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Providing Adaptive Learning Contents and Assessments in MOOCs Using Classification Algorithms

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Declaration

This is to declare that the thesis entitled " Providing Adaptive Learning Content and Assessment in MOOCs, Using Classification Algorithms" under the supervision of Dr. Ahmad Ewais & Prof. Mohammed Awad, is my own work and does not contain any unacknowledged work or material previously published or written by another person, except where due reference is made in the text of the document.

Dedication

I would like to dedicate this work to my parents' pure spirits, who supported me in every step in my life. I would also like to thank all my family, who are always willing to provide any support. I dedicate this work to my brothers and sisters. I would like to thank each of my instructors & colleagues in my university featured (AAUP). Also, I would like to thank all dear friends for their support.

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Abstract

With the spread of e-learning platforms across the Internet, including the large online learning courses called MOOCs (Massive Open Online Courses), there is a wide range of learning resources related to different educational topics and courses. Therefore, learners with different backgrounds, culture, skills, and knowledge level, are able to follow educational online courses to help them to acquire knowledge about different topics, develop their abilities and enable them to master different skills, without being limited to time or place. However, this openness characteristic of MOOCs can be a reason for overwhelming learnrs in the middle of mass learning resources.

Another important aspect is related to the fact that the current offered courses are mainly developed based on teacher oriented approach. This means the contents and the assessements resources are mainly based on the course author's experience. As such, the learning outcomes of each course are static and based on what have been introduced by the course author. This can be considered as shortcome as the course contents is not suitable to the learner's knowledge or the course contents might not satisfy the expected or intended learning outcomes form the learner's point of view.

To overcome previous obstacles, there are various efforts and attempts have been proposed in the litreture to provide adaptation techniques to MOOCs. Proposed adaptation techniques are mainly related to dynamically adapt learning resources, assessment tools, content presentation, logical sequence of learning path using data mining and classification algoritms. Similarly, this thesis aims at providing an approach to support adaptation to content and assessment tools to cater learners' needs.

The proposed approach in this research work is innovatiove as it considers adaptation from twfold aspects. First, it utlizes the Support Vector Machine algorithm to

autmaticlly map learning resources and Intended learning outcomes. Second, it utilizes Fuzzy Logic algortihm to determine the levels of assessment, such as questions and examinations at different levels: easy, medium and difficult and generate exams based on the current knowledge level of the learner.

To validate the proposed approach, a proof of concept has been developed by utlizing the two algorithms (SVM and Fuzzy Logic). Moreover, a dataset related to learning resources for a specific course in Coursera MOOC platform was collected to be classified using SVM according to their relevance to a number of identified learning outcomes. Moreover, a number of questions and exams were collected from the same course. The developed prototype was provided with the learning contents and assessements for a specific course and it was evaluated. The results were promising proved accurate and satisfactory outcomes for both classifications of learning resources and assessment tools as the accuracy indicators were 71.5%.

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List of Abbreviations

MOOCs: Massive Open Online Courses

ILOs: Intended Learning Outcomes

LM: Learning Material

LC: Learning Concept

SVM: Support Vector Machine

ARFF: Attribute-Relation File Format

TP Rate: True Positive Rate

FP Rate: False Positive Rate

TN Rate: True Negative Rate

FN Rate: False Negative Rate

P: Precision

R: Recall

ROC Area: Receiver Operator Characteristic Curves

GPA: Grade Point Average

COG: Center of Gravity

SOLO: Structured of Observed Learning Outcome

CHAPTER 1

INTRODUCTION

CHAPTER 1 :INTRODUCTION

1.1 Overview

This first chapter is structured as follows. Section 1.2 presents a background about educational platforms related to MOOCs. After that, section 1.3 explains the research problems and challenges related to supporting MOOCs with adaptation. Section 1.3 shows research motivation to solve the obstacles and drawbacks related to MOOCs platforms. Section 1.4 explains the research methodology in three phases for equping MOOCs with adaptation techniques to enhance learning process by providing suitable learning resources and assessments. Finally, section 1.5 shows an outline of this thesis.

1.2 Background

The MOOCs stands for "Massive Open Online Courses" which are related to web based applications that provide online courses including different learning resources, such as electronic books, presentations, audio and video lectures, quizzes, exercises, tests, exams, and computer programs. Such resources are used to transfer knowledge to a wide number of learners. Also, MOOCs include various courses in different domains, such as science, literature, engineering, medicine, etc. Furthermore, MOOCs enable learners from different locations to learn about different topics. There are different MOOCs platforms such as Coursera[1], Udacity[2], edX[3] in the United States of America. Furthermore, there are MOOCs

[1] https://www.coursera.org/
[2] https://www.udacity.com/
[3] https://www.edx.org/

platforms which have different online courses in Arabic language such as Rawaq[4] in Saudi Arabia and Edrak[5] in Jordan.

Recently, MOOCs are rapidly entering the mainstream and becoming one of the best methods to deliver different levels of degrees, such as professional degrees, undergraduate degrees, program degrees (Emanuel. 2013). This reflects the rapid adoption of MOOCs from both Higher Education Institutions and individual learners from all over the world. It also takes advantage of the widespread use of mobile devices by supporing MOOCs to be responsive and usable for mobile learning.

The rapid adoption of MOOCs enables learners from different countries, cultures, backgrounds, and ages to follow different courses in MOOCs (Onah & Sinclair. 2016). Unfortunately, most of the delivered courses via MOOCs are designed for all learners without considering the individual needs, knowledge level, background, culture,.. etc. This is considered as one of the limitations that got researchers' interests to propose different solutions (Firssova et al. 2016; Gutiérrez-Rojas et al. 2014). One of the possible proposed solutions is to deliver adaptive courses in MOOCs which take the learner's characteristics into consideration. In other words, each learner will be delivered different learning resources, navigation sequence between learning resources, suitable assessment tools depending on learner's needs, (Sonwalkar. 2013; Gutiérrez-Rojas et al. 2014).

[4] https://www.rwaq.org/
[5] https://www.edraak.org/

Many of Machine Learning Algorithms are used and implemented in the online adaptive MOOCs platforms for analyzing, classifying , clustering and extracting information in order to acquire knowledge and taking decisions (Ardchir et al. 2017), so there are two kinds of these Machine Learning can apply in learning systems as follows :
"Supervised Learning" and "Unsupervised Learning". To Realize adaptively in MOOCs ,a number of algorithms used such as Bayesian Network, Fuzzy Logic, Neural Networks, Genetic Algorithm, Support Vector Machine (SVM) etc. to provide personal learning experiences based on assessments results (like exams) (Rosen et al. 2017). This approach allows learners to move within a course in MOOCs according to their learning needs. For instance, (Ardchir et al. 2017) presented a framework based on a hybrid technique to provide the learner with an adapted learning content according to the participant’s learning performance. The proposed solution used a fuzzy logic algorithm to classify learning materials according to the learner’s prior knowledge.

In this research work, both learning contents and assessments tools are considered in the adaptation process. To validate this idea, classification algorithms has been adopted, to classify the levels of learning resources, based on the classified learning content and assessment tools. The adaptive learning path which means learning content has been displayed. Furthermore, assessment tools (as exams in three levels)have been delivered for the learner to master his skills and satisfy his needs.

1.3 Research Problem

Despite the huge success of MOOCs, there are several challenges related to high dropout rates, and overwhelming learners in the middle of wide range of courses related to the same topic. For instance, although many thousands of participants enroll on different MOOC courses, the completion rate for most courses is below 13% (D.F.O.Onah et al 2014). Furthermore, recent reports showed that the completion rate in MOOCs is below 5% (Feng et al 2019). Such drawbacks are related to the lack of motivation for completing followed courses or the level of courses might be very easy or too difficult to learn (Kay et al., 2013). Other drawbacks are also highlighted in litreture such as the availability of wide range of courses in the same MOOC platform or in different MOOC platforms. This can be a reason for following some courses and quite it after a while.

Among the different solutions for previous mentioned obstacles is the use of adaptation techniques in MOOCs. Most of the proposed adaptation approaches are related to delivering a content presentation based on the learner's profile (Abdullah et al., 2015; Yarandi, 2013; Ewais & Duaa Abu Samra 2017; Ardchir et al. 2017). Others are related to support assessements inside MOOCs (Rosen et al., 2017; Archer et al., 2017; Sein-Echaluce et al., 2016). However, to the best of our knowledge, there is no research work conducted to consider adaptation to learning content and assessement together. This research work proposed a solution for considering delivering both learning contents or materials and assessment tools adaptively using classifications algorithms. Furthermore, the proposed adaptation critera is mainly depending on both intended learning outcomes and knowledge level of the learners who are following specific course.

1.4 Research Motivation and Objectives

Supporting learners with adapted learning content showed some interesting results to encourage learners to complete the learning process of a MOOC course. Moreover, supporting learner oriented approach is also important in MOOCs similar to any elearning application. Therefore, enabling learner to select and identify in advanced the learning outcome of MOOC course will satisfy requirments for supporting learner oriented approach.

The previously mentioned challenges are considered as a motivation to conduct our research work and to investigate the use of adaptation in MOOCs to improve the learning experience and progress and to support learners during their learning process. As such, we have proposed a conceptual framework for considering automatic mapping between both learning content and assessment tools which will be delivered adaptively, by utilizing classification algorithms to offer a suitable learning experience for learners.

In this research work, the three main objectives related to the proposed solution are as follow:

- The automatic mapping between learning materials (LM) and learning concepts (LC) or chapters based on ILOs. We proposed and implemented a model, with a number of features, which depends on machine learning technique, such as support vector machine (SVM) to classify the best learning materials (LM) that are suitable for learning concepts related to a specific course based on ILOs.
- Automatic generation for assessment tools like exams according to three levels (easy, medium and hard). Therefore, automatic generation of exams depends on the difficulty level of questions when weights(values) are entered manually by expert and the current learner knowledge. This step is accomplished by utilizing fuzzy logic technique to determine the exam level which fits the learners' requirments.
- Automatic mapping between Grade Point Average (GPA) for the learner and the level of assessment (exams) using the fuzzy logic technique to generate a suitable exam for advanced, medium or beginner learner.

1.5 Research Methodology

The research methodology used in our work to achieve the objectives is based on utilizing machine learning techiniques to classify different learning materials based on intended learning outcomes and generating exams that fits users' knowledge level. To proof the effectiveness of the proposed approach, a number of steps have been conducted.

As a first step, data collection is performed by colleacting learning materials and related ILOs out from a course in MOOCs. Here it is important to point out that the database was collected manually from a global website (Coursera). The dataset contains two different courses named (Data Mining and Artificial Intelligence (AI)), but we adopted the first course with all learning materials format (PDF, MP4, PPT,.. etc.), using (144) files (LM), (17) intended learning outcomes (ILOs), with (28) learning concepts or learning chapters related to ILOs.

After that, A web-based prototype was developed to use the collected resources and utuilze the two algorithms so that specific learning materials and exams will be delivered to the leaners based on his intended learning outcomes and knowledge level. The developed prototype uses the classifier Support Vector Machine (SVM) to classify automatically the high probability of learning material which fits the learning concepts (LC) or chapters which depend on selected ILOs by the learner. On the other hand, fuzzy logic algorithm is implemented to generate exams automatically. To do so, an expert is required to add a number of related questions and assign a specific rate to each entered question. Manually entering the rate of questions (weights) by an expert determines the level of the exam (easy, medium, hard), which can be delivered for the learner later on. As a result, a question bank for each group learning concepts (or chapters) will be generated. Finally, the exams will be generated using fuzzy logic technique to deliver exams based on learner's GPA.

To validate the effectiveness of our proposed adaptive learning course based on (ILOs), it was assessed by many measurement tools, such as Precision and Recall indicators, True Positive (TP) Rate, False Positive (FP) Rate, Receiver Operator Characteristic Curves (ROC) Area, etc. were used in order to measure the quality of the system.

1.6 Thesis Structure

Outline of the Thesis. This thesis is structured as follows:

- **Chapter 1**: introduces some important concepts about MOOCs. Then, it shows the problem of the study. After that, both research objectives and motivation are presented. Finally, it explains the research methodology that has been adopted in this thesis to create an adaptive MOOCs.
- **Chapter 2**: presents a brief description of previous work and literature review related to our research about online adaptive learning systems in MOOCs, then we talk about machine learning techniques used in MOOCs as adaptation techniques, such as Support Vector machine, Fuzzy Logic (FL) technique, and Naïve-Bayes Algorithms. Finally, it shows the learning outcomes and Bloom's Taxonomy Theory.
- **Chapter 3**: explains the details of the research methodology, the adaptive conceptual framework and the proposed Adaptive Learning system in MOOCs **architecture** presented in two phases, based on Intended Learning Outcomes (ILOs). Finally, it shows the case study for our adaptive system.
- **Chapter 4**: presents the experiment and evaluation of the results created by the proposed system, then we present the assessment tools as Precision and Recall, and ROC Area. Finally, it explains the Fuzzy Logic Center of Gravity (COG).
- **Chapter 5**: concludes our thesis work and discusses the results. Finally, it gives directions for the possible future work to develop the research work.

CHAPTER 2

BACKGROUND

AND

LITERATURE REVIEW

CHAPTER 2
BACKGROUND AND LITERATURE REVIEW

2.1 Overview

This chapter presents the works that cover different subjects related to our thesis. This section starts with a background about the MOOCs, definition, types and the purpose of creating learning platforms in section 2.2, then section 2.3 references to global platforms which provide MOOCs, such as coursera, edX ...., etc. Section 2.4 explains adaptive MOOCs and related works and literature reviews. Section 2.5 illustrates machine learning types, such as SVM, Fuzzy Logic, Naïve Bayes, Decision Trees, and their characteristics. Section 2.6 presents the importance of learning outcomes are related to research adopted in MOOCs in general. Section 2.7 explains the learner performance taxonomies and presents Bloom's and SOLO's Taxonomies. Finally, the last section presents a summary of this chapter.

2.2 Background.

The first learning platform was started by Salmam Khan in 2008 ,which was known as khan Academy [6], which is a free online and non-profit educational platform. After that, Dave Cormier and Bryan Alexander introduced Massive Open Online Courses (MOOCs). In 2008, online courses belonging to the Manitoba University were offered. So, this platform was considered a new trend in the technology field (Smith& Eng 2013). The abbreviations of MOOCs terms reflect the initials that contain this definition. The word “massive” in Massive

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[6] https://www.khanacademy.org/

Open Online Courses (MOOCs) refers to the fact that this education expands to a great mass of learners. The word “Open” refers to the courses which are open for free to any learner willing to participate. The word “Online” refers to the fact that these courses are done on the internet through interactive tools, such as presentations, audios, and videos, (Kesim& Altınpulluk 2015). Therefore, MOOCs provide interactive users with forums to support community interactions between participants and teaching assistant professors. Figure 1 shows the meaning of abbreviations.

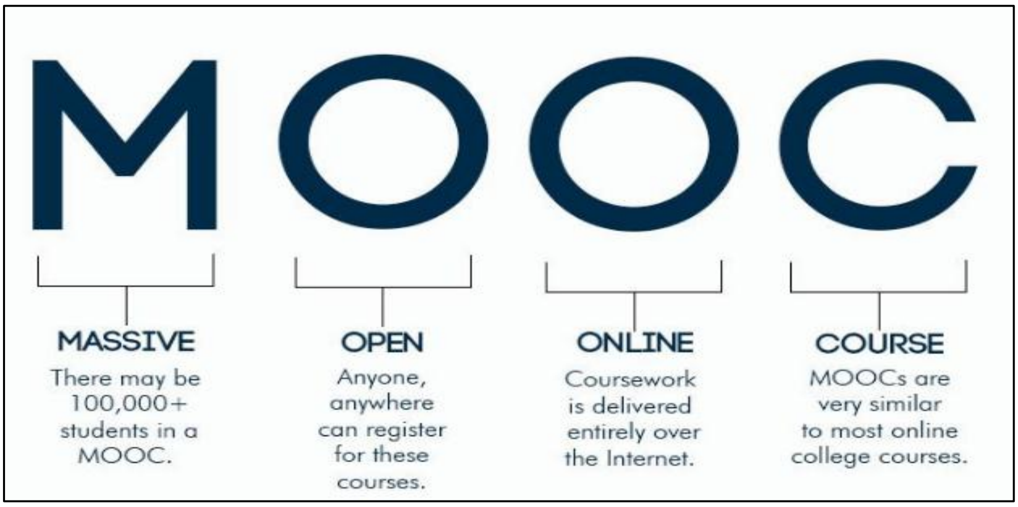

Figure 1: MOOCs abbreviation meaning[7] .

Also, Figure 2 represents the learning curve in MOOCs between 2011-2017.

[7] http://learningfrommoocstonyamichael.blogspot.com/ .Accessed [11 08 2018].

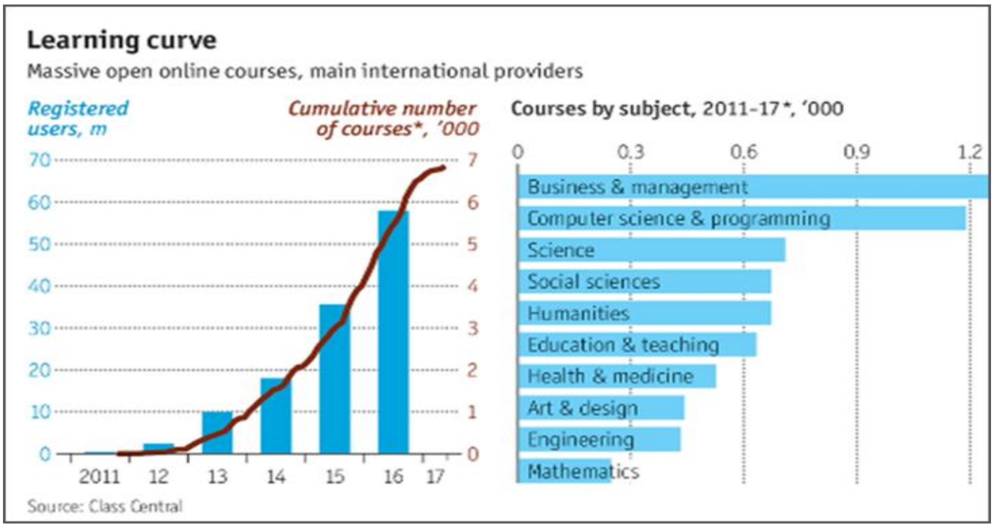

Figure 2: Growth of MOOCs (Based on class-central report,2017)[8] .

MOOCs platforms were categorized into two known types “cMOOCs” and “xMOOCs” (Smith& Eng 2013). The first one is based on connectivism theory which supports the self-organized learning process,the learners are actively participating to contribute in building their skills through sharing learners’ views with their peers by using blogs of experiences and they can get benefits from existing resources, such as images, videos, (Mccallum et al. 2013). So, in this case, the learners are considered as the focus of the educational process while instructors have a secondary role.

On the other hand, the second type "xMOOCs" is mainly based on, behaviorism, and social learning theories. It is currently considered as a new technique of teaching and learning because it enables learners to communicate with their peers inside the MOOCs platform. Also,

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[8] **https://www.economist.com/special-report/2017/01/12/established-education-providers-v-new-contenders**. [Accessed [11 08 2018].

it is based on e-Tests which offers predefined learning objectives by the teachers (Milligan et al. 2013). In contrast, there are attempts to merge previous two types or propose new ones (Mccallum et al. 2013).

Despite the different types of MOOCs, they share the same aim; that is, they provide free and open learning to learners. Every type of MOOCs has a different learning environment and various ways to deliver knowledge and both depend on learners or teachers, so the goal of MOOCs is to open learning and a free access to university education for the massive number of learners around the world. Consequently, many of the learning platforms have been developed by different learning institutions to provide open courses either free or paid, such as Udacity, edX, and coursera, etc.

2.3 Global Platforms Providing MOOCs:

Now let's talk about some important platforms that provide MOOCs worldwide as Khan Academy, edx, Coursera, Udacity, .. etc.

- **Khan Academy**: As we mentioned before, it is a well-known free online learning platform and non-profit learning organization started by Salman Khan in 2008 with significant backing from Google and Bill & Melinda Gates Foundation. This platform provides a massive number of lectures as videos in learning subjects with automated exercises and assessment (Yuan & Stephen 2013; Kolowich 2013).
- **edX**: It is a non-profit MOOCs platform founded by Harvard University and Massachusetts Institute of Technology. It provides many educational subjects, such as computer science, public health, chemistry, .. etc. Learners who mastered subjects can pay a modest fee for a certificate when the course is completed (Yuan & Stephen 2013; Kolowich 2013).

- **Coursera**: It's a profitable company which deals with some university partners, namely Stanford University, Pennsylvania, etc. Currently, it offers many courses in various subjects, including mathematics, computer science, social science, engineering, education, and others. Some universities offer credits for Coursera classes to learners who want to pay a fee to have extra assignments and work with a teacher and are assessed (Yuan & Stephen 2013; Kolowich 2013).

  Udacity: It is another profitable start-up founded by David Stavens, Sebastian Thrun and Mike Sokolsky. This platform currently offers many online courses in mathematics, general sciences, computer science, entrepreneurship, and programming. When the learners complete a learning course, they receive a certificate of completion, indicating their level of achievement signed by the instructors, without cost, but the learners who take the final exam can pay a fee in an effort to make the certification to be more academic and recognized by employers (Yuan & Stephen 2013).

2.4 Adaptive MOOCs and Related Works

Many of the literature reviews and related works to our thesis ,discuss studies about MOOCs platforms to develop the strategies for teaching, which introduce several proposed techniques to enhance the MOOCs learning and learner's skills through adaptive content or assessment tools based on learning outcomes.

So, in this section, we will present some of the related works based on adaptive MOOCs within content and assessment tools or intelligent systems as learning machine algorithms which are applied in proposed systems. Let's take a view of the definition of adaptation. It can be defined as actions that are conducted to change the functionality and information of the system based on many requirements, such as user characteristics and needs, device specifications and context, .. etc. (Ewais @ Duaa Abu Samra 2017).

So, adaptivity is a basic characteristic that MOOCs should include in order to realize successful results (Nicolas & Francies 2017). And there were many attempts conducted to consider learning outcomes in the process of delivering adapted learning resources in the context of open educational resources (OER) (Huang 2015). The following related works present the researchers conducted to solve-to some extent- the issues related to the challenges of MOOCs. (Nicholas & Francis 2017) suggested Adaptive MOOCs foster personalized Learning. They mentioned that Adaptive MOOC Design Framework AMDF is based on Felder and Silverman's Learning Style Model (FSLSM) (Viola, S.R., Graf, S, Kinshuk et al, 2006); and Flexi-OLM model (Dimitrova, V. 2003),which explain the hierarchy of concepts, lecture structure, prerequisites, to deal with MOOC problems, such as high dropout rates and a low number of cooperative activities among learners. Their approach aims to create a learning system that directly meets the different needs for participants.

Another related work was presented by (Hemavathy & Harshini2017), who suggested to use an approach called "Content and Language Integrated Learning" (CLIL), to provide learner's needs. This approach should create algorithms to support online learning experiences and content. They introduced a novel technique to help participants cope with, and develop their language skills, to improve their ability to learn a foreign language, because one of the problems of MOOCs is the obstacle of the English language for courses. Using the CLIL approach mixes learning content with another language to achieve more improvement for learners to understand the content more effectively than using traditional classrooms. (Rosen et al. 2017) re-designed adaptive assessment tools in edX platform. Additionally, the work aims to establish the foundation for future study of adaptive functionality in MOOCs platform on learning outcomes to reduce drop-out rates by applying the fuzzy logic technique. The adaptation of this type leads to a higher efficiency of learning, so a learner goes faster through the course. (Rosen et al. 2017) are adding pre- and post –assessment tools for courses, using Tutor Gen SCALE Adaptive Engine, to focus on improving learning. The result of their comparison shows more efficiency.

Researchers (Ewais & Duaa Abu Samra 2017) aimed through their work to provide participants with suitable learning resources and arrange them in a method that matches a learner's profile. Their work depended on delivering adaptive courses based on (ILOs). They proposed a conceptual framework to achieve the adaptation process. Their proposed work depended on the Brusilovsky's adaptation technique which is considered as one of the most popular ones in the domain of adaptive hypermedia in general. They used Bayesian Knowledge Tracing algorithm which allows the learner to learn about learning concepts and move to the next one after completing exams, quizzes,.. etc.

(Vigentini and et al. 2016), they introduced a hypothesis to explore the impact of course design on the learner's engagement. They talked about the flexible and adaptive potential of a MOOC designed to meet the different needs of participants, there is flexibility for the learners to choose their learning paths. All learning activities, modules, videos, lectures, and assessment tools have been available for participants since the beginning of the course. Several algorithms were applied, such as X-means clustering, classification algorithm as K-NN and Naive Bayes to predict their performance in the open course to prove their hypothesis. (S. Ardchir et al. 2017), they proposed an adaptive learning framework of MOOCs that was able to generate suggestions of learning paths adapted to the profile of each participant. It depended on existing adaptive methodologies of adaptation system applying machine learning techniques as Fuzzy Logic. So, the framework allows for an increased contextualization and personalization of learning experiences.

(Alzaghoul & Tovar 2016), they proposed a framework which considered a list of recommendations of instructional material, depending on the Participant's profile and experience. It was built by implementing the Fuzzy Logic technique. The recommendation system must contain four important characteristics: low complexity, adaptation, auto-updated and dynamic. The proposed approach places the learner at the center of the design process during the learners' interaction with MOOCs system and provides learners with a suggested learning required to meet their current preferences.

(Gutiérrez-Rojas et al. 2014), they proposed a "MOOC rank" prototype that enables the participant to explore a number of recommended MOOCs, depending on the intended learning outcomes (ILOs). The recommendation is applied at courses level instead of learning materials so that the model will propose a list of possible MOOCs courses that related to the selected ILOs.

(Hmedana et al. 2017), they proposed an approach to track and identify the participant's learning styles, then they provided them with the appropriate learning materials, activities,.. etc. They applied the Neural Network algorithm as an intelligent learning system through an adaptive recommendation system. (Verdu et al. 2008), their proposed research work evaluated the participants by designing the exam sheets, then generating and delivering the learning paths based on learning progress for learners. The fuzzy logic technique was applied in their research. (Agarwal et al. 2015), their proposed research was determined and they adapted the knowledge level of a participant in online test systems. The systems were implemented by using Fuzzy logic classifier.

2.5 Machine Learning in MOOCs

The benefit from the implementation of adaptive learning techniques is making MOOCs courses more personalized. Course designers, participants, or managers, of learning institutions, might benefit from the exploitation of all the data MOOCs collected, and use them to enhance educational activities, courses delivered, and investment of entire learning offers. (Daniel et al. 2015), agents analyzing the participant’s profile could customize a learning course as follows: adjusting course content according to the participants’ pre-requisites or educational background; changing course content with regard to location, or language,.. etc. (Buffardi & Edwards, 2014).

Many machine learning algorithms were applied in adaptive MOOCs platforms. They can be utilized for classification, clustering, filtering data, .. etc, in order to achieve intended goals. Machine Learning Algorithms can be classified into two categories: "supervised learning" and "unsupervised learning" (Ardchir et al. 2017). Supervised learning – can be defined as a system which is supplied with a set of training examples, consisting of inputs and corresponding outputs, and is required to discover the relationship between them.

For example Support Vector Machine (Yahya 2011, Joachims 1998, Liu et al. 2013), Random Forests(Ghatasheh 2015, Breiman 2001), Neural Network (Hmednaet al. 2017), Bayesian Network (Agarwal, Jain, & Dholay, 2015, Decision Trees (Topîrceanu & Grosseck 2017), (Caruana & Niculescu-Mizil 2006),.. etc.

Also, unsupervised learning can be defined as a system which is supplied with a set of training examples consisting only of inputs and is required to discover for itself what appropriate outputs should be as a Kohonen Network.

Here let's talk about some machine learning algorithems for prediction and classifications .

2.5.1 Decision Tree (DT) Algorithm

Decision trees are considered as popular and powerful tools for prediction and classification. It contains rules that can be understood by humans and utilized in the knowledge system as a database. (Prajwala 2015). The decision tree classifier is important in the analysis of the decision process, which contains a series of decisions or successive nature states.

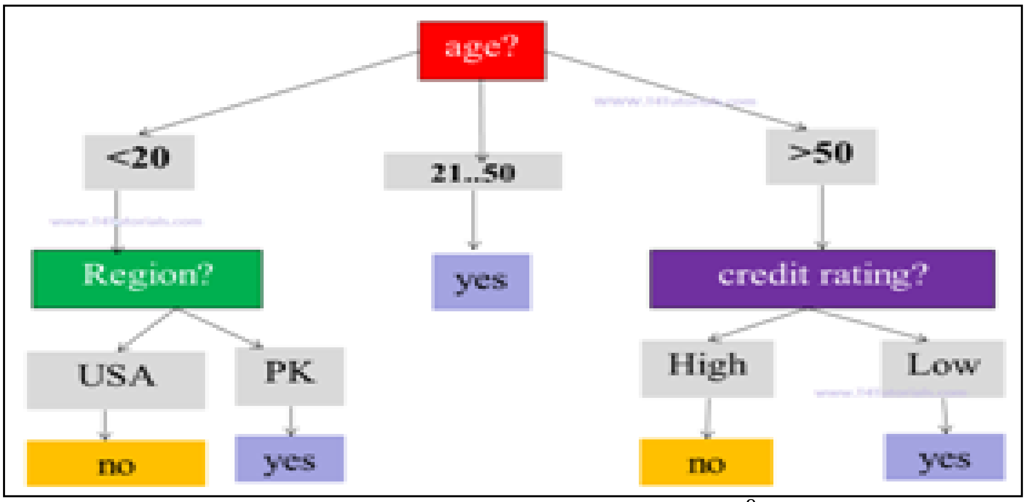

Figure 3:Example of a Decision Tree[9]

The decision tree is a Quantitative, graphical, and graphic representation of the decision-making issues, which is useful to see all branches of the decision-making process, explain all system situations and possible states for decision-making (Prajwala, 2015), (Rokach & Maimon, 2014). Figure 3 represents in general, an example of a decision tree technique. The decision tree tool refers to the basic decision as well as secondary decisions that can be subdivided into more secondary decisions, depending on specific probability values.

[9] [https://t4tutorials.com]. **[**Accessed [1**1** 0**8** 2018].

There are many applications for decision tree such as statistics, pattern recognition, decision theory, signal processing, machine learning and artificial neural networks (Murthy ,1998)

2.5.2 Support Vector Machine (SVM) Technique

SVMs were already known as a tool that very effective for discovering informative patterns and features or attributes (Guyon , 2002).

In the early 1990s, The SVM technique was introduced by the Vapink researcher (Boser, Guyon, & Vapnik, 1992). It is one of the machine-learning techniques, specifically, it is a supervised learning, which is based on the statistical learning theory. This technique (SVM) Support Vector Machine was created to solve pattern recognition problems by specific hyperplane for the data to be separated.

SVM technique is becoming famouse , important and effective method in the field of prediction (Das & Padhy, 2012), classification (Bhavsar & Panchal, 2012), and regression in machine learning techniques (Wang L., 2005), (Support Vector Machines for Classification and Regression, 1998). So we adopted this technigue(SVM) in our proposed system.

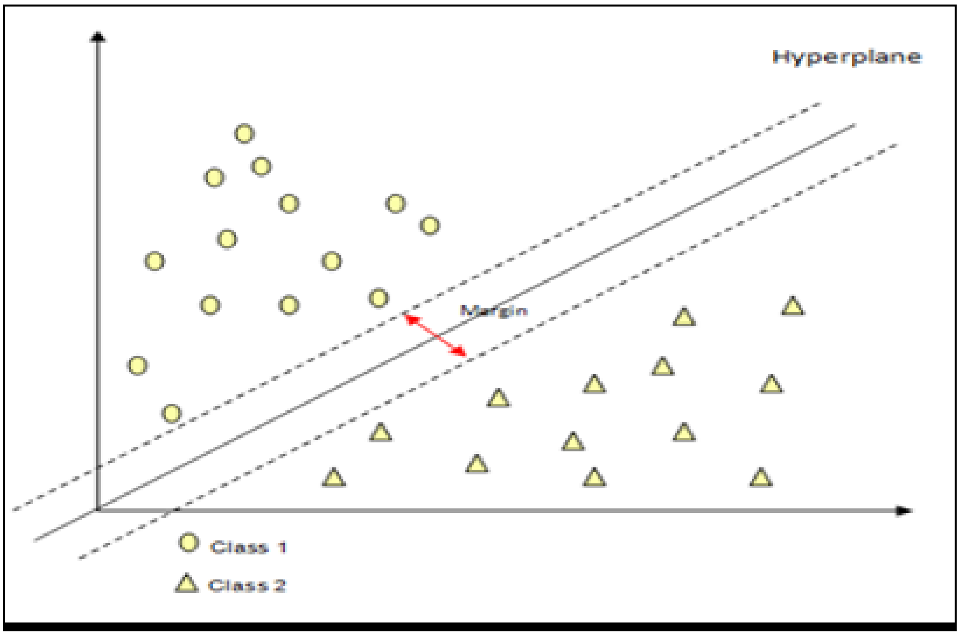

Figure 4:Hyperplane for 2- dimensions space & large margin. (Han & kamber, 2012)

SVM works for the classification process (Han & kamber, 2012), depending on the training dataset. SVM model was constructed to predict a class for cases that contain only attributes, which are not known by its class. Figure 4 explains the SVM technique. The first goal of SVM is to find the best hyperplane for the data to be separated and categorized. The hyperplane is the dividing line between the data represented in the space, which separates it into two classes in the simplest cases of SVM, which can be calculated by the following equations:

$$W.X + b = 0 \qquad \text{(Guyon, 1996). (1)}$$

$$W.X + b = \pm 1 \qquad \text{(Guyon, 1996). (2)}$$

Where W represented the weight vector of input variables that is $W = \{W1, W2, \ldots\ldots, Wn\}$, n is a number of variables**,** X is the set of training data associated with class and b is a scalar bias.

2.5.3 Naive-Bayes Classification Algorithm

The Bayesian Classification is considered as a supervised learning method which is a statistical method for classification. It assumes an underlying probabilistic method which allows taking uncertainty about the model in a principled way by determining probabilities of the outcomes. (Chai, K.; H. T. Hn, et al. 2002). It deals with diagnostic and predictive problems. Bayesian classification provides practical learning algorithms, prior knowledge and observing the data collected. It provides understanding and evaluating many learning algorithms. It computes explicit probabilities for hypothesis and it can be robust to noise in input data. We can use this classifier in many fields as medical diagnostics (AL-Aidaroos et al. 2012), adaptive e-learning system (Rajeswari et al., 2017). Bayes' theorem is stated mathematically as the following equation:

$$\frac{P(h/D)=P(D/h)*p(h)}{P(D)}$$ (Rajeswari et al., 2017). (3)

$p(h)$ Prior probability of hypothesis h.

$p(D)$ Prior probability of training data D.

$P(h/D)$ Probability of h given D

$P(D/h)$ Probability of D given h

The work of (Ewais & Duaa Abu Samra.2017), aimed to provide participants in MOOCs platform with a suitable learning course organized in style which can match the user's profile, using Bayesian algorithm, which enables the student to learn more and to move through the learning path successfully and (Agarwal et al.2015) in their proposed model, using Bayes classifier for determining and adapting the knowledge level of students in online test systems, (Vigentini and et al. 2016) proposed work to explore the effect of course designer on learner engagement. Naive Bayes algorithm is used to predict their intents and performance in the open course.

2.5.4 Fuzzy Logic Techniques

2.5.4.1 Basic Concepts

Problems in the real world are often very complex due to the element of uncertainty. Although probability theory has been an old and effective tool to handle uncertainty, it can be applied only to situations where the system characteristics are based on random processes.

Fuzzy logic in such situations offers a huge potential for effective solving of uncertainty in the problem. It was developed by Lotfi A. Zadeh [1960s-1970s] (Jesiek 2010), and it represents a kind of mathematical logic. Values between 0 and 1 represent uncertainty in decision-making, which represents the membership degrees. (0 indicates a false value, 1 a true value). So, if a fuzzy set a value A is not restricted by the values 0 or 1, but from the real interval [0,1]. (Thrift 1991).

Fuzzy logic is an extension of Boolean logic which deals with the concept of partial truth, where the range of truth value is in between completely false and completely true.

In classical logic, we express everything in the form of 1 or 0, true or false, or, white or black. But fuzzy logic replaces Boolean truth-values with some degree of truth.

There are many applications for Fuzzy Logic in medicin , machine learning and computer science . The applications of fuzzy logic has transformed industrial process control and enabled new product development strategies. (Dutta, 1993).

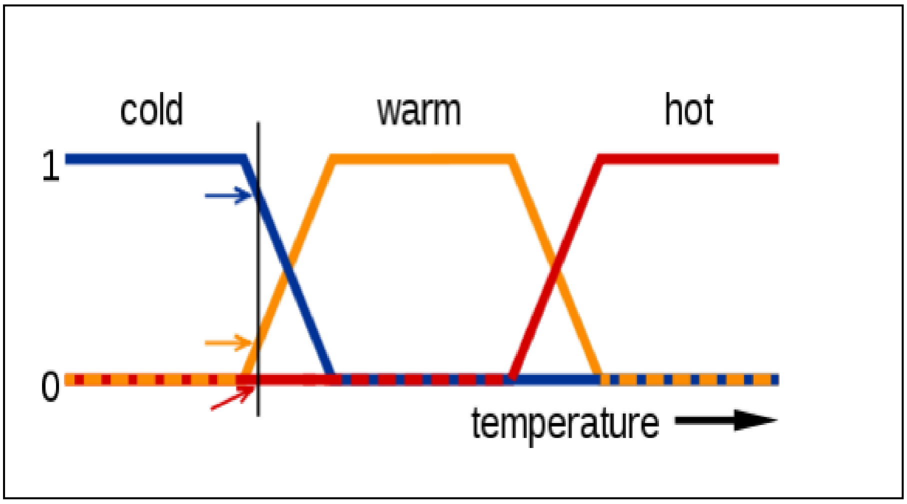

Figure 5: The Fuzzy Logic concept [10]

This degree of truth is used to get the imprecise modes of reasoning that play an important role in the ability of a human being to make decisions in an environment of uncertainty and imprecision. The linguistic variables are words used in fuzzy logic concepts as “cold”, “warm,”

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[10] [http://teaching.csse.uwa.edu.au].[Accessed [1**0** **09** 2018].

"hot," and so on. Figure 5 represents the general concept for Fuzzy Logic Concept. In this section, the following table 1 summarizes the previous related works for adaptation in MOOCs as an e-learning intelligent system.

Table 1: Summary of e-learning intelligent system to support adaptation in MOOC

Authors	Year	Contribution	Machine Learning Algorithm
Verdu et al.	2008	Evaluated the participant by building the exam sheets and then generating Learning paths based on learning progress for every participant.	Fuzzy logic classifier
Agarwal et al.	2015	Determined and adapted the knowledge Level of participant in online test systems.	Naive Bayes Classifier
Alzaghoul & Tovar	2016	Built a recommendation system with four important characteristics: complexity, adaptation, low, auto updated and dynamic.	Fuzzy logic classifier
S. Ardchir et al.	2017	Generate suggestions of learning paths adapted to the competences profile of each participant to allow for an increased personalization of learning experiences.	Fuzzy logic classifier
Ewais & Duaa Abu Samra	2017	Proposed conceptual framework to achieve adaptation process, to deliver adaptive courses base on intended learning outcomes (ILOs) according the learner profile.	Naive Bayes Classifier
Vegintini et al.	2016	Design a new course to explore the impact of this course on learner engagement, provide flexible and adaptive learning path MOOC designed to meet the needs of participants.	X _mean clustering Naive Bayes Classifier
Hmedna et al.	2017	Proposed approach to track and identify participant's learning styles, then provide them with the appropriate learning materials, activities, etc. through adaptive recommendation system.	Neural Networks

2.6 Learning Outcome

The traditional patterns of education tend to focus on the content of the courses and what the teacher can offer to the students, while the recent trends have shifted to focus on the learner and put him at the center of the learning process. This requires describing and expressing the courses in terms of what the student is supposed to be able to know or do after finishing the study of courses in general. The terms that describe what the student is expected to know or be able to do after completing the course are called Intended Learning Outcomes(ILOs), thus describing the expected accomplishment of the students' knowledge and skills as a result of the learning process. Learning outcomes can be identified in several fields within the educational process, namely knowledge, skills, and emotions. So, learning outcomes is all acquired by the learner of knowledge, skills, attitudes, and values, as a result of passing through a particular educational experience or study of a particular method.

It can be said that the learning outcomes are the objectives of the subject after it has been achieved, in addition to what the educational institution and the teacher planned to provide the learners with knowledge, skills, and values, using different sources of knowledge. Learning outcomes are the end product of the educational institution, which appears in the form of learners, possessing a certain amount of knowledge, skills, attitudes, values, and behavior, based on what they have acquired. A lot of the literature in the field of learning outcomes show a number of similar definitions. For instance, "a learning outcome" is defined as “an explicit description of what a learner should know, understand and be able to do as a result of learning" (Bingham, 1999). Others defined "learning outcomes" as “statements of what is expected that the student will be able to do as a result of a learning activity.” (Jenkins and Unwin, 2001).

"A Learning outcome" is also defined as "a statement of what a learner is expected to know, understand and/or be able to demonstrate at the end of a period of learning". Moreover, a learning outcome is considered as a set of sentences that determine what a student desires to achieve after completing successfully his study of the course content, so ILO should be measurable and observable for knowledge, skills, and attributes which were implemented by the learner (Yildirim & Baur 2016).

Learning outcomes consider the important matters in the educational process for learners or teachers. Some of these matters aim to organize teacher's work to facilitate student's acquisition of intended learning outcomes away from disorder to focus on important priorities which commensurate with student's needs, also identify learning activities that achieve desired objectives.

On the other hand, learning outcomes realized many benefits for learners, such as achieving better learning, where all efforts of the learning institutions are directed towards the acquisition of intended learning outcomes for learners. Also, learning outcomes encourage self-study in specific subjects; that is, he selects activities and tasks according to his intentions and preparations to achieve these goals. Learning outcomes also archives active collaboration between learners and teachers in the framework of the acquisition of learning outcomes.

So, the importance of learning outcomes in educational institutions is that the major aim of higher education is to produce high quality learning outcomes in its graduates (Hussey et al. 2003).

Therefore, some researchers who adopted learning outcomes in MOOCs in general, such as (Gosling & Moon 2001), they mentioned a new direction in learning systems in higher education institutions; that is, moving to apply online adaptive MOOCs systems in order to shift from teacher-centered to learner-centered. This shift helps participants reduce cost and time, so any learner can register in the learning course and participate in the assessment. Other researchers (Gutiérrez-Rojas et al. 2014), proposed a "MOOC rank" prototype that enables participants to explore a number of recommended MOOCs, depending on ILOs. The recommendation is applied at course level rather than learning materials so that the model will propose a list of possible MOOCs that are related to the selected ILOs.

Also, (Ewais & Duaa Abu Samra 2017), Proposed a conceptual framework to achieve an adaptation process, to deliver adaptive courses based on ILOs according to the learner's profile. (Teixeira et al 2016), they considered the adaptive MOOCs system as an intelligent system capable of adapting content and presentation to each participant according to their needs, objectives, and interests. Also, (Rosen et al. 2017), they provided adaptive assessment tools in MOOCs, depending on the participant's objectives. Other researchers as (Sonwalkar 2013), he proposed adaptation based on five learning styles throughout the diagnostic assessment, depending on the participant’s goals and preferences. But (Onah & Sinclair 2015), they proposed an adaptation to determine the learning path explicitly, but it does not depend on pedagogical relationships between the various learning concepts.

2.7 Learner Performance Taxonomies

Several taxonomies contributed to develop a learner's performance. Bloom and Biggs Taxonomies were considered the most famous theories in this domain". (Biggs & Collis 1982). The Structure of the Observed Learning Outcome (SOLO's) taxonomy was developed by the Australian academics Biggs and Collis in (1982), which is a style of describing the level of increasing complexity in a learner’s understanding of a subject through five stages (Hattie & Brown, 2004). SOLO's taxonomy can be useful in the teaching process based on the progressive levels for the development of exam questions and learning objectives.

The five levels of the SOLO's taxonomy improve a learner’s ability to coherently relate concepts together and connect concepts to new ideas. They are considered as systematic ways of describing how a learner’s performance develops from simple to complex Levels (Chan et al. 2010). Bloom's Taxonomy is a good tool for teachers in planning and evaluation, so it focuses on the cognitive domain but does not focus much on the learner. In contrast, SOLO's Taxonomy is based on theories of teaching and learning rather than knowledge-based theories. It is also a learning model that helps both teachers and students develop and understand the learning process. (Borutaite et al. 2001).

Bloom's Taxonomy describes six stages, namely: Knowledge, Comprehension, Application, Analysis, Synthesis, and Evaluation. However, SOLO's Taxonomy consists of five stages, namely Pre-structural, Uni-structural, Multi-structural, and Relational and Extended Abstract.

SOLO's Taxonomy is defined as: "a simple and effective way to illustrate how learning outcomes grow from simple understanding to deep understanding". (Biggs & Collis 1982). So, applying SOLO's Taxonomy in learning and evaluation realizes more benefits, such as developing a deeper understanding of the subject for the learners and enhancing their knowledge and skills beyond the course content, as well as in other fields. Also, this model helps students' thinking at a high level (assessment and creativity). In addition, it encourages self-learning, where students can take responsibility for their own learning. Finally, SOLO's Taxonomy improves teaching, learning and evaluation, and guides students to learn in the light of specific goals that accurately explain what is expected from them. (Hattie & Brown 2004).

SOLO's Taxonomy describes five-phased stages of the learner's cognitive complexity: Stages of knowledge acquisition by SOLO's Taxonomy is explained as follows:

1-Phase one: (Pre-structural): Students do not have any knowledge or understanding of the subject, and so the student's response is: "I do not understand".

2-Phase two (Uni-structural): Students have limited or simple knowledge of the topic, and so the student's response is: "I have some understanding of this subject".

3-Phase three (Multi-structural): Students have some knowledge about the subject, but they are unable to relate to each other. So, the student responds: "I know something about it" or "I've collected some information about it."

4-Phase four (Relational): Here students begin to move towards higher levels of thinking. Students become able to structure and analyze and explain many ideas about the subject. The student's response at this stage is: "I can see relationships between my gathered information ".

5-Phase five (Extended abstract): This is the final stage where not only is a student able to link information and facts with each other, but he also extends to connect them with major ideas and concepts. The student's response at this level is: "Through what I have learned I can look at the subject more broadly and connect it to new ideas".

Therefore, some researchers as (Chan et al. 2010), conducted a comparative application between three different educational taxonomies in measuring students' cognitive learning outcomes. These are (SOLO) taxonomy, Bloom's taxonomy, and reactive thinking measurement model. The three educational taxonomies seemed to be closely related to each other; each could complement the weaknesses of the others. SOLO's taxonomy was applicable in measuring cognitive learning outcomes in different types of subjects among different levels of learners and on different types of assignments. (Biggs & Collis, 1982; Hattie & Purdie, 1998).

Also, three alternative approaches were applied to the assessment of exam responses in an undergraduate Biochemistry course. Phenomenography approach was used to categorize written exam responses into an inclusive hierarchy, and the responses to the same question were similarly categorized based on SOLO's taxonomy. Finally, all questions in the midterm and final exams were ranked according to their level of Bloom's taxonomy (more details later).

The comparative objective was to specify the relationship between student exam responses across hierarchical categories that explain an increase in understanding and application level. Also, a significant relationship was observed between deep learning scores and performance at the comprehension level on the midterm exam but not on the final exam, although the results approached statistical significance in the final exam (Newton & Martin 2013). During the year

2007, all Danish university curricula were reformulated to explicitly set course goals due to the adoption of a new Danish national grading scale which stipulated that grades were to be given depending on how well students meet explicit course goals.

The Faculties of Science at the University of Aarhus and the University of Southern Denmark interpreted "course goals" as "Intended Learning Outcomes" (ILOs) and systematically formulated all such as competencies using SOLO's Taxonomy that consists of five-numbered progressive levels of competencies. The researchers investigate how the formulation of ILOs, using SOLO's Taxonomy, provides information about educational traditions, competence progression, and various science subjects. They use all the course curricula (in total 632) from the two colleges to analyze and compare undergraduate and graduate courses within different departments. (Brabrand & Dahl 2009). The following figure presents SOLO's Taxonomy.

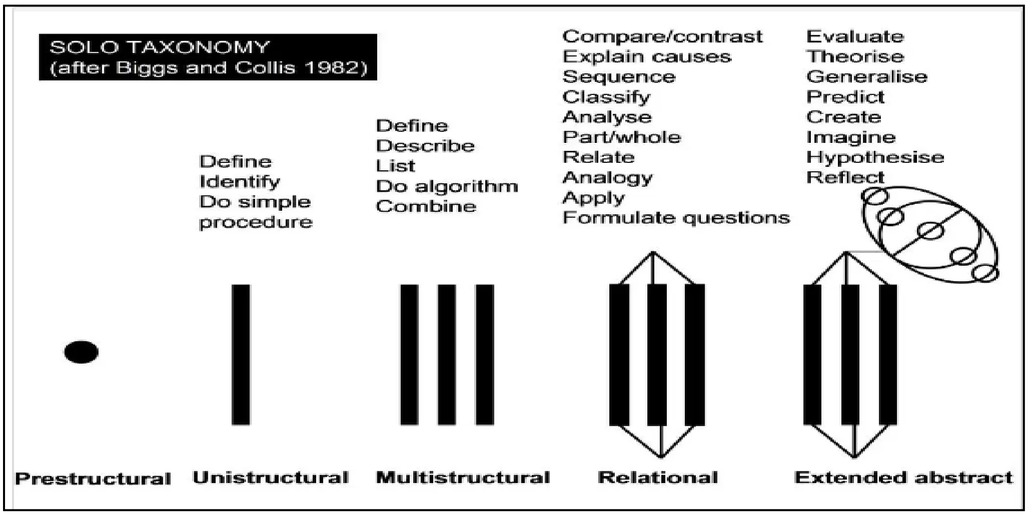

Figure 6: SOLO's taxonomy[11]

[11] https://leadinglearner.me/2013/04/14/redesigning-classrooms-using-solo-to-increase-challenge/ Accessed [15 9 2018]

On the other side, Bloom's taxonomy is one of the key references in the process of formulating output terms and taking into account different levels of knowledge. Bloom developed a classification of objectives in the cognitive domain. Dr. Benjamin Bloom was the first scholar of educational psychology at the University of Chicago in 1956. In this context, it is important to mention that the main education theory is Bloom's taxonomy theory (Bloom, 1956), which is often used in cognitive learning and was developed under his supervision. Bloom’s Taxonomy categorized the learning method into three domains, cognitive domain, affective domain, and psychomotor domain. The cognitive domain is often used to evaluate the learner’s performance through assessment and exams. Also, it focuses on mental learning outcomes and divides the thinking into six levels, starting from the simplest recall to the most complex mental of them. These levels were explained as follows (Halloun, 2017; Yugandhar, 2016):

1. ***Knowledge***: the ability of learners to memorize learning materials learned.

2**. *Comprehension***: the ability to understand what the learning material contains

Concepts and meanings.

3. ***Application*****:** the learners have the ability to employ the learning materials in new situations which are implementable.

4**. *Analysis*****:** the ability to return the learning materials to its major elements in a way that serial structure can be understood.

5. ***Synthesis***: the learners have the skill of merging the parts to form the overall structure.

6. ***Evaluation:*** the learners have the ability to evaluate the learning materials for determined goals.

The levels mentioned above were considered original and old Bloom's taxonomy, so it was enhanced and updated by Bloom's former student, Lorin Anderson in the mid-1990s. He revisited Bloom's taxonomy and added some modifications to the cognitive domain in order to introduce an accurate and effective form of levels of thinking. Lorin Anderson's improvements are converting the names in the six levels from noun to verb forms. Also, these levels have been reordered as shown below. (Anderson et al. 2001; Pohl 1999). The following figure illustrates the original and revised leveled categories of Bloom's taxonomy:

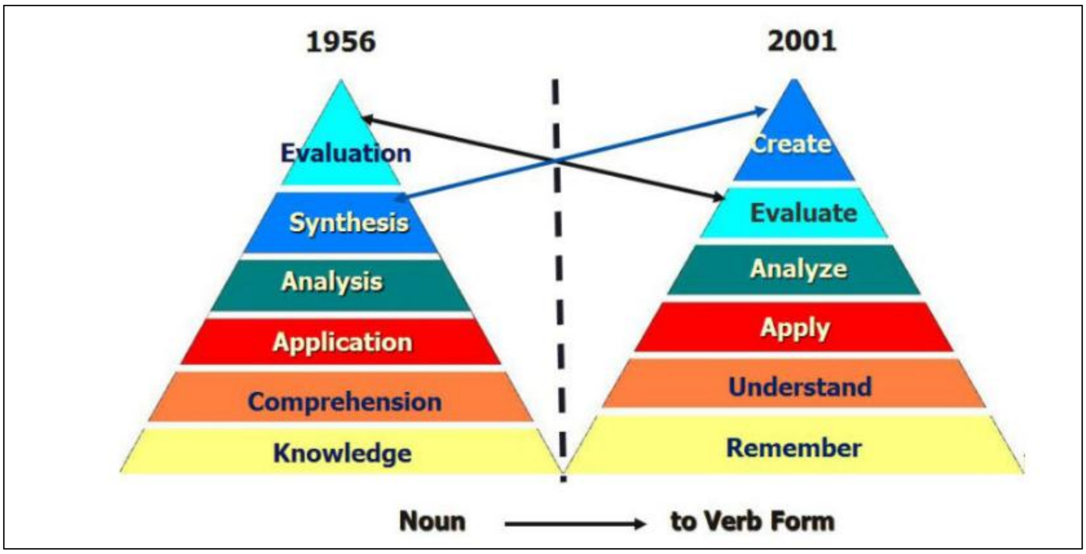

Figure 7: Original and revised categories of Bloom's cognitive taxonomy [12].

[12] https://thesecondprinciple.com/.[Accessed [13 09 2018

2.8 Summary

This chapter reviewed a different research work related to the adaptive learning process in MOOCs platforms. Then, it presents MOOCs overview and definition, techniques used by online adaptive learning frameworks, and the machine learning algorithms, such as Support Vector Machine, Decision Tree, Naïve Bayes, and Fuzzy Logic algorithms, and how they were applied in adaptive MOOCs domain as an intelligent system for solving problems. It mentioned learning outcomes definitions and learner performance taxonomies such as SOLO and Bloom Taxonomies. Finally, it showed original and revised categories of Bloom's cognitive taxonomy.

CHAPTER 3

THE PROPOSED APPROACH

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3.1 Overview

In this chapter, section 3.2 explains adaptive MOOCs approach, that presents an adaptive course for learners to support MOOCs in three levels, and section 3.3 presents an adaptive conceptual framework, therefore presented the adaptation aspects. Section 3.4 presents a classic flowchart for MOOCs platform, then section 3.5 explains an overview of the proposed system and how the mapping between LMs and LC related to ILOs, and then it presents the proposed architecture flowcharts in two main phases. Section 3.6 shows the implementation phase and execution of the different phases of the proposed system Finally, section 3.7 summarizes this chapter.

3.2 Adaptive MOOCs Approach

In this section, we present an adaptive learning course for learners to support MOOCs. This adaptation was applied in many stages as follow:

In the first stage, the placement test was used for the learning course to determine the level of the learner. The manual mapping between LCs which the learner selected ILOs ,and LMs. After that, the adaptation is applied using the automatic techniques based on Support Vector Machine Classifier to match the ILOs and related learning concepts (LC) in order to retrieve effectively the (LM). Generate a learning path depends on the retrieval of the learning materials related to learning concepts in different learning styles. The second stage of the proposed approach is dealing with adaptive assessment as exams, by manual entering the weights (values) to every question by the expert. The system provides the adaptive assessment tools which depend on the (GPA) for the learner. It was divided into three levels (easy, medium, and hard) based on Fuzzy logic techniques and rules as in (Appendix E) to determine the level of assessment which is generated and delivered to the learner according to his level.

3. 3 Adaptive Conceptual Framework

Any conceptual framework presents the basic idea for any problem research that should be solved or to enhance the level of delivering the best solutions, in which to explain the sequence work or flowcharts to achieve the goals for learning platforms. So we will present the flowcharts for our adaptive proposed system to offer high-quality learning for learners and provide effective and adaptive learning courses to MOOCs platform or any learning institution.

3.3.1 Adaptation Aspects

Before talking about our proposed system solution, it is necessary to explain the meaning of adaptation techniques in MOOCs environment. There are many attempts to execute these techniques , hypermedia system has been used in MOOCs platform (Onah et al. 2015; Lerís et al. 2017). These hypermedia domains are investigated in literature, such as Brusilovsky proposed many adaptation techniques that can be implemented into content, presentation and navigation (Brusilovsky 2001; Brusilovsky 2004). The content in the proposed adaptation techniques is defined as follows:

- Additional explanations: that are used to hide or display additional information.
- Prerequisite explanation: that is inserting automatically the explanations of prerequisite learning concepts that the participant is unfamiliar with.
- Comparative explanation: that is used to provide differences and similarities between related learning concepts.

- Explanation variant: This supports the learner with a various explanation about a specific learning concept.

On the other hand, adaptive navigation support and presentation can be offered in forms, such as direct guidance, sorting, annotation, and hiding based on specific attributes from the participant's model (Brusilovsky, 1996). For instance, as follows:

- The direct guidance that is used to suggest a link to be followed from the current page.
- Sorting that is used for ordering relevant learning objective so that relevant resources are present first while least relevant resources are present last.
- Annotation that is used to annotate relevant links to learning objectives with verbal textual or indication such as traffic light theme (red, orange and green).
- Finally, hiding that is used to hide automatically the links to irrelevant learning objectives. (Bra & Calvi 1998).

So, this work is mainly based on the Brusilovsky's adaptation techniques that are considered as one of the most common adaptive hypermedia domain (Brusilovsky 2004) . The proposed techniques indicate what can be adapted and which techniques can be used, depending on determining attributes from the participant's model, such as knowledge, background, preferences, etc. It is important to mention that this research work uses a number of attributes to be considered in the adaptation process as well as ILOs, the content, navigation, assessment tools, and GPA for the learner.

3.3.2 Framework Requirements

In order to provide adaptive MOOCs, some requirements should be considered. The researchers (Alshammari et al. 2014; Abdullah et al. 2015) referred to these requirements and presented them as the following:

1. **Learner-oriented**: Which is considered as one of the indicators in learning to support learner-oriented education instead of teacher-oriented education. This requirement should enable the learner to select the (ILOs) for a specific course that is oriented for the learner in specific aspects.

2**. Pedagogical-oriented:** In the educational domain, the relationships between different learning concepts should be considered as pedagogical relations when specifying an adaptive course that will be covered. (Baldiņš 2016).

3. **Adaptive-specific**: To realize adaptation online education, there is a need for offering a repository of the adaptation techniques, which can be applied to courses' navigation representation, content and assessment tools. (Brusilovsky 2004; Brusilovsky 2001).

4. **Web-based**: Delivering adaptive MOOCs environment should allow easy access to various learning materials online.

3.3.3. Classic Flowchart For MOOCs Platform

Classic Flowchart is the most widely-used method for MOOCs platform that allows the learners to follow the courses weekly and study the learning materials. So, it provides assessment tools or quizzes that the learner has to get solutions or answers to ensure that he has mastered the courses exactly on time. (Ardchir et al.2017), then the platform model allows students to move to another course after evaluation.

One of the challenges of MOOCs implementation system , is that learners attend the same learning course without taking into consideration the behavior and qualities of each participant. In order to deal with this case in the traditional MOOC system, there is a need for an adaptive system that takes into account the levels and qualities of each participant before the start of every week. (Ardchir et al.2017). In the following part, we have to discuss our proposed system. Figure 8 presents the classical MOOC system flow chart. (Ardchir et al. 2017).

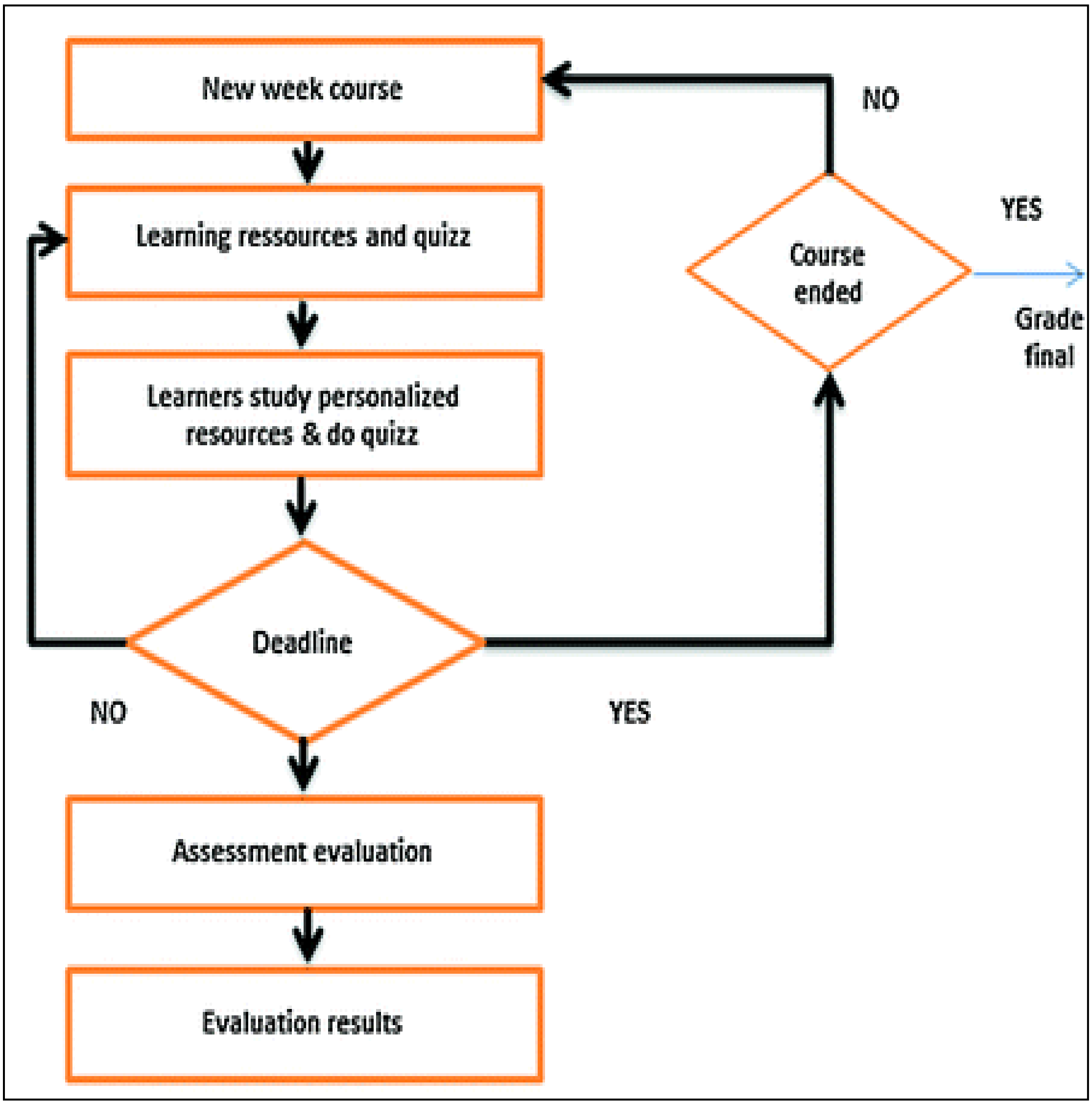


Figure 8: Classical MOOC system flow diagram.

3.4. General Overview of the Proposed System

This part presents a general overview of the proposed adaptive MOOCs, as a first prototype, where adaptation is applied using the manual mapping between LM and LC related to (ILOs). Then support vector machine (SVM) Classifier, was implemented to match ILOs and related concepts to retrieve learning materials effectively. So**,** it is necessary to mention that the proposed adaptive MOOCs system has been performed in two major phases as shown in the two flowcharts in figures (9,10), the first phase focuses on matching between (LMs) and (LCs) related to ILOs, and the second phase focuses on adaptive assessment tools.

3.4.1 Manual Mapping between LMs and LCs related to ILOs.

Through this phase, the system was implemented depending on manual mapping between learning materials and learning concepts related to Intended Learning Outcomes (ILOs). This mapping is mainly done by determining the ILOs firstly. Then, generating the learning path into consideration with the pedagogical relationships between various learning concepts ,so the learner can't navigate through the learning path , without learn the previous learning concept which related to them.

3.4.2 Automatic Classification between LMs and LCs using SVM Classifier

Before talking about classification, it is necessary to explain what (ILOs) means, learning concepts or learning chapters which are related to ILOs, learning materials (LM) and the levels of the learners to classify the exams according to their abilities and GPAs. So we show some tables to explain the intended meaning. The table 2 views the Learning Outcomes (ILOs) in Data Mining course. For example the ILOs were used, and will be selected by the learner, as: "Use technologies of search engines, including Google's PageRank, link-spam", and the "Implement the Frequent-item set mining, including association rules, market baskets, the A-Priori Algorithm and its improvements", and the "learning about the Algorithms for clustering very large, high-dimensional datasets"..etc.

Also, the table 3 shows the learning materials and learning concepts related to (ILOs) which are used in Data Mining course. For instance the learning concept (LC) "Link Spam" is related to the ILO "Use technologies of search engines, including Google's PageRank, link-spam", and this (LC), contains the learning material (LM) "12_Spam_Farms_8-00", also the (LC) "hubs-and-authorities" is related to same ILO which explained as follows .

Table 2: Some of ILOs in a Data Mining course

1	Use technologies of search engines, including Google's PageRank, link-spam
2	Use technologies of search engines, including Google's PageRank, link-spam
3	Use technologies of search engines, including Google's PageRank, link-spam
4	Implement the Frequent-itemset mining, including association rules, market baskets, the A-Priori Algorithm and its improvements.
5	Implement the Frequent-itemset mining, including association rules, market baskets, the A-Priori Algorithm and its improvements.
6	Implement the Frequent-itemset mining, including association rules, market baskets, the A-Priori Algorithm and its improvements.
7	Implement the Frequent-itemset mining, including association rules, market baskets, the A-Priori Algorithm and its improvements.
8	learning about the Algorithms for clustering very large, high-dimensional datasets.
9	learning about the Algorithms for clustering very large, high-dimensional datasets.
10	learning about the Algorithms for clustering very large, high-dimensional datasets.
11	learning about the Algorithms for clustering very large, high-dimensional datasets.
12	learning about the Algorithms for clustering very large, high-dimensional datasets.
13	Explorate two key problems for Web applications: managing advertising and recommendation systems.
14	Explorate two key problems for Web applications: managing advertising and recommendation systems.
15	Explorate two key problems for Web applications: managing advertising and recommendation systems.
16	Explorate two key problems for Web applications: managing advertising and recommendation systems.
17	Explorate two key problems for Web applications: managing advertising and recommendation systems.
18	Explorate two key problems for Web applications: managing advertising and recommendation systems.
19	Explorate two key problems for Web applications: managing advertising and recommendation systems.
20	Explorate two key problems for Web applications: managing advertising and recommendation systems.
21	Explorate two key problems for Web applications: managing advertising and recommendation systems.
22	Explorate two key problems for Web applications: managing advertising and recommendation systems.
23	Explorate two key problems for Web applications: managing advertising and recommendation systems.
24	Explorate two key problems for Web applications: managing advertising and recommendation systems.
25	Explorate two key problems for Web applications: managing advertising and recommendation systems.
26	Study of Algorithms for analyzing and mining the structure of very large graphs, especially social-network graphs.
27	Study of Algorithms for analyzing and mining the structure of very large graphs, especially social-network graphs.
28	Study of Algorithms for analyzing and mining the structure of very large graphs, especially social-network graphs.
29	Study of Algorithms for analyzing and mining the structure of very large graphs, especially social-network graphs.

Therefore the ILO "Implement the Frequent-item set mining, including association rules, market baskets, the A-Priori Algorithm, and its improvements" contains the (LC)"Frequent Itemsets", which the learning material " 09_Frequent_Itemsets_29-50". is related to this learning concept.

Table 3 : LCs and LMs related to ILOs

	The learning concepts or chapter (LCs)	The learning materials (LMs)
1	Link Spam	12_Spam_Farms_8-00
2	Link Spam	13_TrustRank_10-05
3	hubs-and-authorities	10_Hubs_and_Authorities_15-16_Advanced
4	Frequent Itemsets	09_Frequent_Itemsets_29-50
5	Frequent Itemsets	10_A-Priori_Algorithm_13-07
6	Frequent Itemsets	11_Improvements_to_A-Priori_17-26__Advanced
7	Frequent Itemsets	12_All_or_Most_Frequent_Itemsets_in_2_Passes_14-40_Advanced
8	Clustering	01_Overview_of_Clustering_8-46
9	Clustering	02_Hierarchical_Clustering_14-07
10	Clustering	03_The_k-Means_Algorithm_12-49
11	Clustering	04_The_BFR_Algorithm_25-01
12	Clustering	05_The_CURE_Algorithm_15-13_Advanced
13	Computational Advertising	06_Computational_Advertising-_Bipartite_Graph_Matching_24-47
14	Computational Advertising	07_The_AdWords_Problem_19-21
15	Computational Advertising	08_The_Balance_Algorithm_15-16
16	Computational Advertising	09_Generalized_Balance_14-35_Advanced
17	Recommender Systems	01_Overview_of_Recommender_Systems_16-51
18	Recommender Systems	02_Content-Based_Recommendations_21-00
19	Recommender Systems	03_Collaborative_Filtering_20-52
20	Recommender Systems	04_Implementing_Collaborative_Filtering_13-46_Advanced
21	Recommender Systems	05_Evaluating_Recommender_Systems_6-09
22	Recommender Systems	14_Latent-Factor_Models_16-11
23	Recommender Systems	15_Latent-Factor_Recommender_System_14-16
24	Recommender Systems	16_Finding_the_Latent_Factors_13-20
25	Recommender Systems	17_Extension_to_Include_Global_Effects_9-42_Advanced
26	Analysis of Large Graphs	01_Community_Detection_in_Graphs-_Motivation_5-44
27	Analysis of Large Graphs	02_The_Affiliation_Graph_Model_10-04
28	Analysis of Large Graphs	03_From_AGM_to_BIGCLAM_8-48
29	Analysis of Large Graphs	04_Solving_the_BIGCLAM_9-19

In the first phase, the framework of the proposed adaptive MOOCs system is based on matching between LCs related to (ILOs) and learning materials (LM) in an automatic classification, using one of the most popular machine learning algorithms called Support Vector Machine (SVM) Classifier algorithm (Tang et al .2009). Therefore, an automatic mapping between ILOs and learning materials is done by determining the learning concepts (LC) that are related to both learning materials (LM) and ILOs.

After that, learning concepts which have been identified out of the ILOs are added to a repository ILOs named learning concept list. Also, the learning concepts that have been identified out of the learning materials are added to a repository (LM) too, which is called learning concepts of learning materials list. Both lists will be considered as an input for the SVM algorithm to do important processes to select and retrieve the highest probability learning materials, by matching each(ILO) with corresponding (LM), through the related learning concept, and the classifier can adapt each learning concept (LC)with corresponding(LM) learning materials.

3.4.3. Manual Weight for Learning Materials (LM) and Questions.

In phase two in our proposed model that uses the manually entered weights for each LM corresponding ILO by an expert to determine how is the LM covers the specific LC in specific percentage, and in the same manner manual weights for each question that is added from the chapter or the LC is identified by the expert to determine the difficullty level for each question.

After that, the system can generate and prepare various exams to determine the level of the learners, such as (easy, medium and hard) exams, to suit the level of the learner, such as (beginner, intermediate and advanced). On the other hand, this proposed adaptive system added a new technique; that is, Grade Point Average (GPA) for each learner to enable the system to generate exams (easy, medium, hard) to fit the level of the learners, using fuzzy logic technique, to specify exactly the level of exams or the level of learners based on divisions for their GPAs intervals, such as (0.0-0.50) % gets easy exam,(35-75) % gets medium exam and the final (70-100) % gets hard exam. Notice that these classes or intervals were categorized into three levels. We considered that the total degree of GPA equals 100, so the values of degrees are explained as afuzzy logic technige .

So, these classes would be considered to handle the levels of exams and GPA for the learner.

3.5 Proposed Architecture

This architecture of our system is divided into two phases: (classification phase and assessment tools phase). As mentioned earlier, the first phase is to classify the learning materials (LMs) related to (ILOS), using SVM classifier, whereas the second phase is to explain the assessment section as exams, depending on fuzzy logic technique and GPA for the learner as explained as follows:

1-The first phase:

- The learner or participant when using adaptive MOOCs platform, he can select the course subject which he desires, then he should execute the placement test which is comprehensive for the whole course.
- When the learner passes the placement test, a list of ILOs is shown to enable him to select the most suitable ILOs.
- Learning concepts or atitle of chapter was identified, then the repositories for ILOs and LMs determined the learning concepts related to ILOs and LMs.
- After that, the classifier Support Vector Machine (SVM) was applied to classify the learning materials related to LC or ILO in training and predicting phase.
- The mapping between learning material classes and learning concepts lists or chapters to generate the learning path based on pedagogical relationships.
- At this stage, the manual weight by an expert for each learning material, and then manual weight for each question by an expert, too.
- Finally, end this phase.
- The following figure 9 presents the architecture of the proposed adaptive flowchart phase one. (Classification phase).

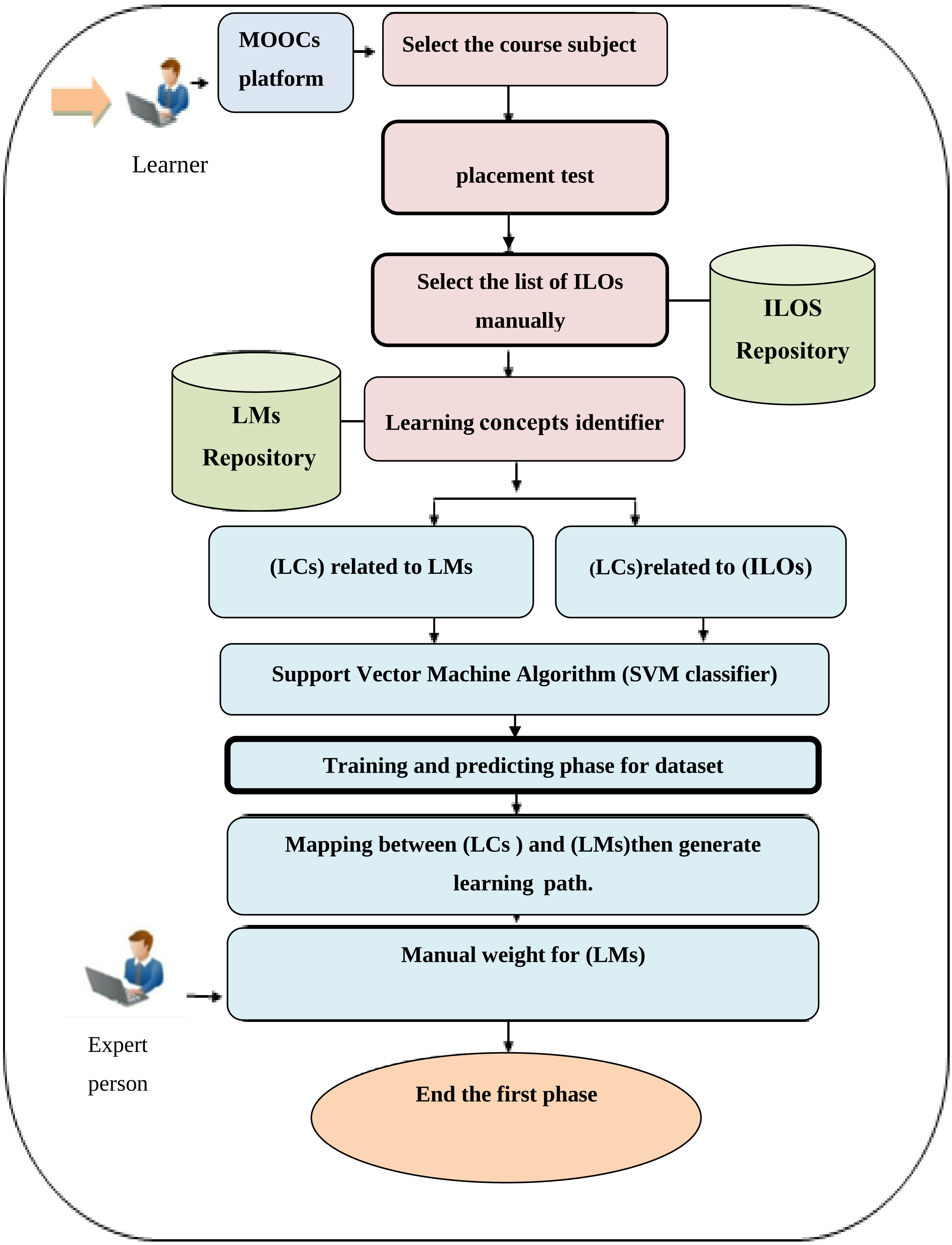


Figure 9:The Adaptive proposed system flowchart phase one

2-The second phase:

The proposed system as explained as follows sequentially:

- Firstly, the system generated questions bank for each learning concept LC or learning chapters through learning materials LMs (generate database).
- Manual classification by expert person, for introducing the weights (values) for each question into three levels: easy, medium and hard.
- The system generated and prepared different levels of exams based on Fuzzy Logic technique, which also has three levels (easy, medium and hard).
- Depending on the Grade Point Average (GPA) for the learner, the system selects a suitable exam level (easy, medium and hard) to fit his level and abilities if he is a (beginner, intermediate, or advanced) learner, the system is matching between GPA and level exam.
- At this final stage, the system delivered the different exams based on the degree of difficulty that is three levels as follows:
    - IF 0%<GPA <=50 % then easy exam.
    - IF 35%<GPA <=75% then medium exam.
    - IF 70%<GPA <=100% then hard exams.
- Finally, learning course is complete.

The following figure 10 presents the architecture of a targeted adaptive flowchart Phase Two: (Assessment phase).

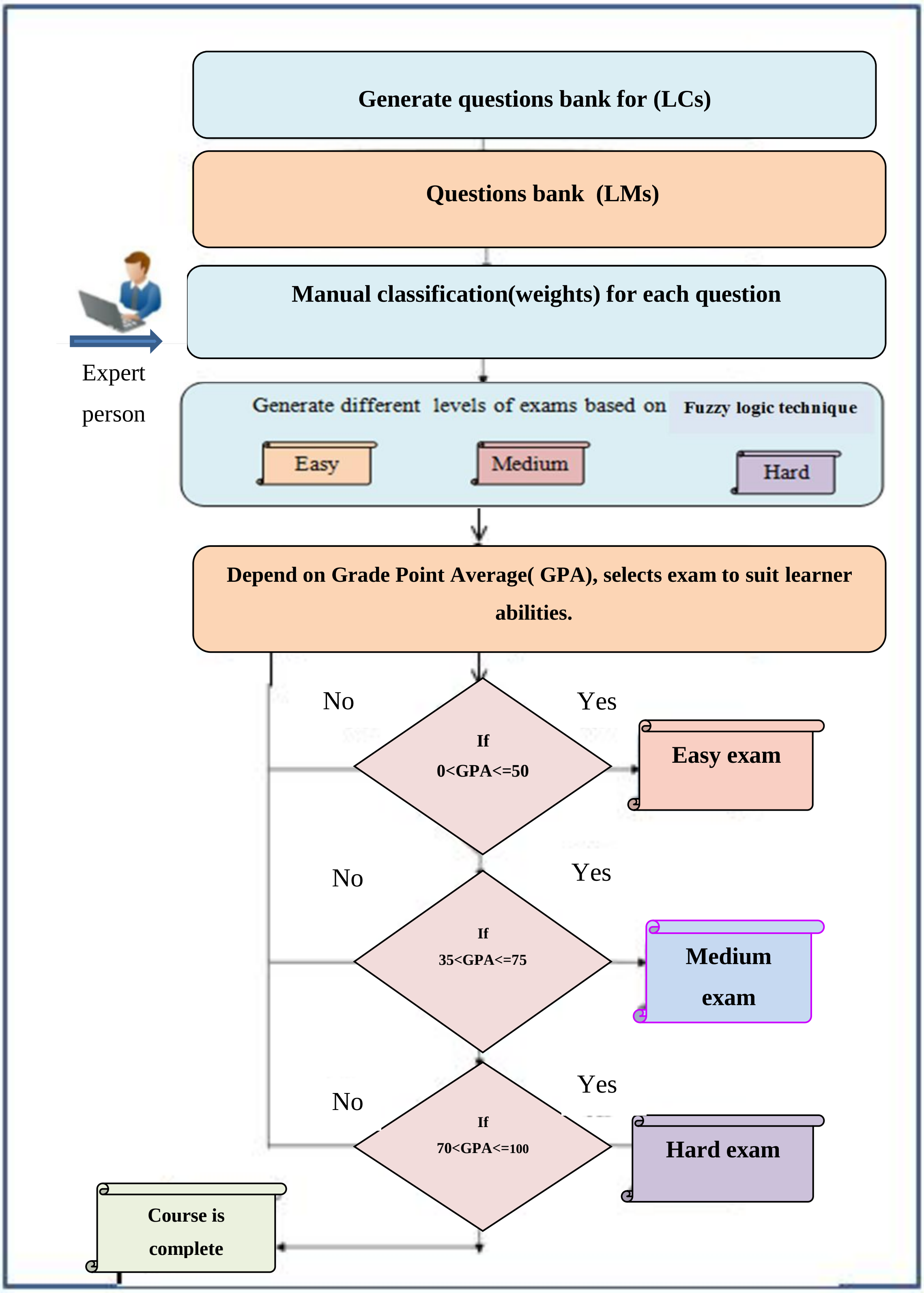


Figure 10:The second part of proposed approach flowchart is the assessments phase (phase two)

3.6 Implementation Phase

This section presents a proof of concept related to the targeted approach. First, it presents the adopted technology that is used to implement the prototype. After that, it shows a learning scenario, using the proposed prototype. The prototype of our targeted system was implemented, using many technologies to integrate the code and implementation as follows:

- Java programming language 8, and WEKA library.
- Net Beans IDE 8.0.1, SQL Navigator 6.2.1.
- Web application, using Java Server Faces (JSF), Oracle Database, Web server Glassfish4.
- The fuzzy logic technique, using java based on JFuzzy library
- Support vector machine (SVM) technique.

The targeted system in our thesis includes a sequence of screenshots to explain the work, starting from the first screen by selecting the course which the learner needs. In the beginning, each course will have a placement exam for the student to determine his level in the course in general, so that the exam will include all learning concepts or learning chapters. An easy exam was chosen using the Fuzzy logic technique. Levels are divided as follows as we mentioned earlier:

• 0.00% - 50%: easy level

• 35% -75%: medium level

• 70% - 100%: difficult level.

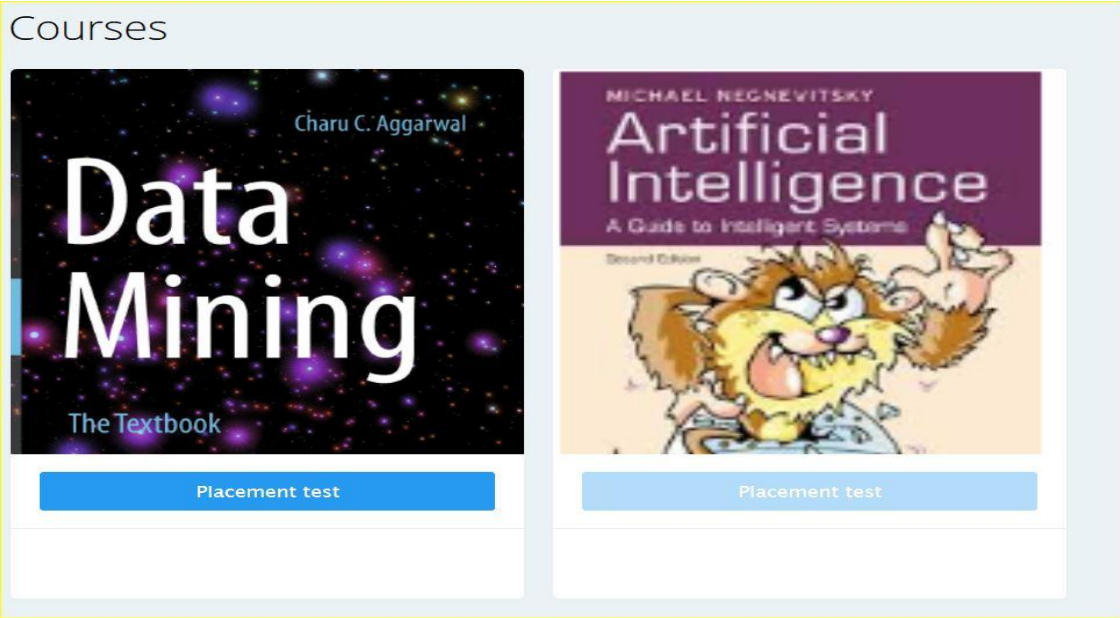


Figure 11: Shows the Placement Test at the Beginning of Learning Courses

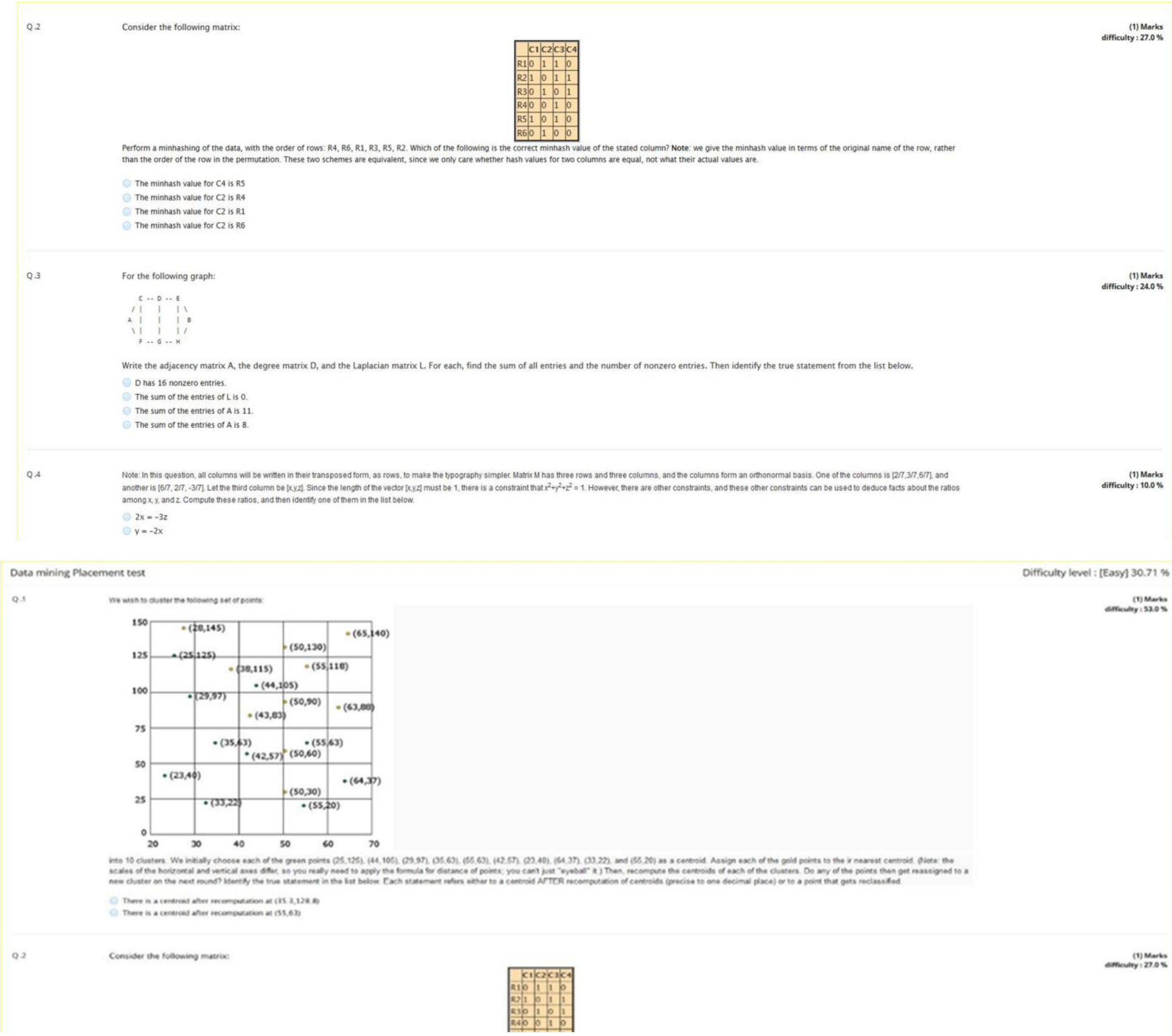


Figure 12:Example of a Placement Test

After the student completes the placement test, the result will be shown (60%) and according to the level of the student, the next exam difficulty level will be chosen from the three levels mentioned above. In this case, a medium level exam will be chosen (33.34% - 66.66%).

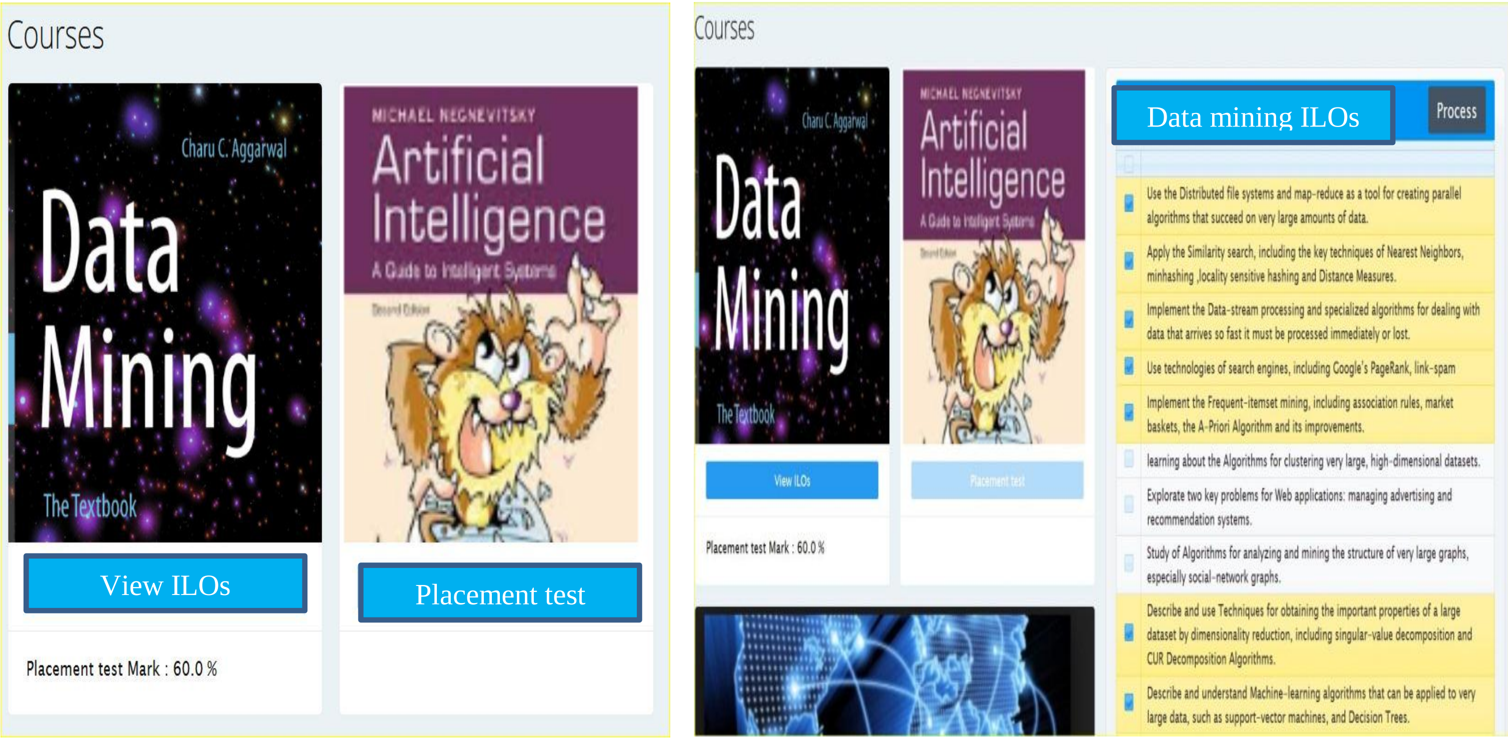


Figure 13:Placement Value and ILOS

Students will then review the courses relevant to ILOs and create a suitable Learning Path, which consists of a set of concepts and learning materials.

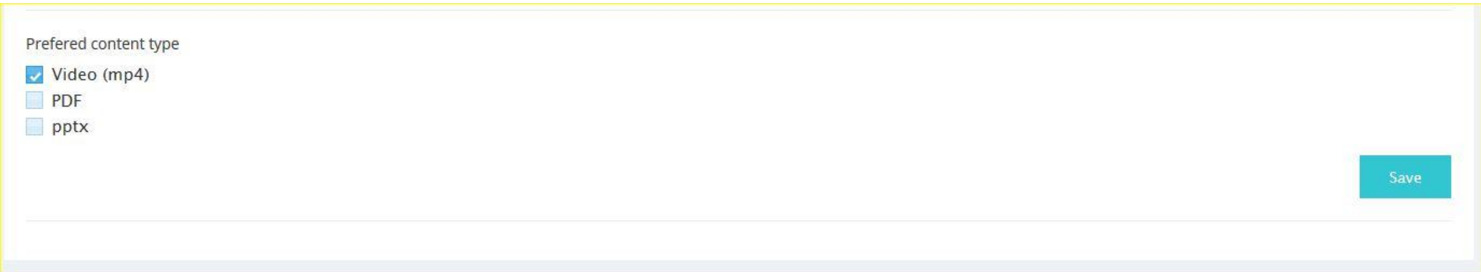
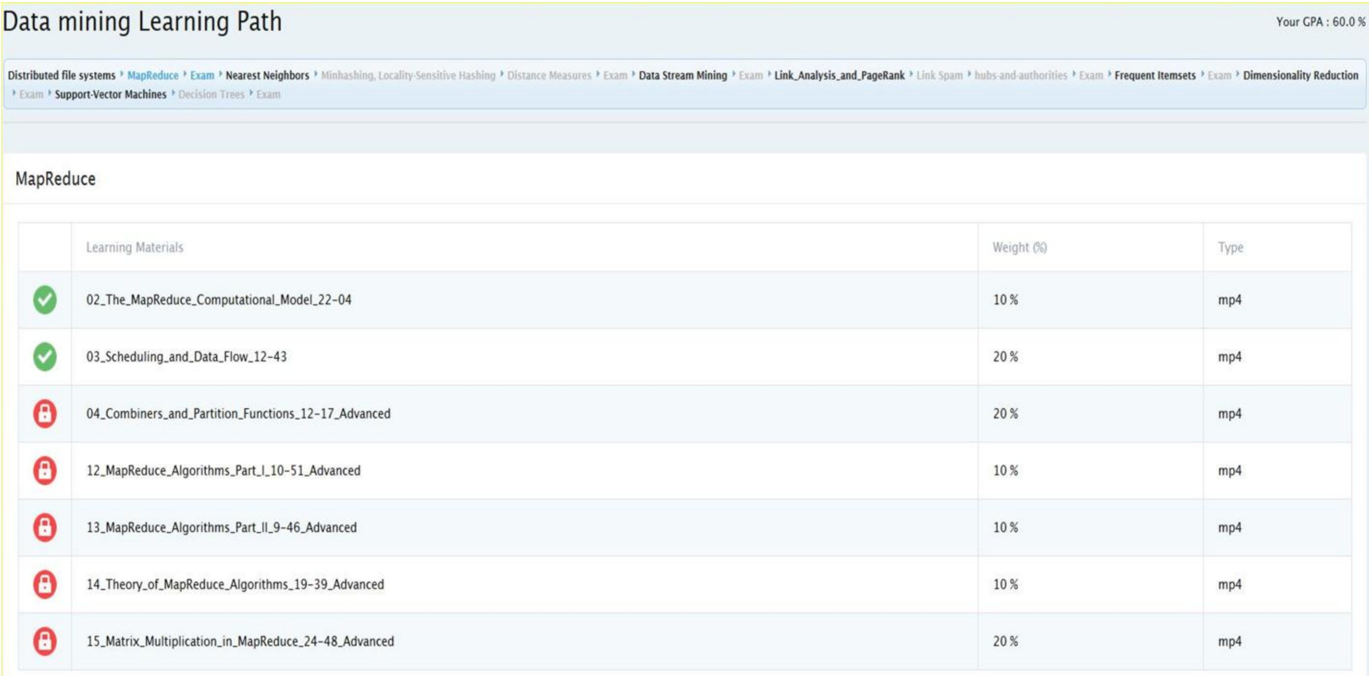


Figure 14:Learning Materials format



This screen shows some points as follows: Learning Path is created which consists of a set of concepts or chapters and each chapter contains a set of learning materials and each learning material has a weight of the chapter.

- For example:

The_ Map Reduce_Computational_Model_22-04 represents 10% of Map_ Reduce_ chapter, the weight of each learning material is determined by the system administrator. There is a question bank for each learning material. When designing an exam, the questions are selected according to the weight of each learning material and the level of difficulty is determined using Fuzzy logic. There is a relationship between the chapters so that one of them may be a requirement for the other as well as educational materials may be an educational material required for the other. For each set of chapters, an exam will be designed with more than one copy in advance at different levels to be chosen according to the level of the student at the time of sitting for of the exam.

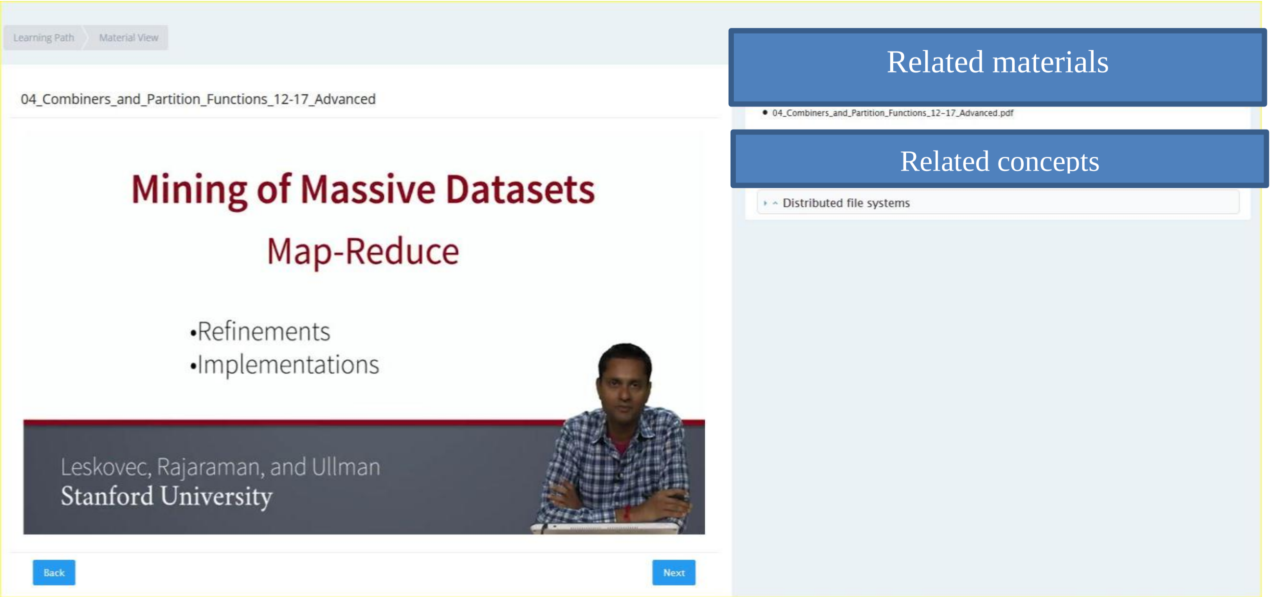


Figure 15:Proposed Learning Material Related to ILOs

When reviewing any educational material, the system proposes educational materials that may be related to the learning material currently being read (any educational material within the same concept). Also, any concept may be related to the learning material (any concept within the same ILO for the educational material currently being reviewed) .

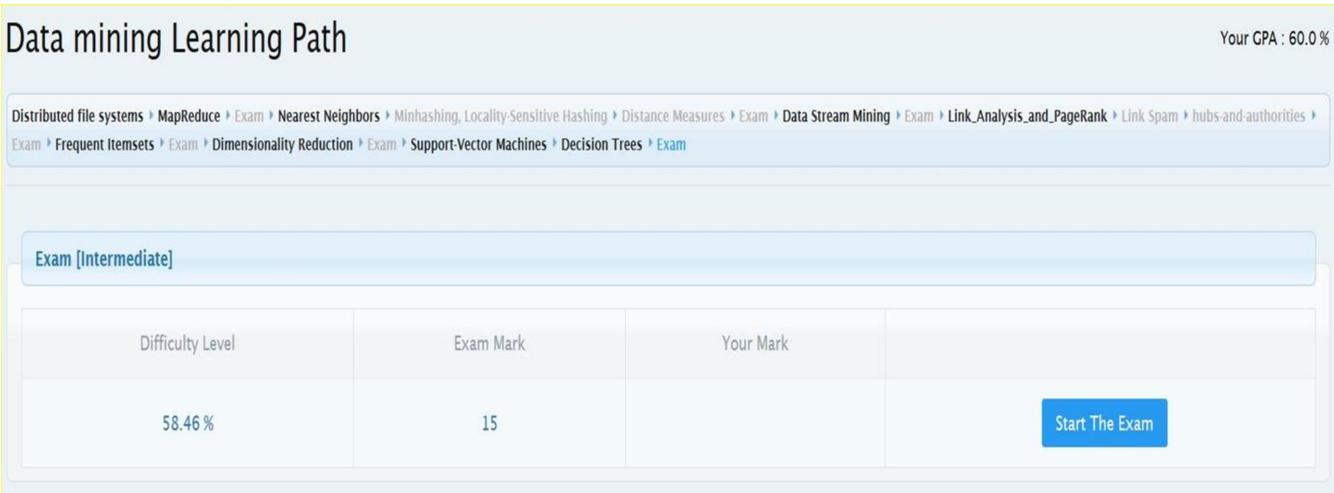


Figure 16:GPA Percentage and the Difficulty Level of Exam Intermediate to Start the Exam.

In figure 17, after completing a review of a group of Chapters, the student should take the exam. As shown in the screen above, the system is selected for a medium level examination (58.46%) because the current student level is also intermediate (60.0%).

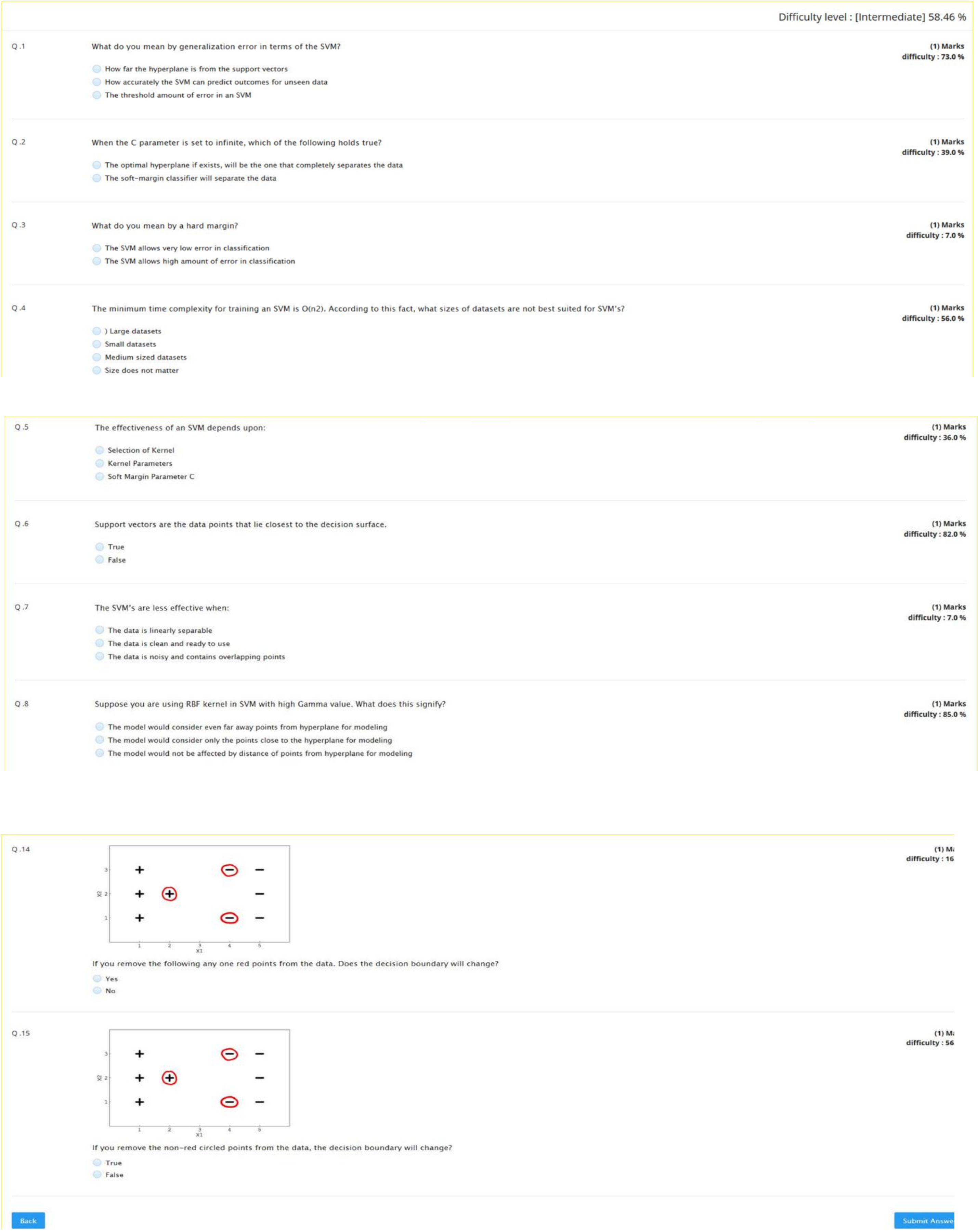


Figure 17:A sample of exam questions

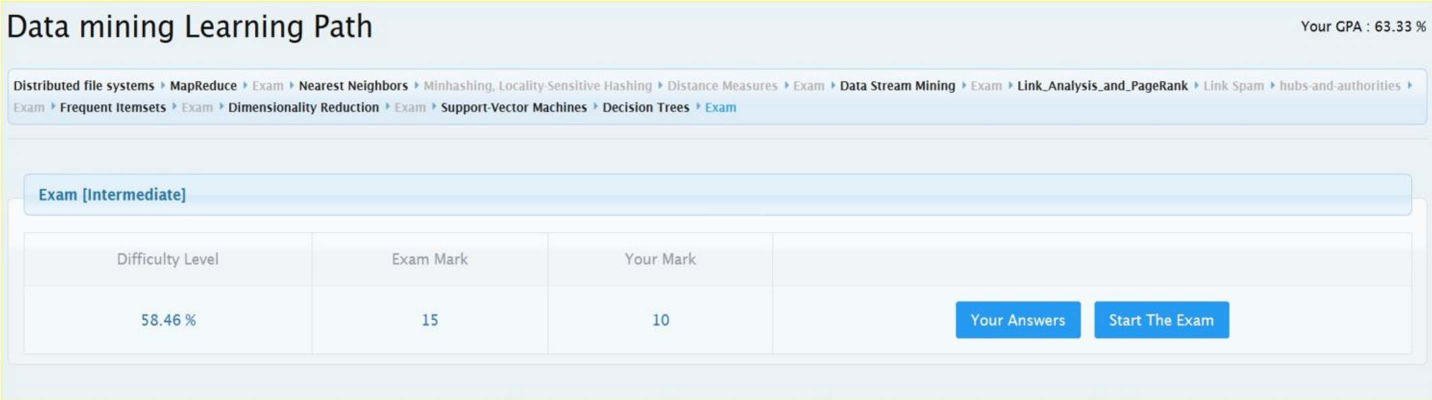


Figure 18:Sample of the mark for pass answers

After the student completes the exam, his mark (10/15) appears and the student's GPA changes from 60.0% to 63.33%; consequently, the average is used for all students' exams as shown below.

- (10/15) × 100% = 66.67%
- (60.0 + 66.67) / 2 = 63.33%.

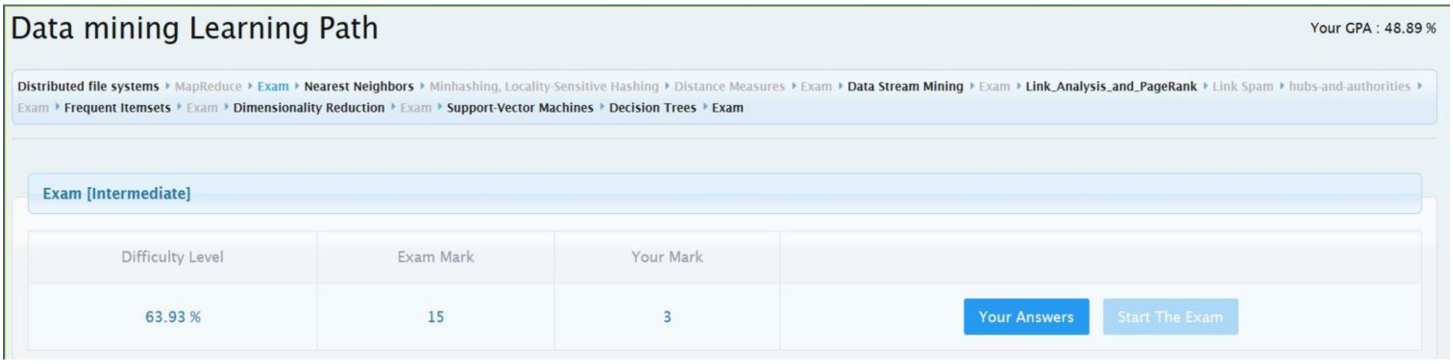


Figure 19:A sample of the mark for fail answers

- Another evaluation scenario:

If the student does not succeed in the exam (should be more than 50% of the exam mark as in figure 20 the exam mark equals 15 ,the succsess mark should be >=7.5) , the student's answers will be examined to determine the questions that he did not answer properly and to review the learning materials related to these questions before he can take the exam again, as shown in the next screen.

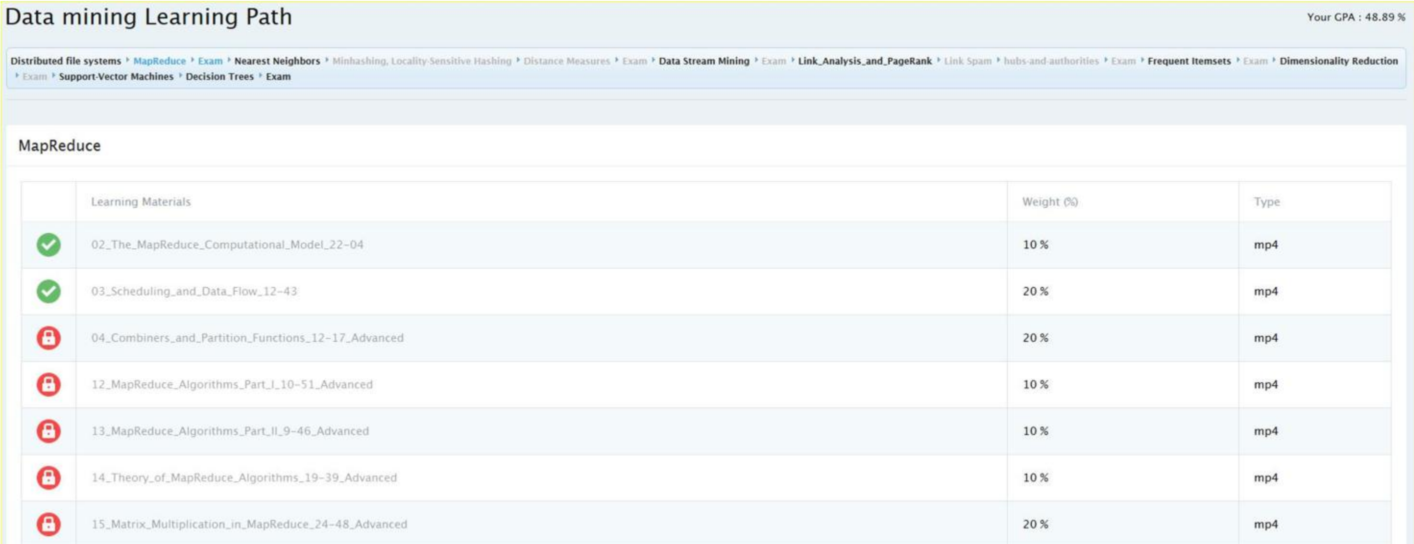


Figure 20:Learning material correctly passed or not.

-  Green-colored learning materials are the ones in which all the questions were answered correctly.
-  The red ones are not correctly answered and must be reviewed again.

Figure 21:Learning path for learning material

The previous screen shows the learning concepts for distributed file systems and Map_ Reduce exam. The exam consists of 15 questions. The system administrator or the expert should specify the number of questions per chapter. Here are 5 questions for distributed file systems and 10 questions for Map_ Reduce exam.

Some notes regarding the weight of each learning material and its relation to examinations are explained as follows: According to the weight of each learning material, the system divides the questions; for example, 10 questions for Map Reduce, which are divided as follows:

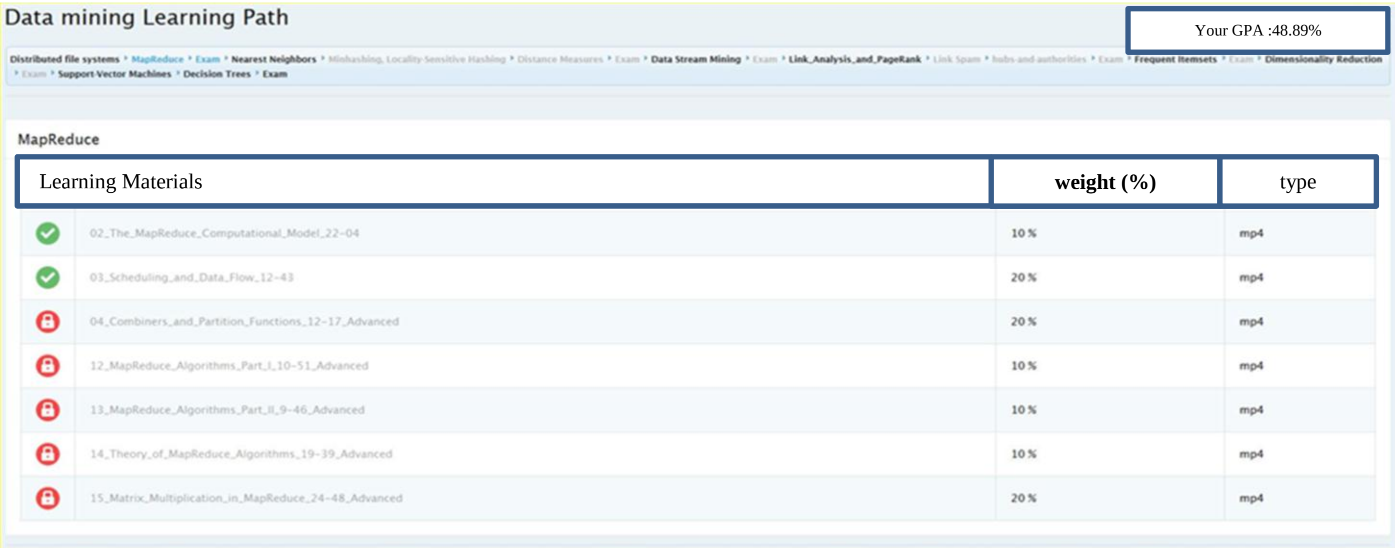


Figure 22:Determining the ratio of questions.

02_The_Map_Reduce_Computational_Model_22-04: 10 questions * 10% = 1 question.

03_Scheduling_and_Data_Flow_12-43: 10 questions * 20% = 2 questions, and so on.

Table 4 below explains a short part of the database SQL navigator, how the expert entered manually the weights for learning materials related to concepts or chapter. Therefore, as we see the CONC_ID means "concept _id" and the MAT_ID means "learning material _id". The weight here is considered 1 which means 100% - the high value for weight and the fractions mean the ratios of weights as 0.2, 0.1, etc. So, if we take an example for CONC_ID number 2, it has several learning materials _ id MAT_ID, and everyone has a different weight. To integrate and combine all the percentage weights to be 1 (0.1+ 0.2+ 0.2+0.1+ 0.1+ 0.1+ 0.2) =1 and the ratio 0.2, it means (0.2*100%) =20% the weight for one learning material, and so on.

Table 4: The Weights for LM related to LC or chapters

Row #	CONC_ID	MAT_ID	WEIGT
1	1	1	1
2	2	2	0.1
3	2	3	0.2
4	2	4	0.2
5	2	5	0.1
6	2	6	0.1
7	2	7	0.1
8	2	8	0.2
9	3	9	1
10	4	10	0.05
11	4	11	0.05
12	4	12	0.05

3.7 Summary

This chapter presents the proposed framework in two phases: the first one is the manual selection of ILOS by the learner, and automated classification by using SVM algorithm to classify the LMs related to chapters or LCs. However, the second phase presents the fuzzy logic classifier to determine the level of exams (easy,medium and hard) based on GPA for the learner(beginner,medium,advanced). We are also talk about the technologies used in our framework and explain the different screenshots from the system and show the implementation sequentially.

CHAPTER 4

EXPERIMENT AND RESULT

CHAPTER 4
EXPERIMENTS AND RESULTS

4.1 Overview

This chapter, "Experiments and Results" presents the validation of proposed adaptive MOOCs and the results of the experiments as follows: Section 4.2 shows the requirements for the implementation of the prototype. Section 4.3 presents the evaluation methodology and results to evaluate the performance and results for SVM algorithm in three phases, in addition to evaluating the exam and Fuzzy Logic technique; therefore, this section shows the Fuzzy Logic Center Of Gravity (COG). Finally, section 4.4 presents a summary of this chapter.

4.2 Experiment Procedure for Prototype

Our proposed system implemented by Java programming language 8, Net Beans IDE 8.0.1, SQL Navigator 6.2.1 .

Web application, using Java Server Faces (JSF), Oracle Database, the learning machine support vector machine (SVM), and fuzzy logic technique under Windows 7 .

4.3 Evaluation Methodology and Results

In this section, we have talked about the basic flowchart of the prototype for our system and divided it into three figures. So, we viewed the flowcharts with the results in each stage.

4.3.1 Evaluate Support Vector Machine (SVM).

The first flowchart represents the beginning of the prototype of the system; that is, selecting the course subject and determining the placement test which is comprehensive for the content of all the learning course. Then, the learner can select manually the ILOs which meets his needs and what he wants to learn. So, in this stage the learning materials repository for each learning concept or chapter was provided, and the machine learning Support Vector Machine Algorithm was applied to classify the suitable learning materials, as automatic mapping between the learning materials (LMs) with the learning concepts (LC) related to ILOs in training and prediction phase.

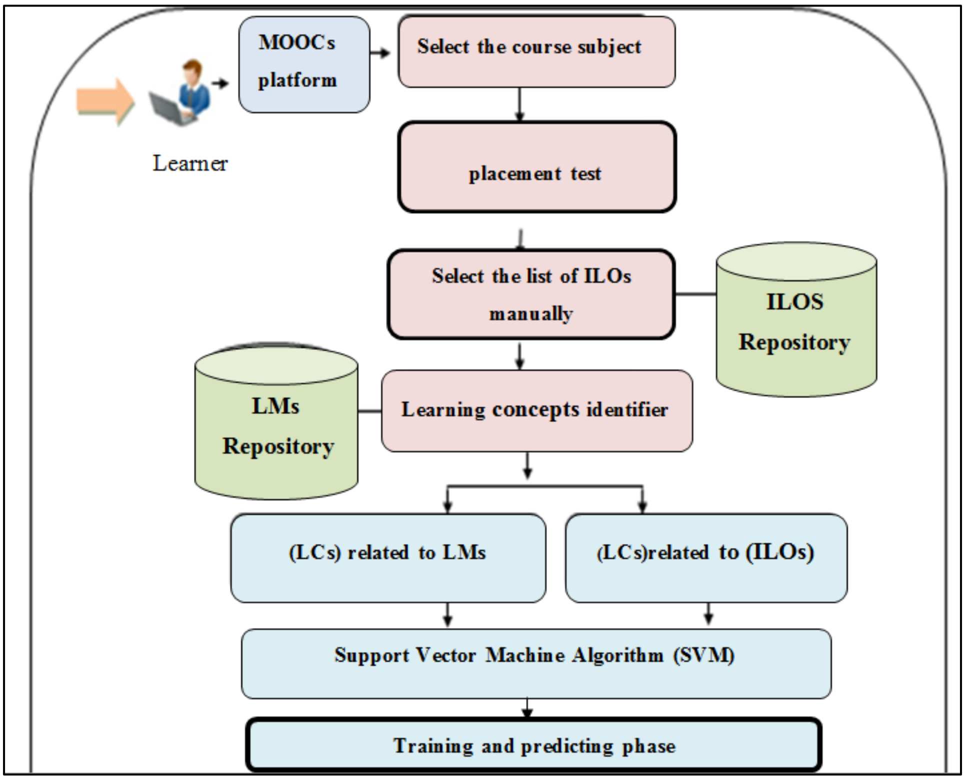


Figure 23:Flowchart1 used (SVM)) technique to classify the LM and LC related to ILOs.

4.3.2 Learning Materials Classification Using SVM Classifier

In this section we should explain some techniques related to the implementation which needed in the classification stage as follows:

- **WEKA**: an open source software package, that is a collection of machine learning algorithms for data mining tasks, which is able to analyze and extract data. These algorithms can be easily applied to a set of data directly through the WEKA program interface. The first step of the analysis using WEKA is to use data that can be understood by WEKA. (ARFF) formula. (Hornik 2007).

- **ARFF:** it is an abbreviation (Attribute-Relation File Format). It is a file format that WEKA handles for data analysis. It is said that an ARFF file is like a table that contains a set of data represented by a number of columns and rows. Where the columns represent Attributes or, while the rows represent instances or forms, and one row consists of several values of attributes. (Benjamas et al .2014).

- **Stop Words**: In computing, words which are filtered out before or after processing of natural language and metadata, "stop words" usually refers to the most common words in a language, as "The", "Who", "or" "That", "is", "at", and so on, to be easy for retrieval and dealing with data. (Wilbur 2015).

- **Stemming:** It is considered in linguistic morphology and information retrieval, the process of reducing inflected (or sometimes derived) words to their word stem, base original term or root form as a noun. Since the 1960s, algorithms for stemming have been studied in computer science. Many search engines treat words with the same stem a kind of query expansion. (Lovins 1968)

- **K-Fold Cross Validation**: is a technique for estimating and evaluating the performance of a particular model of a sample of data, relative to a future data, by dividing data into two groups: the first group is the training group that is being applied, and the second one is a testing group that calculates the resulting error ratio. A common choice is k = 10, when it is defined correctly it can reduce the use of data in the testing process. (Bengio et al 2004).

- **String Tokenizer class:** As used in the java package, it means dividing a particular text into pieces in which each one is called a token. (Forman et al 2008).

So, this stage, explains how the classifier is implemented through three phases:

- **Phase1: Data Preparation:**

  The dataset used to build and evaluate the classifier is located on disk storage and consists of about 144 documents distributed on 28-labeled classes,[13] the process of converting learning materials into ARFF file is carried out using the WEKA library using Java customized classes. The String to Word Vector WEKA java class is used to tokenize each document into a list of terms. After that, the terms are filtered using stopwords list to eliminate not important terms like is, as, the… etc., then the terms are stemmed using the Porter stemmer algorithm (Willett 2006). After that, the document terms are appended to the ARFF file. The process of data preparation is depicted in figure 25:

[13] Learning Courses downloaded from (http://academictorrents.com/browse.php) which are named (Data Mining, Artificial Intelligence) courses.

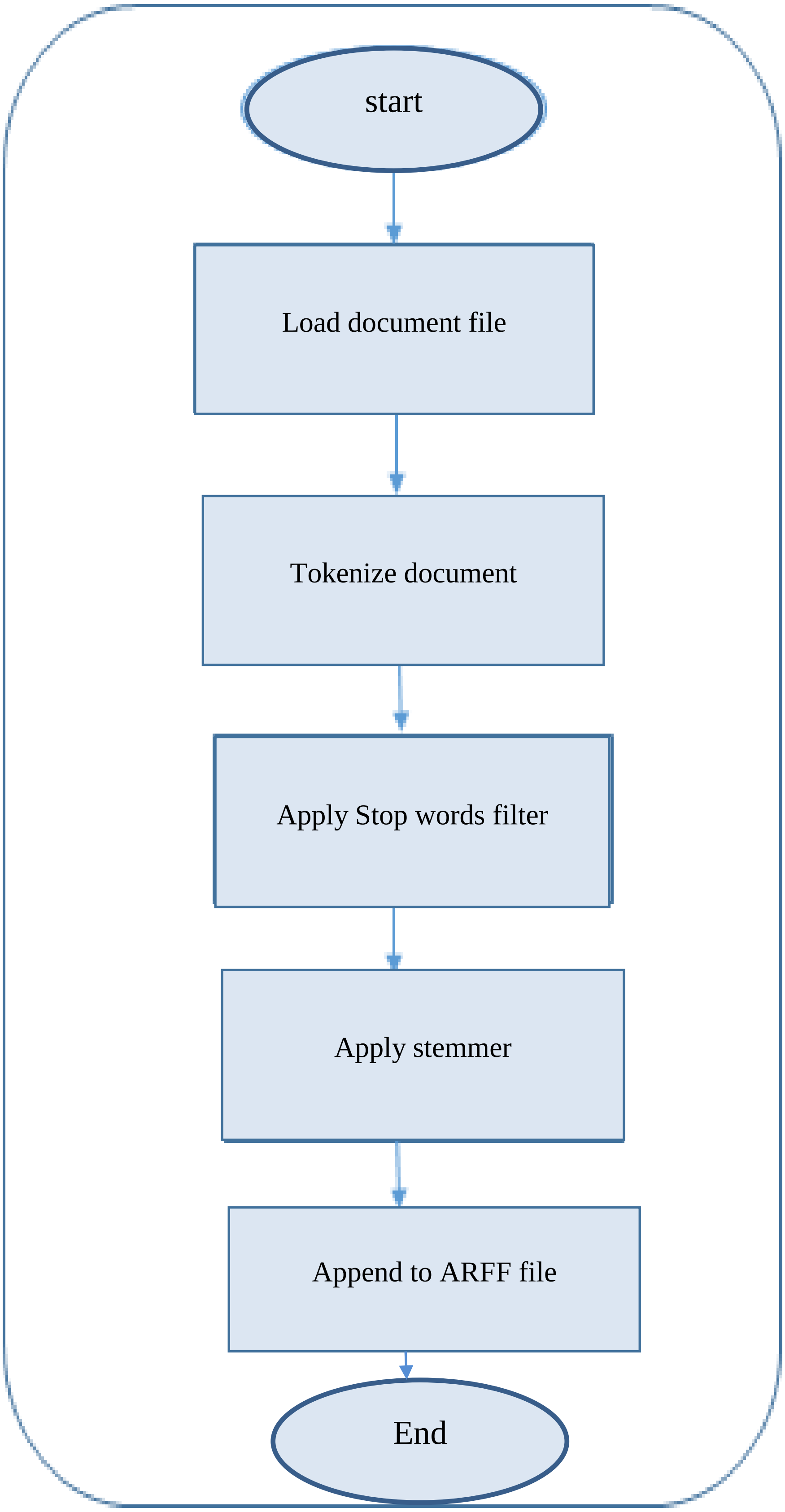


Figure 24:Data preparation for SVM classifier

```
Public void load Dataset(String file Name) { try }
        Text Directory Loader  = new Text (Directory Loader);
        Loader set Directory=(new File(file Name));
        String To Word Vector filter = (new String To Word Vector);
        Instances raw Data = (loader get Data Set);
        Word  Tokenize rTokenizer    = (new Word Tokenizer);
        String delimiters = " \r\t\n.,;:\'\"()?!-><#$\\%&*+/@^_=[]{}|`~0123456789";
        tokenizer.  Set  Delimiters(delimiters);
        filter.  Set Tokenizer (tokenizer);
        SnowballStemmer stemmer = (new SnowballStemmer);
        stemmer.setStemmer("porter");
        filter.setStemmer(stemmer);

        filter.setStopwords(new File("d:\\stopwords.txt"));
        filter.setTFTransform(true);
        filter.setIDFTransform(true);
        filter.setStopwordsHandler(stopwordsHandler);
        filter.setLowerCaseTokens(true);
        rawData.setRelationName("khetam");
        filter.setInputFormat(rawData);
        trainData = Filter.useFilter(rawData, filter);
        trainData.setRelationName("khetam");
            { catch (Exception e) }
        System.out.println("Problem found when reading: " + fileName);
```

Figure 25: The Code used in Java language to present the process for data preparation.

```
(public void evaluate) { try }
            trainData.setClassIndex(0);
             filter = new StringToWordVector();
             WordTokenizer tokenizer = new WordTokenizer();
            String delimiters = " \r\t\n.,;:\'\"()?!-><#$\\%&*+/@^_=[]{}|`~0123456789";
            tokenizer.setDelimiters(delimiters);
            filter.setTokenizer(tokenizer);

               filter.setTFTransform(true);
            filter.setIDFTransform(true);
            filter.setStopwords(newFile("E:\\project\\stop        lists\\stop        lists\\stopword
list2.txt"));
             filter.setLowerCaseTokens(true);
            classifier = new FilteredClassifier();
            classifier.setFilter(filter);
             if (classifierName.equals("SMO"))
              {  classifier.setClassifier(new SMO());}
             Evaluation eval = new Evaluation(trainData);
            eval.crossValidateModel(classifier, trainData, 4, new Random(1));
           classifier.buildClassifier(trainData);
        { catch (Exception e) }
           ( e.printStackTrace);
           {System.out.println("Problem found when evaluating");}
```

Figure 26:Building and evaluation SVM classifier

- **Phase2: Building And Evaluation SVM Classifier**

In this phase, the SVM classifier is built using the ARFF file that was generated in phase 1. The classifier building process is executed, using WEKA java classes and evaluated, using 10-Fold Cross Validation model.

- **Phase3: Classification of Learning Materials (LMs).**

In this phase, each file in the testing dataset or each material in the learning system is classified to specify to which ILO it belongs, using the classifier that was built previously, the process works as shown in the figure28:

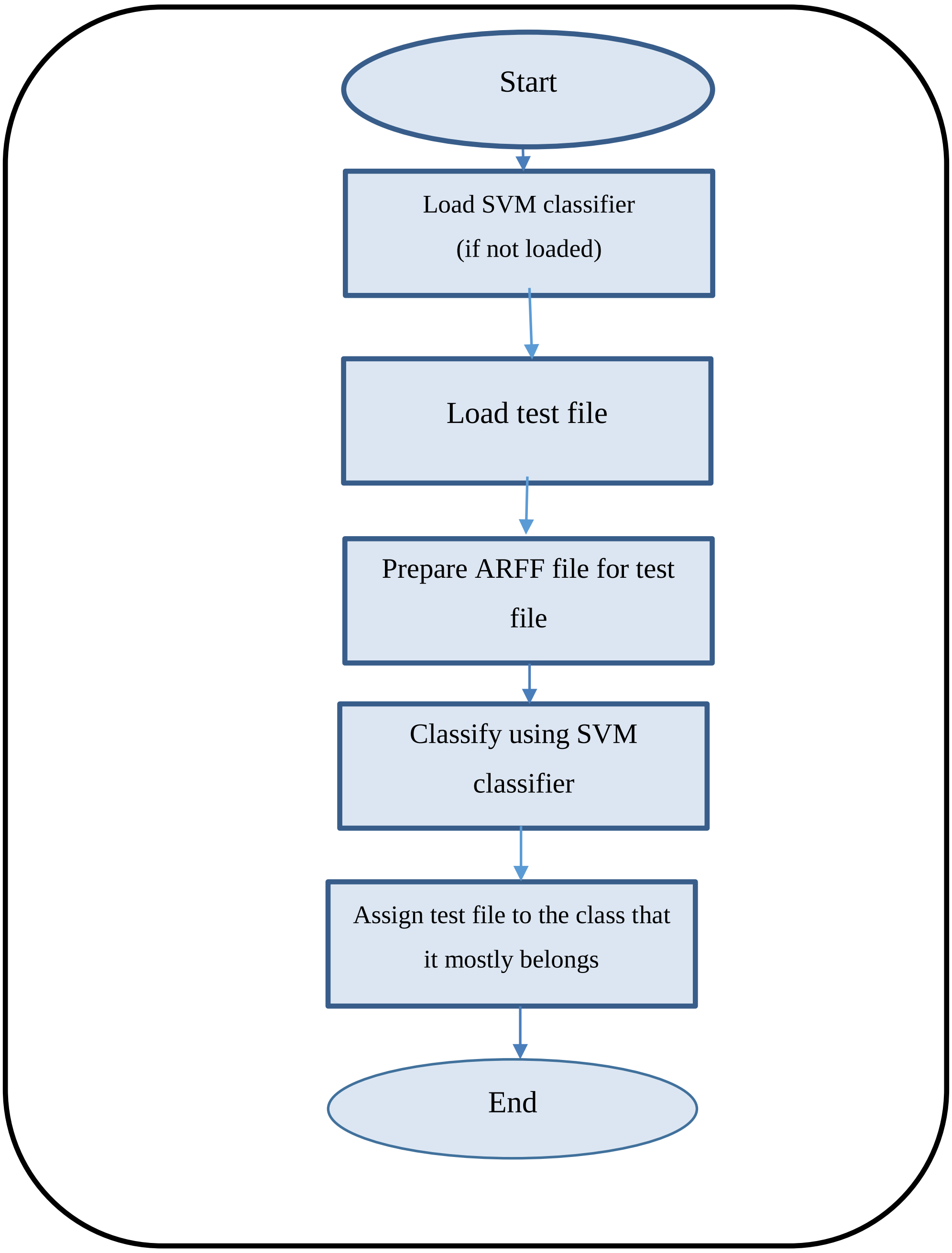


Figure 27:Classification of learning materials (LM)

The following Pseudo Code shows the SVM classifier algorithm.

Algorithm 1. Support Vector Machine Classifier Algorithm

```
Begin
 Load dataset (path);
  For a labeled class in dataset loop ;
       For file is labeled –class loop;
        Tokenize (file);
          Apply to stop words (file);
            Stem (file);
            IF/IDF (file);
              Add to ARFF (file);
        End loop;
   End loop;
      Build SVM classifier (ARFF);
        Store SVM classifier ( );
End;
```

The classified portion of the code for SVM classifier is depicted as follows:

```
(public void classify) {try }
        // filteredClassifier is the loaded SVM classifier object
         double[] preds = filteredClassifier.distributionForInstance(instances.instance(0));

         for (int i = 0; i < preds.length; i++) {

             System.out.println("preds[" + i + "]=" + preds[i]); }

         for (int i = 0; i < preds.length; i++) {
             if (preds[i] > 0) {
                 System.out.println(instances.classAttribute().value((int) i) + " =" + preds[i]) }

         // pred is the index of the predicted class
         double pred = filteredClassifier.classifyInstance(instances.instance(0));

          System.out.println("Class predicted: " + instances.classAttribute().value((int)
pred));

       } catch (Exception e) {

         System.out.println("Problem found when classifying the text");
         e.printStackTrace();
```

Figure 29:The Classified Portion of the Code for SVM Classifier4.3.3 Evaluate SVM Classifier and Results

In table 5, the classifier SVM provides the accuracy rate results. It classified the learning materials and learning concepts related to ILOs for the proposed system as percentage 71.5%. All the files used were 144; the incorrectly classified instances were 41. The other details were viewed, too. These percentages were considered promising and the following table explains the different rates.

Table 5: Accuracy Rate for SVM classifier

Correctly Classified Instances	103	71.5278 %
Incorrectly Classified Instances	41	28.4722 %
Kappa statistic	0.6933	
Mean absolute error	0.069	
Root mean squared error	0.1838	
Relative absolute error	98.0461 %	
Root relative squared error	98.1046 %	
Total Number of Instances	144	

Table 6 presents the accuracy rate for Precision and Recall measurements for classes (files of concepts) for learning materials, so the remaining measurements explained more details about the meaning of the measurement tools in this table. Firstly, we should talk about these concepts related to indicators for measurement as well as Sensitivity and Specificity.

Sensitivity and specificity: They are considered as important statistical measures for the accuracy and performance of the dual classification test. As defined in statistics they are considered as statistical classifications and can be used to estimate the probability for existing relationship between two classifications or not to be. (Anthony K Akobeng 2007).

- **Sensitivity** is known as the true positive rate ($TP\ Rate$), as called in some areas, is a measure of positively-defined things, which are complementary to the true negative rate.
- **Specificity** is also known as the true negative rate ($TN\ Rate$), is a measure of negatively-defined things, which are correct and complementary to the true positive rate.

$$Sensitivity = true\ positives/(true\ positive\ +\ false\ negative)$$

$Sensitivity = TP/\ (TP + FN)$ (Akobeng et al. 2007) (4)

$Specificity = true\ negatives/\ (true\ negative\ +\ false\ positives)$

$Specificity = TN/\ (TN\ +\ FP).$ (Akobeng et al. 2007) (5)

While $(\ TP = 1\text{-}FN)$ and $(FP = 1\text{- } TN).$

In this thesis, this rate presents the accuracy measurements, as True Positive Rate ($TP\ Rate$)which show the classification test values and the degree of conformity as well as correct or true test, within using SVM classifier to classify the classes or files that contain the learning materials and automated mapping between them and learning concepts related to selected ILOs with weighted Avg =0.715, and this is acceptable ratean .

The False Positive Rate ($FP\ Rate$) explains how the system provides a probability when the false classification becomes a true test with weighted Avg=0.028. Another indicator which is used to evaluate our system is Precision and Recall (P/R) that is utilized in pattern recognition, information retrieval and binary classification. Precision which is named positive predictive value, is a part of relevant cases among the retrieved cases, while recall which is named sensitivity, is a part of relevant cases that have been retrieved over the total amount of relevant cases. Both $Precision\ and\ Recall$ are therefore based on understanding and measure of relevance between the cases. $Precision\ and\ Recall$ (P/R) are calculated as:

$Precision\ =\ True\ Positive\ Rate\ /(\ True\ Positive\ Rate\ +\ False\ Positive\ Rate\ )\ .$

$Precision\ =\ TP/(TP\ +\ FP)\ .$ (Anthony K Akobeng 2007) (6)

$Recall\ =\ True\ Positive\ Rate\ /(\ True\ Positive\ Rate\ +\ False\ negative)\ .$

$Recall\ =\ TP/(TP\ +\ FN).$ (Anthony K Akobeng 2007) (7)

The $Precision/Recall$ (P/R) indicators were used to measure the quality of the obtained outcomes in our work.

As shown in table 5, we note that the precision indicator results range between $0\ and\ 1$ and the weighted $Avg\ = 0.738\ and\ 0.715$. This means that SVM classifier offers acceptable results and almost effectively in terms of retrieving and recall the learning materials related to learning concepts based on selected Intended Learning Outcomes (ILOs).

- $F-measure$**:** The $F-measure$ is defined as a harmonic means of $precision\ (P)$ and $recall(R)$. (Sasaki et al.2007).

$$F-Measure = \frac{2*precision*Recall)}{(precision+Recall)} \quad \text{(Tang et al .2009).} \quad (8)$$

As shown in table 6, the accuracy value weighted Average of $F-Measure$ is 0.678.

Table 6: Accuracy rate for measurement tools for LM

	TP Rate	FN Rate	FP Rate	TN Rate	Precision	Recall	F-Measure	ROC Area	Class
	1	0	0.023	0.977	0.8	1	0.889	0.989	Analysis of Large Graphs
	0.8	0.2	0	1	1	0.8	0.889	1	Clustering
	0.75	0.25	0	1	1	0.75	0.857	1	Computational Advertising
	0.333	0.667	0.007	0.993	0.667	0.333	0.444	0.959	contextual text mining
	0.2	0.8	0	1	1	0.2	0.333	0.979	Data Stream Mining
	0.6	0.4	0	1	1	0.6	0.75	0.98	Decision Trees
	1	0	0.007	0.993	0.889	1	0.941	0.996	Dimensionality Reduction
	0	1	0	1	0	0	0	0.122	Distance Measures
	0.25	0.75	0	1	1	0.25	0.4	1	Frequent Itemsets
	0	1	0	1	0	0	0	0.122	hubs-and-authorities
	0	1	0	1	0	0	0	0.989	Link Spam
	0.9	0.1	0.03	0.97	0.692	0.9	0.783	0.98	Link_Analysis_and_PageRank
	1	0	0	1	1	1	1	1	MapReduce
	1	0	0.076	0.924	0.545	1	0.706	0.962	Minhashing, Locality-Sensit
	0.667	0.333	0	1	1	0.667	0.8	0.992	Natural language processing
	0	1	0	1	0	0	0	0.122	Nearest Neighbors
	0.333	0.667	0	1	1	0.333	0.5	0.999	paradigmatic relations
	0.778	0.222	0.007	0.993	0.875	0.778	0.824	0.982	Recommender Systems
	0.5	0.5	0	1	1	0.5	0.667	0.962	sentiment analysis
	1	0	0.007	0.993	0.857	1	0.923	0.996	Support-Vector Machines
	0.8	0.2	0	1	1	0.8	0.889	0.996	syntagmatic relations
	0	1	0	1	0	0	0	0.122	text categorization
	0	1	0	1	0	0	0	0.151	text clustering
	0.25	0.75	0.007	0.993	0.5	0.25	0.333	0.971	Text Mining and Analytics
	0.667	0.333	0	1	1	0.667	0.8	0.995	text representation
	0.938	0.062	0.148	0.852	0.441	0.938	0.6	0.9	topic analysis techniques
	0	1	0	1	0	0	0	0.954	word association mining
Weighted Avg.	0.715	0.285	0.028	0.972	0.738	0.715	0.678	0.939	

ROC Area: Receiver Operator Characteristic Curves or ROC analysis is a useful complement to sensitivity and specificity assessment in test evaluation studies. In the current usage, ROC curves are a good way to see how any predictive model can distinguish between true positives or true negatives and has values $between(0 - 1)$. (Kumar et al.2001).

The table 6 also reviewed the values to make an impression that it is a good evaluation.

In the prototype of proposed approach system, there are examples of ROC area for classes or concepts explained as in plots or figures which present the values of $x = false$ $positive\ rate$ $(FP\ Rate)$ that means specificity, and y represents $true\ positive\ rate$ $(TP\ Rate)$which considers sensitivity, and this plot gets high values as seen in Area under $ROC = 0.9598$ for "$Text\ Mining$ and $Analytics\ class$ "or concept and *0.9848* for "$Analysis\ of\ Large\ Graphs\ Class$", and *0.9935* for "$Decision\ Trees$" and *0.9927* for "$Map\_Reduce$, that provided excellent results because whenever the graph is approaching from $y - axis$, that means, the classifier is able to discriminate between positives and negatives effectively. So the following screens explain more details.

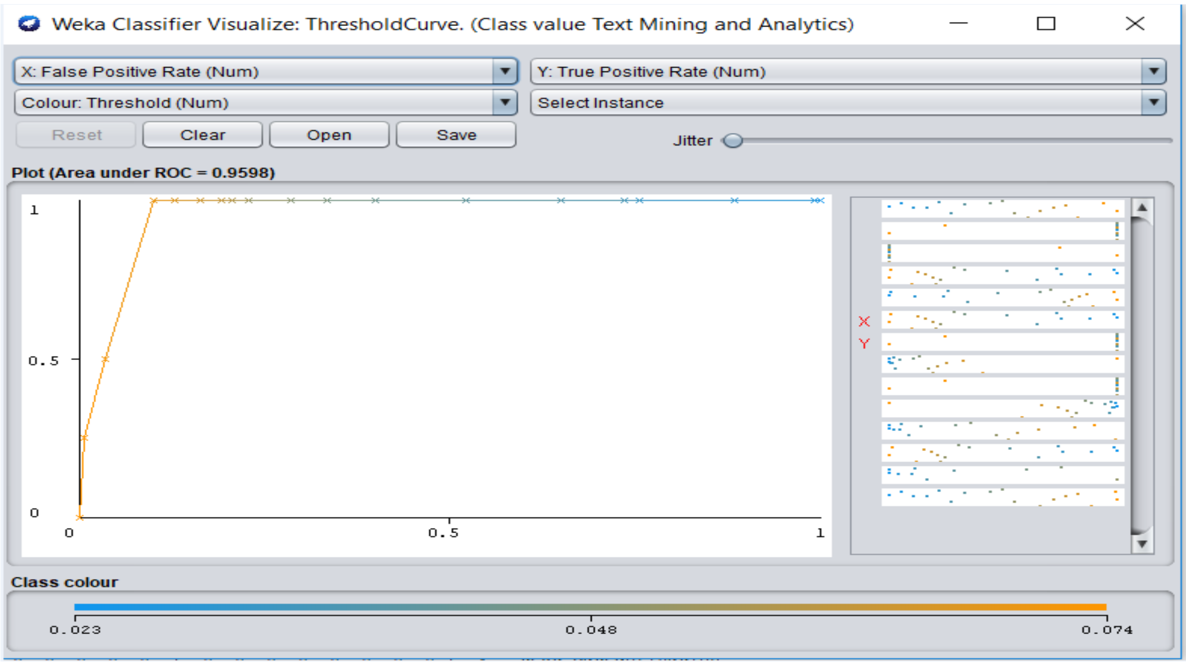


Figure 28:The plot ROC area and the values of x and y for "Class Text Mining and Analytics"concept.

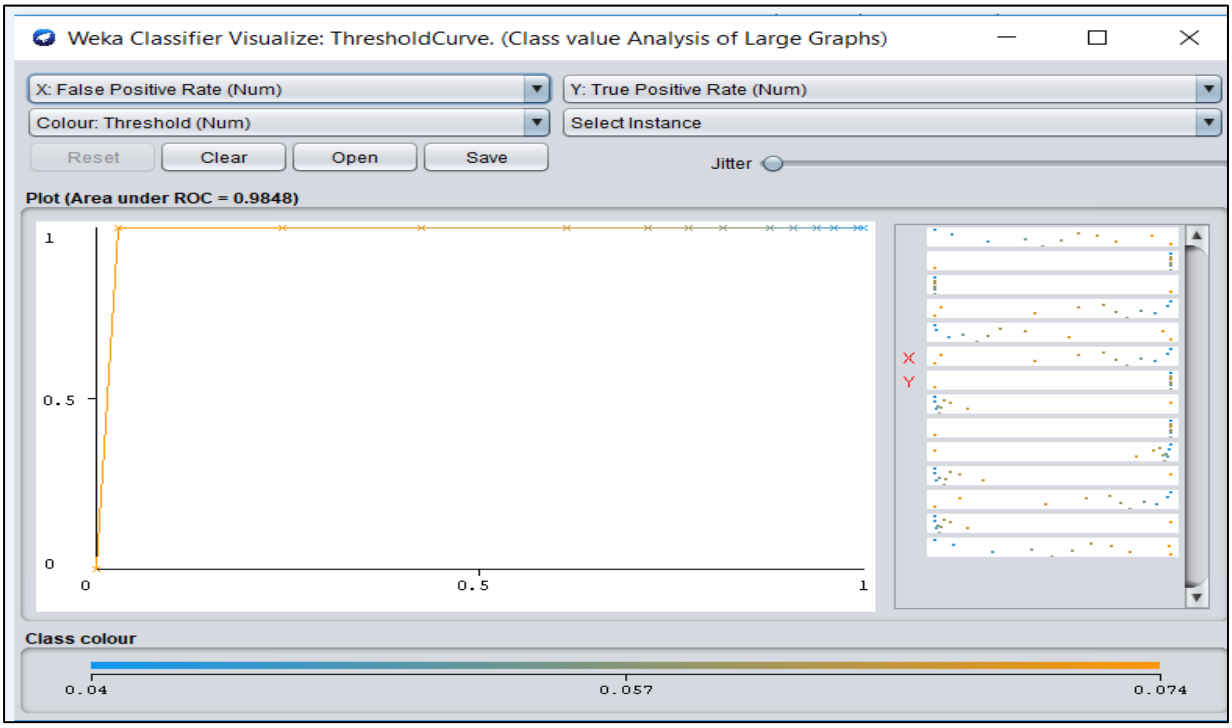


Figure 29:The plot ROC area and the values of x and y for Class "Analysis of Large Graphs"

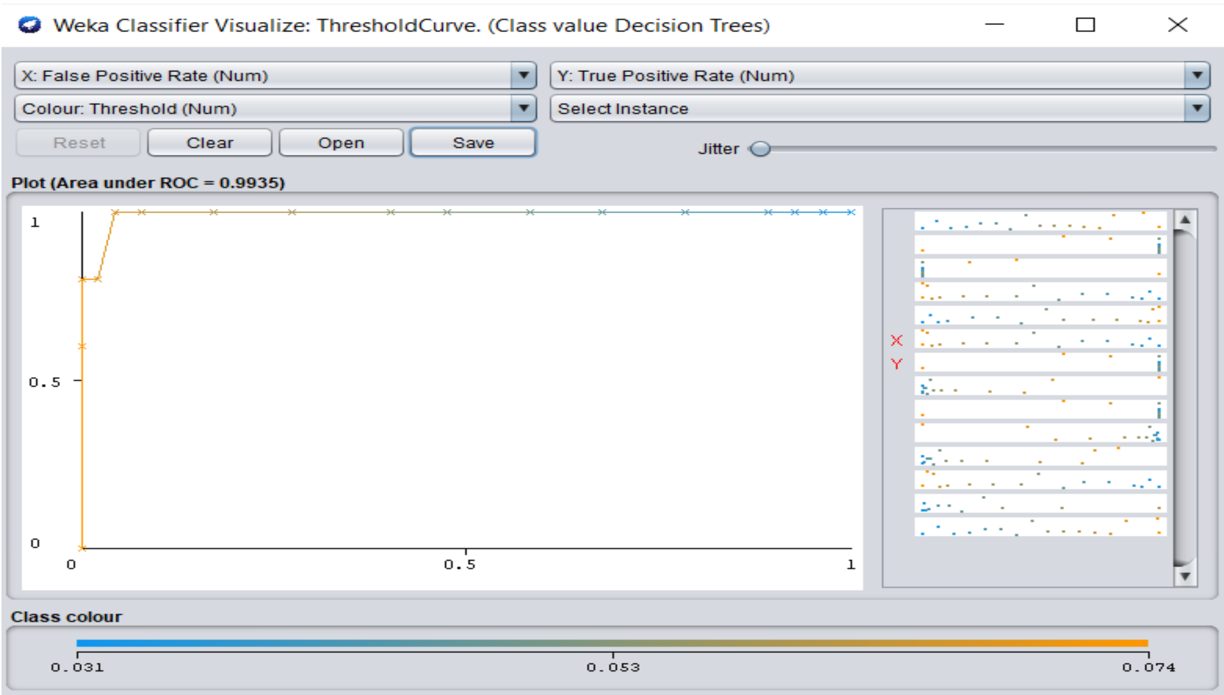


Figure 30:The plot ROC area and the values of x and y for class "Decision Tree"

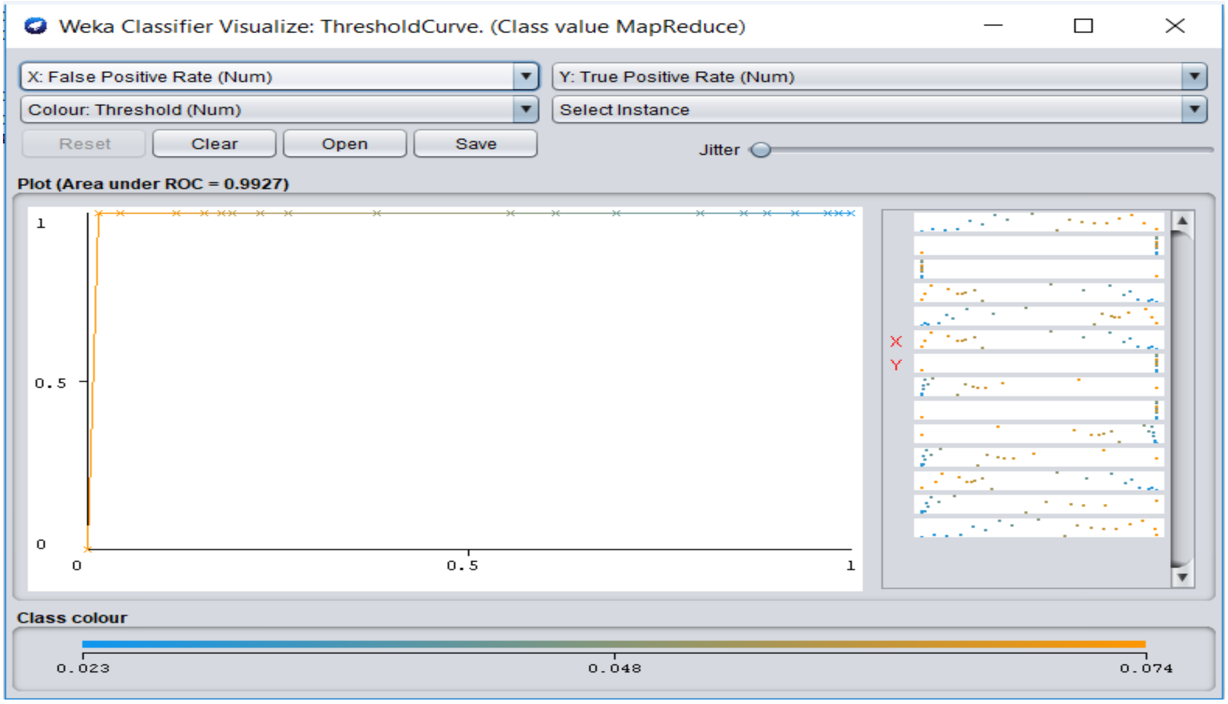


Figure 31:The plot ROC area and the values of x and y for class "Map_ Reduce"\

4.3.4 Evaluate Exam Results

This section presents the mapping between learning concepts list related to ILOs and learning materials classes as the desire of the learner, to generate the learning path. Then the expert person or the manager of the system can determine manually the weight of each learning material and all the questions according to the level of difficulty for every question (hard, medium, easy) using Fuzzy Logic technique, so we provided a bank of questions for each learning concept or chapter and learning material. In other words, when the system generates any exam, then selecting the question is done according to the weight of the learning material which was selected before.

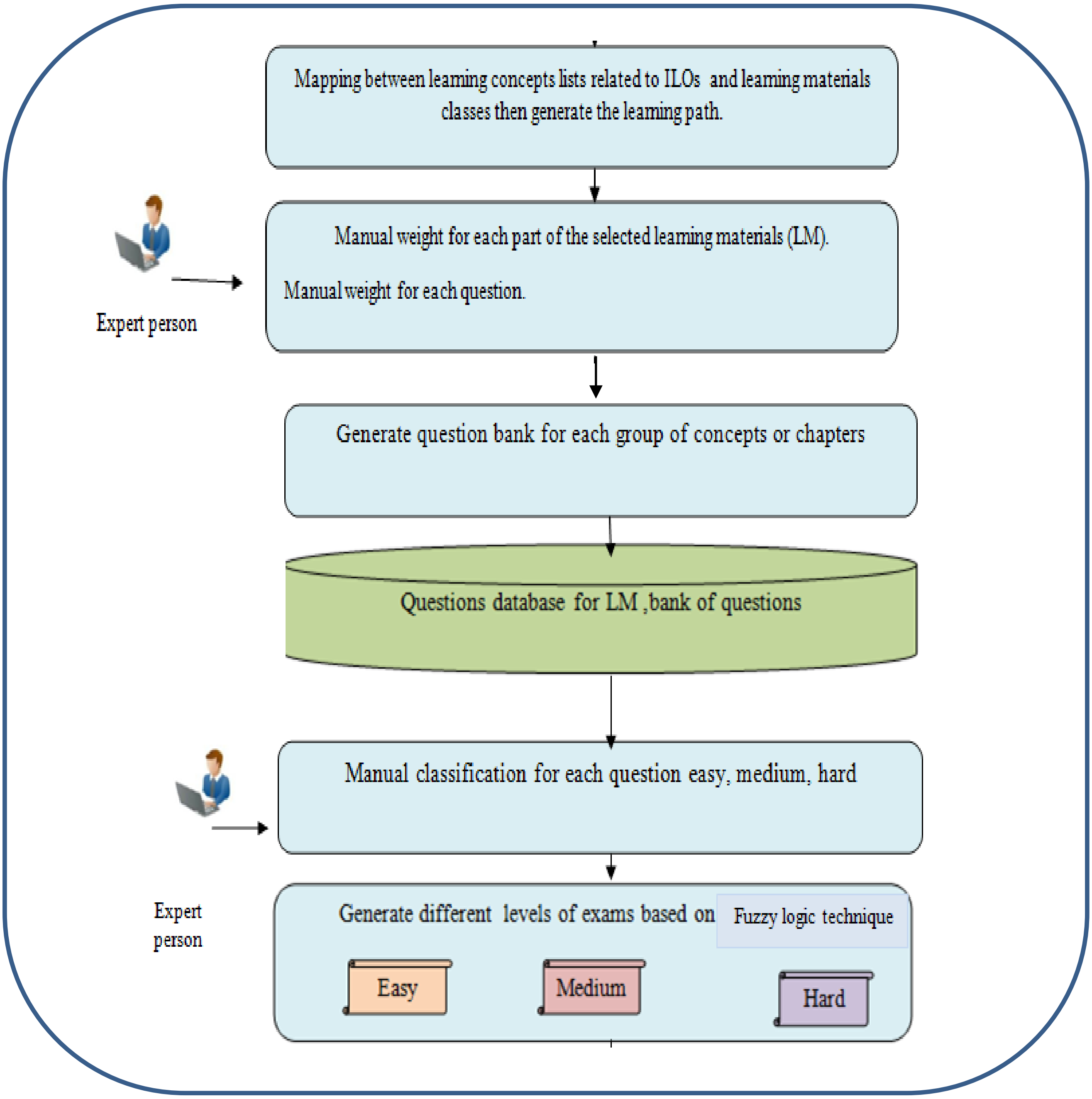


Figure 32:The second phase of the flowchart for the prototype

As shown in the example in figure 35, the query in our proposed model is sent to extract 20 questions randomly so that 5 questions on educational material 1 , 5 questions on educational material 2, and 10 questions on the educational material 3.

```
SELECT   q_id,
        hard_perc,
        (SELECT   fl.lvl
          FROM   fuzzy_lvls fl
         WHERE   hard_perc BETWEEN fl.from_mark AND fl.to_mark)
          AS lvl
  FROM   (SELECT   q_id, hard_perc
          FROM   (SELECT   a.q_id, a.hard_perc
                    FROM   questions a, mat_q_mapping m
                   WHERE       a.q_id = m.q_id
                          AND a.hard_perc IS NOT NULL
                          AND m.mat_id = 1
                ORDER BY   DBMS_RANDOM.VALUE)
         WHERE   ROWNUM <= 5
        UNION
        SELECT   q_id, hard_perc
          FROM   (  SELECT   a.q_id, a.hard_perc
                    FROM   questions a, mat_q_mapping m
                   WHERE       a.q_id = m.q_id
                          AND a.hard_perc IS NOT NULL
                          AND m.mat_id = 2
                ORDER BY   DBMS_RANDOM.VALUE)
         WHERE   ROWNUM <= 5
        UNION
        SELECT   q_id, hard_perc
          FROM   (  SELECT   a.q_id, a.hard_perc
                    FROM   questions a, mat_q_mapping m
                   WHERE       a.q_id = m.q_id
                          AND a.hard_perc IS NOT NULL
                          AND m.mat_id = 3
                ORDER BY   DBMS_RANDOM.VALUE)
         WHERE   ROWNUM <= 10)
```

Figure 33:The query for extract questions from database randomly

In this step, the result for this query is explained by determining the question ID number and the difficulty percentage and difficulty description for the level of question as an easy, intermediate or hard question as shown below:

After that, the system determines the percentage of questions: (easy, medium and difficult). For example, The ratio of easy questions (8/20)× 100% = 40%. Medium question Rate (7/20) × 100% = 35%. Hard question rate (5/20) ×100% = 25%. The fuzzy logic technique is used according to these ratios to determine the difficulty level of the exam. This process is repeated to design more than one model at different difficulty levels and store them in the database for use by students according to their levels.

Table 7: The results for the query to retrieve the percentage and descriptions of questions

Question ID	Difficulty %	Difficulty Description
4647	1	Easy
4704	11	Easy
4700	11	Easy
4682	15	Easy
4715	18	Easy
4730	25	Easy
4676	26	Easy
4708	30	Easy
4593	40	Intermediate
4723	42	Intermediate
4624	42	Intermediate
4636	43	Intermediate
4697	54	Intermediate
4679	54	Intermediate
4689	66	Intermediate
4983	71	Hard
4633	72	Hard
4984	77	Hard
4693	79	Hard
4618	100	Hard

4.3.5 Evaluate the Fuzzy Logic Technique

This is the last phase of the Flowchart-Figure 35-in our model which depends on the Grade Point Average (GPA) of the student, so the system selects the suitable exam level (hard, medium, easy) using Fuzzy Logic to suit the abilities of the learner (beginner, intermediate, advanced). The categories have been adopted in our model are as follows:

• 0.00% - 50% : easy level, then select easy exam.

• 35% - 75% : intermediate level, then select medium exam.

• 70% - 100% : difficult level, then select hard exam.

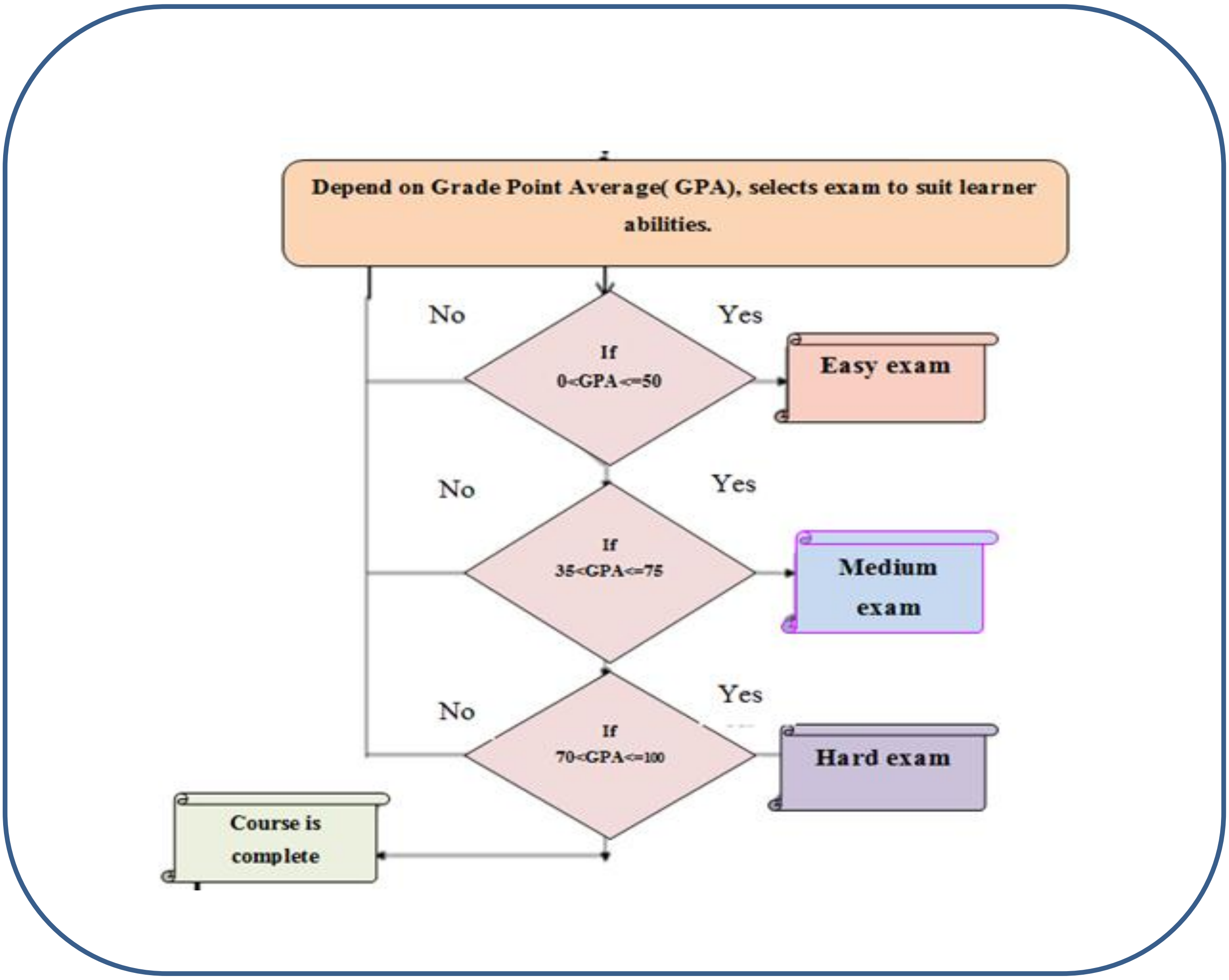


Figure 34: The last phase of the flowchart to select level exam according to (GPA)

4.3.5.1 Fuzzy Logic Results

Figure- 36 explains how we can manually determine the level of difficulty of questions: easy, medium or hard questions. In addition to the level of difficulty, we entered the ratios of difficulty levels as, 10, 30, and 60 respectively.

The code figure below explains how we divided the fuzzy logic into three Categories; that is, easy questions, medium questions, and hard questions. For more details, as an example for easy questions, we divided the categories into memberships (from 0 to 1) and intervals from (0 to 100) to low easy := (0.0, 1.0) (40.0, 1.0) (50.0, 0.0), medium easy:=(35.0, 0.0) (70.0, 1.0) (75.0, 0.0), and the high easy := (70.0, 0.0) (80.0, 1.0) (100.0, 1.0), to provide us with accurate results. The rest of the code was left for the medium and hard questions and the tip (output) shown in the figure.

```
// Get default function block
FunctionBlock fb = fis.getFunctionBlock(null);

// Set inputs
fb.setVariable("easyquestions", 10);
fb.setVariable("mediumquestions", 30);
fb.setVariable("hardquestions", 60);


        JFuzzyChart.get().chart(fb);
```

Figure 35: The Ratios of difficulty levels for questions entered manually

```
FUZZIFY easy questions
            TERM low Easy: = (0.0, 1.0) (40.0, 1.0) (50.0, 0.0);
            TERM medium Easy: = (35.0, 0.0) (70.0, 1.0) (75.0, 0.0);
            TERM high Easy: = (70.0, 0.0) (80.0, 1.0) (100.0, 1.0);
      END_FUZZIFY
      FUZZIFY medium questions
            TERM low Medium: = (0.0, 1.0) (40.0, 1.0) (50.0, 0.0);
            TERM medium Medium: = (35.0, 0.0) (70.0, 1.0) (75.0, 0.0);
            TERM high Medium: = (70.0, 0.0) (80.0, 1.0) (100.0, 1.0);
      END_FUZZIFY
      FUZZIFY hard questions
            TERM low Hard: = (0.0, 1.0) (40.0, 1.0) (50.0, 0.0);
            TERM medium Hard: = (35.0, 0.0) (70.0, 1.0) (75.0, 0.0) ;
            TERM high Hard: = (70.0, 0.0) (80.0, 1.0) (100.0, 1.0);
      END_FUZZIFY
      DEFUZZIFY tip
            TERM easy: = (0.0, 1.0) (40.0, 1.0) (50.0, 0.0);
            TERM hard: = (70.0, 0.0) (80.0, 1.0) (100.0, 1.0);
            TERM medium: = (35.0, 0.0) (70.0, 1.0) (75.0, 0.0);
            METHOD: COG;
            DEFAULT: = -1.0;
            RANGE: = (0.0 . 100.0);
                        END_DEFUZZIFY
```

Figure 36:The part of code used to determine the classes of questions and the levels of memberships in fuzzy logic

The figure 39 shows some of the rules that are used in fuzzy logic to illustrate the outputs (tip) and the Center of Gravity (COG), whose Tip value: 59.36. It means that the exam difficulty is medium exam according to the categories of fuzzy logic ratios.

```
RULEBLOCK No1
        ACT: MIN;
        ACCU: MAX;
        AND: MIN;
RULE 1: IF ((easy questions IS low Easy) AND (medium questions IS medium Medium)) AND (hard questions IS low Hard) THEN tip IS medium;
RULE 2: IF ((easy questions IS medium Easy) AND (medium questions IS low  Medium)) AND (hard questions IS low Hard) THEN tip IS easy;
RULE 3: IF ((easy questions IS high Easy) AND (medium questions IS low Medium)) AND (hard questions IS low Hard) THEN tip IS easy;
RULE 4: IF ((easy questions IS low Easy) AND (medium questions IS low Medium)) AND (hard questions IS low Hard) THEN tip IS easy;
RULE 5: IF ((easy questions IS low Easy) AND (medium questions IS low Medium)) AND (hard questions IS medium Hard) THEN tip IS medium;
RULE 6: IF ((easy questions IS low Easy) AND (medium questions IS low Medium)) AND (hard questions IS high Hard) THEN tip IS hard;
RULE 7: IF ((easy questions IS low Easy) AND (medium questions IS medium Medium)) AND (hard questions IS low Hard) THEN tip IS medium;
RULE 8: IF ((easy questions IS low Easy) AND (medium questions IS medium Medium)) AND (hard questions IS medium Hard) THEN tip IS hard;
END_RULEBLOCK
    END_FUNCTION_BLOCK
Tip value: 59.36
```

Figure 37:The part of code of rules block to extract the result (Tip) that is fuzzy logic value.

4.3.5.2 Fuzzy Logic Center of Gravity (COG) (tip)

This stage includes many figures which show how our system can give the kind of exam according to the groups of fuzzy logic classes. Therefore, the last figure explains the value of the center of gravity (tip) which gives the result 59.36. This percentage represents the kind of exam that is medium in level, according to the levels of fuzzy logic which includes the medium level (35-75) %.

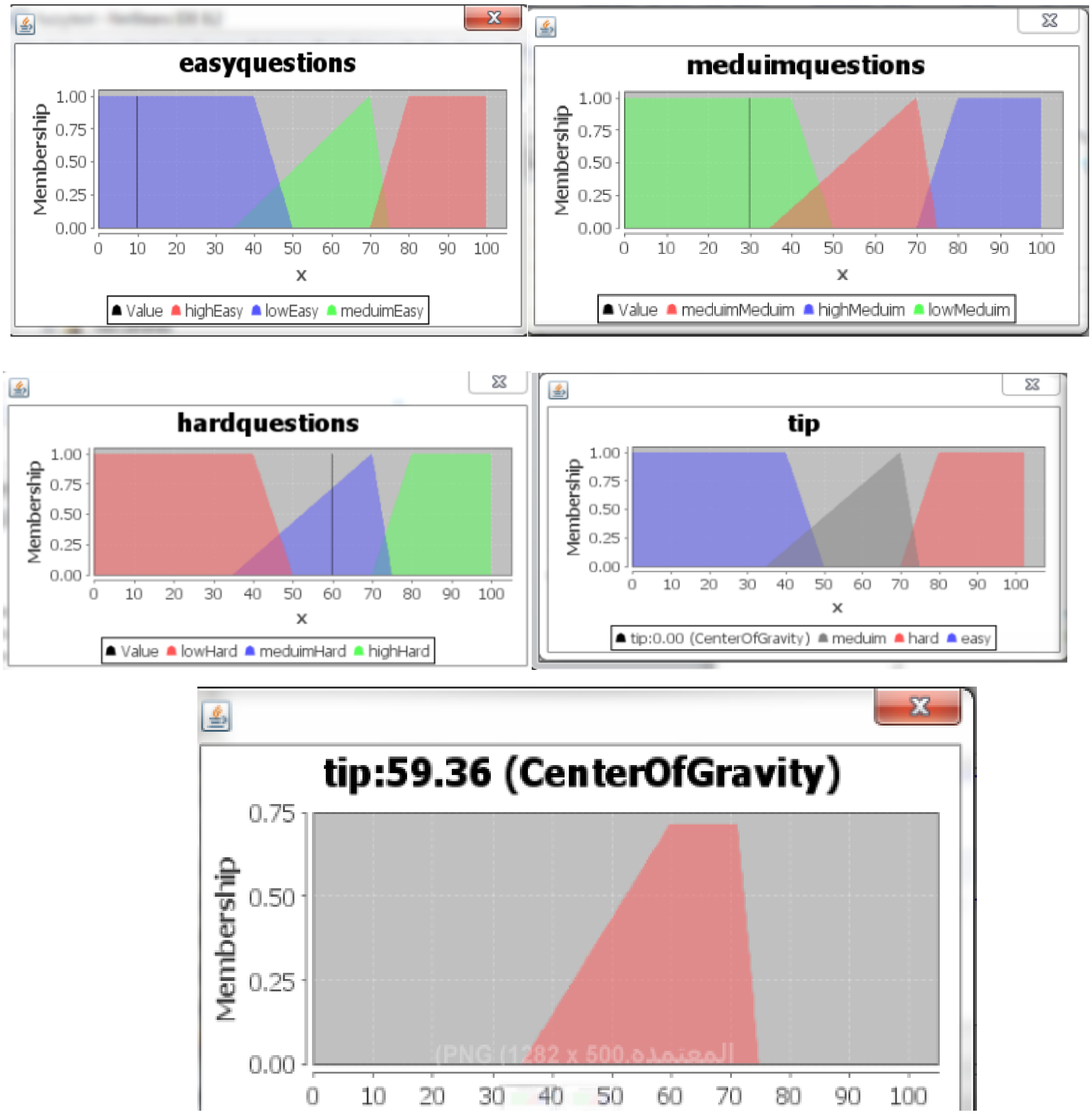


Figure 38: Value of (COG) to define the level of exam according togroups of questions' levels.

As shown in the above example the figure 40 ,the result of the exam produce in this example a medium level, this will be effective when we went to select the exam level depending on the student level.   Fuzzy logic is an excellent method when we used to evaluate the student test. which it's easy to determine the exam level to be suitable for students level.

4.4 Summary:

In this chapter, we talked about experiments, results and the evaluation of the approach system, and we explained the evaluation for (SVM) classifier. We also presented the accuracy rate for measurement tools and indicators as precision and recall. Moreover, we provided more plots and figures for evaluation of a ROC area and Fuzzy Logic results as the (COG) to classify the exams and evaluate the results.

CHAPTER 5

DISCUSSION AND CONCLUSION

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DISCUSSION AND CONCLUSION

This final chapter presents the discussion and conclusion about the proposed system in addition to the outline of future work which can develop the ideas and techniques to improve the performance of the proposed system. This chapter is organized as follows: Section 5.1 includes the discussion that presents the evaluation results obtained when the proposed system has been carried out. Section 5.2 includes the conclusion that presents a summary of this thesis and highlights the techniques and framework that have been implemented in the proposed system. Section 5.3 provides the future work that is related to using the techniques and ideas to enhance the adaptive MOOCs system.

5.1. DISCUSSION

At the end of this thesis, the proposed system enables the learner to follow a course based on his intended learning outcome instead of following a predefined traditional course which is more teacher-centered rather than learner-centered. This system has developed the idea of having a learning course which is learner-oriented by delivering a group of learning materials that meet his objectives and goals. Therefore, the proposed system has been evaluated to ensure that this idea has been achieved. The evaluation process has been divided into three main stages as follows:

- **The First Stage**

  The effectiveness of the proposed system was evaluated on the basis of comparing the manually matching results among learning concepts (LCs) related to ILOs, learning materials and recommended resources to results have been obtained using the Support

Vector Machine (SVM) algorithm. To achieve this goal, several indicators were used as the Accuracy Rate for SVM, TP Rate, FP Rate, the Precision and Recall indicators, and F-Measure and finally the ROC Area. These indicators were applied in the system, which showed that the results were promising in the classification process.

- **The Second Stage**

Evaluation of this stage focused on the learner's assessment designed by the proposed system as taking an exam. When the query is sent to the system to extract questions randomly, the results are provided by determining the questions ID number, the difficulty percentage or ratios and the difficulty specifications for the level of questions (easy, medium, hard), so Fuzzy Logic technique was applied at this stage to determine the difficulty level of the exam as an appropriate level for the learner.

- **The Third Stage**

The evaluation of this stage focused on Grade Point Average (GPA) for the learner. So, the system selects the most suitable exam level (easy, medium, or hard) to suit the learner's abilities and his level (beginner, intermediate, or advanced). This stage applies the Fuzzy Logic technique, which is divided into three categories, such as easy questions, medium questions, and hard questions. After that, each category is divided into three levels: "easy questions" which consists of "low easy", medium easy" and "high easy" levels, and so on. So, the evaluation of (COG), that the system managed to deliver the suitable kind of exam for the learner, exactly according to Fuzzy Logic categories or classes.

To the best of my knowledge, there is no similar work to compare the obtained results with them. Most of the proposed work as discussed in litreture are mainly proposing data mining for selecting learning materials or assessemts in each approach. This work is considered unique in term of combining two different data mining algorithms for selecting both learning materials and assessement together.

Finally, the proposed system realized the main idea which aimed to provide adaptive learning content and assessment tools in MOOCs, using classification algorithms whose idea has been ideal and which is considered as an important improvement for the learners and educators involved in the learning process.

5.2 CONCLUSION

Recently, online adaptive MOOCs is considered one of the most important platforms of online learning in higher education institutions. So, this thesis offered an innovative solution which enhances online adaptive MOOCs to deliver a new technique for delivering learning materials, content and assessment tools. Moreover, the learners will be able to access the courses's contents and exams that meet their requirments in terms of learning contents that are suitable for him.

Many techniques and frameworks have been offered to create online adaptive MOOCs platforms, but these frameworks and techniques suffer from drawbacks and challenges. One of the most important challenges is the dropout rate which is high. Therefore, this proposed system delivered some solutions to overcome such challenges, where the adaptive MOOCs framework was presented to enhance the learner's performance which is based on (ILOs) that were selected by the learners. To make it simple, the following scenario shows how a learner can start following a course in MOOC:

- Firstly, the learner should take the placement test, to determine his level and to enable him to go through the learning course.

- The system provides the learner with more options for the selection of the ILOs which meet his requirements and needs, so the learning process can be learner-centered or oriented rather than teacher-oriented.
- The learner explores the learning materials through specific learning paths, which will be generated adaptively, and enable the learner to move from a level to another and the pedagogical relationships were taken into consideration between the learning concepts.
- Learning style also was considered in the delivering of learning materials for learning concepts to achieve the variance to the learning process.
- The manual mapping between the learning concepts (LCs) and learning materials LMs.
- The automatic mapping between (LCs) and learning materials by using the support vector machine (SVM) Classifier algorithm.
- Manual weights for learning materials and the questions which consist of the exams or assessment tools.
- Automated generation of assessment tools, such as exams with three levels (easy, medium, and hard), was based on the fuzzy logic technique categories.
- The automated mapping between Grade Point Average (GPA) for the learner and the level of assessment using the Fuzzy Logic technique, to deliver a suitable exam for a beginner, intermediate, or advanced learner.

Therefore, the evaluation of the proposed adaptive MOOCs system based on the ILOs was carried out at three phases:

1-**The First Phase:** The proposed system was evaluated by using several indicators, such as the Accuracy Rate for Support Vector Machine (SVM), TP Rate, FP Rate, the Precision and Recall, F-Measure and finally the ROC Area. These indicators showed that the results were interesting and provided good results in the classification process.

2-**The Second Phase:** The evaluation focused on the learner's assessment when the query was sent to the system to extract questions randomly. The results were provided by determining the difficulty specifications for the level of questions (easy, medium and hard), so Fuzzy Logic technique was applied to determine the difficulty level of the exam to suit the learner's level.

3- **The Third Phase:** The evaluation concentrated on Grade Point Average (GPA) for the learner. Accordingly, the system selects the suitable exam level (easy, medium, or hard) and delivers it to the learner according to his level (beginner, intermediate, or advanced). Also, applying the Fuzzy Logic technique, which is divided into three categories, such as easy questions, medium questions, and hard questions. So, the evaluation of (COG), that the system managed to deliver the suitable level of the exam (easy, medium, or hard) for the learner, depended exactly on the aforementioned categories of Fuzzy Logic.

Consequently, the results were promising as shown in all the indicators previously mentioned, in the classification process ,which were conducted in the proposed system on classes or LCs which contain LMs, such as acuuracy rate for SVM classifier equals by 71.5%, and the weighted Average for TP Rate = 0.715, FN Rate =0.285, FP Rate =0.028, TN Rate =0.972, Precision = 0.738, Recall =0.715, F-Measure =0.678, and finally ROC Area= 0.939. In addition, Fuzzy Logic Technique provided promising results to deliver an exam according to difficulty levels to is compatable with the level of the learner depending on his Grade Point Average (GPA).

5.3 FUTURE WORK

As more efforts provided many theses or studies to enhance or develop online learning as MOOCs platforms throughout the world, this Master's thesis was accomplished successfully. It was also satisfying, which aimed to deliver adaptive MOOCs system, but there is a need to keep pace with evolution according to the requirements for the learning process and learners. A number of research directions can be summarized as follow:

- Using different machine learning algorithms to classify more accuracy and achive high ratios for mapping automatically between learning materials (LMs) and learning chapters or concepts related to ILOs and assessments,such as Nural Networks ,Genetic Algorithems or Random Forests,Decision Trees etc..

- Generalize and experiment this proposed work to the educators for utilization and application in the educational institutions and MOOCs platforms, where this system provides an effective classification for learning materials, and selects the most suitable exam.

- Investigating the effectiveness of the proposed approach in delivering courses that will be explored by employees in a specific company and follow up the achieved LO. As such, more research work will be required to integrate a learner model in the proposed approach.

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APPENDICES

Appendix A:

The Code used in Java language to present the process for data preparation for SVM classifier

```
Public void load Dataset(String file Name) { try }
        Text Directory Loader  = new Text (Directory Loader);
        Loader set Directory=(new File(file Name));
        String To Word Vector filter = (new String To Word Vector);
        Instances raw Data = (loader get Data Set);
        Word  Tokenize rTokenizer    = (new Word Tokenizer);
        String delimiters = " \r\t\n.,;:\'\"()?!-><#$\\%&*+/@^_=[]{}|`~0123456789";
        tokenizer.  Set  Delimiters(delimiters);
        filter.  Set Tokenizer (tokenizer);
        SnowballStemmer stemmer = (new SnowballStemmer);
        stemmer.setStemmer("porter");
        filter.setStemmer(stemmer);

        filter.setStopwords(new File("d:\\stopwords.txt"));
        filter.setTFTransform(true);
        filter.setIDFTransform(true);
        filter.setStopwordsHandler(stopwordsHandler);
        filter.setLowerCaseTokens(true);
        rawData.setRelationName("khetam");
        filter.setInputFormat(rawData);
        trainData = Filter.useFilter(rawData, filter);
        trainData.setRelationName("khetam");
            { catch (Exception e) }
        System.out.println("Problem found when reading: " + fileName);
```

Appendix B :

Building and evaluation SVM classifier

```
(public void evaluate) { try }
        trainData.setClassIndex(0);
         filter = new StringToWordVector();
         WordTokenizer tokenizer = new WordTokenizer();
        String delimiters = " \r\t\n.,;:\'\"()?!-><#$\\%&*+/@^_=[]{}|`~0123456789";
        tokenizer.setDelimiters(delimiters);
        filter.setTokenizer(tokenizer);


          filter.setTFTransform(true);
        filter.setIDFTransform(true);
        filter.setStopwords(newFile("E:\\project\\stop lists\\stop lists\\stopword
list2.txt"));
         filter.setLowerCaseTokens(true);
        classifier = new FilteredClassifier();
        classifier.setFilter(filter);
         if (classifierName.equals("SMO"))
          {  classifier.setClassifier(new SMO());}
         Evaluation eval = new Evaluation(trainData);
        eval.crossValidateModel(classifier, trainData, 4, new Random(1));
       classifier.buildClassifier(trainData);
     { catch (Exception e) }
       ( e.printStackTrace);
       {System.out.println("Problem found when evaluating");}
```

Appendix C:

The Classified Portion of the Code for SVM Classifier

```
(public void classify) {try }
        // filteredClassifier is the loaded SVM classifier object
         double[] preds = filteredClassifier.distributionForInstance(instances.instance(0));

         for (int i = 0; i < preds.length; i++) {

            System.out.println("preds[" + i + "]=" + preds[i]); }

         for (int i = 0; i < preds.length; i++) {
            if (preds[i] > 0) {
               System.out.println(instances.classAttribute().value((int) i) + " =" + preds[i]) }

         // pred is the index of the predicted class
         double pred = filteredClassifier.classifyInstance(instances.instance(0));

          System.out.println("Class predicted: " + instances.classAttribute().value((int)
pred));

       } catch (Exception e) {

         System.out.println("Problem found when classifying the text");
         e.printStackTrace();
```

Appendix D:

The query for extract questions from database randomly.

```
SELECT   q_id,
        hard_perc,
        (SELECT   fl.lvl
           FROM   fuzzy_lvls fl
          WHERE   hard_perc BETWEEN fl.from_mark AND fl.to_mark)
           AS lvl
  FROM   (SELECT   q_id, hard_perc
           FROM   (SELECT   a.q_id, a.hard_perc
                     FROM   questions a, mat_q_mapping m
                    WHERE       a.q_id = m.q_id
                            AND a.hard_perc IS NOT NULL
                            AND m.mat_id = 1
                  ORDER BY   DBMS_RANDOM.VALUE)
          WHERE   ROWNUM <= 5
         UNION
         SELECT   q_id, hard_perc
           FROM   (  SELECT   a.q_id, a.hard_perc
                     FROM   questions a, mat_q_mapping m
                    WHERE       a.q_id = m.q_id
                            AND a.hard_perc IS NOT NULL
                            AND m.mat_id = 2
                  ORDER BY   DBMS_RANDOM.VALUE)
          WHERE   ROWNUM <= 5
         UNION
         SELECT   q_id, hard_perc
           FROM   (  SELECT   a.q_id, a.hard_perc
                     FROM   questions a, mat_q_mapping m
                    WHERE       a.q_id = m.q_id
                            AND a.hard_perc IS NOT NULL
                            AND m.mat_id = 3
                  ORDER BY   DBMS_RANDOM.VALUE)
        WHERE   ROWNUM <= 10)
```

Appendix E

The part of code used to determine the classes of questions and the levels of memberships in fuzzy logic**.**

```
FUZZIFY easy questions
    TERM low Easy: = (0.0, 1.0) (40.0, 1.0) (50.0, 0.0) ;
    TERM medium Easy: = (35.0, 0.0) (70.0, 1.0) (75.0, 0.0) ;
      TERM high Easy: = (70.0, 0.0) (80.0, 1.0) (100.0, 1.0) ;
END_FUZZIFY
FUZZIFY medium  questions
    TERM low Medium: = (0.0, 1.0) (40.0, 1.0) (50.0, 0.0) ;
    TERM medium Medium: = (35.0, 0.0) (70.0, 1.0) (75.0, 0.0) ;
    TERM high Medium: = (70.0, 0.0) (80.0, 1.0) (100.0, 1.0) ;
END_FUZZIFY
FUZZIFY hard  questions
    TERM low Hard: = (0.0, 1.0) (40.0, 1.0) (50.0, 0.0) ;
    TERM medium  Hard: = (35.0, 0.0) (70.0, 1.0) (75.0, 0.0) ;
      TERM high Hard: = (70.0, 0.0) (80.0, 1.0) (100.0, 1.0) ;
END_FUZZIFY
DEFUZZIFY tip
    TERM easy: = (0.0, 1.0) (40.0, 1.0) (50.0, 0.0) ;
    TERM hard: = (70.0, 0.0) (80.0, 1.0) (100.0, 1.0) ;
    TERM medium: = (35.0, 0.0) (70.0, 1.0) (75.0, 0.0) ;
    METHOD : COG;
    DEFAULT: = -1.0;
    RANGE: = (0.0 .. 100.0);
END_DEFUZZIFY
```

Appendix F:

The part of code of rules block to extract the result (Tip) that is fuzzy logic value.

```
RULEBLOCK No1
    ACT: MIN;
    ACCU: MAX;
    AND: MIN;
    RULE 1: IF ((easy questions IS low Easy) AND (medium  questions IS medium Medium)) AND (hard questions IS low Hard) THEN tip IS medium;
    RULE 2: IF ((easy questions IS medium  Easy) AND (medium questions IS low  Medium)) AND (hard questions IS low Hard) THEN tip IS easy;
    RULE 3: IF ((easy questions IS high Easy) AND (medium questions IS low  Medium)) AND (hard questions IS low Hard) THEN tip IS easy;
    RULE 4: IF ((easy questions IS low Easy) AND (medium questions IS low  Medium)) AND (hard questions IS low Hard) THEN tip IS easy;
    RULE 5: IF ((easy questions IS low Easy) AND (medium questions IS low Medium)) AND (hard questions IS medium Hard) THEN tip IS medium;
    RULE 6: IF ((easy questions IS low Easy) AND (medium questions IS low Medium)) AND (hard questions IS high Hard) THEN tip IS hard;
    RULE 7: IF ((easy questions IS low Easy) AND (medium questions IS medium Medium)) AND (hard questions IS low Hard) THEN tip IS medium;
    RULE 8: IF ((easy questions IS low Easy) AND (medium questions IS medium Medium)) AND (hard questions IS medium  Hard) THEN tip IS hard;
END_RULEBLOCK
END_FUNCTION_BLOCK
Tip value: 59.36
```

الملخص

مع انتشار منصات التعلم الإلكتروني عبر الإنترنت، ومن ضمنها المساقات التعليمية الضخمة المفتوحة على الإنترنت بما تسمى (MOOCs)، توفرت ثروة من مصادر التعلم المتاحة حول مواضيع علمية ودورات تعليمية متنوعة. لذلك، يمكن للمتعلمين والمهتمين من ذوي الخلفيات المختلف[ومستوى العلم والمعرفة]حول موضوع ما، البدء بتعلم دورات تعليمية لأسباب عدة، منها أن المتعلمين يحتاجون لتعلم دورات تعليمية مختلفة مناسبة لمستواهم العلمي والمعرفي مما يساعدهم على تطوير قدراتهم وتمكينهم من إتقان بعض المهارات العلمية بغض النظر عن حدود الزمان والمكان، حيث أن هناك دورات تعليمية قد يكون من الصعب تعلمها، وأخرى من السهل جدًا تعلمها وأن نتائج ومخرجات التعلم في الدورات التعليمية ليست نتيجة التعلم المقصودة أو المرجوة لهم. ولمناقشة هذه الأسباب والتغلب عليها، هناك جهود ومحاولات مختلفة لتوفير التكيف مع منصات MOOCs التعليمية من حيث مصادر التعلم، وأدوات التقييم، وعرض المحتوى، والتسلسل المنطقي لمسار التعلم للوصول الى الهدف، لذلك تهدف هذه الأطروحة إلى تقديم إطار ونموذج تعليمي تكيّفي مقترح للمتعلم- كدورة تعليمية تكيفيّة - من خلال المحتوى وأدوات التقييم التي تحسن من مستواه التعليمي وتوفر احتياجاته التعلمية. وبالرغم من عملية التكيف هذه، لا تزال هناك حاجة لمواكبة واستكشاف التقنيات الممكنة للربط التلقائي بين كل من مصادر التعلم بوسائلها المختلفة وأدوات التقييم على أساس المخرجات التعليمية المحددة والمرغوبة من أجل تحسين المستوى التعليمي ودعم متطلبات المتعلمين.

لذلك، ساهمت هذه الأطروحة بشكل أساسي في استخدام خوارزميات تصنيف تلقائي، للتكيف والملاءمة مع منصات MOOCS التعليمية، للخروج بنتائج أفضل عند تطبيق النظام، حيث تم استخدام تقنيات التعلم الآلي مثل شعاع الدعم الآلي (Support Vector Machine (SVM، للمطابقة التلقائية بين مصادر التعلم التي تم جمعها من أكثر من منصة تعليميه وخاصة موقع كورسيرا الإلكتروني، والمفاهيم التعليمية، لتصنيفها بطريقة مناسبة حسب مدى صلتها وعلاقتها بمخرجات التعليم المقصودة (ILOs)، وقد بينت مقاييس ومؤشرات الدقة، نتائج محسنة بمقدار % 71.5 ، وكذلك تم استخدام تقنية المنطق الضبابي Fuzzy Logic لتحديد مستويات أدوات التقييم كالأسئلة والامتحانات وتصنيفها بمستويات مختلفة (سهلة ومتوسطة وصعبة)، حسب تقسيمات معينه وإدخال قيمها وأوزانها يدويا من قبل الخبير أو مدير النظام. وقد تميزت هذه الأطروحة، بالاعتماد على نتيجة الطالب أو المتعلم في امتحان المستوى Placement، حيث تم استخدام الربط التلقائي بين معدل الطالب التراكمي (GPA) في امتحان المستوى ومستوى الامتحان level exam، إن كان سهلاً أو متوسطا أو صعبا، لاختياره وتقديمه للطالب والمتعلم حسب مستواه التعليمي- مبتدئاً أو متوسطاً أو متقدماً -، وقد أثبت تطبيق وتجربة هذا النموذج المقترح نتائج دقيقة ومرضية، لتصنيف مصادر التعلم وأدوات التقييم بما يتناسب ويتكيف مع قدرات واحتياجات المتعلمين.