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# Analyzing Students Academic Performance Using Fuzzy Association Rule Mining

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**ABSTRACT**
To extract information from a data set and transform it into a structure that can be used further, a method known as data mining is used. There are various data mining approaches, including association rule mining, clustering analysis, classification analysis, and regression analysis. Finding frequent patterns, relationships, and correlations among them is done using ARM. Association rules are used to express how objects that co-occur are related to one another. A technique has been created by expanding classical association rule mining with fuzzy sets. The fuzzy association rule mining method was developed to efficiently mine the quantitative data that is typically found in databases. Huge amounts of rules are generated, which is one of association rule mining's limitations. In a wide range of applications, including market basket analysis, medical diagnosis, student performance evaluation, protein sequences, census data, etc., association rule mining can be utilized to enhance decision-making. Fuzzy-apriori algorithm is employed in the current system for analyzing student academic performance to mine intriguing patterns that could track students' engagement with specific socio-economic issues. Here, concerns regarding students' poor academic achievement are made known through a few socioeconomic issues. The suggested system makes use of the SS-FIM (single scan frequent item sets mining) technique, which only has to scan the transactional database once in order to extract frequent item sets. As a result, scanning should go more quickly than with the aprioritechnique.-
**Keywords:** Data Mining, Classifications, Associate Rule Mining, Frequent Patents, Co-relations, SS-FIM;

## I. INTRODUCTION

Data mining using fuzzy logic involves clustering and processing the data based on likely predictions. The "true or false" standard is used in the traditional method. Fuzzy logic-based algorithms are being used more often across a variety of disciplines to aid with database mining. The clustering of breast cancer data, which enables physicians to find and assess breast cancer risks like malignant tumors, is one of the possibly practical applications of fuzzy logic algorithms revealed in clinical trials. The top cause of death for women globally is today breast cancer, which is also one of the major health issues [1]. It is well known that breast cancer is the second most common reason for cancer-related deaths among women. If detected early, it is also one of the cancer forms that is most treatable [2]. Therefore, one of the most important strategies to enhance the prognosis of the disease is by early detection of cancer risks.

Despite the fact that mammography is one of many radiological techniques that can be utilized in the early detection of breast cancer risks, radiologists frequently find it challenging to appropriately assess breast cancer data due to the massive amounts of data these techniques produce [3]. Based on the planned course of treatment for each individual case, clinical results, tumor features, and molecular markers are combined to establish various risk categories [4].

Information on risk factors and mammographic results is one of the main factors in breast cancer databases. Even if the root causes of cancer are not yet understood, a number of risk factors have been found and can therefore be classified. Tumors can typically be classified as benign or malignant (cancerous). Malignant tumors typically grow quickly, frequently causing the loss of healthy tissues, and eventually spreading to every region of the body. Contrarily, benign tumors usually stay put and develop gradually, with little to no metastasis to other body organs. Consequently, when malignant tumors are found in an individual, the risk of breast cancer growth is typically increased [9-12].

Fuzzy logic clustering methods can be

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used to group diverse data components into various membership levels based on how closely they are related when dealing with uncertainties in databases. Mammogram data, for instance, may have some degree of fuzziness during the assessment of breast cancer risks, such as poorly defined forms, fuzzy borders, and varying densities. In this sense, one of the best methods for dealing with the fuzziness of breast cancer data is to use a fuzzy clustering algorithm. Fuzzy logic data mining techniques are an intelligent method that not only offers good data analysis but can also be used to provide precise outcomes that are simple to use [15, 16].

## II. ASSOCIATION RULE MINING

In order to determine the relationship between a huge number of data objects, association rule mining (ARM) is used. Due to the enormous amount of data stored in repositories, as seen in figure 1, many businesses are concerned about their database mining association policies. The identification of the exciting connected links between vast quantities of transaction data might, for instance, support cross-marketing, catalog design, and other commercial decision-making processes. The analysis of market baskets is a typical ARM application. By looking for connections between different things that customers pack in their packs, this strategy investigates consumer purchasing behaviors. By offering a summary of the things these partnerships typically purchase jointly, marketers will be able to expand their communication campaigns by identifying these partnerships [19-21].

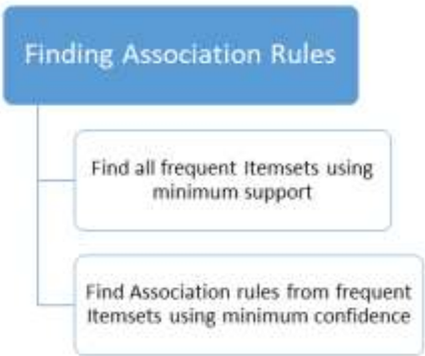


**Figure 1: Generating Association Rules**

For association rule mining, there are essentially three algorithms.

1. Apriori
2. FP-Growth
3. SS-FIM

The subsequent section provides an explanation of SS-FIM, on which the present study is based.

## III. SS-FIM ALGORITHM

The term SS-FIM refers to Single Scan Frequent Itemset Mining. To eliminate the limitations of other two algorithms i.e., the great sensitivity to changes in the minimal support threshold set by the user, which is determined by scanning the complete database at each pass to determine the support of all generated item sets, Youcef Dje-Nouri proposed an novel approach [22]. This needs the transactional database to be scanned just once in order to retrieve the frequently used item sets [23].

It has the special ability to generate a predetermined number of candidate item sets regardless of the minimal support criterion. The goal of SS-FIM is to find frequent item sets while reducing the number of database scans and generated candidates. To produce every conceivable item set for each transaction is the core goal of SS-FIM. A generated item set's support is increased by one if it was already created when handling a previous transaction. If not, its support is created and set to one. Up till every transaction in the database has been handled, the procedure is repeated [24, 25].

## IV. METHODOLOGY

There are some factors that affect student's academic performance like student's interest, family background, peer influence, health condition, habits etc. Based on these are factors there some questionnaires that students have to attempt. The information in the questionnaire will be able to capture student's enrolment number, name, class, CGPA and some factors values.

The questionnaire will be made up of six attributes covering various socio-economic factors. These all six attributes affects student's academic performance. The students responses are in five categories: strongly agree, agree, undecided, disagree, and strongly disagree. Assign a crisp value to the question by analyzing how impact on factors.

The input data is student's enrolment number, name, class, CGPA and Factors values like student's interest, family background, peer influence, health condition, habits etc. Student'sinterest factor describes that which kind of activities that student interested. Students family background describe that student belongs from which types of family. Peer influence related to the students having relationship or not, responsibilities,

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friend circle etc. Student health condition is also shows in health condition factor. Habits factor describe what kind of students habits. Then fuzzyfication process is applied on this input data.

Fuzzyfication process means converting this quantitative data into fuzzy data with the use of fuzzy set approach. Membership function is also used to covert quantitative data into fuzzy data. With the use of SS-FIM algorithm on these fuzzyfied data fuzzyassociation rules are derived.

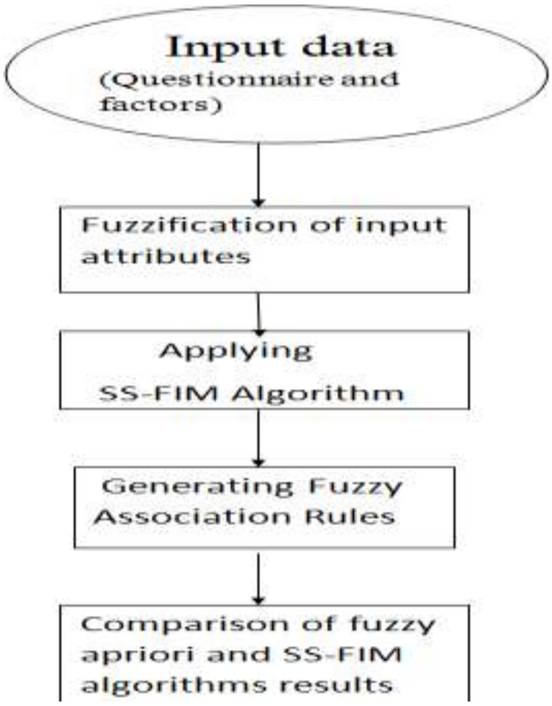


**Figure 3: Flow of Proposed System**

There are some limitations of association rule mining like many unnecessary frequent patterns are generated that will put more efforts for decision makers. Huge numbers of rules are generated quantitative association rules. Partitioning of quantitative attributes leads to information loss. To minimize this information loss, the fuzzy set concept is used.

In existing systemapriori algorithm is used, but in proposed work SS-FIM (Sin- gle Scan Frequent Item sets Mining) algorithm is usedon . SS-FIM is better than other association algorithms like apriori, FP-growth etc. for single scan database.

The main idea of SS-FIM is to generate all possible item sets for each transaction. Ifa generated item set has already been created when processing a previous transaction, then its support is incremented by one. Otherwise, its support is created and initialized to one. The process is repeated until all the transactions in the database have been processed. Single Scan Frequent Item sets Mining (SS-FIM) requires a single scan of the transactional database to extract the frequent item sets. After getting patterns of SS-FIM algorithm, SS-FIM rules are compared with fuzzy apriori rules.

## V. RESULTS AND DISCUSSION

The survey of more than 100 student's feedback from different classes are used. There are so Students interestfactors that affect student's academic performance like following factors

- Students interest
- Family background
- Peer influence
- Health condition
- Habits

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| 2 | ER.NO. | STUDENT'S NAME | CLASS | INTEREST | FAMILY BACKGROUND | PEER INFLUENCE | HEALTH CONDITION | HABITS | PAST CGPA |
|---|---|---|---|---|---|---|---|---|---|
| 3 | | | | | | | | | |
| 4 | 1 | NAITIK TALIA | MSCIT | 12 | 25 | 23 | 23 | 32 | 4 |
| 5 | 2 | KHYATI Y. DALAL | MSCIT | 10 | 27 | 15 | 25 | 32 | 3.5800 |
| 6 | 3 | HETVI SHAH | MSCIT | 12 | 27 | 20 | 23 | 22 | 3.4900 |
| 7 | 4 | ZEEL LATHIYA | MSCIT | 0 | 25 | 10 | 23 | 26 | 3.8000 |
| 8 | 5 | PATEL ZINAL | MSCIT | 14 | 26 | 33 | 26 | 12 | 3.5000 |
| 9 | 6 | MONIKA B. PATEL | MSCIT | 20 | 12 | 43 | 2 | 27 | 3.4600 |
| 10 | 7 | GAJJAR DRASHTI | MSCIT | 16 | 28 | 38 | 16 | 33 | 2.8400 |
| 11 | 8 | RAHUL KHANDELWAL | MSCIT | 8 | 28 | 38 | 26 | 27 | 3 |
| 12 | 9 | ASHIK PATEL | MSCIT | 8 | 28 | 33 | 26 | 27 | 3 |
| 13 | 10 | YASH D. RANA | MSCIT | 10 | 17 | 27 | 24 | 17 | 3 |
| 14 | 11 | BHARGAV PATEL | MSCIT | 4 | 25 | 27 | 30 | 18 | 3.2000 |
| 15 | 12 | NISARG PATEL | MSCIT | 11 | 20 | 27 | 30 | 18 | 4 |
| 16 | 13 | APURV PATEL | MSCIT | 14 | 17 | 37 | 30 | 32 | 3.3000 |
| 17 | 14 | SHREYANS SHAH | MSCIT | 14 | 17 | 37 | 30 | 32 | 4.1000 |
| 18 | 15 | PRAGYA SHAH | MSCIT | 14 | 17 | 37 | 30 | 32 | 2.7000 |
| 19 | 16 | SHREYA SHAH | MSCIT | 14 | 27 | 37 | 30 | 32 | 3.9500 |
| 20 | 17 | TANMAY PATEL | MSCIT | 14 | 17 | 37 | 30 | 32 | 3.2000 |
| 21 | 18 | HENALI PATEL | MSCIT | 14 | 17 | 37 | 30 | 32 | 3.2000 |
| 22 | 19 | ABHIJIT PILUDARIA | MSCIT | 2 | 28 | 20 | 0 | 2 | 3.8500 |
| 23 | 20 | HANY PATEL | MSCIT | 9 | 30 | 30 | 28 | 25 | 3 |
| 24 | 21 | MONIKA PATEL | MSCIT | 20 | 22 | 43 | 2 | 24 | 3.4100 |
| 25 | 22 | PILUDARIA ABHIJIT | MSCIT | 2 | 28 | 20 | 0 | 2 | 3.4100 |
| 26 | 23 | JYOTI PANDAY | MSCIT | 9 | 25 | 28 | 18 | 17 | 3.5000 |
| 27 | 24 | JENIL TOPIWALA | MSCIT | 9 | 30 | 28 | 18 | 17 | 3.8000 |
| 28 | 25 | NENSI RANA | MSCIT | 13 | 31 | 33 | 10 | 10 | 4 |
| 29 | 26 | RUCHI PATEL | MSCIT | 11 | 26 | 23 | 10 | 10 | 3.5000 |
| 30 | 27 | KOMAL VEKARIYA | MSCIT | 0 | 20 | 15 | 12 | 12 | 3.2000 |
| 31 | 28 | DHANASVI S. PATEL | MSCIT | 2 | 30 | 17 | 12 | 17 | 3.1000 |
| 32 | 29 | KATARIYA NILKANTH | MSCIT | 0 | 20 | 18 | 12 | 17 | 3.1000 |
| 33 | 30 | PATEL NIRMAL | MSCIT | 0 | 20 | 20 | 12 | 17 | 3 |
| 34 | 31 | PAREKH HETAL | MSCIT | 17 | 20 | 21 | 40 | 20 | 4 |
| 35 | 32 | PAREKH KEVIN | MSCIT | 28 | 22 | 13 | 0 | 10 | 4 |
| 36 | 33 | MAMTA | MSCIT | 10 | 32 | 19 | 0 | 26 | 3.1000 |
| 37 | 34 | NAIK VIVEK | MSCIT | 10 | 30 | 19 | 0 | 26 | 3.4000 |
| 38 | 35 | AMNITHA | MSCIT | 2 | 32 | 25 | 8 | 26 | 4.2500 |
| 39 | 36 | SEJAL PATEL | MSCIT | 24 | 15 | 34 | 18 | 23 | 3.6900 |
| 40 | 37 | KARAN PATEL | MSCIT | 14 | 25 | 38 | 25 | 23 | 3.1000 |
| 41 | 38 | MANSI PATEL | MSCIT | 34 | 22 | 35 | 34 | 18 | 4 |
| 42 | 39 | NILA | MSCIT | 10 | 30 | 25 | 8 | 30 | 4.3000 |
| 43 | 40 | GAJJAR DRASHTI | MSCIT | 16 | 28 | 34 | 16 | 33 | 2.8000 |
| 44 | 41 | HONEY PATEL | MSCIT | 25 | 25 | 38 | 25 | 23 | 4.1000 |

**Figure 4: Factors affecting student performance**

Based on these factors there some questionnaires that students have to attempt. The information in the questionnaire will be able to capture students Enrolment no, Name, Class, CGPA and some factors.

The questionnaire is made up of six attributes covering various factors on socio-economic factors. These all are input attributes for student academic performance. For each attribute there are five questions that students have to attempt.

The students responses are in five categories: strongly agree, agree, undecided, disagree, and strongly disagree. To assign a crisp value according to how question has impact on the factors as related this analysis. In this input data as a student's Enrolment no, Name, Class, CGPA and Factors values like students interest, family background, peer influence, health condition, habits etc. As an output we get fuzzy association rules. Student's interest factor describes that which kind of activities that student interested. Students family background describe that student belongs from which types of family. Peer influence related to the students having relationship or not, responsibilities, friend circle etc. Student's health condition is also shows in health condition factor. Habits factor describe what kind of students habits. Then fuzzification process is applied on this input data.

| Int low | Int Ave | Int Hig h | Fa m low | Fam Avg | fam Hig h | Per low | Per Avg | Per Hig h | Hea low | hea Ave | hea Hig h | Hab low | Hab Ave | Hab Hig h | CGP A 1 | CGP A21 | CGPA 22 | CGPA 3 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 1 | 0 | 0 | 1 | 0 | 0 | 0.6 | 0.4 | 0 | 1 | 0 | 0 | 0 | 1 | 0 | 0 | 0 | 0 | 1 |
| 1 | 0 | 0 | 1 | 0 | 0 | 1 | 0 | 0 | 1 | 0 | 0 | 0 | 1 | 0 | 0 | 0 | 0 | 0.5 |
| 0 | 0 | 1 | 1 | 0 | 0 | 0 | 0.1 | 0.9 | 1 | 0 | 0 | 0 | 1 | 0 | 0.4 | 0 | 0 | 0 |
| 0 | 0.3 | 0.7 | 1 | 0 | 0 | 0 | 0.9 | 0.1 | 0 | 0.7 | 0.3 | 0 | 0 | 1 | 1 | 0 | 0 | 0 |
| 1 | 0 | 0 | 1 | 0 | 0 | 0 | 1 | 0 | 0.2 | 0.8 | 0 | 0 | 0.5 | 0.5 | 0.6 | 0 | 0 | 0 |
| 0 | 0 | 1 | 1 | 0 | 0 | 0 | 0.7 | 0.3 | 1 | 0 | 0 | 0 | 0.5 | 0.5 | 0.4 | 0 | 0 | 0 |
| 0 | 0.5 | 0.5 | 1 | 0 | 0 | 0.8 | 0.2 | 0 | 1 | 0 | 0 | 0 | 1 | 0 | 0 | 0.6 | 0 | 0 |
| 0 | 1 | 0 | 1 | 0 | 0 | 0.4 | 0.6 | 0 | 0.2 | 0.8 | 0 | 0.6 | 0.4 | 0 | 0 | 0 | 0.7 | 0 |
| 0 | 0.1 | 0.9 | 1 | 0 | 0 | 0.8 | 0.2 | 0 | 1 | 0 | 0 | 0 | 0.5 | 0.5 | 0 | 0.3 | 0 | 0 |
| 0 | 0.3 | 0.7 | 1 | 0 | 0 | 0 | 1 | 0 | 0.3 | 0.2 | 0 | 0.4 | 0.6 | 0 | 0 | 0.2 | 0 | 0 |
| 0 | 1 | 0 | 1 | 0 | 0 | 0.4 | 0.6 | 0 | 0.6 | 0.4 | 0 | 0 | 0 | 1 | 0.2 | 0 | 0 | 0 |
| 0 | 0 | 1 | 1 | 0 | 0 | 0.8 | 0.2 | 0 | 1 | 0 | 0 | 0 | 1 | 0 | 0 | 1.0 | 0 | 0 |
| 0.2 | 0.8 | 0 | 1 | 0 | 0 | 0.4 | 0.6 | 0 | 0 | 1 | 0 | 0 | 0.7 | 0.3 | 0.2 | 0 | 0 | 0 |
| 0 | 0 | 1 | 1 | 0 | 0 | 0 | 0.7 | 0.3 | 0.4 | 0.6 | 0 | 0 | 0 | 1 | 1 | 0 | 0 | 0 |
| 0 | 0 | 1 | 1 | 0 | 0 | 0 | 0.9 | 0.1 | 1 | 0 | 0 | 0 | 0.3 | 0.7 | 1 | 0 | 0 | 0 |
| 0.6 | 0.4 | 0 | 1 | 0 | 0 | 0 | 1 | 0 | 0.2 | 0.8 | 0 | 0 | 0.3 | 0.7 | 0 | 0 | 0.7 | 0 |
| 0.4 | 0.6 | 0 | 1 | 0 | 0 | 0.4 | 0.6 | 0 | 0.4 | 0.6 | 0 | 0 | 0.9 | 0.1 | 0 | 0 | 0.9 | 0 |
| 0.4 | 0.6 | 0 | 1 | 0 | 0 | 0 | 1 | 0 | 1 | 0 | 0 | 0 | 0.1 | 0.9 | 0 | 0 | 1.01 | 0 |
| 0 | 0.5 | 0.5 | 1 | 0 | 0 | 0.6 | 0.4 | 0 | 1 | 0 | 0 | 0 | 0 | 1 | 0 | 0.6 061 | 0 | 0 |
| 0 | 0.7 | 0.3 | 1 | 0 | 0 | 0 | 1 | 0 | 0 | 1 | 0 | 0 | 0.1 | 0.9 | 0.6 0 | 0 | 0 | 0 |

**Figure 5: quantitative values**

Here we have an input as a five socio-economic factors values from student's feedback. So in this fuzzification process mamdani approach is used to convert these quantitative values into fuzzy values, as shown in Figure 4. In this approach triangular membership is used.

| Socio-economic factors | Values |
|---|---|
| **Interest** | |
| Strongly agree | 0 |
| Agree | 2 |
| Undecided | 5 |
| Disagree | 8 |
| Strongly disagree | 10 |
| **Family background** | 10 |
| Strongly agree | 8 |
| Agree | 5 |
| Undecided | 2 |
| Disagree | 0 |
| Strongly disagree | |
| **Peer influence** | 10 |
| Strongly agree | 8 |
| Agree | 5 |
| Undecided | 2 |
| Disagree | 0 |
| Strongly disagree | |
| **Health condition** | 0 |
| Strongly agree | 2 |
| Agree | 5 |
| Undecided | 8 |
| Disagree | 10 |
| Strongly disagree | |
| **Habits** | |
| Strongly agree | 0 |
| Agree | 2 |
| Undecided | 5 |
| Disagree | 8 |
| Strongly disagree | 10 |

**Figure 6: Factor Values**

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These factors values are categorized in low, average and high for each and every factors as shown in Figure4. Like as shown in figure 4 that value of interest is 20, that having three membership values. After converting quantitative value into fuzzy value this is performed apriori algorithm and SS-FIM algorithm on fuzzy data to get the fuzzy association rules or the fuzzy patterns. On the basis of CGPAs conditions it predicts current semesters CGPA. These all are based on the socio-economic factors values form student's database. As shown in Figure 5 all the factors are available with their positive and negative responses and weightage of their questionnaire. As shown in Figure 5 that some questionnaire's weightage started from 0 to 10 and some are started from 10 to 0.

After getting fuzzy values here apriori and SS-FIM algorithms are performed on these data. First apriori algorithm is performed on only 20, 50 and 100 data. As shown in Figure 6 there are number of fuzzy rules displayed. This algorithm also counts the support and confidence for this data. This algorithm is also displayed the time of fetching rules. In these figures these rules are displayed that student's academic performance on the basis of factors values. Like student's performance are low, average or high in particular factors.

Command Window

```
time_ruleFetch =

    0.1122

------------------Apriori based associated fuzzy rules are as follows-------------------
```

| RULE_NO | INTEREST | FAMILY | PEER | HEALTH | HABIT | GRADE | SUPPORT | CONFIDENCE |
|---|---|---|---|---|---|---|---|---|
| 1 | low | low | low | low | avg | CGPA21 | 8.6957 | 100 |
| 2 | low | avg | low | low | avg | CGPA21 | 4.3478 | 100 |
| 3 | low | avg | low | low | low | CGPA22 | 8.6957 | 66.6667 |
| 4 | low | avg | avg | avg | low | CGPA22 | 8.6957 | 100 |
| 5 | low | low | high | low | avg | CGPA22 | 4.3478 | 100 |
| 6 | low | avg | avg | low | avg | CGPA22 | 4.3478 | 100 |
| 7 | low | avg | avg | avg | avg | CGPA22 | 8.6957 | 66.6667 |
| 8 | low | low | avg | low | low | CGPA22 | 8.6957 | 100 |
| 9 | low | low | avg | avg | low | CGPA22 | 4.3478 | 50 |
| 10 | low | low | avg | avg | low | CGPA21 | 4.3478 | 100 |
| 11 | low | low | avg | avg | avg | CGPA22 | 17.3913 | 80 |
| 12 | low | low | avg | avg | avg | CGPA21 | 4.3478 | 100 |
| 13 | low | avg | avg | avg | avg | CGPA21 | 4.3478 | 100 |
| 14 | low | avg | low | low | low | CGPA21 | 4.3478 | 100 |
| 15 | low | low | high | low | low | CGPA22 | 4.3478 | 100 |

fx >>

**Figure 7: Apriori algorithm on 20 data**

After performing apriori algorithm on 20 and 100 data, number of generated rules are increased. As number of fuzzy rules are generated then sup- port, confidence and time of fetching rules are changed.

Command Window

```
time_ruleFetch =

   0.1011

------------------SS-FIM based associated fuzzy rules are as follows------------------
```

| RULE_NO | INTEREST | FAMILY | PEER | HEALTH | HABIT | GRADE | SUPPORT | CONFIDENCE |
|---|---|---|---|---|---|---|---|---|
| 1 | low | low | low | low | avg | CGPA21 | 8.6957 | 100 |
| 2 | low | avg | low | low | avg | CGPA21 | 4.3478 | 100 |
| 3 | low | avg | low | low | low | CGPA22 | 8.6957 | 66.6667 |
| 4 | low | avg | avg | avg | low | CGPA22 | 8.6957 | 100 |
| 5 | low | low | high | low | avg | CGPA22 | 4.3478 | 100 |
| 6 | low | avg | avg | low | avg | CGPA22 | 4.3478 | 100 |
| 7 | low | avg | avg | avg | avg | CGPA22 | 8.6957 | 66.6667 |
| 8 | low | low | avg | low | low | CGPA22 | 8.6957 | 100 |
| 9 | low | low | avg | avg | low | CGPA22 | 4.3478 | 50 |
| 10 | low | low | avg | avg | low | CGPA21 | 4.3478 | 50 |
| 11 | low | low | avg | avg | avg | CGPA22 | 17.3913 | 80 |
| 12 | low | low | avg | avg | avg | CGPA21 | 4.3478 | 20 |
| 13 | low | avg | avg | avg | avg | CGPA21 | 4.3478 | 33.3333 |
| 14 | low | avg | low | low | low | CGPA21 | 4.3478 | 33.3333 |
| 15 | low | low | high | low | low | CGPA22 | 4.3478 | 100 |

**Figure 8: SS-FIM algorithm on 20 data**

As like apriori algorithm, SS-FIM algorithm is performed on the same fuzzy data. In Figure 8, support and confidence for 20 student's data is shown, along with time for fetching rules.It is easily compared with the apriori's fuzzy rules that the time of fetching rules are less than apriori. As per the theory of SS-FIM, it needs less time as compare to apriori algorithm. Because in SS-FIM algorithm, scanning process is done only one time ondata. In apriori algorithm there are multiple scans requires.

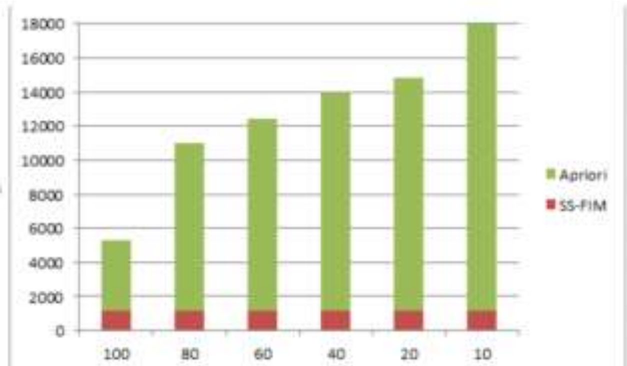


Figure 2. SSFIM and Apriori approaches for different support(%)

It is easily compared with the apriori's fuzzy rules that the time of fetching rules are less than apriori. As per the theory of SS-FIM, it needs less time as compare to apriori algorithm. Because in SS-FIM algorithm, scanning process is done only one time ondata. In apriori algorithm there are multiple scans requires.

## VI. CONCLUSION

When mining frequent patterns from a single scan database, SS-FIM performs better than other algorithms, and it takes less time to construct fuzzy association rules than the apriori algorithm with fuzzy set approach. Through these socioeconomic aspects, it will be easier for institutions to keep track of students' academic progress and act as a benchmark for students. The suggested methodology will make students more conscious of the impact of socioeconomic circumstances. Additionally, it will assist in balancing the student's participation in socioeconomic activities. Additionally, it will be

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used as a model by schools to track students' academic progress in relation to socioeconomic aspects and help them make better decisions.

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