Arab American University

Faculty of Graduate Studies

Evaluation and Forecasting of University Students Performance Using Neural Networks and Fuzzy Logic Models

By

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Dedication

I dedicate this work to my parents, teachers, colleagues, brother, sisters, my friends, and my supervisor Prof. Dr. Mohammed Awad.

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I would like to express my gratitude to my supervisor Prof. Dr. Mohammed Awad, who has been the best thesis supervisor. Where his sage advice, support, and patient encouragement aided the writing of this thesis in the best ways.

Abstract

The quality of education is the most important objective for the higher educational institutions. It can be evaluated by learning and teaching process. The education quality has many definitions which differe based on the culture, one of these defintions is an all-inclusive term in which environments as well a slearners for education are content is relevant, healthy, teaching is student-centered and Outcomes that encompassattitudes, knowledge and skills which are linked to national goals for education. The quality of the learning and teaching process depends on different parameters, some of these parameters are teaching methods, content, learning environment etc. There are many of metrics used to measure and track academic progress and achievement, like GPA and rank in class. One of these important metrics is the student's academic performance, where through this metric when it is predicted early, more information about the class or the major can be gathered and then analyzed to detect the reasons for low student's performance which may be from student, teacher, content, learning environment or teaching methods. After gathering this information, the specialists can handle and improve the reasons which will lead to improvement in the education quality. The low academic performance of university students whether they are newly admitted students or current university students is a problem that higher education institutions must assess to avoid the disapproval of the courses, which affect the education level on; wasting time, money, and effort.

Artificial intelligence techniques can be applied to forecast the academic performance of university students, to detect the factors that influence their learning process and allow instructors and universities administration to take more effective actions of counseling the students that require it. The process of forecasting the university student's performance can focus on the first year student and on the performance of the current students.So, identifying the performance of students will identify the quality of education which will be through analyzing and forecasting the student performance at the course level using many of factors like, attendance, exam marks and project marks, for the course and the student level one semester to forecast the performance in the whole degree.

In these two stages, a hybrid Adaptive Neuro Fuzzy Inference System (ANFIS) model, and a Fuzzy Logic model are used to perform the forecasting process. In this way, based

on the datasets from the first examinations collected from the Arab American University selected courses, or from the dataset collected of the computer systems engineering degree. Future results can be forecasted and suggestions can be made to carry out a corrective exercise to improve the final results.

On the other hand, K-means clustering and fuzzy c-means clustering methods are used to optimize the best distribution of the course grades from percentage grades to letter grades, to generate the optimal and efficient scale fairly. The experiments result of the applied models performed that the Adaptive Neuro Fuzzy Inference System (ANFIS) outperforms the Fuzzy Logic model in most cases, especially the ANFIS-Grid, wherein each model it gets the lowest error; in FRM dataset the Model get 0.7% where it just fails in one sample from thirteen samples, while the ANFIS-Cluster after modification it gets 0.15%. Where Fuzzy Logic is suitable for models of courses which contain only two inputs. Also, a graphical user interface application using python programming language developed. Also, a promising result of using clustering methods for distributing students' grades for a course.

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List of Abbreviations

ANFIS	Adaptive Neuro Fuzzy Inference System
NF	Neuro Fuzzy
FL	Fuzzy Logic
FCM	Fuzzy C-means Clustering
K-Means	K-Means Clustering
FIS	Fuzzy Inference System
AAUP	Arab American University Palestine
SAP	Students' Academic Performance
CS	Computer Skills
CSE	Computer System Engineering
FM	Final Mark
Mid	Midterm Exam
GPA	Grade Point Average
FGPA	Final GPA
CGPA	Cumulative GPA
ANNS	Artificial Neural Networks
RMSE	Root Mean Square Error
MLP	MultilayerPerceptron
LM	Levenberg-Marquardt
RNN	Recurrent Neural Networks
NFES	NewFuzzyExpertSystem
MF	Member-ship Function
AI	Artificial Intelligence

SOM	Self-Organization maps
FRM	Fundamental of ResearchMethods data set
CSC	Computer Skills data set
Genfis	Generate a Fuzzy Inference System

Chapter 1

Introduction

1 Introduction

The improvement of university teaching methods, raising the quality of graduates, achieving higher academic performance are some of the main concerns of researchers [3]. The phenomenon of low levels of student achievement in the first year of university degrees is a common problem. This problem is mainly reflected in a high rate of academic dropouts. This has been a cause for concern in higher education institutions studies.The failure or abandonment of students entering the university system represents a financial cost for the University, as well as a deterioration of its reputation as an educational institution. So, the educational institution is often interested in discovering factors that influence negatively in the efficiency of the teaching process [50] where it attaches great importance to devise strategies that improve it. forecasting the academic success of students is very valuable and provides information of interest to organize actions that contribute to reducing the academic risk of the students.

Education quality in universities is a very important issue. So, to deliver a high-quality education, improving student performance is needed which is an important factor in improving the quality of education, where the student performance is the extent to which a student has attained his long or short-term educational goals and its measured through various methods like examinations [49]. Universities are seeking to integrate student performance predictions in their educational processes in order to give students better support by arranging additional efforts for low-performing students. Nowadays, many of organizations are using data mining methods for exploring the vast amounts of data and extracting beneficial information that can be used for helping in making potential decisions.

Nowadays, data mining methods are used widely in the educational areas to extract new knowledge and significant information, to improve the learning process and guide the students' learning where applying these methods will lead to advance the quality of education and the students' performance [1,2,3].The evaluation of Student Academic Performance Assessment (SAP) is a very important practice used for many reasons. Some of them are: to obtaining an indicator of student learning level, to decide on failure and success in courses, and providing information on the effectiveness of teaching [13]. The ever-growing educational databases contain potentially hidden information that remains to be discovered in order to improve the academic performance of students. Educational data mining explores large educational databases to extract hidden information which is important for further processing. The information will be useful for many educational processes such as forecasting students' performance which allow the instructors to explore more about student's information level such as the potential knowledge of them not only in determining course, but also in the whole degree. There are many of techniques used for extracting information from the educational databases such as classification, regression, and clustering [10].Student's performance affected by many factors like academic, socio-economic, personal, and other environmental variables [10]. Where the knowledge about these factors and their impact will give the ability to managing and controlling their impact on student's performance. Forecasting students' performance is critical in educational settings. The main goal of all academic institutions is to increase student academic level. If the academic institutions forecast students' performance early, then additional efforts can be made to arrange appropriate support for weak students to improve their studies so that they can succeed [11].

The universities in general contain the data available in repositories so, machine learning techniques can be used to classifying, grouping, and forecasting. Artificial intelligence is a thriving technological field capable of changing every aspect of our social interactions. In the field of education, Amnesty International has begun to produce new learning and teaching solutions which are now being tested in different contexts [2, 3]. The Word is in a big data age, where it all leaves behind individual effects on information, leads to an abundance of information, allows objectively identifying human and societal behavior, and therefore, easy to track, and to some extent to forecast. This phenomenon called "datafication" which also affects the education field [42].

Artificial intelligence techniques have proven their ability to solve complicated problems efficiently. Soft computing techniques contributed to the development of more efficient models to forecast the Students' Academic Performance (SAP) with higher accuracy than the standard hard computing models. So, it recognized as an alternative to the standard hard computing models. There are many soft computing techniques used in this field, some of these techniques are: decision tree, artificial neural networks, fuzzy logic, neuro-fuzzy systems, clustering, and regression [10, 12].The soft computed methods help students, decision-makers, parents, and evaluators in order to obtain more understandable and reliable data about student's achievement. It is important to note that the proposed method is not intended to replace the traditional methods; rather, it is to strengthen the existing system by providing additional information to assist in decision-making [12]. Fuzzy Logic and ANFIS (Adaptive Neuro Fuzzy Inference System) [19] are used in this work to forecast the student's performance in selected courses and one of the university degrees. On the other hand, clustering model is used to optimize the best distribution of the course grades from percentage grades to letter grades. Defining of the grading scale for the course from the instructor may be not efficient because sometimes many of students need only one mark to achieve the upper grade like from A- to A+, so it is good to use a system that can define the grading scale fairly. The process of the defined grading scale for the course will depend on grading level in that course. So, the model will use clustering algorithms to inform the instructor about the extent of justice of his Grading scale define.

In this work, it is interested in improving students' academic performance which will lead to improvement in the educational sector. So, two algorithms which are Fuzzy Logic (FL) and Neuro-Fuzzy (NF) with the same data with optimizing for some parameters of these algorithms were consolidated to solve the problem. NF is an effective algorithm than FL when dealing with a large number of inputs. Also, the clustering algorithm by using the Find-Clustering tool is the best for distributing grades. Furthermore, the evaluation phase was processed fairly and consistently, considering the data selection reasons and the way of performing different tests. Fuzzy logic and ANFIS (Adaptive Neuro Fuzzy Inference System) used to forecast students' performance in different two courses, where these courses include all university students, like computer skills and fundamentals of research methods. Also, they are used to forecast students' performance for a specific degree of computer system engineering. After applying Fuzzy logic and ANFIS, the forecasted results are compared to detect which one is better to be used in order to help students to improve their performance and achievements. The main contribution of this research is to detect which method is better to be used in students' performance forecasting.

1.1 Objectives of the Study

The general objectives of this thesis are to improve the education quality and the Student academic performance through forecasting the students' academic performance (SAP) earlier as possible for specific courses and a university major using the proposed models. Also, there is another model for distributing the grades, which will improve the grading system in the university.

The study has the following specific objectives

- ✓ Developing artificial intelligence models used to forecast the students' academic success in a determined by courses that represent all the students in a university.
- ✓ Determining the most suitable artificial intelligence models used to forecast the students' academic success in a determined university degree, depending on his academic level on a semester.
- ✓ Designing graphical user interface that can be used to forecast the above missions.
- ✓ Developing an artificial intelligence model that used to distribute the student marks from percentage form to letters from reasonably.

1.2 Contribution of the Study

In this thesis, we presented several models were presented in order to forecast student's academic performance. These models applied on several data sets such as Computer Skills (CS), Fundamentals-Of-Research methods (FRM) and taking into consideration that these courses are university requirement. In the other forecasting application, Computer System-Engineering (CSE) degree was selected to forecast the student's performance in the whole degree. These models are evaluated using data sets which are collected from Arab American University Palestine (AAUP) through verifying the gained results from the models after applying them on random samples based on the actual results in the datasets. The accuracy of our models is high which makes them compete with other models in the same field. The conceived modelsare also applicable as a predictive model to other academic fields. The produced model presents an automated tool that allows to forecast the academic performance of students.The designed models from the results of the forecasting model constitute references for both managers and lecturers to improve their methodological work and achieve the successful academic of the students in a specified course or whole degree.On the other hand, K-means clustering and Fuzzy c-means clustering methods are used to optimize the best distribution of the course grades from percentage grades to letter grades in order to generate the optimal and efficient scale fairly.

1.3 Motivation

Through this work values will be added to the learning process in which the supervisor, head of department or any decision maker can use the predicted results to improve the process and it differs from one to the other:

1- Supervisor: allowing the supervisor to follow up with students in early stages to avoid any future bad results.

2- Head of department: through the results he can follow up with the instructors to check which is the problem if the percentage of the bad students' performance high in early stages, because sometimes the reason refers to the course content, major study plan or in the instructor himself.

3- Decision makers: like the students' parents or the students, it gives them early information about their status in the future which will help to avoid any bad results in the future. For example, the students in early stages can change his major if he already knows that it is not good to continue in it from the predicted information.

1.4 Overview

The rest of the thesis is presented with the following arrangement. Chapter 2, presents a background that includes a description of the datasets used in this thesis, literature review includes works in the same field related to our work. In chapter 3, models of performance evaluation are presented, and its usefulness for the design of one that allows the prediction of academic success in university students. The methodology of this thesis work includes firstly, the description of the preprocessing stage on the datasets. Secondly, the Fuzzy Logic, neural networks, neuro-fuzzy, and clustering methods also explained in this section. In chapter 4, all the experiments on the datasets will be illustrated with a summary of results from the models. Finally, the conclusions and recommendations derived from the research, and the bibliography are presented.

Chapter 2

Background

2 Background

The academic efficiency is understood as the ability to obtain desired academic results and it is is defined as the extent to which a school uses its time in the academic development of all its students[53]. Starting from this concept, it is recognized that low academic efficiency is currently a problem not solved by university institutions. Forecasting the students' academic performance can be either in a class or in a course, where each one has different parameters and different data which means that different data sets are needed. The academic performance can be measured by observing the results translated into test scores and grades during the course in semester or semester in the whole degree. Analyzing the results of university students allows universities to perform plan targeted actions to increase perseverance in students in higher education programs. The academic performance is the product of the motivation, the will, the capacity and the influence of the social component and mentions that some elements must be considered to increase performance are the advice to students, to improve the learning methods-based conditions, ensuring the existence of links between theory and practice, strive to take care of workloads and follow up on advances or setbacks of students.

The performance evaluation depends on forecasting the student's marks in semester course using preliminary assessments of the course, like first and second exams or assignment, etc., or in the whole degree depending on the student's marks level in one semester, will be a useful way to forecast the students' performance. Artificial intelligence models as neuro-fuzzy and fuzzy logic will be applied to achieve this objective.

These data sets are collected from AAUP, (which is a higher education institution with 11000 enrollment students in 10 faculties and more than 50 academic degree, more than 500 lecturers serve the students to obtain their knowledge) whether for forecasting courses results or for a degree results. Concepts are addressed by the literature which is linked to academic efficiency in higher education. The variables with the highest incidence on academic success and some approaches are to obtain our forecast. Fundamental theories that allow the development of a model to forecast students' academic success are presented in the literature review.

2.1 Datasets Description

The digitization of academic processes in the universities allows the generation of large electronic data concerning students since it provides information that can help both lecturers and administrations on the improving process of the students' academic performance. The main purpose of artificial intelligence methods is to extract meaningful insights from the data itself. It is also important for the educational institution that the level of success achieved by the students reflects the quality of the provided teaching. There are many studies that, through the application of artificial intelligencetechniques seek to make forecasting of the academic performance of the students. It is a difficult task to be achieved since studies indicate that academic performance depends on multiple factors both personality types such as socio-economic, psychological, and other variables. Correct forecasting allows to detect, in advance, those students who would have difficulties in passing the courses or passing the degree, which helped to make correct decisions such as providing additional support in the form of tutoring or counseling, changes or adjustments by lecturers. In the case of students in a specified course, a certain percentage of them does not succeed, and in the case of students in a specified degree, a small percentage leaves the degree during the study. One of the tangible parameters which could be forecasted about academic performance is the use of indicators of analysis of individual progressions at the end of a study of one course or in the whole degree study stage, so it should be considered, in advance, with sufficient data. As it is said before, the students' academic performance for specified courses and selected degree should be forecasted, so more than one data set will be used to forecaste the students' academic performance in one course and one data set to forecaste the specified degree.

To forecaste the students' academic performance in one course, more than one-course data set will be used . Computer skills and Fundamentals of Research Methods, these courses were selected because they present all the university students and they have different types of primary assessments. In the case of a specified degree, a computer system engineering degree will be choosen . On the other hand, for the fair distributing grades, the same data sets used to forecast the performance at courses will be used. The selected data sets to perform our experiments are done based on some reasons that will be explained in section 3.1.

2.1.1 Computer Skills Course-CSC DataSet

CSC dataset contains data collected from the AAUP in the first semester in 2018. This course is selected because it includes all students' majors. CSC dataset has 819 sample, so, this facilitates performing the experiments on this dataset without the need for more subsets that can be obtained randomly. Table 2.1 presents an illustration of the CSC dataset parameters.

Table 2.1: Records from the CSC dataset.

Mid term/25	Participation/10	Practical/10	Final Exam/40	Lab/10	Project/5	Absence Rate	Mark	Withdrawal Absence
10	0	0	24	4.75	3.50	0.13	F	0
12	9.50	7	25	7.57	3.50	0	C	0
19	10	7.50	28	7.75	4	0	B	0
15	9.50	9	28	9	5	0	B	0
12	10	4.50	18	8	3	0	D+	0
15	10	7.50	20	6	4	0	C-	0
15	10	4	20.50	7.50	4	0	C-	0

20	10	7	22	7.75	2.50	0.03	C+	0
6	10	5	19	7.25	4	0	D	0
11	8	4.50	13	3.75	0	0	F	0
16	9	6	28	5.50	3.50	0	C+	0
14	9.50	1	19	7.25	2.50	0.06	D	0
9	10	1.50	12	7	2.50	0	F	0
13	10	6	26	8	3.50	0.03	C	0
14	0	2	22	1.50	5	0.06	F	0
12	8	4	19	4.75	2	0.03	D	0
18	10	3.50	20	5	3.50	0.03	C-	0
16	9	9	23	8	4	0	C+	0
16	9.50	8.50	27	6	5	0	B-	0

This dataset consists of nine parameters but we picked six parameters will be picked as defined in table 2.2.

Table 2.2: CSC-Dataset features description.

Feature Name	Description	Affect to the output
Midterm exam (Mid)	It represents the collected marks for the students at the midterm exam	High effect on the output
Practical	It represents the collected marks for the students at the practical exam	High effect on the output
Participation	It represents students' participation during the course	Medium effect on the output
Lab	It represents the collected marks for the students in the computer skills lab	High effect on the output
Project	It represents the students marks obtained based on their work on the project for the course	Low effect on the output
Final Mark (FM)	It is the final mark for the students at the course, and this is the output of our model.	

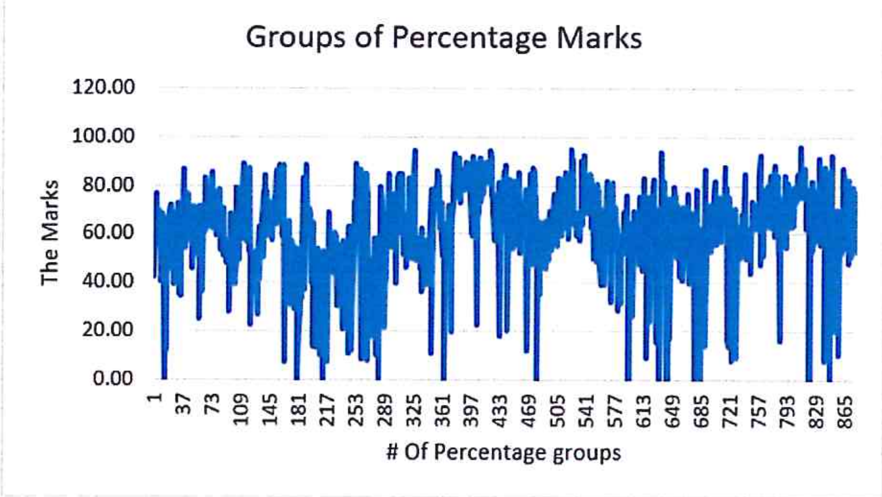

Figure 2.1: CSC Dataset as groups of percentagesmarks.

The other three parameters are ignored because there is no diversity in their values that causes them to not affect the final result of the forecasting process.The marks in this selected course presented as groups of percentage marks as shown in figure 2.1.In the following figure 2.2, the CSC marks represented as a group of characters.

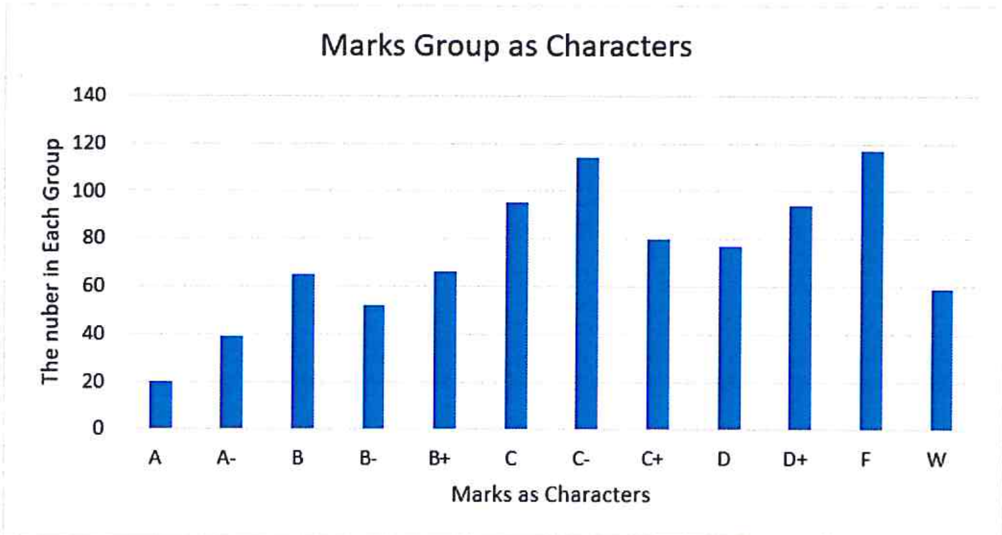

Figure 2.2: CSC Marks as a group of charactersmarks.

2.1.2 Fundamental of Research Methods -FRM DataSet

FRM dataset is also collected from AAUP university too. FRM dataset is about Fundamentals of Research Methods course for the first semester ofthe 2018.Also, this is an obligatory coursefor all the university students. FRM dataset has 325 samples .The following table presents an illustration of the FRM dataset parameters.

This dataset consists of six parameters but three parameters will be picked as defined in Table 2.3.

Table 2.3: FRM-Dataset features description.

Feature name	Description	Affect to the output
Midterm exam (Mid)	It represents the collected marks for the students at the midterm exam	High effect on the output
Participation	It represents students' participation during the course	High effect on the output
Final Mark (FM)	It is the final mark for the students at the course, and this is the output of our model.	

Table 2.4: Records from the FRM dataset.

Mid term/35	Participation/15	Final Exam/50	Mark	Withdrawal Absence
20	20	38	B	0
22	16	35	B-	0
22	20	34	B	0
19	16	34	C+	0
23	17	27	C	0
14	12	29	D+	0
13	17	34	C	0
23	13	37	B-	0
23	18	34	B-	0
23	16	34	B-	0
25	14	38.54	B	0
23	16	30	C+	0
29	20	40	A-	0
27	20	38	B+	0
20	13	37	C+	0
24	18	36	B	0
15	11	14	F	0
18	11	23	D	0
23	15	31	C+	0

21	18	34	B-	0
16	15	25	D+	0

The Midterm exam mark and Participation parameters have the same effect on the output, so they got the same weight. The other parameters ignored because there is no diversity in their values that causes them to not affect the final result of the forecasting process.

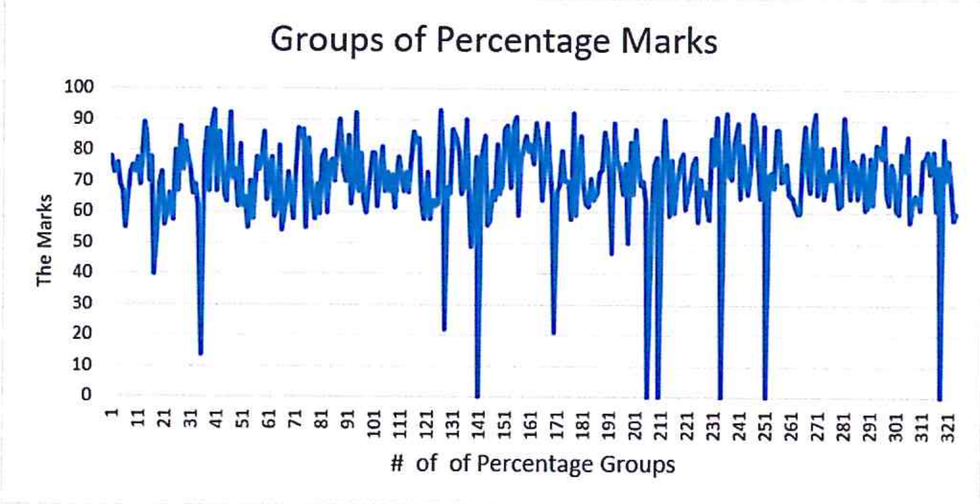

Figure 2.3: FRM marks as a group of percentage marks.

This dataset is smaller than the CSC dataset, but also, it's large enough and complete as CSC dataset. So, this facilitates performing the experiments on this dataset.The marks in this selected course presented as groups of percentage marks shown in figure 2.3.In the following figure 2.4, the FRM marks represented as a group of characters.

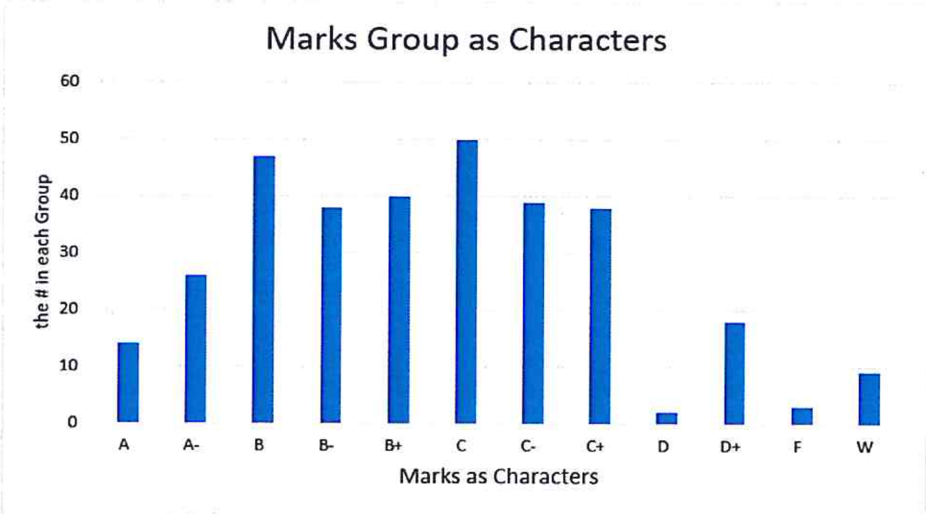

Figure 2.4: FRM marks as a group of charactersmarks.

2.1.3 Computer System Engineering-CSE DataSet

CSE dataset, the same as previous datasetsitis collected from AAUP university, consists of two combined datasets; the first one represents some selected courses marks for students during their study period; the second one represents students' GPA for each semester and the Cumulative GPA for each semester. CSE dataset is about a computer system engineer major. CSE dataset has 30 samples which means that it is a small dataset. Three larger datasets were derived based on the data from the smaller one. Where the first one has fifty samples, the second has eighty samples and the third has a hundred samples .This dataset consists of twelve parameters but sixparameters were picked from them as defined in table 2.5.

Table 2.5: CSE- Dataset features description.

Feature name	Description	Affect to the output
Math	It represents the collected marks for the students at math courses	Medium effect on the output
Programming Fundamentals C++	It represents the collected marks for the students at C++ courses.	High effect on the output
Digital Logic Design (DL)	It represents the collected marks for the students at the Digital Logic Design course	Medium effect on the output

Fourth GPA	It represents the GPA for the students after finishing four semesters	High effect on the output
High School	It represents the final mark of the students got at the high school	Mediumeffect on the output
Final GPA	It represents the final GPA for the students after finishing all courses, and this represents the output of this dataset.	

The other parameters were ignored due to several reasons; there is no diversity in values of some **parameters like "student probations** and period of study".Also, for other parameters, there is no meaning to have them in our models like GPAs for all semesters after the second year, because forecasting students after passing three years does not have any meaning. And some of the parameters after analyzing the data have little effect on the final mark.The following table 2.6 and figure 2.5 present an illustration of the datasets that make up the CSE dataset parameters.

id	school_avg	semester	semester_gpa	cum_gpa	course_no	course_name	mark	join_semester	period of study	student probations
0102	81.90	20,122	1.74	2.07	759	PROGRAMMING FUNDAMENTALS II	C+	20,092	7	0
0020	98.40	20,111	3.94	3.94	620	PROGRAMMING FUNDAMENTALS (C++)	A	20,111	5	0
0020	98.40	20,111	3.94	3.94	343	CALCULUS I	A	20,111	5	0
0020	98.40	20,112	3.93	3.93	344	CALCULUS II	A	20,111	5	0
0020	98.40	20,112	3.93	3.93	759	PROGRAMMING FUNDAMENTALS II	A	20,111	5	0
0020	98.40	20,112	3.93	3.93	1,737	DIGITAL LOGIC DESIGN	A	20,111	5	0
0020	98.40	20,121	4	3.95	1,060	ENGINEERING MATHEMATICS I	A	20,111	5	0
0020	98.40	20,122	3.95	3.95	1,134	ENGINEERING MATHMATICS II	A	20,111	5	0
0112	84	20,111	2.27	2.27	343	CALCULUS I	C	20,111	5	0
0112	84	20,111	2.27	2.27	620	PROGRAMMING FUNDAMENTALS (C++)	B-	20,111	5	0
0112	84	20,112	2.32	2.29	759	PROGRAMMING FUNDAMENTALS II	D	20,111	5	0
0112	84	20,112	2.32	2.29	344	CALCULUS II	C+	20,111	5	0
0112	84	20,112	2.32	2.29	1,737	DIGITAL LOGIC DESIGN	C-	20,111	5	0
0112	84	20,113	3.54	2.54	1,060	ENGINEERING MATHEMATICS I	B	20,111	5	0
0112	84	20,121	2.92	2.65	1,134	ENGINEERING MATHMATICS II	C+	20,111	5	0
0294	87	20,111	3	3	620	PROGRAMMING FUNDAMENTALS (C++)	A	20,111	5	0
0294	87	20,111	3	3	343	CALCULUS I	B+	20,111	5	0
0294	87	20,112	3.11	3.05	759	PROGRAMMING FUNDAMENTALS II	B+	20,111	5	0
0294	87	20,112	3.11	3.05	1,737	DIGITAL LOGIC DESIGN	B	20,111	5	0
0294	87	20,112	3.11	3.05	344	CALCULUS II	A-	20,111	5	0
0294	87	20,121	3.54	3.22	1,060	ENGINEERING MATHEMATICS I	B+	20,111	5	0
0294	87	20,122	2.60	3.06	1,134	ENGINEERING MATHMATICS II	B	20,111	5	0
0323	95	20,111	3.59	3.59	620	PROGRAMMING FUNDAMENTALS (C++)	W	20,111	5	0
0323	95	20,111	3.59	3.59	343	CALCULUS I	A	20,111	5	0
0411	81.50	20,111	2.60	2.60	620	PROGRAMMING FUNDAMENTALS (C++)	B-	20,111	5	0
0411	81.50	20,111	2.60	2.60	343	CALCULUS I	B+	20,111	5	0
0411	81.50	20,112	3	2.80	344	CALCULUS II	B	20,111	5	0

Figure 2.5: Screenshot for some records from the first dataset.

Table 2.6: Records from the second dataset

id	School average	Semester	Semester gpa	Cum gpa	Cum earned hrs	Student probations
0102	81.90	20,122	1.74	2.07	78	0
0102	81.90	20,131	1.98	2.12	94	0
0102	81.90	20,132	0.67	2	100	0
0102	81.90	20,141	1.91	2.03	118	0
0102	81.90	20,142	1.27	1.94	131	0
0102	81.90	20,143	3.17	2	137	0
0102	81.90	20,151	2.79	2.16	154	0

0102	81.90	20,152	4	2.20	163	0
0020	98.40	20,111	3.94	3.94	18	0
0020	98.40	20,112	3.93	3.93	36	0
0020	98.40	20,121	4	3.95	52	0
0020	98.40	20,122	3.95	3.95	70	0
0020	98.40	20,131	3.94	3.95	87	0
0020	98.40	20,132	4	3.96	103	0
0020	98.40	20,141	3.91	3.95	118	0
0020	98.40	20,142	3.98	3.96	135	0
0020	98.40	20,143		3.96	141	0
0020	98.40	20,151	3.93	3.95	156	0
0020	98.40	20,152	4	3.96	163	0

The following table presents an illustration of the CSE dataset parameters, where table 2.7 displaying the CSE dataset before the parameters selection process, but in table 2.8 displaying the CSE dataset after the parameters selection process.

Table 2.7: Records from the CSE dataset before the selection process.

STID	Math	C++	DL	1st	2nd	3rd	4th	Tawjihi	4GPA	FGPA	HPassed4th	Period
20	4	4	4	3.94	3.93	4	3.95	9.2	3.95	3.96	70	5
112	2.33	1.8	1.7	2.27	2.32	2.92	1.76	2	2.44	2.42	73	5
294	3.33	3.8	3	3	3.11	3.54	3.6	3.5	3.06	3.07	63	5
411	2.33	2.5	4	2.6	3	2.08	1.6	1	2.43	2.29	65	5
561	4	4	4	4	4	3.92	4	8	3.98	3.84	74	5
588	1.67	2.2	2	1.93	2.8	2.08	1.73	5	2.2	2.13	65	5
832	4	4	4	3.94	3.93	3.98	3.6	8	3.87	3.79	69	5
2	2.33	3.8	1.7	3.17	2.59	2.37	2.33	1.1	2.78	2.72	72	5
7	2.33	2.7	1	3	2.14	2.71	2.69	4.4	2.63	2.81	65	5
108	1.33	2.2	1.7	2.38	1.88	2.05	2.56	10	2.27	2.59	63	5
166	2	2.5	1.3	3.38	2.08	2.14	2.33	9.8	2.51	2.74	72	5

Table 2.8: Records from the CSE dataset after the selection process.

Math	C+	DL	4GPA	Hschool	FGPA
100	100	100	99.375	9.2	99.5
79.125	72.5	70.875	80.5	2	80.25
91.625	97	87.5	88.25	3.5	88.375
79.125	81.25	100	80.375	1	78.625
100	100	100	99.75	8	98
70.875	76.875	75	77.5	5	76.625

100	100	100	98.375	8	97.375
85	89.375	87.5	87.625	5.7	87.75
79.125	95.875	87.5	84	7.4	86.25
79.125	97.5	70.875	84.75	1.1	84
79.125	83.375	62.5	82.875	4.4	85.125
66.625	76.875	70.875	78.375	10	82.375
75	81.25	66.625	81.375	9.8	84.25
79.125	91.625	70.875	86.875	2.7	83.875
79.125	70.875	66.625	73.125	2.7	74.625
91.625	91.625	75	93.5	7.3	92.75

In the figure 2.6, students' final GPA from the CSEdataset represented.

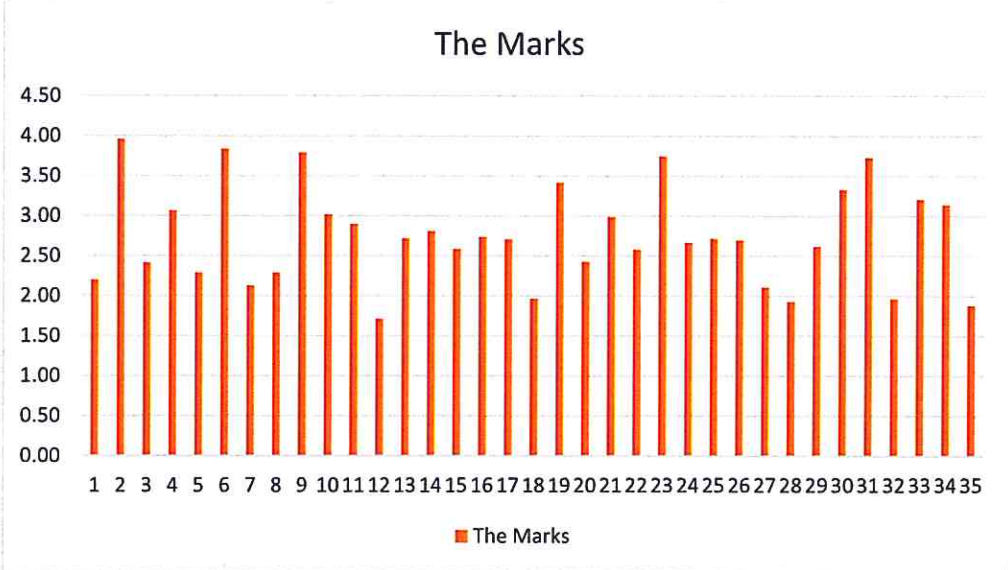

Figure 2.6: Students Final GPA from CSE dataset

2.2 Related Works

Nowadays, the universities are operating in a very competitive environment in the field of the graduated level in each course or the degree. The new technologies of artificial intelligence can help to improve the quality of education, improve results of learning, and allow achieving better administrative systems of education. Deep analysis of the university student's performance in courses or the whole specialization degree will help the university lecturers and administrations to identify the problems and estimate the future performance of each student in each course or the whole specialization degree, which produce a classification of the student's groups depends in learning parameters. The best way to deal with this problem is to have timely information about the academic performance of the students enrolled in the courses at the beginning of a semester or the first level of the students in the whole degree. This can be applied by using AI models, which use the performance measures as input and produce the forecasted result of this students. On the other hand, the design of a smart model that depends on the best distribution of letter grades to percentage values by using a clustering model,which can be useful in the process of assigning letter grades to the students reasonably.

One of the AI models is fuzzy logic, which used in education systems and initiated by Zadeh (Zadeh, 1965). The idea of fuzzy membership values and sets provides a possible model for subjective judgments and inexact concepts for all types of evaluations. This performance evaluation system involves many hedges like "bad", "good", "excellent" ... etc. which are involve a substantial amount of fuzziness. The researchers in literature used FL model or AI models, in general, in the field of education like forecasting, classification...etc. Some of the most important of these researches will be shown.

In [20] authors presented a new model for evaluating and forecasting the performance of students, where they used in there model an Artificial Neural Networks (ANNs) for the forecasting using a multilayer perceptron (MLP), and WEKA used to experiment. In this study two types of attributes used, first academic attributes that are related to the academic details like; unit test mark, attendance, the interest of study, and assignment mark. Then another one is the personal attributes related to the personal details of the students that affect the student study like; parent's education and family status.In [21], in this study,authors used six different artificial neural networks (ANNs) algorithms for forecasting the performance of students' academic to detect the best algorithm for the forecasting process, where three measures Standard deviation, Absolute average error, and Linear correlation used to compare between algorithms. Two experiments applied to those algorithms, firstly fifteen variables were used inputs, and secondly, six variables were used as inputs, and in both experiments,the exhaustive Prune method gets the best rating.

In [22], authors presented a new model for forecasting the academic performance of second-year engineering students using Artificial Neural Networks (ANNs) to forecast if the student can continue in studying engineering programs. In this study, 10 variables were used as input to the model, where these variables depend on the first year of study and the high school. In their model, a Multilayer Perceptron (MLP) used, where one input layer for (10 inputs), one hidden layer (6 inputs), and one output layer (4 inputs). And the back propagation algorithm used for training.In [23], authors introduced a new model for forecasting the academic performance of engineering students. In this study, six variables were used as inputs for the model; marks of these courses: Digital systems, Signal and System 2, Mathematics 2, Materials, and English 1. Adding to that the CGPA3(Grade of the third semester) to get a one output. The output of this model is the CGPA 8 (Grad of the eighth semester). 70% of the collected data used for training by using the Levenberg-Marquardt (LM) Algorithm and 30% of data used for testing.

In [24],authors introduced a new model for forecastingthe final grades of students. In this study, a different type of Neural Networks used not like the previous, where a Recurrent Neural Networks (RNN) used in this model, this type of neural network usesa recursive loop to handling time series data. 9 variables were used here as inputs for the model to introducing one output (final grade). The final results of the experiment shown that the

RNN have accuracy above 90% for predicting the final grade while using data until 6th week about students.In [25], comparing two techniques Artificial Neural Networks (ANN), Clustering and Decision tree for forecasting the academic performance of students. The data used in this model is about Computer Science students, where 60% of data used for learning and 40% for validating the results. The result of the model is to classify students into two groups: successful students and unsuccessful students.

In [26], authors presented a new method for performance evaluation using a Fuzzy Logic System, where they used the exam result for students. The study presents a new method for evaluation of the students'performancebased on the Fuzzy Logic System. Also, in this study they compare the result of the Fuzzy Logic system with Classical Method results.In [27], authors presented a new method for performance evaluation, where in this study the Fuzzy Logic used based on the Mamdani technique.This technique applied on three parameters considered in this study "attendance, internal marks, and external marks". At the final, the technique applied on a real sample, and two results have been produced and compared.

In [9], authors presented a new method for performance evaluation applied to Academic staff and students for Sudanese Universities. In this study, the Fuzzy Logic used with TOPSIS and AHP techniques. Also, they applied the method on nine criteria as the main, and another 41 as a sub-criterion which divided into three levels. Also, a New Fuzzy Consistency algorithm used to evaluate and check the consistency of the surveyed data and tools introduced to understand and trace the roots of inconsistency.In [28], authors presented a new method for performance evaluation, where the method applied of 20 students in 4 classes in a period of two semesters. The Fuzzy Logic used in this method depends on three parameters "the solution submitted by the students, a total of time has been needed to finish, the number of commands executed and the route which the student followed".

In [34], authors presented a new method for students' achievement evaluation using Fuzzy rules and Fuzzy membership functions "Fuzzy Logic". In this study, the researcher considers the complexity, importance, and difficulty of questions for students' answer scripts. The author provides a useful way to highlight the order of the student order with the same result. Wang and Chen [14] authors presented two methods for evaluating the answer scripts of students using Fuzzy Logic. In [4], authors proposed a new model for forecasting the performance of the students at the final examination for Mathematics courses. Four training algorithms applied to the Artificial Neural Network in order to identify the best algorithm for building an accurate forecasting model. The four algorithms used are (Broyden-Fletcher-Goldfarb-Shanno "BFGS", Levenberg-Marquardt "LM", Resilient Backpropagation "Rprop" andModifiedSpectral Perry "MSP"), based on the experiments the MSP get the best result. Also, in this study, they presented a developed software tool for forecasting the performance of the students using Artificial Neural Networks. The user of this tool can choose the training algorithm and the classification of the output, where there are two classification types: 2-Level (Pass, Fail) and 3-Level (Fail, Good, Very Good).

In [5], a comparison has been achived between fuzzy logic and another 3 methods for calculating the performance of the students. The three methods applied are Arithmetic mean, The university of Kazakhstan system, and the University of Liverpool system for master students. Each method has a different methodology for calculating the performance. In Fuzzy logic, the method of Mamdani applied to inputs using MATLAB to get the output "Final evaluation". The four methods applied to a group of thirteen students using data collected from a log system of the teacher. Four factors have been taken as inputs "Estimates for the lecture course, estimates for the practical training course, estimates for independent work and Estimates for the exam of the course" to get the final evaluation. Using the results for each method from the experiments we conclude that the Fuzzy logic more palatable for the evaluation of students' performance.

In [6], authors proposed a new model using Decision Tree for forecasting the final grade (GPA) of students based on their grades in previous courses. In this study, data for 236 graduated students about the final GPA and all courses collected. WEKA toolkit used to apply the classification on data to identify the most courses that affect the final GPA for students using the J48 decision tree algorithm. After applying the J48 decision tree on the collected data they concluded the most important courses that affect the final GPA, where the most one related to the final GPA is the "Software Engineering" course. The decision tree applied on each semester courses to identify the most related course for each semester:

Table 2.9: The most important course in each semester.

SEMESTER	COURSE
3	JAVA 1
4	DATABASE
5	SOFTWARE ENGINEERING 1
6	INFORMATION SECURITY
7	COMPUTER ETHICS
8	PROJECT 2

In [7], fuzzy logic is used to evaluate the performance of students, where the result of the fuzzy logic compared with traditional technique to prove that the fuzzy technique suitable and better than the traditional technique for evaluating the performance of students. The academic and personality traits of students considered in this study to get a better evaluation of the performance. A stage-wise fuzzy logic approach has been used, where the fuzzy system divided into different stages and in every stage, we have a different result, wherein stage 1 knowledge analysis applied on academics and communication skills attributes, and punctuality analysis applied on behavior and Attendance attributes, then the result of the knowledge and punctuality combined and used as input for performance analysis, finally the result of performance analysis combined with extra-curriculum attribute to get the overall rating. Finally, after five trials, the authors proved that the fuzzy logic is better than the traditional technique for evaluating the performance of students, and it can be used in other areas, like employees, faculty, etc.

In [8], three different models presented for forecasting the cumulative GPA of the students (CGPA). Models presented in this study are, artificial neural network, decision tree, and linear regression using SAS enterprise miner.Data used for the experiments is about 206 students, where the correlation coefficient analysis used to determine the relationship of the independent variables with dependent variables. After experiments finished for the three models, results compared by using the square root of average squared error (RASE) to identify the best model for CGPA forecasting,and the best results were pointing on Artificial neural network, where we can see the results below in the table 2.10:

Table 2.10: Forecasting models results.

RASE	ANN	REG	DT
Training	0.208	0.220	0.212
Validation	0.1714	0.1848	0.1769

So, from the table, it is seen that the ANN produced the smallest RASE, so it is the best model.In [15], a new fuzzy expert system (NFES) proposed for forecasting the performance of the students. The system applied on two inputs “examination mark of semester-1, examination mark of semester-2” about every student to get the performance for each student. The inputs passed on three steps before getting the output, the first step converting the crisp value for inputs to fuzzy values using a "Fuzzification" and then moved to the second step "Rules and Inference generation", where this step determining the membership functions for input and output which will be used in the inference process. After determining the membership function for the output, the fuzzy number for the output will be converted to the crisp value using a Centroid technique where this step known as "Defuzzification". The experiment for the NFES in this study applied on 20 computer science students in their second year. The same experiment applied using fuzzy logic type 1 and fuzzy logic type 2 to compare the results with the NFES result, where the result of the comparison indicates that the NFES more suitable for forecasting students' performance.

In [16], the Artificial neural networks (ANN) model presented for forecasting students' yearly performance to improve that personal factors like family education and living area will affect students' performance. The data used in this study collected from students through an online survey, where 120 students replied to the survey. MATLAB tool used for processing the data (filtering unnecessary data) before inserting them into the model. After MATLAB filtration, thirteen factors taken as inputs to the model (Class test marks, Class performance, Class attendance, Assignment, Lab performance, Previous semester result, Study time, Family education, Living area, Social media interaction, Drug addiction, Affair, and Extracurricular activity) were not only academic data taken as inputs to the model, the output is the Year final result. Also using the MATLAB, the supervised neural network with Levenberg-Marquardt backpropagation algorithm used for training the network. Where after calculating the GPA from the model, the actual GPA of the student will be compared to check the accuracy and errors, where if errors found then they will backpropagate to the system to adjust the weights. After the experiment applied randomly on seven students, they improved that the performance affected not only by academic factors, also personal factors will affect student performance.

In [17], a new model for forecasting students' performance using Adaptive Neuro Fuzzy Inference System (ANFIS). The dataset used for this study is about 100 computer science students, were mark of 5 courses taken as inputs to get the final GPA as an output. Three different membership functions that are used to define the ANFIS parameters: Gaussian MF(gaussmf), Generalized Bell MF(gbellmf), and Triangle MF(trimf). Where through applying the Root mean square error (RMSE) on experiments, the best membership function has been detected to be used for building the system, and the gbellmf gets the best results.

The present work tries to address the academic problems of the university students presented in the framework of a computer-based system through the using of artificial intelligence techniques to forecast the students' performance in one course or specialization degree. on the other hand, a clustering model used to distribute the course marks from percentage to letters, in a fair enough way. In the first stage, fuzzy logic and ANFIS (Adaptive Neuro Fuzzy Inference System) models were used to forecast the 3 different datasets collected from Arab American University Palestine (AAUP). these datasets selected carefully to present the majority of the students at AAUP. CSC and FRM datasets were used to verify the model's performance for a one-course case. In the second stage, the mentioned models were applied on a specialization degree dataset, for this stage, we used the CSE dataset with speciated features. For the grading distribution system, we used two different algorithms, the first one is K-means clustering and the second is a combination between fuzzy and clustering called Fuzzy c-means clustering.

After applying Fuzzy logic and ANFIS we compared the forecasted results to detect which one is better to be used to help students to improve their performance and achievements. And we did the same for clustering algorithms to detect which algorithm is better to be used.

Chapter 3

The Proposed Models

3 The Proposed Models

The general idea of using AI techniques to forecast the academics performance of the university students is to infer the value of an attribute or some aspect of the data from a combination of other aspects within the data. Forecasting in general is normally done through the creation of models that are made using techniques such as classification, regression, and categorization [10]. The most used techniques in forecasting are neural networks, fuzzy logic, evolutionary computation, regression analysis, and hybrid systems that combine two of the AI techniques which are used in our application. In this chapter, the proposed models are illustrated. This chapter represents four sections. It starts with how the datasets is collected. Then, the next section talks about the preprocessing on the collected data, the third section illustrates how the models are built and the last section shows how the build models were tested. Figure 3.1 shows the block diagram of the forecasting model in general.

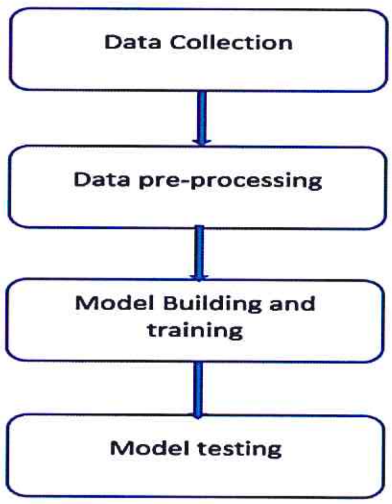

Figure 3.1: General block diagram for the forecasting model.

3.1 Data Collection and Selection Consideration Phase

The collected datasets are used to establish the training datasets for the applied AI models. The datasets collected from the AAUP database to forecast the academic performance of the students' at AAUP. The collected data presented two types; academic data about the students are still in the university and pre-university data (high school), where personal data about the students couldn't be collected because it's a confidential data and not accurate enough. Three different datasets are used, these datasets are divided into two types. First type related to the students' academic performance at a single course, and the second type related to the students' academic performance at the whole major.

For the first type of datasets, two different courses were selected, the first course is Fundamental of Research Methods (FRM) course, this course was selected because it combines all university students as it is a university requirement course. The second course is Computer Skills course (CSC), also this course combines all university students except information technology and engineering students. This course was selected for two reasons, the first one is the same the first course was selected, where this course approximately combines all university students, and the second one is, this course which has a large number of students for one semester. This leads to build a model that can deal with all students in the university, and this can help decision-makers in deciding on the course, like separating the students based on the performance level for the students, like separate information technology students from finance students, etc.

For the second type of datasets, a Computer System Engineering major was selected to forecast the student's academic performance to a whole degree for many reasons. Firstly, as everyone know, s that the engineering discipline is a critical study where mathematics and scientific knowledge are used to develop the whole range of medicine, industry, and many other specializations. Now, the importance of having strong students in this field is seen . Secondly, because the computer system engineering near to our major, knowledge about computer system engineering study plan is available and about how every course affects the student. Finally, a Computer system engineering major is a long major compared to other majors in the university, where the student in a normal case needs five years to graduate.

3.2 Data Pre-Processing Phase

Once the datasets and the parameters in each dataset have been determined in the previous phase. Incomplete, missing, or inconsistent information is discarded to prevent data being analyzed that could create errors when executing the artificial intelligence applied models. In the data cleaning stage, some parameters have been removed because it's not accurate, like the absence rate and withdrawal absence, these data entered by the lecturer, and normally he did not take the absence in each lecture, which means that the data may be not real data. The data goes through different processing stages before it is ready for use and this phase called data pre-processing. Data pre-processing involves many steps depending on the nature of data. different pre-processing steps were used ; they included coding and feature selection too.

3.2.1 Data Coding

In this step, codes for final output values were set, where the AAUP system dealing with GPA and letter grade while our models dealing with percentage grade. Two codes mapping for a letter grade to be suitablefor the course prediction model were created, where each letter mapped to a code number as shown in table 3.1 and 3.2.Where ranges for a letter with percentage mapping may differ from course to another based on the scale of mark distribution. For GPA grade, It is mapped with percentage. Table 3.2 shows a code for each grade.

Table 3.1: Mapping for Letter with percentage for courses.

Letter Grade	Range
A	>=90
A-	>=85&< 90
B+	>=80&< 85
B	>=75&< 80
B-	>=72&< 75
C+	>=68&< 72
C	>=64&< 68
C-	>=59&< 64
D+	>=54&< 59
D	>=50&< 54
F	<50

Table 3.2: Mapping for Letter with GPA.

Letter Grade	Numeric Grad out of 4
A	=4
A-	=3.67
B+	=3.33
B	=3
B-	=2.67
C+	=2.33
C	=2
C-	=1.67
D+	=1.33
D	=1
F	<1

3.2.2 Data Cleaning and Feature Selection

The collected datasets consist of a set of features, some of these features are not important or cannot be used. So, in the feature selection step, features wereselected and excluded .In this step, some features have been ignored in the process of forecasting the students' performance in one course (CSC, FRM). For the second application of forecasting that applied on the CSE dataset which includes 12 features before pre-processingas shown in the following table 3.3 .From these features, the first six features were selected based on the effect of them on the final output, and this increased the performance of the prediction model because processing six features take less time than processing twelve features. For CSC and FRM datasets, as mentioned in the 2.1.1 and 2.1.2 sections before pre-processing the FRM includes six features shown in table 3.4 and the CSC includes 9 features shown in table 3.5.

The final exam, absence, and withdrawal features from these datasets were excluded . Where the model used before the student gets the final exam, absence does not affect the final output, and withdrawal does not have enough samples for model training.

Table 3.3: CSE dataset features.

Number	Feature Name
1	High School avg
2	GPA for each semester
3	Drop
4	C++ I
5	C++ II
6	Calculus I
7	Calculus II
8	Math I
9	Math II
10	Digital Logic Design
11	Period of Studying
12	Final GPA

Table 3.4: FRM dataset features.

Number	Feature Name
1	Midterm exam
2	Participation
3	Absence
4	Withdrawal_Absence

5	Final exam
6	Final mark

Table 3.5: CSC dataset features

Number	Feature Name
1	Midterm exam
2	Practical
3	Project
4	Lab
5	Participation
6	Absence
7	Withdrawal_Absence
8	Final exam
9	Final mark

The final mark for CSC and FRM datasets represented in letters not numeric. In the data cleaning step, the letter features converted to numeric features. Also, for CSE dataset some features represented in letters, where these are course marks and also converted to numeric. Also, GPA features for each semester represented in GPA scale, where these features converted to a percentage scale to increase the accuracy of the output.

Table 3.6: CSC-2 dataset features.

Number	Feature Name
1	Midterm exam
2	Practical
3	Absence
4	Withdrawal_Absence
5	Participation
6	Final mark

High school (Tawjihi) feature is represented in percentage scale, but due to its low-medium effect on the output, it was converted to tenth scale. Using data cleaning, two different datasets from the CSC dataset were created, where the primary one mentioned in section 2.1.1, and after applying data cleaning on the primary one, a new one with features was gotten as shown in table 3.6. Practical, project, and lab features in one feature named as practical were combined.

3.3 Building Models Phase

After datasets prepared, the design of the forecasting models will start. The models will be applied using MATLAB. Also, the python programming language used for building a forecasting application with GUI.

Both Fuzzy Logic and Neuro-Fuzzy hybrid models were used to design theforecasting models on CSC, FRM,and CSE datasets. The clustering algorithm used to build students' grade distribution model. The next section will describe all the applied models in detail.

3.3.1 General Method Procedure

The general procedure which was used in performing all experiments on the determined datasets selected from the AAUP database shown in Figure 3.2 and it is illustrated as follows:

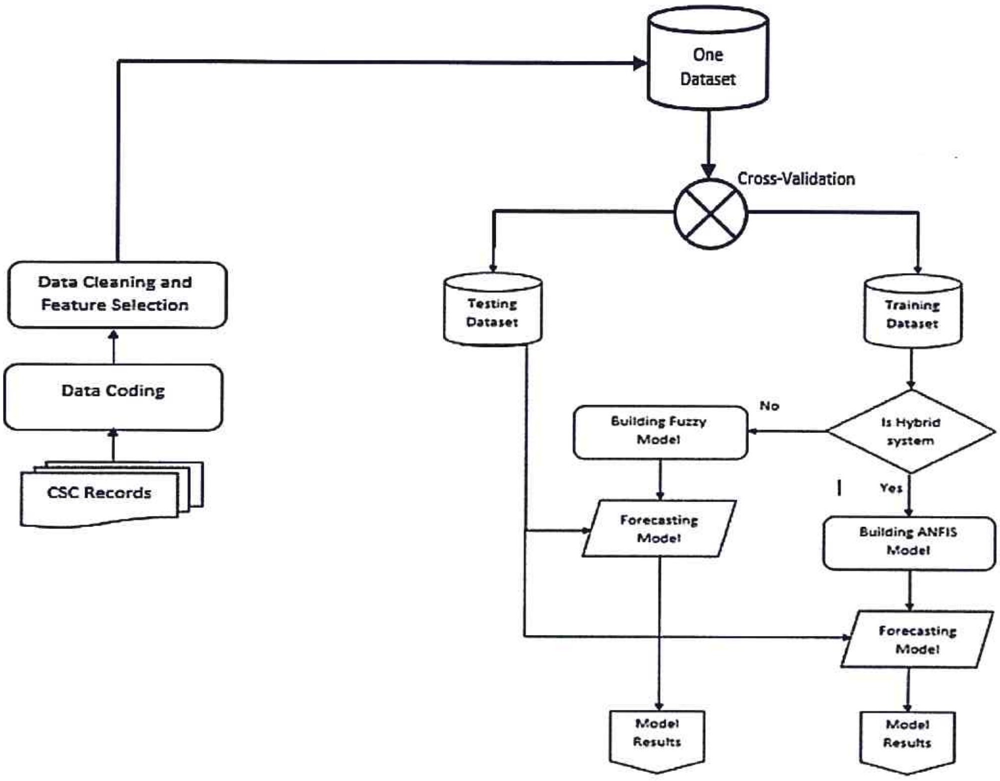

Figure 3.2: The flow chart of the general method procedure.

3.3.2 Fuzzy Inference System (FIS)

Fuzzy Inference System connects the inputs to the outputs using a fuzzy set. This can be either Sugeno or Mamdani. FIS involves 3 steps, Fuzzification, the formation of the rule base, and Defuzzification as shown in Figure 3.3. In the first step, membership functions used to apply the Fuzzification on the inputs as shown in Figure 3.4. In Fuzzification, the crisp data transformed into a fuzzy set. In most cases, singletons are used as fuzzifiers [45].

$$\text{fuzzifier}(x_0) = \overline{x_0}, \qquad (1)$$

$$\mu_{\overline{x_0}}(x) = \begin{cases} 1, \text{for } x = x_0 \\ 0, \text{for } x \neq x_0 \end{cases} \qquad (2)$$

Where,x_0 is the crisp input value. In the second step, from the rule base apply IF-THEN rules on the inputs to select the closest rule as shown in Figure 3.6. And this step has three steps:

1. Find the firing level of each rule.
2. Calculate the output of each rule.
3. Aggregate the rules output individually to obtain the overall output.

In the last step, membership functions of the output used to get the crisp value of the output as shown in Figure 3.7. To transforming the crisp value a defuzzification operator used. The most operator used for a discrete fuzzy set C having the universe of discourse V isCenter-of-Gravity (COG), where it finds the center of the Gravity of the aggregated fuzzy set, represented in the following equation [45]:

$$z_{0(\text{defuzzifier})} = \frac{\sum_{j=1}^{N} z_j \mu_c(z_j)}{\sum_{j=1}^{N} \mu_c(z_j)} \qquad (3).$$

where $Z = \{z_1, \ldots, z_N\}$ is a set of elements from the universe V.

There are different types of membership functions.Trapezoidal, Triangular for linear variation and sigmoidal, Zigmoidal, Gaussian, etc. for nonlinear variation. So, the selected membership function will be depending on the requirement. Both trapezoidal were used as shown in Figure 3.4 for output and triangular as shown in Figure 3.5 for input membership function for FIS. but for NFZ several membership functions like Triangular, Gaussian for inputs and linear, constant for outputs were used.

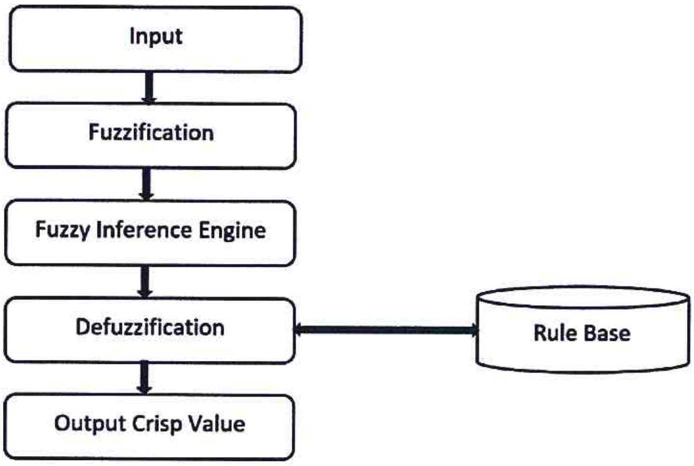

Figure 3.3: Flow of FIS.

Fuzzy logic is related to set theory, in which the degree of membership of an element to a set is determined by a membership function that can take real values. In fuzzy logic, a level of compliance is obtained, the closer to zero, it will be less relevant and when it is closer to 1, it will be more relevant the steps to be followed in assembling a fuzzy inference system are explained as:

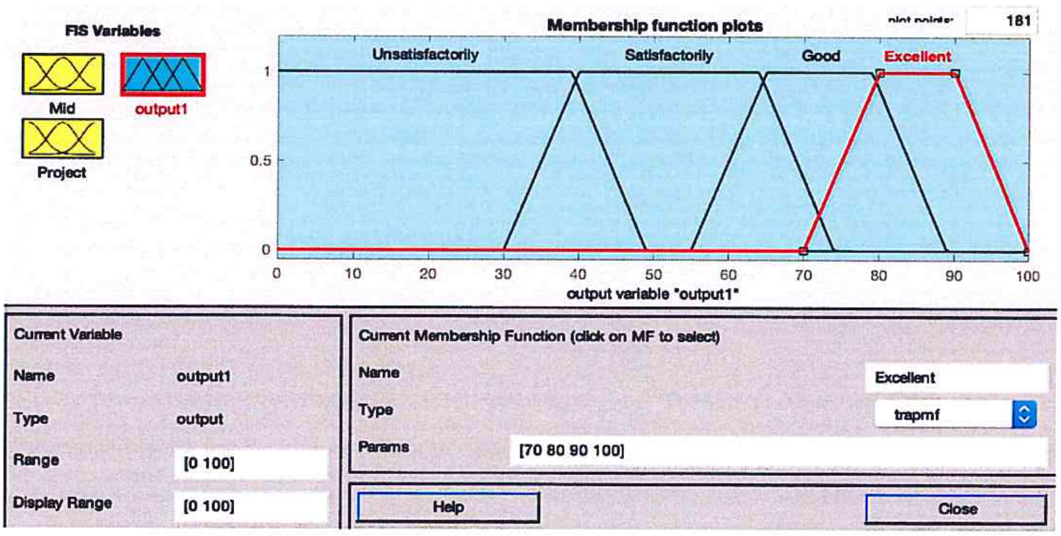

Figure 3.4: Trapezoidal Membership function for output.

The variables have a degree of metalinguistic uncertainty. That is, the range of values of each variable can be classified by fuzzy sets. With this, the values go through a fuzzification process that categorizes them into a membership range between 0 and 1 to a fuzzy set.

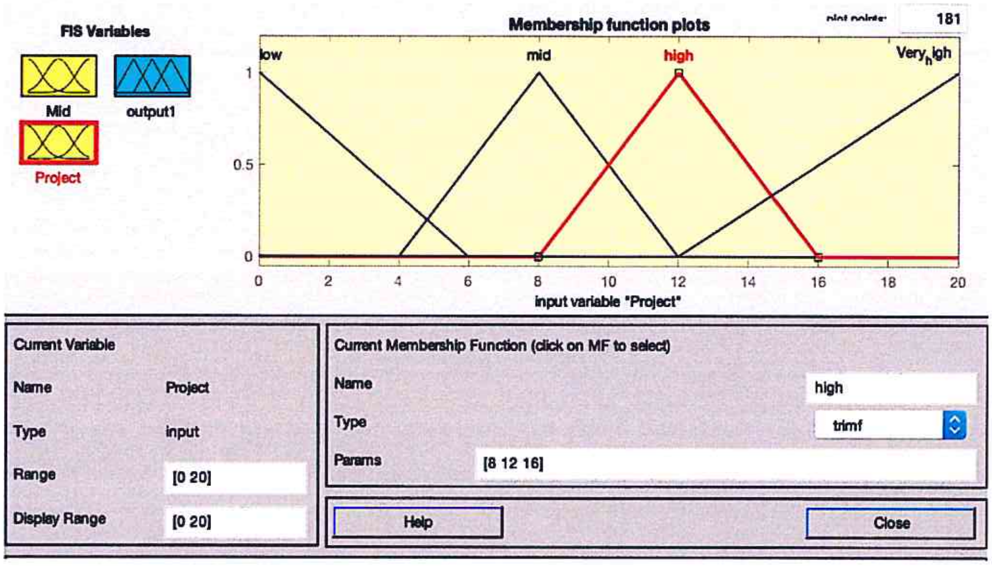

Figure 3.5: Triangular Membership function for Input.

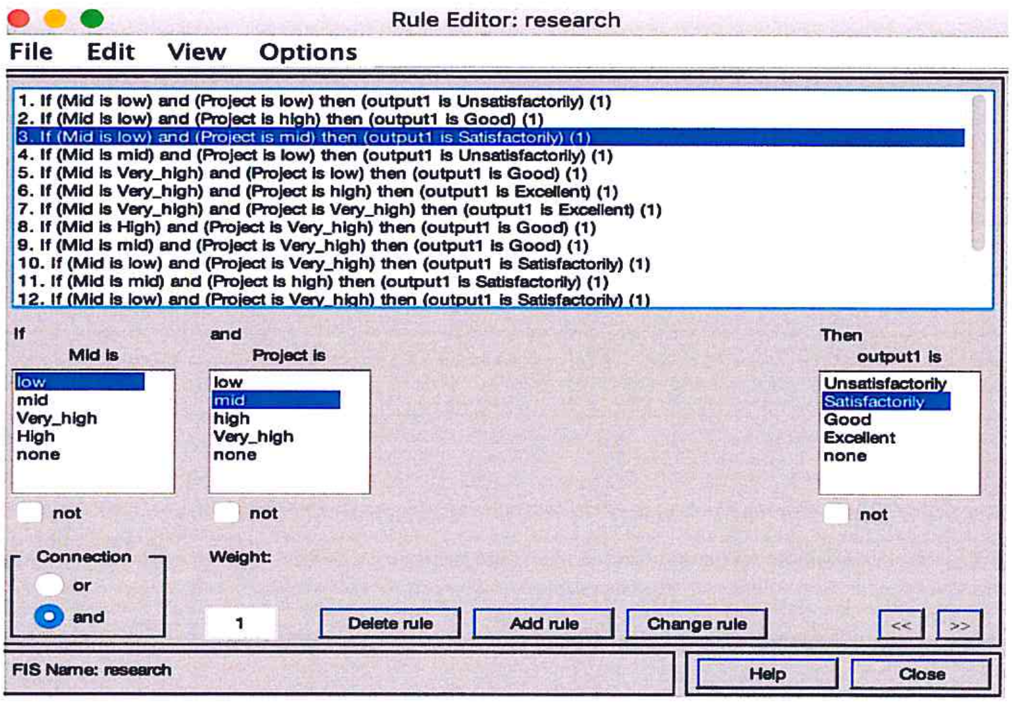

Figure 3.6: Rule Editor for FRM dataset displaying IF-Then Rules.

Then Linguistic rules known as inference are proposed. With this, the degree of membership of each variable is evaluated in a subset of these rules.

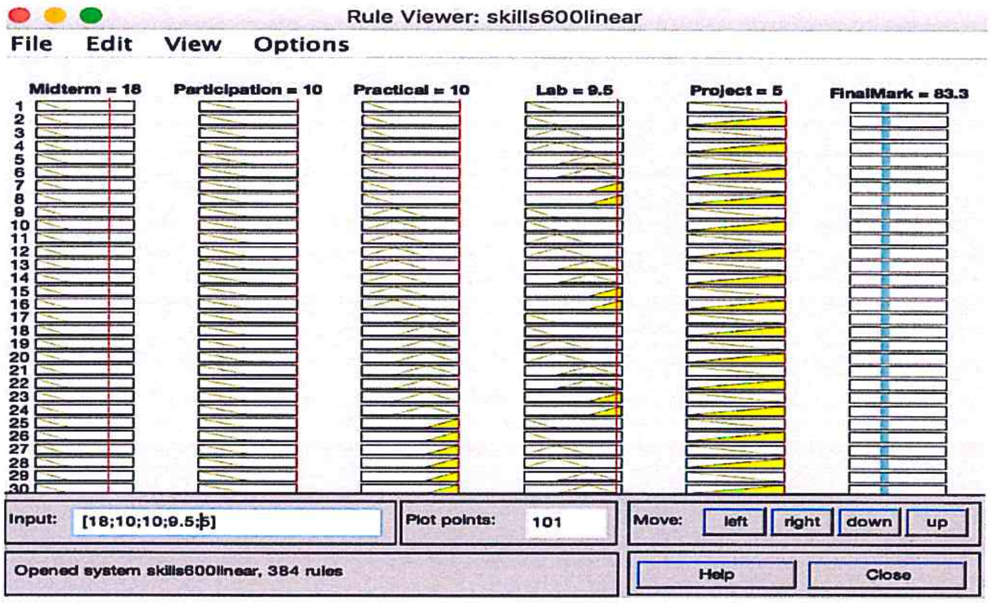

Figure 3.7: Rule Viewer with inputs and output for the CSC dataset.

Finally, the steps of determining the optimal output values, using defuzzification, which consists of passing the degree of membership, arising from the consequence of the activated inference rule, to a clear or real value, to obtain a quantifiable value.The following algorithm displaying the procedure used for building the Fuzzy model which applied on the FRM – data set.

Algorithm 1: The general procedure that was used in building the Fuzzy model

Input: FMR – dataset.

Output: Final Mark.

Data: Training set, Testing set.

1- Data Import.

2- Data Slicing.

3- Data Coding.

4- Data Cleaning.

5- Analyzing Training set.

6- Building Rule Base for Fuzzy Model.

7- Test Set Forecasting.

8- How Accurately Forecasting model is working.

9- Fuzzy Model Enhancement.

3.3.3 Adaptive Neuro Fuzzy Inference System (ANFIS)

Neuro-fuzzy systems arise due to the lack of standard methods to transform human knowledge or experience towards the base of rules and data of a fuzzy inference system. To achieve this objective, requires effective methods to adjust your membership functions as well as how to minimize the measurement of the output error or maximize your performance or efficiency. The Adaptive Network-based Fuzzy Inference System (ANFIS) based on Adaptive Networks, which serves as the basis to build a set of rules fuzzy (if ... then) with appropriate membership functions to generate the Optimal input/output data pairs. ANFIS is a hybrid system introduced by Jang [19] where it is a combination of a fuzzy inference system and neural networks also called neuro-fuzzy(NFZ) [18] as shown in figure 3.8. So, it will gather the advantages of neural networks and fuzzy inference system[19]. The NFZ system is working through training neural networks on the provided data to generate membership functions and fuzzy rules of the fuzzy system. Simple architecture for NFZ consists of 5 layers as in Figure 3.8. The first layer is the input layer, the three hidden layers are for generating membership functions, calculations, and normalization and the fifth layer is the output layer.

There are two types of ANFIS, the first one is ANFIS-Grid as shown in figure 3.8. ANFIS-Grid uses the grid partitioning, and in some cases, it produces a huge number of rules because it enumerates all combinations of inputs' membership functions and it is an exponential relation between the number of rules and number of membership functions.

For example, if there are seven inputs and each one has 3 membership functions, the number of rules will be 3^7 = 2187 where this number is huge. The second one is ANFIS-Clustering as shown in figure 3.9. ANFIS-Clustering uses scattering partitioning by subtractive clustering, where the number of rules will be small and each rule indicates a cluster.

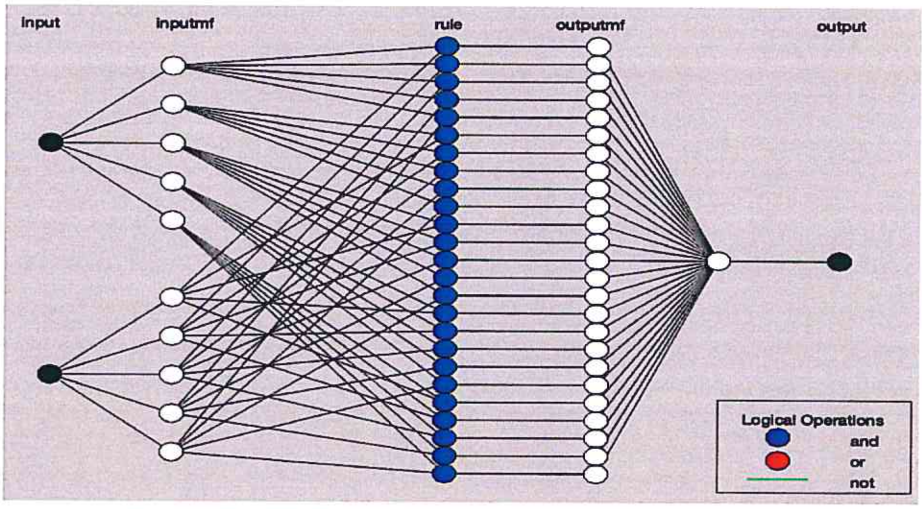

Figure 3.8: Basic block diagram of ANFIS-Grid

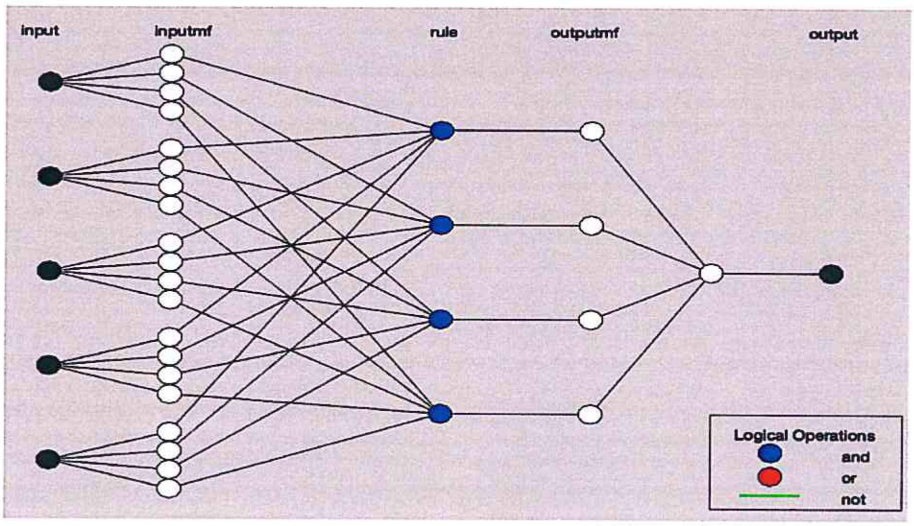

Figure 3.9: Basic block diagram of ANFIS-Clustering with four clusters.

Rules extracted from the ANFIS model are similar to that built-in Fuzzy logic, in the following figures 3.10 and 3.11. the extracted rules from ANFIS for CSE–datasetshown.

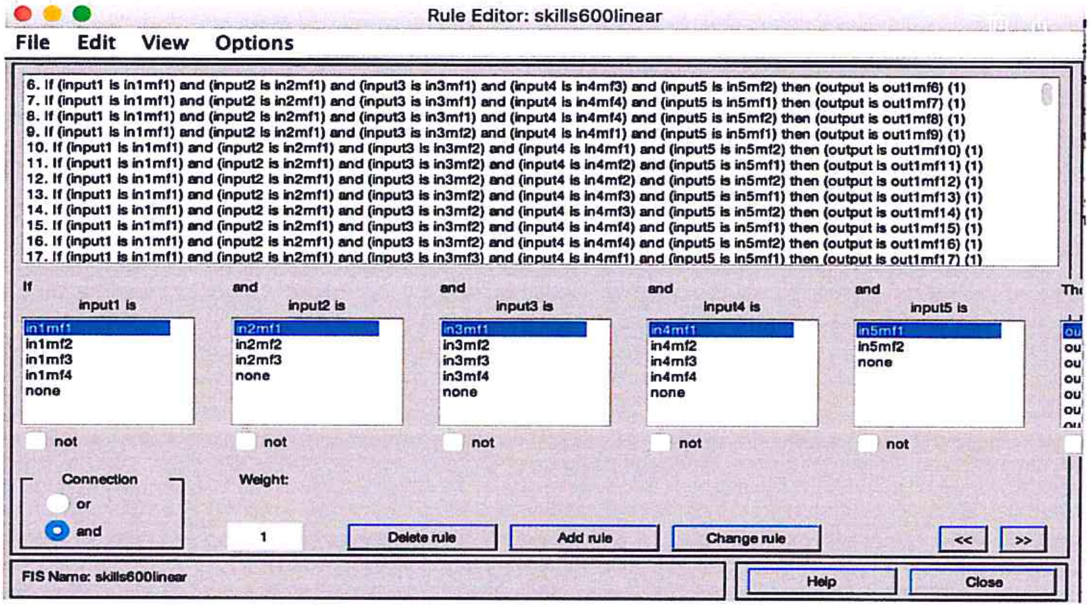

Figure 3.10: Rules Extracted From ANFIS-Grid Model for CSE-dataset (5 inputs).

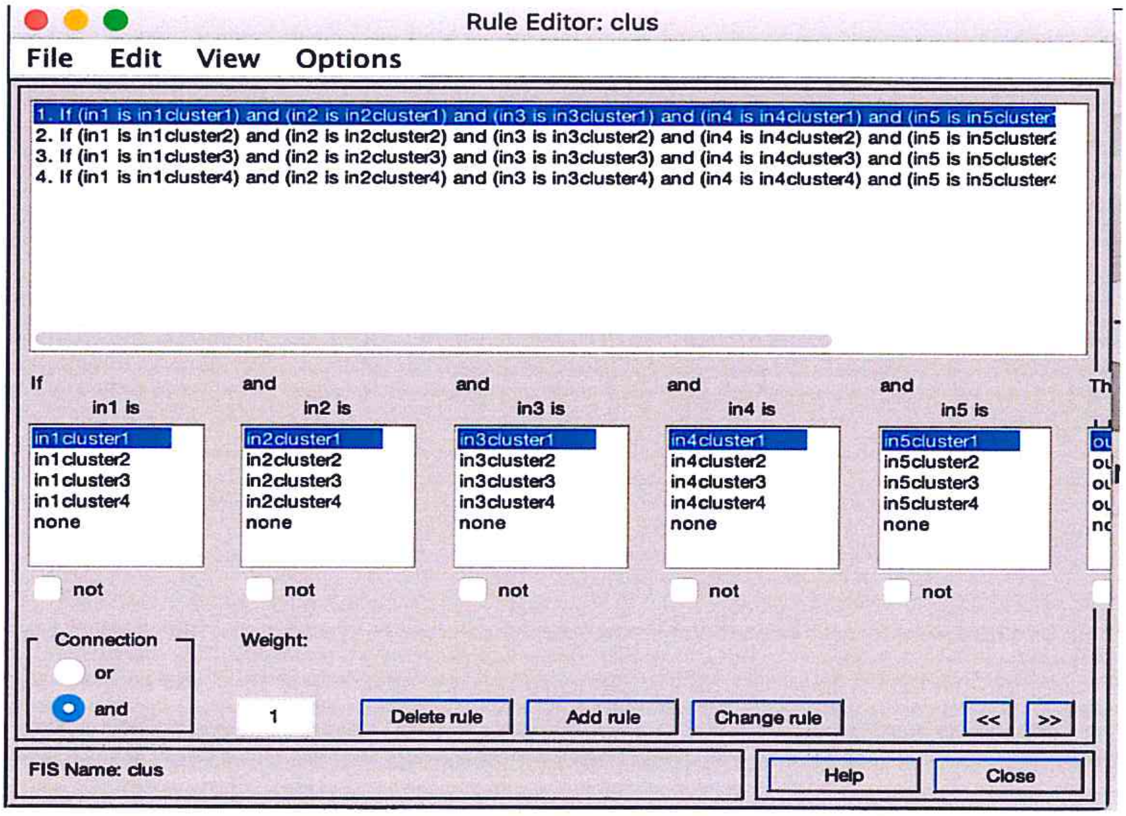

Figure 3.11: Rules Extracted From ANFIS-Cluster Model for CSE-dataset (5 inputs).

The architecture that is proposed for the development of this work is a type of adaptive network, which is functionally equivalent to a fuzzy inference. ANFIS models are a system of fuzzy inference in which its parameters are adjusted by an algorithm of back propagation based on an input/output dataset (data training), which allows the system to learn. Due to the increased speed in training, and the best characteristics of the systems of the first order over those of zero-order, are these with which develops the present work. To explain how architecture works, a system is considered of inference with inputs and one output. ANFIS in which the nodes in the same layer perform Similar functions. The following is a description of the function that each layer in the architecture shown:

Layer 1: The nodes in this layer are adaptive nodes with a node function

$$O_i^1 = \mu_{A1i}(A1) \qquad \text{where i= 1,2,3, ... (4).}$$

Where A is the linguistic value. O_i is the membership function of A_{1i}. The membership value calculated using the Gaussian function as in equation (5).

$$\mu_{A1}(x) = e^{\frac{-(x-c)^2}{2\sigma^2}} \qquad \text{where the } \{\sigma\text{,c}\} \text{ is the parameter set (5).}$$

Layer 2: the nodes in this layer are fixed and the output is the incoming of all incoming signals as in the (6).

$$O_i^2 = w_i = \mu_{A1i}(A1) \times \mu_{A2i}(A2) \times ..... \qquad \text{where i= 1,2,3,..... (6).}$$

Layer 3: The nodes in this layer are fixed nodes. The weight functions normalized by the node by calculating the ratio of the ith rule's firing strength to the sum of all rules' firing strength using (7).

$$O_i^3 = \overline{w_i} = \frac{W1}{W1 + W2} \qquad (7).$$

Layer 4: The nodes in this layer are adaptive nodes and the output represented in the (8).

$$O_i^4 = \overline{w_i} f_i = \overline{w_i}(p_i A1 + q_i A2 + \cdots + r_i) \qquad \text{where i=1,2,3,..... (8).}$$

Layer 5: This layer has a single fixed node where this node computes the overall output as in (9).

$$O_i^3 = \sum \overline{w_i} f_i \qquad (9).$$

The following algorithm displaying the procedure used for building the ANFIS model which applied on the CSC – data set, and this procedure can be applied on CSE – dataset.

Algorithm 2: The general procedure that was used in building the ANFIS model

Input: CSC – dataset.

Output: Final Mark.

Data: Training set, Testing set.

1- Data Import.
2- Data Slicing.
3- Data Coding.
4- Data Cleaning.
5- Train ANFIS model using Grid/Clustering.
6- Test ANFIS model.
7- Transform ANFIS model result to the FIS model.
8- Test FIS model.
9- How Accurately Forecasting model is working?
10- ANFIS Model Enhancement.

3.3.4 Python Programming Language

Python is a programming language; Python offers readable and concise code. While versatile work flows and complex algorithms stand behind Artificial Intelligence (AI) and Machine Learning, the simplicity of Python allows developers to create reliable systems.

Python language close to human language, which makes it easier for understanding and building AI models. We used Python for building the FIS model, wherein python we can set the output in a class like (A, A-, B,C+,F..etc) to get an output similar to the university results. Where the MATLAB dealing only with numbers and the output can't be character. So, the flow of FIS in the Python will differ from the previous flow as shown in figure 3.12. Also, Python used for building an application for students' performance prediction which supports GUI to be used easily by anyone like course instructor.

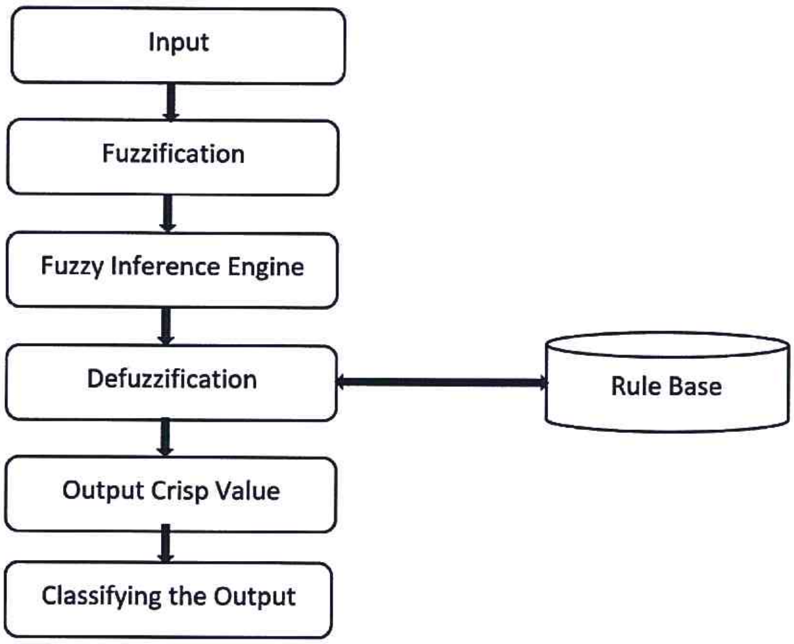

Figure 3.12: Python Application Flow.

3.3.5 Clustering Methods

Clustering algorithm grouping dataset into clusters. The objects in the same cluster are similar and the clusters are different from each other. Clustering is an unsupervised learning algorithm, meaning that there is no output identified previously like in classification. In this thesis, the K-means clustering algorithm will be used but in two ways. First one, K-means clustering alone and thesecond one, Fuzzy C-means clustering (FCM)to build the distributing grade model.

3.3.5.1 K-Means Clustering

K-means clustering is a partitioning method. A set of k clusters from the dataset is the result of the partitioning method, all objects of the dataset are distributed to the k clusters, where each one belongs to one cluster. Each cluster has a cluster representative or centroid [29]. K-means clustering is a data mining algorithm used to clustering datasets. K-means uses an iterative approach to cluster the dataset.K-means working as shown in figure 3.13. Firstly, identifying the number of clusters and the initial means. Secondly, calculating the final means. Thirdly, distributing the objects to the clusters, where in this step each object will be set to one cluster based on the mean of the cluster, where the famous approach for distributing the objects is the shortest distance algorithm. Finally, stop performing the iterations when the algorithm converges.

K-means clustering working steps:

1. Selecting cluster centers in a random way.
2. Using the shortest distance algorithm to calculate the distance between data points and centers, where the distance for each data point will be calculated with all centers to identify the shortest one.
3. Assigning each data point to the nearest center, which identified from the previous step.
4. Using the following equation to recalculate a new cluster center:

$$K_{i=} (1/c_i) \sum_{j=1}^{c_i} x_i \qquad (10).$$

K: refers to the centers.

c_i: refers to the number of data points in each cluster.

I : refers to the cluster number.

X: refers to each data point.

5. Using the shortest distance algorithm again to calculate the distance between each data point and the newly obtained cluster centers.
6. If there are data points that will be reassigned, then repeat from step 3, otherwise stop.

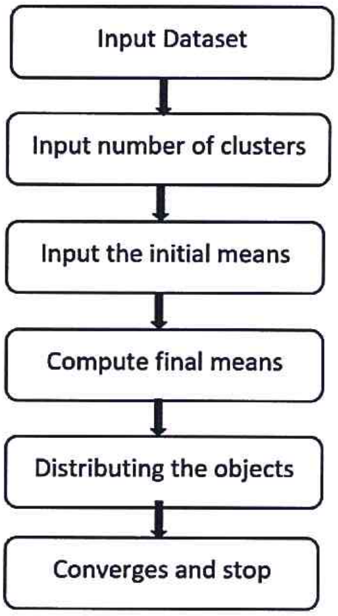

Figure 3.13: K-means clustering Flow.

3.3.5.2 Fuzzy C-Mean Clustering

Fuzzy c-means clustering is a soft clustering method, where each object belongs to a cluster, but with a degree determined by a membership grade.FCM algorithm introduced by Dunn in 1973 [30] and improved by Bezdek [31]. FCM algorithm is a K-means algorithm with fuzzy, which means is the fuzzy model of K-means, and in the FCM the sharp boundaries between the clusters are not taken into consideration [32].Thus, the advantage of FCM is the possibility of any object belonging partially to different clusters instead of belonging to a single cluster [33].

FCM works similarly to K-means, which is consisted of the following steps: firstly, the number of clusters should be identified. Secondly, selecting the center of each cluster randomly. Thirdly, computing the membership matrix (μ) using the following equation:

$$\mu ij = \frac{1}{\sum_{k=1}^{c}(d_{ij}d_{kj})^{\frac{2}{m-1}}} \quad (11).$$

Where i: refers to the cluster. j: refers to the object in the dataset. k,c: refers to the centers of the clusters. m: the fuzziness index. μ: the degree of membership of each object in each cluster. d: the Euclidean distance between the object and the cluster.

Fourthly, calculating the objective function to minimize the fuzzy compactness. Finally, calculating the new fuzzy cluster centers using the following equation:

$$c_i = \frac{\sum_{j=1}^{n} \mu ij.x_j}{\sum_{j=1}^{n} \mu ij^m} \quad (12).$$

3.4 Models Testing Phase

After the models trained using training datasets, it is time to test the models using testing datasets. Now, our models ready for predicting students' performance and distributing students' marksfrom the testing dataset. Now, it is important to find how accurate our models. Models are modified many times during the testing phase to take its final state. For model testing, they were evaluated based on different factors: the first one is the route main square error (RMSE) for the training datasets produced from the neuro-fuzzy tool [46]. RMSE measures how much error between two datasets, through calculatingthe difference between the average data of the squared differences in the estimated values, as in the equation (13):

$$\text{RMSE} = \sqrt{\frac{\sum|x_t - \widehat{x_t}|}{n}} \quad (13).$$

Where n: refers to the number of data, x_t: refers to the actual output and $\widehat{x_t}$: refers to the data processed by the system.

The second one is the difference between the expected and actual results from testing datasets for both neuro fuzzy and fuzzy models, the third one is the performance. RMSE is not taken for the testing data because the neuro-fuzzy results represented in percentage scale, while the final results should be based on the GPA scale which means the RMSE will be high, because for example mark 80 and mark 84 are in the same class and the error, in this case, is zero, but in the tool, it will be high because it will check the difference between 80 and 84.

To evaluate the performance of any AI model, it is necessary to test it on data not seen before (blind data). Performance of the model on the blind data is important because based on it, it is said that our model is over-fitting, under-fitting, or well generalized.

Cross-validation is a technique used to verify the effectiveness of AI models [47, 48]. There are many techniques used for cross-validation, but in our model the most used one called the Train_TestSplit approach is used. In this approach, the data is splitted randomly into training and testing sets[47]. For example, data can be splitted into 70:30, where 70% of original data be the training set and 30% be the testing set.

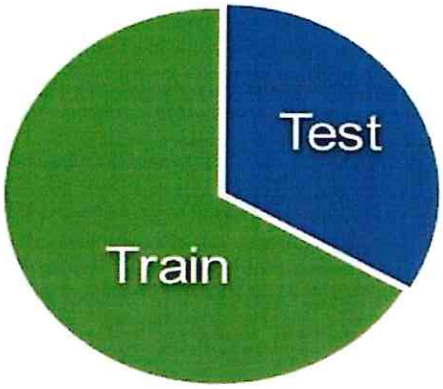

Figure 3.14: Splitting Dataset into Train and Test sets.

In the process of cross-validation, the most used is the k-iterations, which consist of dividing the dataset into k subsets. One of the subsets is used as validation data and the rest (k – 1) as a training data. The process Cross-validation is repeated during k iterations, with each of the possible subsets of validation data. Finally, the one with the highest generalization ability possessed. Since cross-validation allows control of the problem of overfitting, by selecting an appropriate set training that has enough information to model the forecasting problem.

The data manually can be splitted as it was done in the thesis or it can be used a tool for it like **train_test_split**. In the next chapter, all the experiments applied on the datasets will be illustrated with a summary of results from the models, and a comparison between the used models will be done .

3.5 Computing Environment

In recent work, two different devices for Conducting the experiments were used, where at the first device with medium specifications was used and after some issues in the experiment's performance were faced, another device were used with higher specifications. The two devices are:

1. Macbook pro 2013: I5 2.4 GHz, Ram: 8 GB DDR3, HD: 240 SSD with mac OS.
2. XPS 15 9570: I7 8750H 2.2 GHz (12 CPUs). Ram: 16 GB ddr4, HD: 512 SSD m.2 with windows 10.

For build the Forecasting and distribution modes, MATLAB_R2018a was used on both devices, and Py Charm CE version 2019.13 was used for building the python application.

In building our models, the focus was on using Adaptive Neuro Fuzzy Inference System, where it will be used for all forecasting models (FRM, CSC and CSE models) while the Fuzzy Inference System only for FRM model. Also, the contribution will be mainly by using the ANFIS models in the forecasting. There are many of featuresthat this method has that explain why it is used: it's easy to implement, there is no need for prior human expertise, it enables accurate and fast learning and it refines fuzzy rules to describe the behavior of a complex system.In the next chapter, the experiments will be conducted, after that the results will be discussed and compared to identify which model better to be used.

Chapter 4

Experiments and Results

4 Experiments and Results

To forecast the students' academic performance with FL and ANFIS in the two stages of the collecteddatasets, the proposed models in chapter 3 was applied. Measuring the models based on the RMSE, performance, and the accuracy, where the accuracy is the number of examples correctly forecasted in a ratio of all samples. Forecasting models are taking testing datasets and predicting each sample, then finding how many samples are correct and then are divide on the total number of samples in the dataset.The experiments were performed on all datasets, whereas mentioned before each dataset are divided into two datasets one for training and another one for testing. The ANFIS and FL are used to perform forecastingon all datasets. And the clustering performed on the datasets for courses is used to distribute marks. The MATLAB of a well-known tool called Neuro-Fuzzy was used to build the ANFIS model. The Fuzzy Logic tool was used to build the FL model. And for the last one Find-Cluster tool and K-means clustering algorithm is used. The experiments have been conducted every time, weight of the parameters was changed in order to reach the best weights, where the selection was based on the accuracy and the performance.

This chapter is divided into three sections, the first section has the results of ANFIS model that showsome results of our model using Neuro-Fuzzy and Fuzzy Logic tools, the second section is the results of Fuzzy-Logic model that show some results of our model using Fuzzy Logic tool, the last section presents the results of distribution marks model using K-means clustering and FCM clustering using Find-Cluster tool.

4.1 Results of ANFIS Model

ANFIS is a combination of neural networks and fuzzy logic where it is a fast data mining algorithm for solving forecastingproblems at large datasets.ANFIS is used when the dataset large and the number of features more than three with at least three membership functions for each feature.

There are two types of ANFIS as mentioned in 3.3.2 section: ANFIS-Grid and ANFIS-Cluster, these types will be applyed on the same datasets to be fair in judging them.For ANFIS, the datasets used for ANFIS varies based on the dataset, where for CSC-dataset is divided into training and testing data using cross-validation method to check the accuracy, where 75% of data for training and 25% for testing. And for theFRM-dataset we divided it into 70% for training and 30% for testing. And the dataset for FRM-dataset is divided into 70% for training and 30% for testing. Different ANFIS models were applied on the datasets, where ANFIS-Grid differs from ANFIS-Clustering, where in Grid you can detect the type of membership functions and a number of them for the inputs, but in Clustering you can't. The optimal ANFIS model selected based on the Root Mean Square Error (RMSE) and the accuracy of the model. It can't be judged on the model using the RMSE only, because the final results should be in university classes (A,B,C,D,F) and the ANFIS or FIS using the MATLAB tools give the final mark in numbers only.

To calculate the accuracy, the ANFIS result is taken and converted to the FL model in order to be able to test the samples manually and the result of FL model similar to actual final results in the dataset. The accuracy is calculated through dividing the number of true tests to the number of all tests, where these tests are conducted through applying the final

FL model on samples selected randomly from the testing dataset. After getting the output from the FLmodel, this result fall in which class is checked (A,B,C,D,F).

Test 1: After applying ANFIS models on the FRM-dataset, it is found that normal ANFIS-Clustering is not suitable for a small dataset, where FRM consists of only two inputs. In table 4.1, there are some of the samples selected randomly as a comparison between the ANFIS-Grid (Triangular) and ANFIS-Clustering. In figure 4.1, a comparison between model results and the actual results is but in percentage marks.

Table 4.1: ANFIS-Grid vs ANFIS-Cluster vs (M)ANFIS-Cluster Actual Result on FRM-dataset.

Num	ANFIS-Grid	ANFIS-Cluster	Modified ANFIS-Cluster	Actual Result
1	56 (D+)	54 (D)	57 (D+)	55 (D+)
2	67 (C)	66 (C)	67 (C)	66 (C)
3	78 (B)	81 (B+)	81(B+)	78 (B)
4	72 (B-)	73 (B-)	72 (B-)	73 (B-)
5	87 (A-)	87 (A-)	86 (A-)	87 (A-)
6	49 (F)	51 (D)	49 (F)	49 (F)
7	69 (C+)	69 (C+)	69 (C+)	67 (C)
8	83 (B+)	85 (B+)	85 (B+)	83 (B+)
9	58 (D+)	64 (C)	57 (D+)	58 (D+)
10	72 (B-)	73 (B-)	72 (B-)	73 (B-)
11	92 (A)	89 (A-)	92 (A)	92 (A)
12	78 (B)	77 (B)	77 (B)	78 (B)
13	78 (B)	75 (B-)	77 (B)	78 (B)

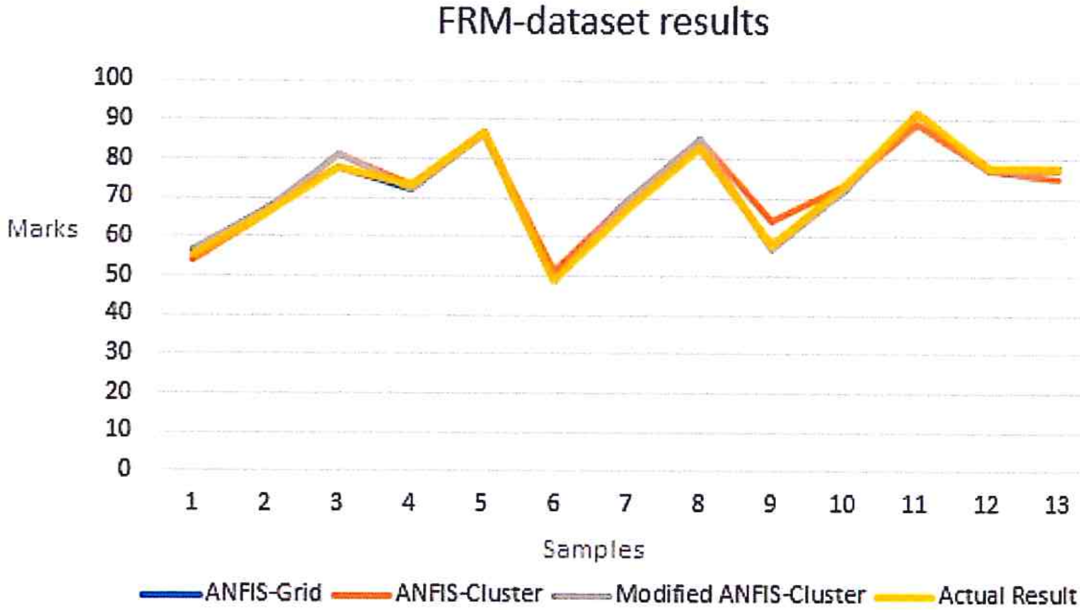

Figure 4.1: FRM-Dataset results in percentage using our Models.

In this experiment, three models are used as the following, the first ANFIS-Grid with eight membership functionshave been determined for each input. The second, Normal ANFIS-Cluster without any modification on the tool. The third, Modified ANFIS-Cluster, where the parameters are modified for clustering Genfis as following:

- Range of influence: .5 => .2
- Accept ratio: .5 => .1
- Reject ratio: .15 => .015

These changes produce a twenty-seven-membership function for each feature, while in the normal ANFIS-Clusterproduce, only three membership functions for each feature.In the following table, the forecasting error for each model based on the selected random samples is displayed.

Table 4.2: Models results in an error on FRM-dataset.

ANFIS-Grid	ANFIS-Cluster	Modified ANFIS-Cluster
7%	53%	15%

The mentioned error which presents the difference between the real grade values and the forecasted grade, calculated through the following equation:

$$e = \frac{\Sigma x}{\Sigma y} \quad (14).$$

where x represents the correct samples, and y represents all samples.

ANFIS-Grid fails in just one sample, as all the other models also failed in this sample.Based on the previous results displayed in table 4.1 and figure 4.1, the ANFIS-Grid was more accurate than ANFIS-Clustering for this kind of dataset.

Test 2: ANFIS-Grid and ANFIS-Cluster models were applied on the CSC-dataset. This dataset is not large as FRM-dataset, where the model consists of five inputs. For ANFIS-Grid, not all inputs have the same number of membership functions, where Mid have four membership functions, Participation have three membership functions, Practical have four membership functions and Project thave two membership functions. The same experiment executed on different membership function types to identify the better one.

For ANFIS-Cluster, changes for some parameters for clustering Genfis are done as following:

- Range of influence: .5 => .2
- Accept ratio: .5 => .1
- Reject ratio: .15 => .015

In figure 4.2, the first round of 10 epochs for the ANFIS-Triangular on CSC-dataset is seen, and in figure 4.3. Also, the second round of another 10 epochs can be seen, where 1.8 RMSE is gotten, but in ANFIS-Clustering better RMSE 1.3 is gotten. Based on the results from applying the ANFIS-Grid (ANFIS-Triangular, ANFIS-Trapezoidal, ANFIS-

Gaussian, ANFIS-Gbell) and ANFIS-Clustering on the CSC-dataset, it is concluded that the ANFIS-Grid based on the accuracy as shown in tables 4.3 and 4.4.

Table 4.3: ANFIS-Grid vs ANFIS-Cluster vs Actual Result on CSC-dataset

Num	ANFIS-Grid	Modified ANFIS-Cluster	Actual Result
1	67 (C)	68 (C+)	67 (C)
2	84 (B+)	84 (B+)	85 (B+)
3	92 (A)	92(A)	96 (A)
4	88 (A-)	92 (A)	87 (A-)
5	68 (C+)	87 (A-)	72 (B-)
6	49 (F)	49 (F)	49 (F)
7	67 (C)	67 (C)	67 (C)
8	58 (D+)	57 (D+)	58 (D+)
9	83 (B+)	85 (B+)	83 (B+)
10	72 (B-)	72 (B-)	72 (B-)
11	82 (B+)	84 (B+)	83 (B+)
12	65 (C)	67 (C)	65 (C)
13	77 (B)	76 (B)	79 (B)

Table 4.4: Models results inan error on CSC-dataset

ANFIS-Grid	ANFIS-Cluster
7%	23%

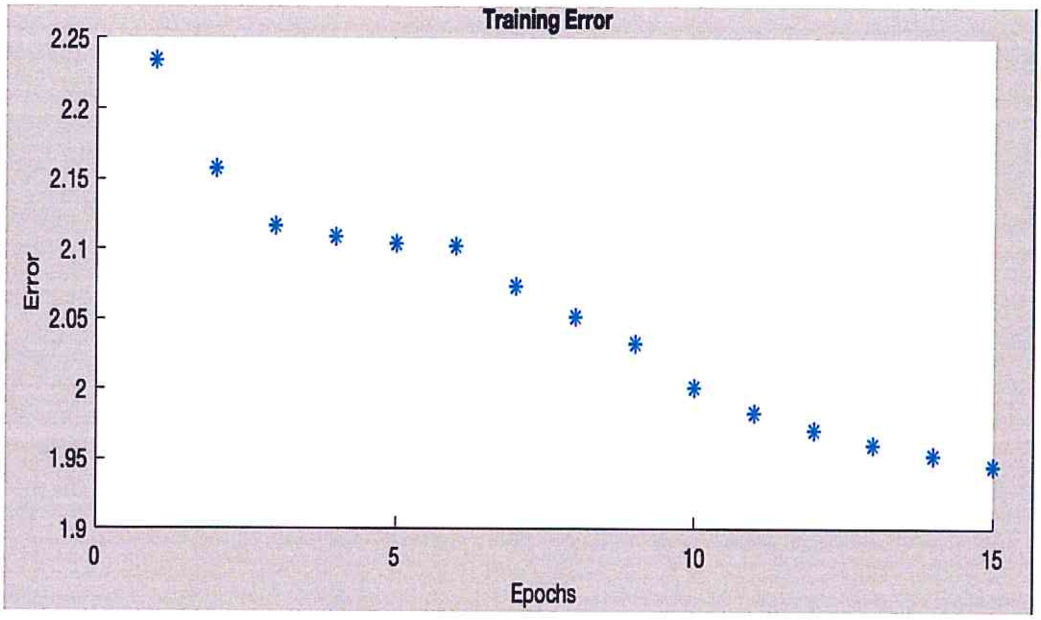

Figure 4.2: Training error show the RMSE for ANFIS-Triangular for the first round of 10 epochs (RMSE=1.9).

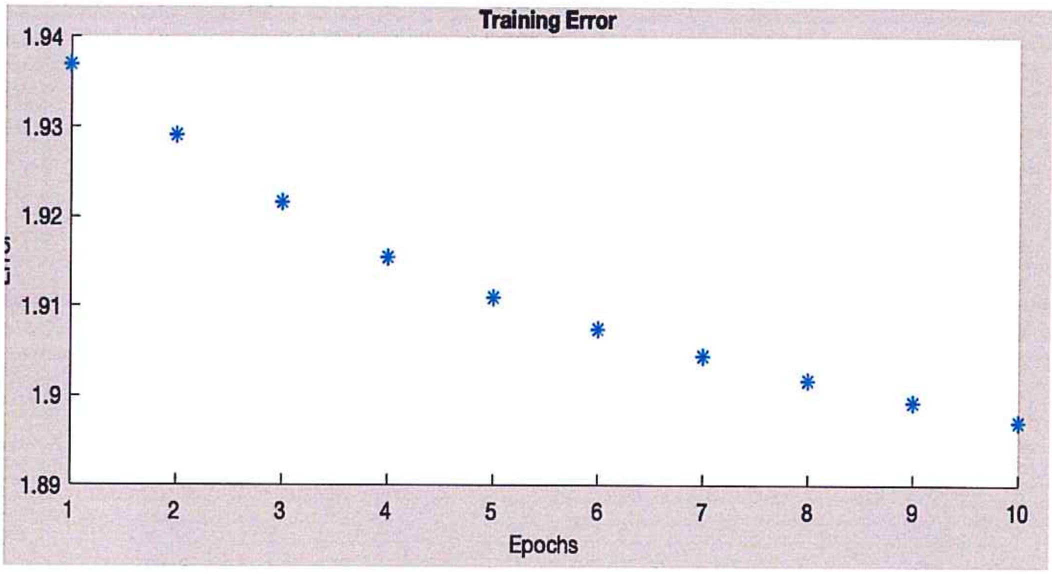

Figure 4.3: Training error show the RMSE for ANFIS-Triangular for the second round of Another 10 epochs (RMSE=1.8).

Figure 4.4 presents a comparison between model results and the actual results, but in percentage marks. Also, based on these results, it is observed that the ANFIS-Grid is better than ANFIS-Cluster.

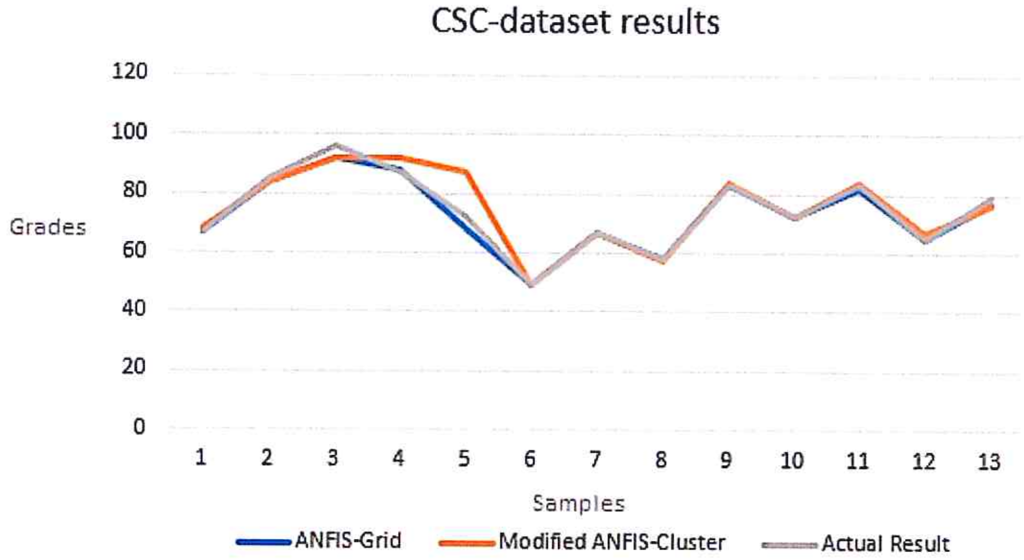

Figure 4.4: CSC-Dataset results in percentage using our Models.

The performance of the device memory also is an important factor for a large dataset like CSC-dataset, where ANFIS-Clustering was better than ANFIS-Grid, where to producing high-quality ANFIS-Grid model is needed for large device memory and high processor. The faced problem in these factors while using the device, where two devices were used as in the following specifications:

1. Macbook pro 2013: I5 2.4 GHz, Ram: 8 GB DDR3, HD: 240 SSD.
2. XPS 15 9570: I7 8750H 2.2 GHz(12 CPUs). Ram: 16 GB ddr4, HD: 512 SSD m.2.

Test 3: ANFIS-Grid and ANFIS-Cluster models were applied on the CSE-dataset, where this dataset is small. This model consists of five inputs. For ANFIS-Grid, not all inputs have the same number of membership functions, where each one differs based on its effect on the output.

ANFIS-Triangular based on the results from test 2 was choosen to be compared with ANFIS-Clustering. For ANFIS-Cluster, changes for some parameters for clustering Genfis were done as following:

- Range of influence: .5 => .2
- Accept ratio: .5 => .1
- Reject ratio: .15 => .015

The models on the dataset in a GPA grade and in a percentage grade are applied and converted from GPA to percentage using the following equation:

$$\text{Percentage} = \text{GPA} * 12.5 + 50 \quad (15).$$

Also, the same equation was used to convert the final result from percentage to GPA for calculating the accuracy. Based on the result of GPA and percentage, a percentage will be choosen because it is more accurate, and this is a sample selected randomly:

Table 4.5: Percentage vs GPA.

Actual result	Percentage	GPA
74.1,1.93	74.7	1.67

After applying the ANFIS-Grid on the dataset, a performance issue was faced because for this dataset needs five features,four features of them are needed four membership functions and the last one is needed for three which will produce a huge number of rules and it was 768 rules, and this makes the model not good for use, so only ANFIS-Clustering was selected.

In the following table, there are some samples selected randomly are used for testing ANFIS-Clustering twice: the first one with five inputs and the second one with six inputs, where the added input in the second test is the first semester GPA.

Table 4.6: ANFIS-Grid vs ANFIS-Cluster vs Actual Result on CSE-dataset.

Num	ANFIS- Clustering 5 features	ANFIS- Clustering 6 features	Actual Result
1	74.7=>1.97=>C-	75.8=>2=>C	74.1=>1.93=>C-
2	83.1=>2.64=>C+	83.3=>2.66=>C+	82.75=>2.62=>C+
3	90.1=>3.21=>B	85.3=>2.82=>B-	90.1=>3.21=>B
4	72.1=>1.77=>C-	75.5=>2.04=>C	73.5=>1.88=>C-

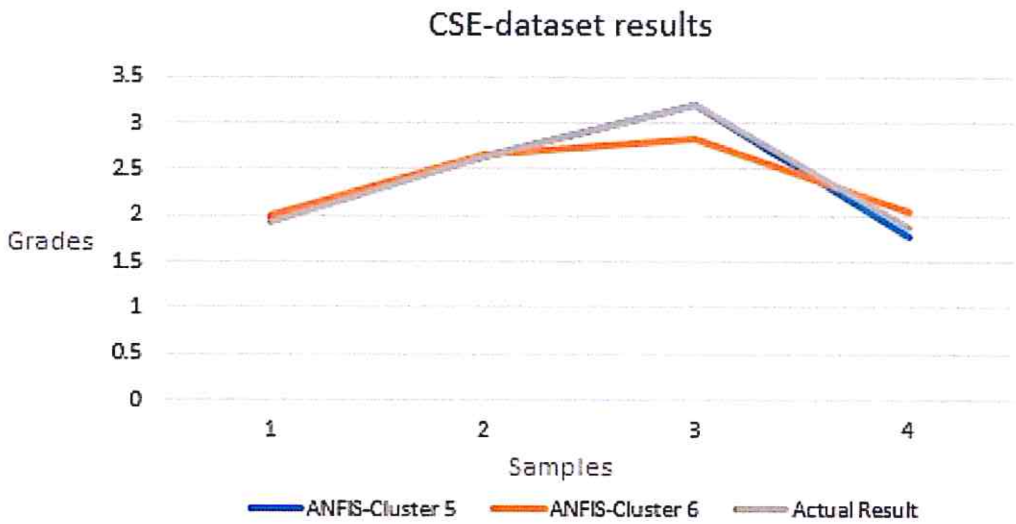

Figure 4.5: CSE-Dataset results in numeric GPA using our Models

Based on the previous results, it is said that ANFIS-Clustering with five features is more accurate than with six features, where the error based on the random samples is Zero for ANFIS-Cluster 5, and as shown in figure 4.5 the ANFIS-Cluster 5 is closer to Actual results than the ANFIS-Cluster 6.

4.2 Results of FL Model

For building a FL model, analyzing the dataset that will be used for testing is needed . This step is done manually, so a dataset with a small number of parameters is selected, because as it is said previously; a large number of parameters will produce a large number of rules and it will be impossible for humans to do it in normal time. the FRM-dataset is selected because it has only two parameters, while CSC-dataset have five parameters.

The accuracy of the FL model is calculated by applying the final FL model on samples selected randomly from the testing data. After the output is provided from the FLmodel, this result is checked fall in which class (A,B,C,D,F). At first, analyzing the data in order to identify the inputs, the weight of each input, and then writing rules suitable to the dataset.

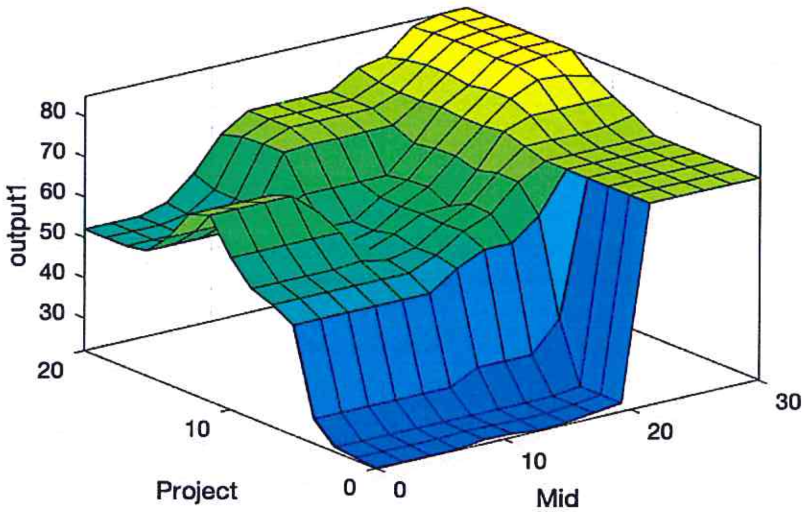

Figure 4.6: Surface for Fundamental of research-FIS with two inputs Midterm and Project.

Test 1: After analyzING the dataset and the FL model built, it is applied on the FRM-dataset. In the following table, there are some of samples selected randomly as a comparison between the FL results and actual results.

Table 4.7: FL-results vs Actual Result on FRM-dataset.

Num	FL Results	Actual Result
1	72	70
2	78	73

3	85	93

Based on these results, it can be judged between FL and ANFIS, where the ANFIS is more accurate than FL alone, where the FL alone is weak for forecasting this kind of data because it needs for a huge effort in analyzing data to get better results.

BY Building an application using Python to represent the FL model to be used without going back to the MATLAB, The same results from MATLAB are obtained from the Python application. In the following figure, an applied sample on the Python application can be seen. and in the figure 4.8, part of our application can be seen where in this part you can control the membership functions without going back to the written code.

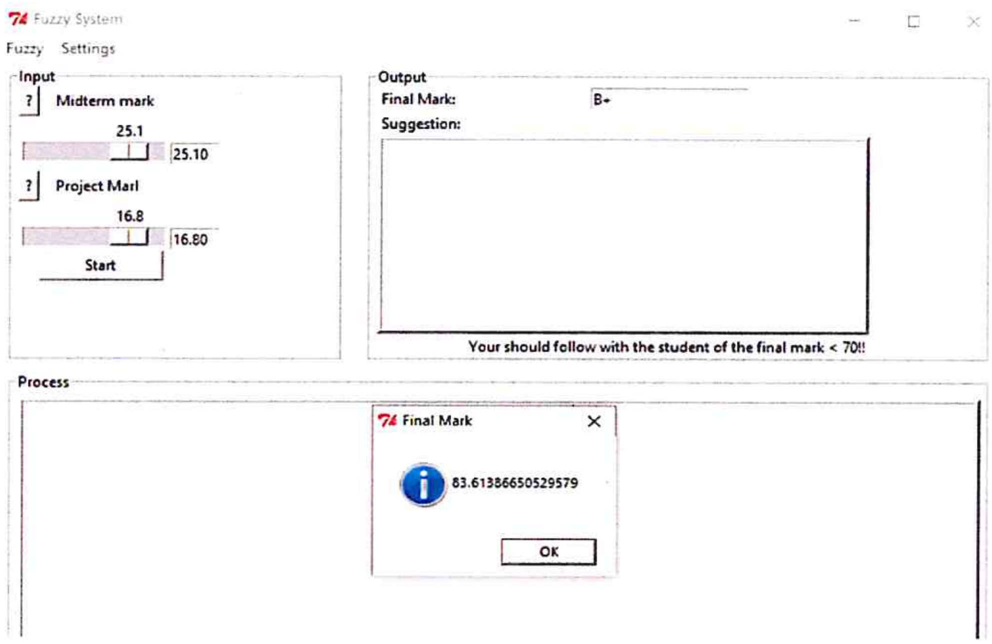

Figure 4.7: Applied example using our application, where the midterm mark is 25 and the project mark is 17 and the final mark is 83 which is B.

It's easy for anyone to use this application, where the user interface is simple and clear. Working more on this application for adding more features to be more usable. The first feature will be added in the next version of our application, is to enable controlling the rules, where through this feature, the user will be able to add, edit, and delete his rules.

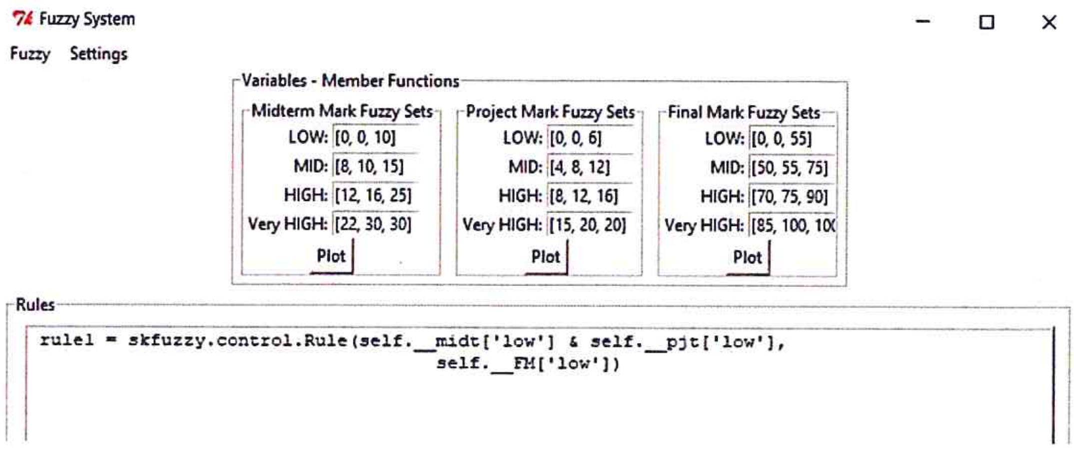

Figure 4.8: From settings page you can change fuzzy sets and rules.

4.3 Results of Grade Distribution Model

As it is said previously, this model aims to be fair in distributing the student's grades over different letter grads. So, to judge between K-means clustering and Fuzzy C-means clustering is important to apply them on real data. They are applied on CSC-dataset, FRM-dataset, and on three different datasets extracted randomly from CSC-dataset,in such a way that marks are maintained of all grades.The first dataset contains a thirty-sevenrecord, the second contains a fifty-three record and the third contains eighty records. the datasets are choosen in different sizes to be able to determine that our model can work fine to any extent.Before applying each test, some changes were done on each dataset to get better accuracy; all marks less than 47 were removed, also outlier marks were removed. The outlier is identified to be from the top marks, where if the first mark greater than the nearest one by three marks, then this mark identified as an outlier; for example: [98, 95, 94, 94, 93, 91] the outlier in this set is 98.

Test 1: In this test, K-means and FCM on CSC-dataset were applied to compare between them.This dataset represents one of the larger courses in the university and the result represented in the following table.

Table 4.8: Result of FCM and K-means on CSC dataset.

Grade	K-means	FCM
A	90	91
A-	83	86
B+	77	80
B	71	75
B-	70	69
C+	64	65
C	59	61
C-	56	57
D+	53	53
D	50	49
F	<47	<49

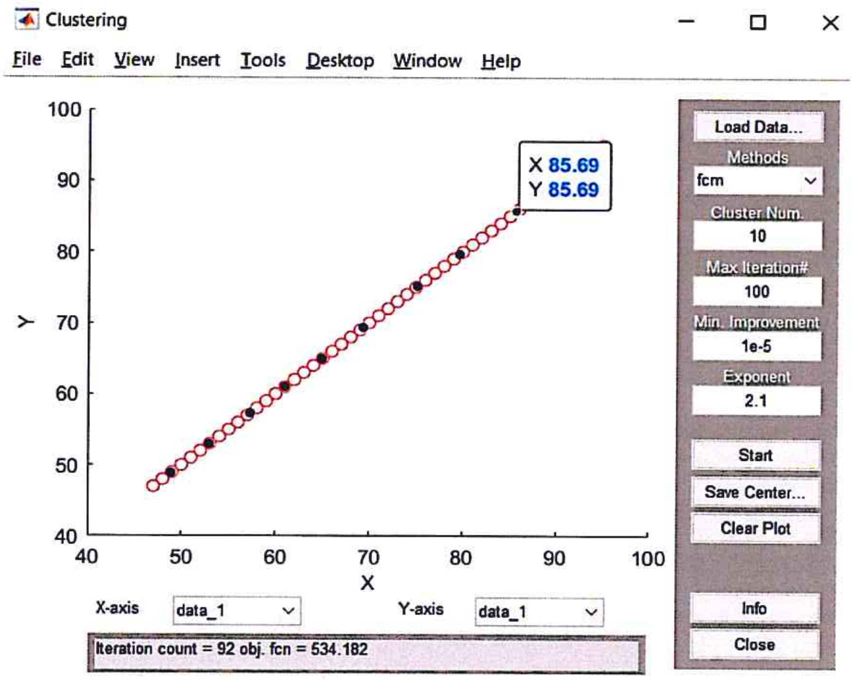

Figure 4.9: CSC-dataset results using FCM-Clustering.

Test 2: In this test, K-means and FCM on FRM-dataset were applied to compare between them. Also, this dataset represents another large course in the university, and the result represented in the following table.

Table 4.9: Result of FCM and K-means on FRM dataset.

Grade	K-means	FCM
A	91	91
A-	86	87
B+	79	82
B	74	78
B-	71	73
C+	69	70
C	66	66
C-	62	62
D+	57	58
D	50	50
F	<47	<50

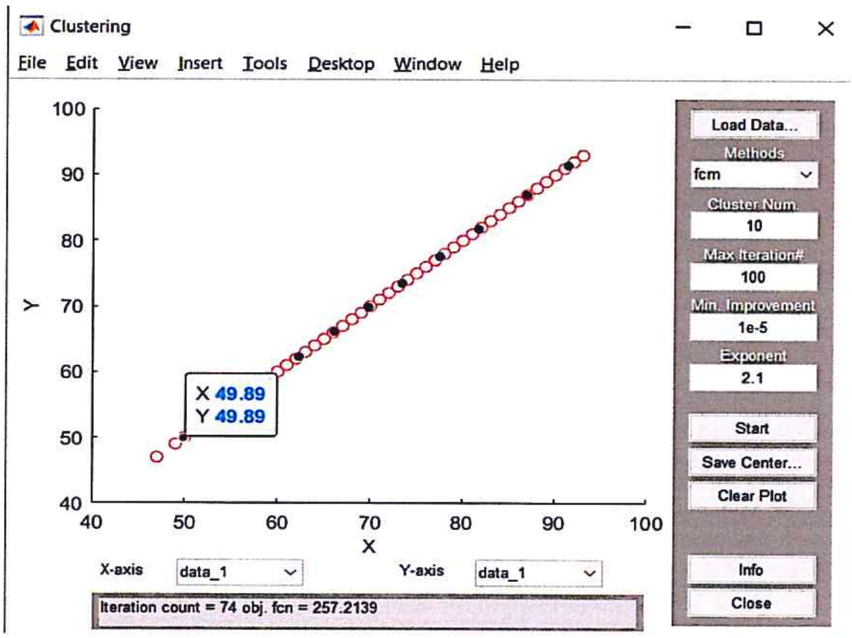

Figure 4.10: FRM-dataset results using FCM-Clustering.

Test 3: K-means and FCM were applied on the three datasets extracted randomly. The difference between K-means and FCM becomes clearerin this test.

At first, the test on the dataset consists of eighty samples was applied. The result of this test is shown in the following table.

Table 4.10: Result of FCM and K-means on First-dataset.

Grade	K-means	FCM
A	90	90
A-	86	86
B+	80	83
B	75	78
B-	69	75
C+	67	73
C	64	66
C-	59	60
D+	54	54
D	48	48
F	<48	<48

The second dataset consistsof fifty samples. The result of this test is shown in the following table.

Table 4.11: Result of FCM and K-means on Second-dataset.

Grade	K-means	FCM
A	91	91
A-	87	87
B+	83	83
B	78	78
B-	74	76
C+	68	73
C	65	67
C-	58	64
D+	55	57
D	49	49

F	<49	<49

The third dataset consists of thirty-seven samples. For this sample, the degree of fuzziness was from 2.1 to 3.2 in order to make this model suitable with a small dataset. The result of this test is shown in the following table.

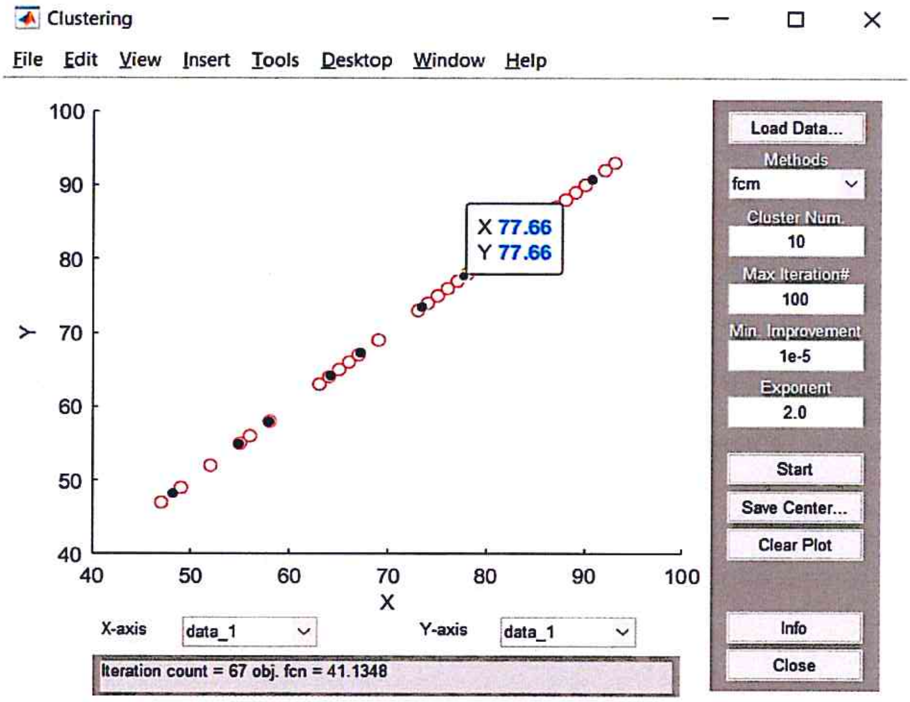

Figure 4.11: Fifty-dataset results using FCM-Clustering.

Table 4.12: Result of FCM and K-means on Third-dataset.

Grade	K-means	FCM
A	91	90
A-	86	86
B+	78	80
B	74	78
B-	69	75
C+	66	73
C	58	69
C-	55	67
D+	52	55
D	48	49

F	<48	<49

With a small dataset, the difference between K-means and FCM was clearer to us, which is a good point to be used to judge between them.

4.4 Results Comparison and Discussion

As it is seen in the previous sections, a lot of experiments were done to compare the algorithms in order to be able enough to judge between them and to detect which algorithm will be suitable for each model. Based on the experiment results related to Fuzzy Logic and Neuro-Fuzzy, it is said that categorically which Neuro Fuzzy is better than Fuzzy Logic. Where that was clear when appling them on the FRM-dataset. For the ANFIS models, experiments were also done on different datasets, where they were done on FRM-dataset and CSC-dataset but they weren't done on CSE-dataset because it cannot be applied ANFIS-Grid on it, where it needs for higher hardware specifications. As it is seen in figures 4.1 and 4.4 the ANFIS-Grid results were closer to the actual results.

For the Distributing grade models, the judgment had been made between the K-means and FCM after their results by an expert (University instructor) was reviewed . After clustering results had been reviewed with the expert, it was judged between them without hesitation, where the Third-dataset was the most assertive ruler because it is the smaller ones, and most courses in the University are similar to it.

4.5 Research Limitations

This study has potential limitations. The main limitation was in collecting data, where non-academic data about the students like; family education living area and Study time cannot be collected because the university refused giving any personal information about the students or any information to contact with them. Also, there is an important factor affecting the students' performance which is: if the student has a scholarship or not, but the university also refused to giving this information. A limitation is also in in the devices used for performance the experiments in this research, where to produce more powerful ANFIS-Grid models, devices were needed with higher specifications.

Chapter 5

Conclusion and Future Works

5 Conclusion and Future Works

Improving education quality is an important issue for every education sector, and forecasting students' academic performance is important for improving education through its importance for decisions. This work proposed forecasting models for students' marks for some courses, and GPA for engineering students after five years of study at Arab American University Palestine (AAUP). Also, there is another model proposed for distributing grades for students. These models were built based on datasets collected from AAUP through registration department. Distributing grade models was built using K-means clustering and FCM clustering in order to obtain a better distribution model, where the judgment between them based on comparing the models result of the data set and reviewing the results with expert (University Instructor).

Two models were built to forecast student's performance after finishing Computer Skills and Fundamentals of Research and Methods courses, and another model to forecast student's GPA after five years of engineering study, using Adaptive Neuro-Fuzzy Inference System by using clustering and grid to obtain better accuracy. And another model was built to forecast student's performance after finishing the Fundamentals of Research and Methods course using normal Fuzzy Logic to compare it with the ANFIS model. Finally, all models were tested using blind data sets.

Data sets collected from AAUP database, and have two categories:

- Pre-university data like high school average.
- University data like GPA and mark of courses.

After all experiments results, it is concluded that using the ANFIS is better than using fuzzy logic alone because in ANFIS, it is benefited from the advantages of neural networks in building the rules, where in some cases for rule base system with 5 inputs the number of rules may exceed 350 rules which is impossible for the human brain to build system with this number of rules. And the accuracy of the ANFIS model higher than the Fuzzy Logic model. Depending on these points it can be concluded that:

- It is possible to forecast through AI techniques the academic performance of students in the selected course or major.
- The main indicators that allow forecasting the academic performance of students, were identified and applied tests that validated the results obtained.
- Four AI techniques were applied to perform academic performance forecasting: ANFIS, Fuzzy Logic, K-means and Fuzzy C-means clustering.
- The quality of the data is very important for this type of research. The data obtained from the university databases came from transactional systems where in many cases the format and type of data were not ideal,where several processes of data cleaning and transformation applied on the data.
- After the comparisons between types of ANFIS, it is concludeded that accuracy of ANFIS with grid is better than using it with the clustering in most cases, which is mean in some cases the clustering is better but it depends on the type of model and data,wherethese cases are little, so we can go with grid.

For distributing grade models after all experiments, we concluded that FCM clustering is better than K-means, where FCM got better results. But the distribution model not suitable for small data set like courses contains less than 25 students.

Our future work will be:

- Building a model for distribution grades for small data sets is better than the proposed one.
- Covering other university disciplines.
- Collecting data from other universities in Palestine is not only AAUP.
- Building a mobile or desktop application that could be used by instructors or by students easily.
- Adding non-academic features to our models, like; living place, family financial status, and parents' education status.
- Using other algorithms and comparing their results with Neuro-fuzzy like; regression and Decision tree.
- Building a forecasting model for high school students, which will help teachers, decision-makers, and students to decide his studying future before starting high school.
- Developing our python application, where it will add more features to improve the usage of it. Some of these features are: controlling the rules from the application without returning to the written code, importing marks file to the application to handle a group of marks at a time.

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الغامض (Adaptive Neuro Fuzzy Inference System – ANFIS) ونموذج المنطق الضبابي (Fuzzy Logic) لتنفيذ عملية التنبؤ. وبهذه الطريقة، واستناداً إلى مجموعات البيانات من الامتحانات الأولى التي تم جمعها من مقررات مختارة من الجامعة العربية الأمريكية، أو من مجموعة البيانات التي تم جمعها من درجة تخصص هندسة أنظمة الحاسوب، يمكن التنبؤ بأخطاء مستقبلية ويمكن تقديم اقتراحات لإجراء عملية تصحيحية لتحسين النتيجة النهائية.

من ناحية أخرى، تم استخدام خوارزميات (K-Means Clustering) و (Fuzzy C-Means) من أجل تحسين عملية توزيع درجات الطلاب في المقرر الدراسي, وذلك من اجل إنشاء المقياس الأمثل والأكفأ والعادل في توزيع الدرجات بين الطلاب. أدت نتائج التجارب للنماذج التطبيقية إلى تفوق نظام الاستدلال الضبابي العصبي التكيفي (ANFIS) على نموذج المنطق الضبابي في معظم الحالات. حيث يكون المنطق الضبابي أفضل لنماذج المقررات الدراسية التي تحتوي على مدخلين فقط. أيضا، تم تطوير تطبيق واجهة مستخدم رسومية باستخدام لغة برمجة البايثون .(Python) بالإضافة لذلك، كانت نتيجة استخدام خوارزميات التجمع (Clustering) لتوزيع درجات الطلاب من النسبة المئوية الى علامات حرفية في المقررات الدراسية واعدة.

الملخص

إن جودة التعليم هي الهدف الاهم لمؤسسات التعليم العالي، والتي يمكن تقييمها من خلال عملية التعلم والتعليم. تحتوي جودة التعليم على العديد من التعريفات التي تختلف بناءً على الثقافة، وأحد هذه التعريفات هو مصطلح شامل للجميع حيث البيئات بالإضافة إلى المتعلمين من أجل التعليم ذات صلة بالمحتوى وصحي ويتمحور التدريس حول الطالب والنتائج التي تشمل المواقف والمعرفة والمهارات المرتبطة بالأهداف الوطنية للتعليم. تعتمد جودة عملية التعلم والتعليم على معايير مختلفة ، وبعض هذه المعايير هي طرق التدريس والمحتوى وبيئة التعلم وما إلى ذلك. هناك العديد من المقاييس المستخدمة لقياس وتتبع التقدم والإنجاز الأكاديمي ، مثل المعدل التراكمي والترتيب في الفصل. أحد هذه المقاييس المهمة هو الأداء الأكاديمي للطالب ، حيث من خلال هذا المقياس عندما يتم توقعه مبكرًا ، يمكن جمع المزيد من المعلومات حول الفصل أو التخصص ثم تحليلها لاكتشاف أسباب انخفاض أداء الطالب والتي قد تكون من الطالب أو المعلم أو المحتوى أو بيئة التعلم أو طرق التدريس. بعد جمع هذه المعلومات ، يمكن للمتخصصين التعامل مع الأسباب التي ستؤدي إلى تحسين جودة التعليم وتحسينها. يعد الأداء الأكاديمي المنخفض لطلاب الجامعات ، سواء كانوا طلابًا مقبولين حديثًا أو طلاب جامعيين حاليين ، مشكلة يجب على مؤسسات التعليم العالي تقييمها لتجنب رفض الدورات التي تؤثر على المستوى التعليمي من خلال؛ إضاعة الوقت والمال والجهد.

يمكن تطبيق تقنيات الذكاء الإصطناعي للتنبؤ بالأداء الأكاديمي لطلاب الجامعات، للكشف عن العوامل الأكثر تأثيرًا على عملية التعلم والسماح للمعلمين وإدارة الجامعات باتخاذ إجراءات أكثر فعالية لإرشاد الطلاب الذين يحتاجون إليها. يمكن أن تركز عملية التنبؤ بأداء الطالب الجامعي على طلاب السنة الأولى وعلى أداء الطلاب الحاليين. لذلك، فإن تحديد أداء الطلاب سيحدد جودة التعليم والتي ستكون من خلال تحليل أداء الطالب والتنبؤ به على مستوى مقرر دراسي باستخدام العديد من العوامل مثل الحضور وعلامات الامتحان وعلامات المشروع لهذا المقرر ومستوى الطالب خلال فصل دراسي كامل من اجل التنبؤ بالأداء في المرحلة الدراسية باكملها.

يركز هذا البحث على التعرف على الأنماط في أداء الطلاب باستخدام نماذج التعلم الآلي التي سيتم تدريبها على التنبؤ بأداء طلاب الجامعة بناءً على علامات التقييم الخاصة بهم على مرحلتين؛ تعتمد

المرحلة الأولى على توقع علامة الطلاب في مقررات دراسية مختارة اعتمادًا على بعض التقييمات لهذه المقررات. أما المرحلة الثانية فهي تعتمد على مستوى الطالب في الفصل الدراسي الواحد لتوقع أداء الطالب في درجة التخصص كاملة. في هاتين المرحلتين، يتم استخدام نموذج النظام العصبي.