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Forecasting of University Students' Performance Using A Hybrid Model of Neural Networks and Fuzzy Logic

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Abstract: Artificial intelligence techniques can be applied in forecasting the academic performance of university students, with aim of detecting the factors that influence their learning process which allows instructors and university administration to take more effective actions to increase the university student's performance. Identifying the students' performance will improve the quality of education which will be through analyzing and forecasting the students' performance at the course level and degree level. This research focuses on first-year students' performance in two university-requirement courses, depending on features such as attendance, assessment marks, exams, assignments, and projects. Forecasting the students' performance in the whole degree will depend on these features; high school average, Grade Point Average (GPA) for each semester, drop courses, selected core courses in the degree, period of study, and final GPA. A hybrid Adaptive Neuro-Fuzzy Inference System (ANFIS) model was used to perform the forecasting process. In this way, based on the datasets collected from the selected courses, or the whole degree, the future results can be forecasted and suggestions can be made to carry out corrective steps to improve the final results. The experiments result of the applied models performed that ANFIS-Grid outperforms the ANFIS-Cluster, wherein each model produces the lowest error of 0.7%, where it just fails in one sample from thirteen samples, while the ANFIS-Cluster after modification produces an error equal to 0.15%.

Keywords: University Student Performance, Forecasting, Fuzzy logic, Neural Network, Adaptive Neuro-Fuzzy Inference System.

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1. Introduction

The improvement of university teaching methods, raising the quality of graduates, and achieving higher academic performance are some of the main concerns of researchers [1]. 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 the high rate of academic dropouts. This has been a cause for concern in higher education institutions' studies, which 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 the efficiency of the teaching process [2] where it attaches great importance to devising 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. Universities are seeking to integrate student performance predictions into their educational processes to give students better support by arranging additional efforts for low-performing students. Nowadays, many organizations are using data mining methods for exploring vast amounts of data and extracting beneficial information that can be used for helping in making potential decisions [3].

Data mining methods are used widely in educational areas to extract new knowledge and significant information, improve the learning process, and guide the students' learning where applying these methods will lead to advance the quality of education and the student's performance [4], [5]. The evaluation of Student Academic Performance Assessment (SAP) is a very important practice used for many reasons. Some of them are: to obtain an indicator of student learning level, to decide on failure and success in courses, and providing information on the effectiveness of teaching [6]. The ever-growing educational databases contain potentially hidden information that remains to be discovered 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 allows the instructors to explore more about students' information level such as their potential knowledge of them not only in determining the course but also in the whole degree. There are many techniques used for extracting information from educational databases such as student performance predictions which are critical in educational settings [7]. The achievement of academic history is one of the basic criteria that high-quality universities consider, that student performance can be obtained through measurement in the assessment of learning in courses and majors. Correct forecasting will make it possible to detect students with difficulties in courses and in majors, which helped to make the right decisions such as providing additional support in the form of tutoring or mentoring, changes, or adjustments by teachers [8]. Artificial intelligence techniques have proven their ability to solve complicated problems efficiently, such as the development of more efficient models to forecast Students' Academic Performance (SAP) with higher accuracy [6]. Different AI models were used such as; artificial neural networks [9], neuro-fuzzy systems [11], clustering [12], and regression [10]. These methods help students, decision-makers, parents, and evaluators to obtain more understandable and reliable data about student achievement. Adaptive Neuro-Fuzzy Inference Systems (ANFIS) [11] are used in this work to forecast the student's performance in selected courses and one of the university degrees.

This research aims to; identify the previous knowledge of the students during university courses, or the major, which leads to discovering academic performance in such courses or the degree. Design and implement ANFIS models to forecast the academic performance of these students, based on their knowledge. Contrast the efficiency of different ANFIS models (NF-grid, NF-cluster) in the forecasting of the academic success/failure of the students based on prior knowledge. The dataset depends on different courses for first-year university students, where these courses include all university students, like computer skills (CS) and fundamentals of research methods (FRM). Also, in this research, we used features from computer system engineering (CSE) majors to forecast students' performance for a specific degree. After applying ANFIS, the forecasted results can be used to help students to improve their performance and achievements. The main contribution of this research is to detect which method of ANFIS is better to be used in students' performance forecasting. The proposed method constitutes 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.

The rest of the paper is presented with the following arrangement. section 2, presents a background that includes a description of the datasets, and a literature review. In section 3, models of performance evaluation are presented, and their usefulness for the design of one that allows the prediction of academic success in university students. The methodology of this research includes the description of the preprocessing stage on the datasets and neuro-fuzzy models. In section 4, all the experiments on the datasets will be illustrated with a summary of the results from the models. Finally, the conclusions and recommendations are derived from the research.

2 Background

2.1 Datasets

Forecasting the students' academic performance can be done either in a course or in a specified major, where each one has different features. Academic performance can be measured by observing the results translated into test scores and grades during the course or semester in the whole major. These data sets were collected from The Arab American University AAUP, which is a higher education institution with 11000 enrollment students in 10 faculties and more than 50 academic degrees, and more than 500 lecturers serve the students to obtain their knowledge.

To forecast the students' academic performance in courses, 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, computer system engineering will be chosen. In the Computer Skills Course- CS Dataset, the dataset was collected from the AAUP in the first semester of 2018. The dataset has 819 samples. The parameters used in this dataset are the Midterm exam, Practical, Participation, Lab, Project, and Final Mark. The Fundamental of Research Methods – FRM Dataset, is an obligatory course for all university students. FRM dataset has 325 samples. The parameters used in this dataset are the Midterm exam, Participation, and Final Mark. The Final dataset is the Computer System Engineering-CSE Dataset, this dataset consists of two combined datasets; the first one represents some selected course marks for students during their study period; the second one represents students' GPA for each semester and the Cumulative GPA for each semester. Three larger datasets were derived based on the data from the smaller ones. 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 six parameters were picked from them as defined Math, Programming Fundamentals C++, Digital Logic Design (DL), Fourth GPA, High School, and Final GPA.

2.2 Related Works

The researchers in the literature used AI models in the field of education like forecasting, classification...etc. Some of the most important of these researches will be shown. In [13] authors presented a new model for evaluating and forecasting the performance of students, they used Artificial Neural Networks (ANNs) depending on types of attributes; academic attributes like; unit test marks, attendance, interest in the study, and assignment mark, and personal attributes like; parents' education and family status. The NNs model produces an accuracy of 91%. In [14], the authors used six different ANNs algorithms for forecasting the academic performance of students to detect the best algorithm for the forecasting process, where three measures of standard deviation, Absolute average error, and Linear correlation were used to compare between algorithms. Two experiments were applied to those algorithms, firstly fifteen variables, and secondly, six variables were used as inputs, and in both experiments, the exhaustive Prune method gets the best rating of 88%.

In [15], the authors presented a new model for forecasting the academic performance of second-year engineering students using Multilayer Perceptron NNs to forecast if the student can continue 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 high school. In their model, a back-propagation algorithm is used for training. the result showed that the Cumulative Grade Point Average (CGPA) accuracy is 84.6%. In [16], the 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 one output. The output of this model is a CGPA of 8 (Grad of the eighth semester). 70% of the collected data was used for training by using the Levenberg-Marquardt (LM) Algorithm and 30% of the data was used for testing. the protection result of MSE is 0.0409 for Matriculation students and 0.0488 for Diploma students. In [17], the authors introduced a new model for forecasting the final grades of students. In this study, a different type of Neural network was used not unlike the previous one, where a Recurrent Neural Network (RNN) was used in this model, this type of neural network uses a recursive loop to handle time-series data. 9 variables were used here as inputs for the model to introduce one output (final grade). The final results of the experiment show that the RNNs have accuracy above 90% for predicting the final grade while using data until 6th week about students. In [18], comparing two techniques Artificial Neural Networks (ANNs), 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 the data is 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 [19], the 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 student's performance based on the Fuzzy Logic System. Also, in this study, they compare the result of the Fuzzy Logic system with the Classical Method resulting in a performance value of 0.679. In [20], the authors presented a new method for performance evaluation, where in this study Fuzzy Logic was used based on the Mamdani technique. This technique was applied to three parameters considered in this study “attendance, internal marks, and external marks”. In the final, the technique was applied to a real sample, and two results have been produced and compared, the fuzzy system results in a 95% confidence level.

In [21], the authors presented a new method for performance evaluation applied to Academic staff and students for Sudanese Universities. In this study, Fuzzy Logic was used with TOPSIS and AHP techniques. Also, they applied the method to nine criteria as the main, and another 41 as a sub-criterion which is divided into three levels. Also, a New Fuzzy Consistency algorithm was used to evaluate and check the consistency of the surveyed data, and tools were introduced to understand and trace the roots of inconsistency. In [22], the authors presented a new method for performance evaluation, where the method was applied to 20 students in 4 classes in two semesters. The Fuzzy Logic used in this method depends on three parameters “the solution submitted by the students, the total of time that has been needed to finish, the number of commands executed, and the route which the student followed”, The deviation was approximately 10% for both low and high marks. In [23], the 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. In [24], the authors proposed a new model for forecasting the performance of the students at the final examination for mathematics courses. Four training algorithms were applied to the ANNs to identify the best algorithm for building an accurate forecasting model. Also, in this study, they presented a developed software tool for forecasting the performance of students using ANNs. 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). MSP and SMO report the best result for more than 86% of accuracy.

In [25], a comparison has been achieved 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 performance. Using the results for each method from the experiments we conclude that Fuzzy logic is more palatable for the evaluation of student's performance result of 83%. In [26], the authors proposed a new model using a 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 were collected. WEKA toolkit was 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 to the collected data they concluded the most important course that affects the final GPA, where the most related to the final GPA is the “Software Engineering” course.

In [27], A stage-wise fuzzy logic approach has been used, where the fuzzy system is divided into different stages and in every stage, we have a different result, wherein stage 1 knowledge analysis is applied to 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, 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 with Fuzzy rating

61%. In [28] artificial neural networks, decision trees, and linear regression using SAS enterprise miner were used. Data used for the experiments is about 206 students, where the correlation coefficient analysis was used to determine the relationship between the independent variables and with dependent variables. The results were compared by using the square root of average squared error (RASE) to identify the best model for CGPA forecasting. In [29], a new fuzzy expert system (NFES) was proposed for forecasting the performance of the students. The system applied two inputs “examination mark of semester-1, and examination mark of semester-2” to get the performance of each student. The experiment for the NFES in this study was applied to 20 computer science students in their second year. The same experiment was 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 was more suitable for forecasting students' performance.

In [30], ANNs model is presented for forecasting students' yearly performance. The data used in this study were collected from 120 students. Thirteen factors were taken as inputs to the model the output is the year's final result. The experiment was applied randomly to seven students, they improved that the performance was affected not only by academic factors but also by personal factors that will affect student performance. The obtained accuracy was between 91-99%. In [31], a new model for forecasting students' performance using ANFIS. The dataset used for this study is about 100 computer science students, who were marked of 5 courses taken as inputs to get the final GPA as an output. Three different membership functions are used to define the ANFIS parameters: Gaussian MF (gaussmf), Generalized Bell MF (gbellmf), and Triangle MF (trimf). Where through applying the RMSE on experiments, the best membership function has been detected to be used for building the system, and the gbellmf gets the best results with a prediction of the student's performance of RMSE as low as 0.193.

The present work tries to address the academic problems of university students using artificial intelligence techniques to forecast the students' performance in one course or specialization degree. ANFIS models were used to forecast the 3 different datasets collected from Arab American University Palestine (AAUP), these datasets were selected carefully to present the majority of the students at AAUP. CS and FRM datasets were used to verify the model's performance for a one-course case. On the other hand, the mentioned models were applied to a specialization degree dataset, for this stage, we used the CSE dataset with speciated features.

3. The Proposed Models

The general idea of using AI techniques to forecast the academic performance of university students is performed through the creation of models that are designed using techniques such as neural networks [32], fuzzy logic [33], and evolutionary computation [34]. The combination of different AI models can produce better accuracy [35] in forecasting the academic performance of university students. In this section, the proposed hybrid models that combine neural networks and fuzzy logic to forecast the academic performance of university students will be presented.

3.1 Data Pre-processing and Feature Selection

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 from being analyzed which could create errors when applied to the hybrid model. The feature selection depends on experts' opinions, for the courses CS and FRM, we ignore absence rate and withdrawal absence, these data were 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 second application of forecasting applied to the CSE dataset which includes 12 features before selection as; High School avg, GPA for each semester, drop, C++ I, C++ II, calculus I, calculus II, math I, math II, digital logic design, period of studying, and final GPA, the first six features were selected based on their 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.

3.1.1 Data Coding

In this phase, codes for final output values were set, where the AAUP system dealt with GPA and letter grade while our models dealt with percentage grade. Two code mapping for a letter grade to be suitable for the course prediction model were created, where each letter mapped to a code number as shown in Table 1. The ranges for a letter with percentage mapping may differ from one course to another based on the scale of mark distribution. For GPA grade, it is mapped with percentage.

Table 1 : Mapping For Letters With Percentages For Courses.

Letter Grade	Range	Numeric Grad out of 4
A	>=90	=4
A-	>=85&< 90	=3.67
B+	>=80&< 85	=3.33
B	>=75&< 80	=3
B-	>=72&< 75	=2.67
C+	>=68&< 72	=2.33
C	>=64&< 68	=2
C-	>=59&< 64	=1.67
D+	>=54&< 59	=1.33
D	>=50&< 54	=1
F	<50	<1

3.2Building Models Phase

Both Fuzzy Logic and Neuro-Fuzzy hybrid models were used to design the forecasting models on CS, FRM, and CSE datasets. The general procedure which was used in performing all experiments on the determined datasets is shown in Figure 1 and it is illustrated as follows:

3.2.1 Fuzzy Inference System (FIS)

A 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 2. In the first step, membership functions are used to apply the fuzzification on the inputs as shown in figure 3. In fuzzification, the crisp data is transformed into a fuzzy set. In most cases, singletons are used as fuzzifiers [36].

$$\text{fuzzifier}(x_4) = \overline{x_4}, \quad (1)$$

$$\mu_{\overline{v,}}(x) = \begin{cases} 1, \text{for } x=x_4 \\ 0, \text{for } x\neq x_4 \end{cases} \quad (2)$$

Where, 〖x〗_0 is the crisp input value. In the second step, from the rule base apply IF-THEN rules on the

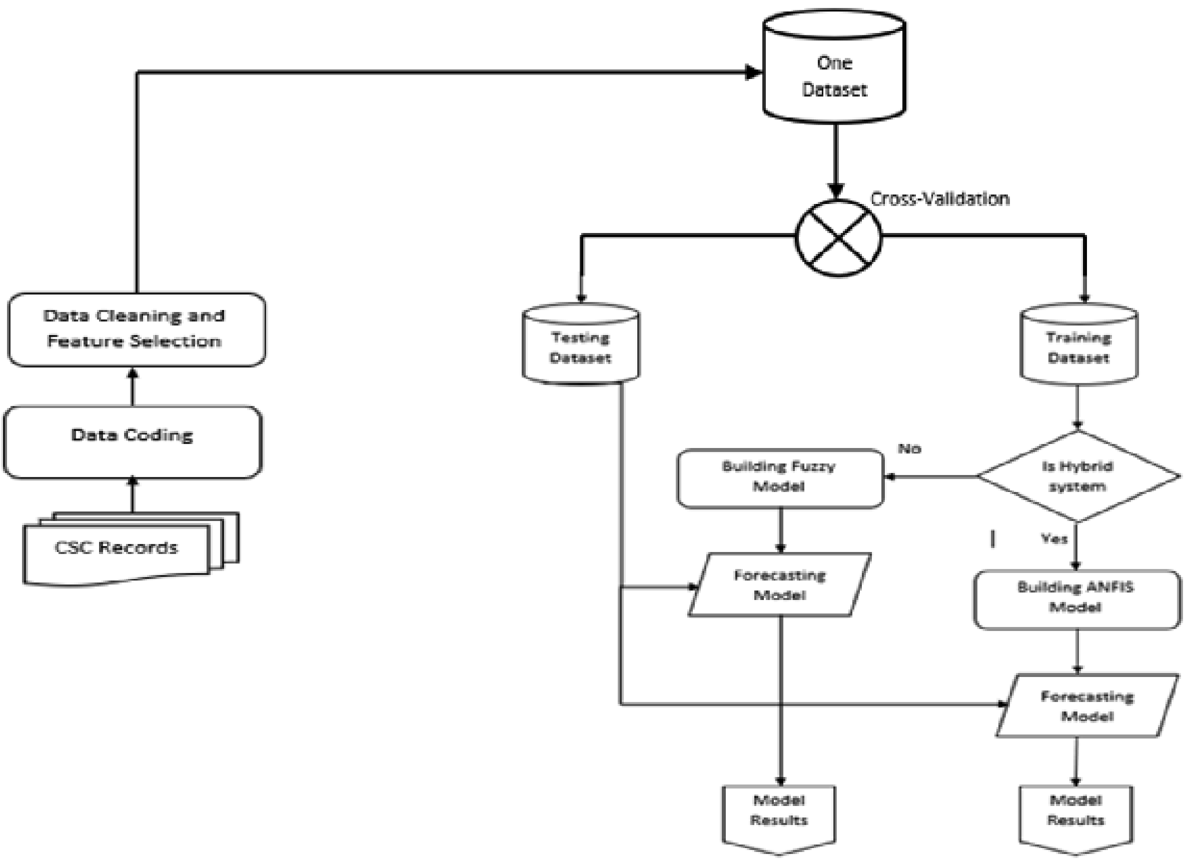

Fig. 1: The Flow Chart of The General Method Procedure.

inputs to select the closest rule as shown in Figure 4, this step has three steps: Find the firing level of each rule, calculate the output of each rule, and aggregate the rule's output individually to obtain the overall output. In the last step, membership functions of the output are used to get the crisp value of the output as shown in Figure 5. To transform the crisp value a defuzzification operator is used. The most operator used for a discrete fuzzy set C having the universe of discourse V is Center-of-Gravity (COG), where it finds the COG of the aggregated fuzzy set, represented in the following equation [36]:

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

where Z = {z1, ..., zN} is a set of elements from the universe V.

There are different types of membership functions, trapezoidal, triangular for linear variation, and sigmoidal, gaussian, for nonlinear variation. So, the selected membership function will be depending on the requirement. Both trapezoidal were used as shown in Figure 3 for output and triangular as shown in Figure 4 for input membership function for FIS. but for NF several membership functions like triangular, gaussian for inputs, and linear, constant for outputs were used.

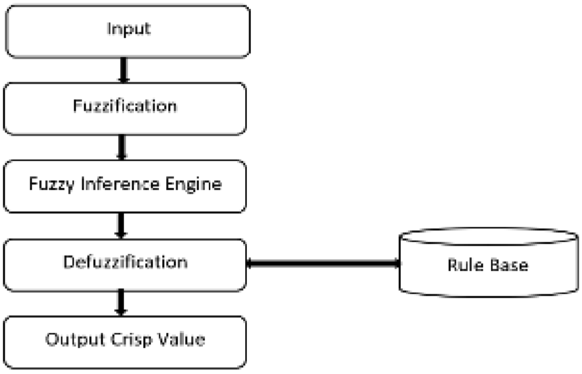

Fig. 2 : The flow of FIS.

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 in fi g 3.

The variables have a degree of metalinguistic uncertainty. That is, the range of values of each

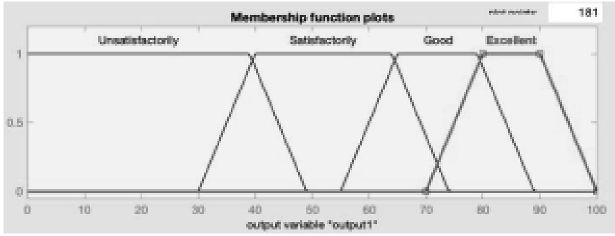

Fig. 3 : Trapezoidal Membership function for output.

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.

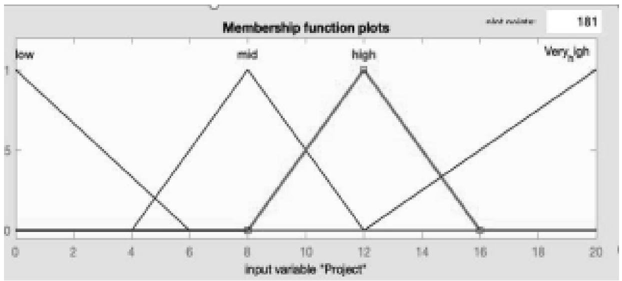

Fig. 4 : Triangular Membership function for Input.

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. 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 displays the procedure used for building the Fuzzy model applied to the FRM – data set.

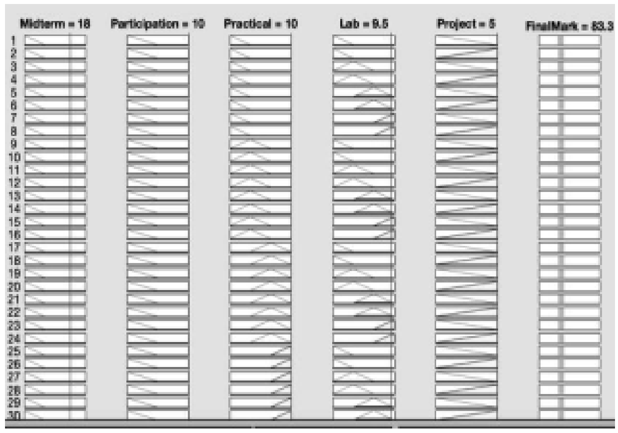

Fig. 5 : Rule Viewer With Inputs and Output for the Csc Dataset.

3.2.2 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. Achieving 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 ANFIS is based on adaptive networks, which serve 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 [37] which is a combination of a fuzzy inference system and neural networks also called neuro-fuzzy (NFZ) [38] as shown in Figures 7, 8. So, it will gather the advantages of neural networks and fuzzy inference systems [37]. The NFZ system is working by 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 7. 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.

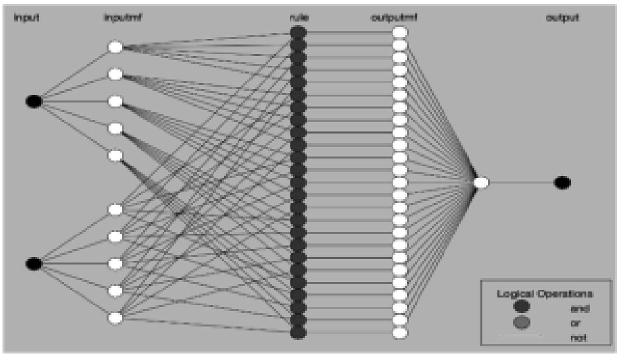

Fig.7: Basic Block Diagram of Anfis-grid

There are two types of ANFIS, the first one is ANFIS-Grid as shown in figure 7. ANFIS-Grid uses 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 the 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 8. ANFIS-Clustering uses scattering partitioning by subtractive clustering, where the number of rules will be small and each rule indicates a cluster. Rules extracted from the ANFIS model are similar to that built-in Fuzzy logic

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 backpropagation 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, these with which develop 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 shows:

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

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

Where A is the linguistic value. Oi is the membership function of A1i. the membership value is calculated using the Gaussian function as in equation (2).

$$\mu_{A1}(x) = e^{\frac{-(x-c)^2}{2\sigma^2}} \quad (5)$$

where the $\{\sigma, c\}$ is the parameter set.

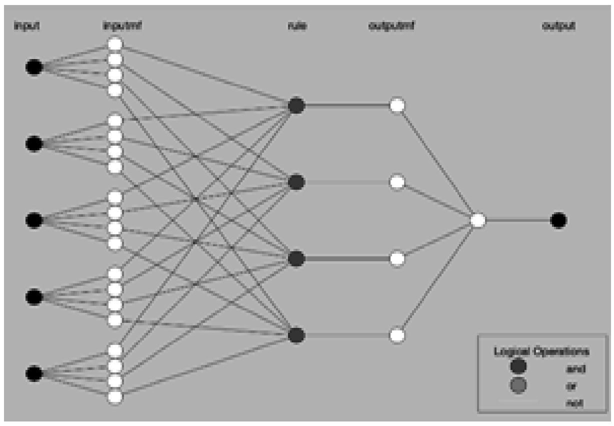

Fig. 8 : Basic block diagram of ANFIS-Clustering for clusters.

Layer 2: the nodes in this layer are fixed and the output is the incoming of all incoming signals as in the (5).

$O_i^2 = w_i = \mu_{A1i}(A1) \times \mu_{A2i}(A2) \times \ldots$

where i=1,2,3,..... (6)

Layer 3: The nodes in this layer are fixed nodes. The weight functions are normalized by the node by calculating the ratio of the ith rule's firing strength to the sum of all rules' firing strength using (6).

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

Layer 4: The nodes in this layer are adaptive nodes and the output is represented in the (7).

$$O_i^4 = \overline{w_i} f_i = \overline{w_i}(p_i A1 + q_i A2 + \cdots + r_i)$$

where i=1,2,3,..... (8)

Layer 5: This layer has a single fixed node where this node computes the overall output as in (8).

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

The following algorithm displays the procedure used for building the ANFIS model which is applied to the CS – data set, and this procedure can be applied to CSE – dataset.

3.3 Models Testing Phase

After the models are trained using training datasets, it is time to test the models using testing datasets. Now, the models are ready for predicting students' performance. Models are modified many times during the testing phase to take their final state. For model testing, they were evaluated based on different factors: the first one is the root main square error (RMSE) for the training datasets produced from the neuro-fuzzy model [39], as in the equation (10):

$$RMSE = \sqrt{\frac{\sum |x_t - \widehat{x_t}|}{n}} \quad (10)$$

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.

RMSE is not taken for the testing data because the neuro-fuzzy results are represented on a 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. The testing data used blind data depends on cross-validation, the data is split randomly into training and testing sets [40].

4. Experiments and Results

Two different devices for conducting the experiments were used; Macbook pro-2013: I5 2.4 GHz, Ram: 8 GB DDR3, HD: 240 SSD with mac OS. XPS 15 9570: I7 8750H 2.2 GHz (12 CPUs). Ram: 16 GB ddr4, HD: 512 SSD m.2 with windows 10. To build the Forecasting and distribution modes, MATLAB_R2018a.

To forecast the students' academic performance with FL and ANFIS in the two stages of the collected datasets, the proposed models in section 3 were applied. Measuring the models based on the RMSE, performance, and 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 divided by the total number of samples in the dataset.

The experiments were performed on all datasets, whereas mentioned before each dataset is divided into two datasets one for training and another one for testing. There are two types of ANFIS: ANFIS-Grid and ANFIS-Cluster, these types will be applied to the same datasets to be fair in judging them. For ANFIS, the datasets used for ANFIS vary based on the dataset, for CS-dataset is divided into training and testing data using a cross-validation method to check the accuracy, where 75% of the data is for training and 25% for testing. FRM dataset was divided into 70% for training and 30% for testing.

The optimal ANFIS model was 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 to be able to test the samples manually and the result of the FL model is similar to the actual final results in the dataset. The accuracy is calculated by dividing the number of true tests by the number of all tests, where these tests are conducted by applying the final FL model on samples selected randomly from the testing dataset. After getting the output from the FL model, this result falls 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 9, a comparison between model results and the actual results is but in percentage marks.

In this experiment, three models are used like the following, the first ANFIS-Grid with eight membership functions has been determined for each input. The second is a normal ANFIS-Cluster without any modification to the tool. The third, modified ANFIS-Cluster, where the parameters are modified for clustering Genfis as follows: Range of influence: .5 => .2

Accept ratio: .5 => .1

Reject ratio: .15 => .015

Table 2 : 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)

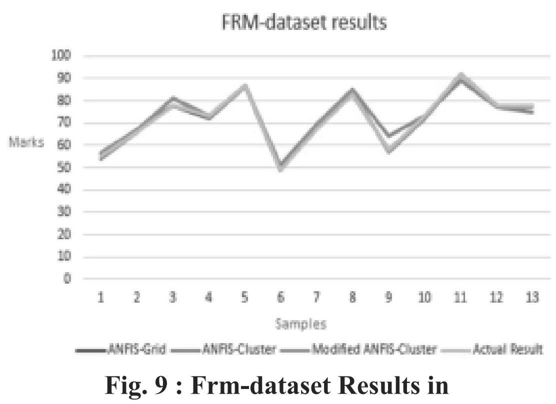

Fig. 9 : Frm-dataset Results in Percentage Using Our Models.

These changes produce a twenty-seven-membership function for each feature, while the normal ANFIS-Cluster produce, 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 3 : Models Result 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 is calculated through the following equation:

$$e = \frac{\sum v}{\sum w} \quad (12)$$

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 Tables 2, 3, and figure 9, the ANFIS-Grid was more accurate than ANFIS-Clustering for this kind of dataset.

Test 2: ANFIS-Grid and ANFIS-Cluster models were applied to the CS dataset. This dataset is not large as the 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 has three membership functions, Practical has four membership functions, has four membership functions, and Project has two membership functions. The same experiment was executed on different membership function types to identify the better one.

Table 4 : Anfis-grid Vs Anfis-cluster Vs Actual Result On Cs-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)

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

Range of influence: .5 => .2

Accept ratio: .5 => .1

Reject ratio: .15 => .015

Table 5 : Models Result in An Error on Csc-dataset

ANFIS-Grid	ANFIS-Cluster
7%	23%

In figure 10, the first round of 10 epochs for the ANFIS-Triangular on CS-dataset is 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 CS-dataset, it is concluded that the ANFIS-Grid based on the accuracy as shown in tables 4 and 5.

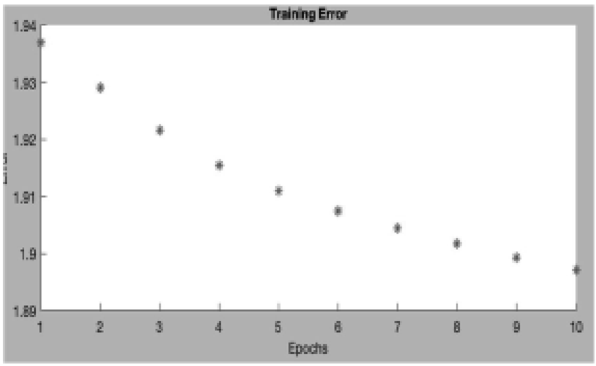

Fig. 10 : Training Error Shows the Rmse for Anfis-triangular for the Second Round of Another 10 Epochs (rmse=1.8).

Figure 11, 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, whereas ANFIS-Clustering was better than ANFIS-Grid.

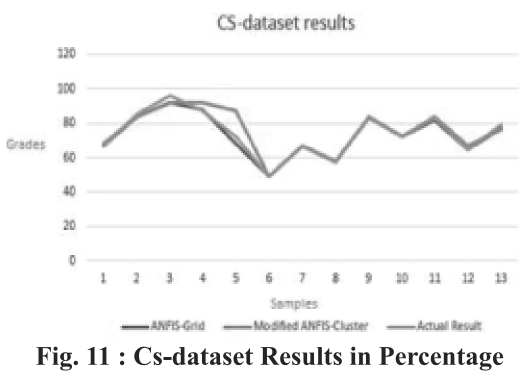

Fig. 11 : Cs-dataset Results in Percentage Using Our Models.

From the model result, it can be concluded that a higher grade in the course as, attendance, assessment marks, exams, assignments, and projects. results, in most cases, better performance

Test 3: ANFIS-Grid and ANFIS-Cluster models were applied to the CSE-dataset, 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 chosen to be compared with ANFIS-Clustering. For ANFIS-Cluster, changes for some parameters for clustering Genfis were done as follows:

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 is applied and converted from GPA to percentage using the following equation:

Percentage = GPA * 12.5 + 50 (13)

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

Table 6 : 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 this dataset needs five features, four features of them are needed for 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, so only ANFIS-Clustering was selected. In the following table, there are some samples selected randomly that 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. ANFIS-Grid vs ANFIS-Cluster vs Actual Result on CSE-dataset.

Based on the previous results, it is said that ANFIS-Clustering with five features is more accurate than

Table 7 : 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 -

with six features, where the error based on the random samples is Zero for ANFIS-Cluster 5, and as shown in figure 13 the ANFIS-Cluster 5 is closer to the Actual results than the ANFIS-Cluster 6.

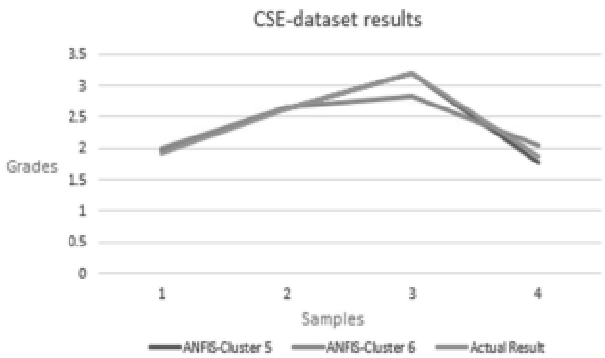

Fig. 13 : Cse-dataset Results in Numeric Gpa Using Our Models

Also, it is common to assume that having studied in a Computer system engineering major is considered excellent have students with higher academic abilities; However, it was found that this is not the case, at least for the sample used since several cases were found in which students got lower performance. It is presumed that there are emotional aspects related to their studies such as motivation, and priorities in their lives.

As it is seen in the previous sections, a lot of experiments were done to compare the algorithms 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 Neuro Fuzzy is better than Fuzzy Logic. Where that was clear when applying them to the FRM dataset. For the ANFIS models, experiments were also done on different datasets, where they were done on FRM-dataset and CS-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. The ANFIS-Grid results were closer to the actual results.

ANFIS constitutes a powerful tool for their application in forecasting the performance of university students, especially those related to academic results. The numerical results obtained in this research should necessarily be taken as valid for other institutions with a similarity in the curriculum, even within our own country, and considering the same type of variables. However, the strategy used in the work and the model to make the forecast is applicable in various scenarios.

Even though this work pursued the objective of having a forecasting tool that could be applied repeatedly in all university courses and majors. This study has 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 to give any personal information about the students or any information to contact them. Also, there is an important factor affecting the student's performance which is: if the student has a scholarship or not, but the university also refused to give this information. A limitation is also in the devices used for performing the experiments in this research, which were to produce more powerful ANFIS-Grid models, devices needed with higher specifications.

5. Conclusion and Future Works

In educational institutions, it is of great importance to forecast the teaching results that could be obtained by the students in the different courses and majors where they enroll. Having this information allows, on the one hand, to make certain organizational decisions, on the other hand, to provide teachers, through more complete and timely information about their students, the ability to develop differentiated methods for their students, which leads to the correction in time of the limitations, to achieve academic excellence. This work proposed forecasting models for students' marks for some courses and majors at Arab American University Palestine (AAUP). This model was built based on datasets collected from AAUP through the registration department. Two models were built to forecast students' performance; Adaptive Neuro-Fuzzy Inference System by using clustering and grid. After all experiments results, it is concluded that using the ANFIS is better than using fuzzy logic alone because, ANFIS, it benefits from the advantages of neural networks in building the rules, wherein 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. The accuracy of the ANFIS model is higher than the Fuzzy Logic model. Given the encouraging results that have been obtained in the work, it would be beneficial to continue working on its improvement and its generalization. It should be tested if it is not yet possible to achieve greater efficiency by making modifications to the current ANFIS architecture and even experimenting with other possible models. After generalization, an application should be designed that allows the forecast for any of the courses and majors in a university. This application must be connected to the databases of the existing teaching control.

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