific exclusive conditions. When implementing the inclusive rule, every amalgamation of membership functions on the input variable corresponds to a suitable rule. In this scenario, if an overlap exists among the membership functions utilized in the input combinations, the outcomes will accurately represent each combination's contribution. Here, we provide examples of the rules used:

$$IF\ (p_1\ is\ few) THEN\ (consequent\ is\ low)$$
$$IF\ (p_1\ is\ normal) THEN\ (consequent\ is\ normal)$$
$$IF\ (p_1\ is\ lots) THEN\ (consequent\ is\ high)$$
$$\dots$$
$$IF\ (p_5\ is\ lots) THEN\ (consequent\ is\ high)$$

The designed inclusive and exclusive rules can be selectively utilized during its implementation, contingent upon encountered problems and user preferences. Inclusive rules typically yield smoother outcomes, while exclusive rules using the AND operand generate sharper results, prioritizing the most robust rules. Moreover, exclusive rules employing a combination of AND and OR operands effectively consider the inputs' roles in the OR operation.

Following the aggregation process, the subsequent step involves defuzzification. Defuzzification is a process that handles fuzzy data, aiming to convert fuzzy sets into precise values that contribute to the decision-making process after evaluating programmer performance. In this study, the Centroid method will be employed for the defuzzification process.

3.5 Evaluation

Building on the advancements in the stages, various student work groups from the Del Institute of Technology enrolled in the Information Systems Development course underwent testing for their project outcomes. Table 2 provides a comprehensive assessment of the ranking results, juxtaposing the outputs obtained through inclusive, exclusive (AND operand), and exclusive (combination operand of AND with OR operands) rules against those generated by the Project Manager (PM) based on the 1st test data.

Table 2 Result of 1st Data Test Comparison

User	Fuzzy Rankings			Ranking PM	Accuracy		
	Inclusive	Exclusive (the AND operand)	Exclusive (combination operand AND with OR)		Inclusive	Exclusive (the AND operand)	Exclusive (combination operand AND with OR)
A	2, 3	1	2	1	55.56 %	55.56%	11.11%
B	1	2	1	2			
C	2,3	5	3	3			
D	4	4	3	4			
E	5	7	3	6			
F	6	6	3	5			
G	7	3	3	7			
H	8	8, 9	3	8			
I	9	8, 9	3	9			

Upon analyzing the comparison results, as we evaluate the rankings derived from the inclusive, exclusive (the AND operand), and exclusive (combination operand AND with OR) rules in contrast to the rankings provided by the Project Manager, it becomes apparent that in specific situations, certain contributions attain identical rankings. This phenomenon can be attributed to notable discrepancies in the assigned values, resulting from considerable variations within each contributor's assigned values.

We executed the experiment across three test data samples. The available test data shows that the minimum requirement for data points is 5, and the inclusive rule achieved a perfect accuracy of 100%. To evaluate the effectiveness of rule implementation, we concentrated solely on the top 5 contributors within each test dataset, regardless of their specific values. To quantify their combined performance, we can compute the average accuracy for these five contributors using Equation (8):

$$accuracy\ (\%) = \frac{\sum_{i=1}^{n} ds}{\sum_{i=1}^{n} dp}\ x\ 100\% \qquad (8)$$

In which:
n: number of data test.
ds: number of true values of fuzzy rankings.
dp: number of total data used in research.
100%: real number.

Table 3 Ranking Comparison: Inclusive VS PM

Data test – 1		Data test – 2		Data test – 3	
Inclusive	PM	Inclusive	PM	Inclusive	PM
A	A	A	A	A	A
B	B	B	B	B	B
C	C	C	C	C	C
D	D	E	D	D	D
E	F	F	E	E	E

Referring to Table 3 we can derive the following average accuracies:

$$\left(\frac{\left(\frac{4}{5}\right) + \left(\frac{4}{5}\right) + \left(\frac{5}{5}\right)}{3}\right) x\ 100\% = \ 86.67\%$$

Table 4 Ranking Comparison: Exclusive (The Operand AND) VS PM

Data test – 1		Data test – 2		Data test – 3	
Exclusive (The operand AND)	PM	Exclusive (The operand AND)	PM	Exclusive (The operand AND)	PM
A	A	A	A	A	A
B	B	B	B	B	B
C	C	D	C	C	C
D	D	E	D	D	D
G	F	F	E	E	E

Referring to Table 4 we can derive the following average accuracies:

$$\left(\frac{\left(\frac{4}{5}\right) + \left(\frac{4}{5}\right) + \left(\frac{5}{5}\right)}{3}\right) x\ 100\% = 86.67\%$$

Table 5 Ranking Comparison: Exclusive (Combination Operand of AND with OR) VS PM

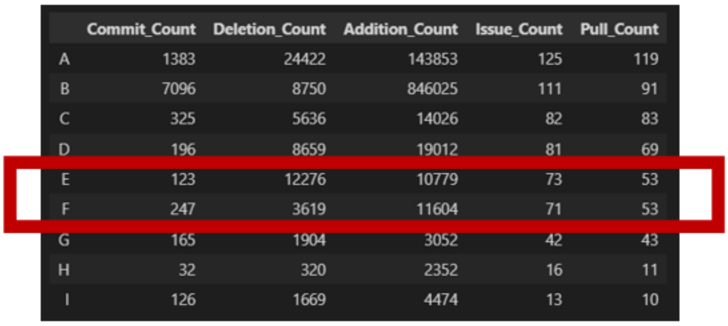
Data test – 1		Data test – 2		Data test – 3	
Exclusive (combination operand of AND with OR)	PM	Exclusive (combination operand of AND with OR)	PM	Exclusive (combination operand of AND with OR)	PM
A	A	A	A	A	A
B	B	B	B	B	B
C	C	C	C	C	C
D	D	D	D	D	D
F	F	E	E	E	E

Referring to Table 5**Error! Reference source not found.** we can derive the following average accuracies:

$$\left(\frac{\left(\frac{5}{5}\right)+\left(\frac{5}{5}\right)+\left(\frac{5}{5}\right)}{3}\right) x\ 100\% = \ 100\%$$

When using the exclusive rule (combination operand of AND with OR), it is evident that only a few contributors obtain scores different from others. This condition results in an average accuracy of 100%, as each contributor brings equal value.

Several factors can give rise to the same productivity score, including the rules employed to determine the role of each contributor's activities. Utilizing the OR operand within the "additions" and "deletions" variables results in consistent values consistently falling within the most influential set category during the assessment. The researcher must scrutinize the conditions of each recorded contribution to understand the variations in rankings when using both inclusive and exclusive (operand AND) rules in contrast to rankings determined by the Project Manager. The analysis of results from implementing inclusive and exclusive (utilizing the AND operand) rules in the rankings conducted by the PM will be explored through an examination using the 1st test data. Referring to Table 2, it becomes evident that contributors E and F rank 5 (E) and 6 (F) in the assessment using the inclusive rule. However, in the rankings performed by the PM, contributor E is positioned at rank 6, whereas contributor F is ranked 5. Figure 5 offers an illustration to visualize each contributor's contributions for every variable.



	Commit_Count	Deletion_Count	Addition_Count	Issue_Count	Pull_Count
A	1383	24422	143853	125	119
B	7096	8750	846025	111	91
C	325	5636	14026	82	83
D	196	8659	19012	81	69
E	123	12276	10779	73	53
F	247	3619	11604	71	53
G	165	1904	3052	42	43
H	32	320	2352	16	11
I	126	1669	4474	13	10

Figure 5 Contrasting the contributions of contributors E and F in the 1st data test

Contributors E and F significantly differ in the values for the variable Deletions.

Referring to Table 2, the exclusive rule (operand AND) ranks contributors A, B, C, and D as 1(A), 2(B), 5(C), and 4(D), respectively. Meanwhile, in the ranking conducted by PM, contributor E occupies the 3rd position. Figure 6 illustrates the recorded contributions of contributors C, D, and E in each variable.

	Commit_Count	Deletion_Count	Addition_Count	Issue_Count	Pull_Count
A	1383	24422	143853	125	119
B	7096	8750	846025	111	91
C	325	5636	14026	82	83
D	196	8659	19012	81	69
E	123	12276	10779	73	53
F	247	3619	11604	71	53
G	165	1904	3052	42	43
H	32	320	2352	16	11
I	126	1669	4474	13	10

Figure 6 Contrasting the contributions of contributors C, D, and E in the 1st data test

To examine the contributions of values using fuzzy logic, we observe the membership function (MF) values of each input variable from the 1st data test, attributed to contributors C, D, and E in Table 6.

Table 6 MF of Contributor C, D, and E

Contributor	Variable	Value	MF		
			Few	Normal	Lots
C	p1	83	0	0	1
	p2	82	0	0.07	0.93
	p3	325	1	0	0
	p4	14,026	1	0	0
	p5	5,636	1	0	0
D	p1	69	0	0.47	0.53
	p2	81	0	0.11	0.89
	p3	196	1	0	0
	p4	19,012	1	0	0
	p5	8,659	0.56	0.44	0
E	p1	53	0.06	0.94	0
	p2	73	0	0.39	0.61
	p3	123	1	0	0
	p4	10,779	1	0	0
	p5	12,276	0	0.96	0.04

Analyzing contributor D as a reference point to compare the impacts of assessments conducted using the exclusive rule (operand AND) with the outcomes of PM assessments reveals that contributor C's contribution value outperforms contributor E's in variables p2, p3, and p4. However, when scrutinizing the membership values, it becomes apparent that contributor E's contribution value in variable p5 substantially influences the utilization of the exclusive rule (operand AND), leading contributor E to surpass contributor C due to the Normal MF.

4. CONCLUSIONS

The challenge lies in integrating research datasets and usage rules into the monitoring process. While public repositories are widely available, they primarily emphasize individual performance within small teams. Among the research findings, it is evident that the distribution of input values is a crucial aspect, alongside the prioritization of input variables. Experimental outcomes, influenced by incorporating AND and OR operands in rule formation, impact the anticipated output. The analysis of programmer performance on the GitHub platform using Mamdani's fuzzy inference system is based on fuzzy logic. The experiments' results underscore the significance of the membership function definition in influencing the employed rules. This assertion is corroborated by the accuracy levels attained in each experiment. Consequently, inclusive rules exhibit an evaluation closer to the Project Manager's assessment, with an average accuracy of 86.67%. However, if the focus centers on the top 5 contributors, a combination of inclusive rules and exclusive rules (operand AND) can achieve similar accuracy. Discouraging the use of exclusive rules (combination operand of AND and OR), as variables taking the OR operand become more dominant, leading to biased assessment outcomes.

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