A Framework for Automatic Exam Generation based on k-means and Genetic Algorithm

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ABSTRACT
Manual generate of test papers is a difficult assignment for instructors, particularly inside a brief timeframe outline. It requires a large amount of work and time to accomplish a standard nature of the test papers. question paper necessarily to consider several items such as difficulty level marks, numericalas well as theoretical contents of the paper, weightage ofquestions, and repetition of exam questions in terms of their characteristics is one of the most important problems in generating the test. The scientific contribution of this research is a proposed framework based on combine between genetic algorithms and unsupervised learning methods (k-means) to generate a test paper according to Bloom's criteria, where the k-means method collects each group of questions with the same features in one group. where address the problem of the repetition of questions that have the same characteristics. In theexam paper, based on the previous step, it will be easy for the genetic algorithm to choose the best exam according to the six levels bloom's. The framework consists of several phases .in the first phase, generate the questions bank in the second phase,the questions were divided into six groups that were similar intheir properties using the k means method, in the third phase, used a random sorting function to randomly arrange each group to ensure that the questions were not repeated when the initial population was created. Used A question bank of 800 questions including all types of questions.

General Terms
Genetic Algorithm, k-means

Keywords
Automated Exam Questions Generator, Bloom's Taxonomy, Genetic Algorithm, k-means

1. INTRODUCTION
The exam is a method of evaluating the instructors that is systematic and ongoing. Prepare for their students with the goal of evaluating their performance on the basis of the learning outcome. [1]. High-quality test questions can determine a student's level of achievement and can also indicate the level of effort put in by teachers and educational institutions. [2][3]. As a result, creating useful exam questions is a critical duty. Essays, short responses, true and false questions, multiple choice questions, and other types of questions can all be found on a normal examination question paper.

Exam question generation is difficult, time-consuming, and time-consuming for instructors. [1]. question paper necessarily to consider several items such as difficulty level marks, numerical as well as theoretical contents of the paper, and weightage of questions according to the marks to cover the several capabilities of students. In addition, the following issues [4] must be addressed. [4].

- Does the question paper take into account both time and grade limits, as well as the level of difficulty?
- Is the material of the question paper appropriate in terms of subject coverage?
- Can questions be used to measure student ability at multiple levels of Taxonomy?

Manual exam paper preparation necessitates a significant amount of effort to ensure that educators adhere to all educational organization standards while preparing exam papers. It is tedious and thorough, with the possibility of human error [2].

Time constraints to generate good quality exam questions based on the institution's requirements, question style that is generated repeatedly over time, examination questions that are biased towards a certain level of difficulty, and exam questions that do not consider all six levels of Bloom's Taxonomy's cognitive domain [5].

The evolution of approaches helps instructors save time and effort when writing test questions. Genetic algorithms (GAs) are search and optimization algorithms that are based on evolutionary concepts. Also, GAs are one of the well-known machine learning algorithms. Conceptually, they mimic process of natural selection. GAsuse a parallel search to randomly select individuals from a population of candidates, apply crossover and mutate the candidates until the system meets some user- defined criterion [7]. This genetic algorithm can automatically combine test papers according to the standard of difficulty degree, knowledge level, and the proportion of questions [8]. As a result, the generator can automatically prepare new exam questions based on the Genetic Algorithm (GA).

This study aims to propose a framework for an Automated Exam Question Set Generator (AEQSG) based on theintegration the k means clustering with Genetic Algorithm (GA) to resolve this problem.

There are five sections to this study. Section two, the prior study, follows the introduction. The research technique is detailed in Section three, which breaks down the phases of the proposed strategy. The recommendations and results are discussed in Section four andfinally, the conclusions and future works.

2. LITERATURE REVIEWS
Abd Rahim, and et al, 2020.This research produced an Automated Exam Question Set Generator (AEQSG) using Utility Based Agent (UBA) and Learning Agent (LA). Moreover, AEQSG stratifies Bloom Taxonomy (BT) scaling to automate Bloom's Taxonomy (BT) difficulty level distribution and Genetic Algorithm (GA) to optimize the generation of exam question set and generate high-quality exam question set that follow educational organization's Standards. The aim of a utility-based agent in AEQSG is to present the users an option to selection actions depended on a user's utility for each generation state. At the same time, the purpose of the learning agent in AEQSG is to learn from its previous exam results [8].

Paul, Dimple Valayil, 2020. The study focuses on the creation of question paper templates and their application in the dynamic generation of examination question papers. This study examines the initial population generation, chromosome encoding, genetic manipulations, and empirically verifies that the created question paper templates are best suited for the dynamic examination paper generation system employing the Genetic Algorithm (GA) and educational taxonomies. In terms of topic coverage, learning domains, and mark distribution, this new strategy outperforms previous techniques that produce assessment exams at random. The study was carried out for the Goa University Examination System. Software Engineering (SE) and Information Technology (IT) are two disciplines taught in the third year of Goa University's three-year computer science bachelor's degree program. The results of the study are a template for a matrix of shape 3 by 3 is well getting generated with a fitness value of 0.9456 which is the optimum solution [9].

Bangera Shanika, et al ,2019. The goal of this project is to make it easier for educators to give an exam question paper using a Genetic algorithm (GA). The generator can auto-generate new exam questions using GA and covers six levels of Bloom's Taxonomy to provide high-quality exam questions that can assess learners at different levels based on Bloom's cognitive scope and chapter selection. In this track, the absolute number of test questions is shown as five. The degree program normally comprises five Multiple Choice investigations. Before test questions can be created, the Automated Exam Question Generator expects teachers to choose a course code, an exam question set, and sections. The fitness value for this model has been defined as the type of test questions weightage rate based on the dimension of the psychological area secured. Because of the low fitness value, high-quality test addresses will be provided. Each experiment used a different number of parts. The weightage rate of exam questions developed using this methodology was estimated to be 70%. The greatest weightage rate for exam questions is 90 percent, while the lowest weightage rate is 40 percent. The reduced number of existing questions for each Bloom's Taxonomy level in the question bank influenced the project's final outcome. [10].

Ashraf Amria, and et al, 2018. This research offered a system based on Bloom's taxonomy that allows instructors to link questions to intended learning goals. It also covers the fundamentals and requirements for creating examinations automatically. It also describes a prototype implementation of an authoring tool for creating tests to assess whether or not intended learning outcomes have been met [11].

Song, Wanli, 2018. The researchers in this paper studied online exam paper composition algorithms depends on a genetic algorithm. Then this technique is used to prepare the structure of the exam paper automatically, composites the examination content. The results of the paper online testing system based on this algorithm show that the GA is effective. On the premise of guaranteeing the quality of the test paper, ALSO improves the efficiency of online testing. The difficulty coefficient has a 30 percent difference, which influences the fairness of the students' evaluation. Furthermore, according to the user-defined circumstances, GA can acquire more than 90% of the exam papers' fitness. [7].

Abd Rahim, Tengku Nurulhuda Tengku, et al, 2017.

This study proposes an automated test question generator to address the issue of creating multiple-choice exam questions. The teacher can auto-generate new exam questions based on the Genetic Algorithm (GA) and six levels of Bloom's Taxonomy to develop high-quality exam questions that can test the various levels of learners based on Bloom's cognitive domains and educator-selected chapters. The prototype, which included 500 sample questions, was run 50 times with different amounts of chapters for each test case. It achieves a score of 90 percent for the greatest exam question weightage, with a score of 70 percent for the average exam question weightage percentage generated. The lowest weighted percentage of exam questions generated is 40%. The result is influenced by the lesser number of questions in the questions bank for each Bloom's taxonomy level. [12].

Havan, Aishwarya, et al, 2016. They came up with a solution in the shape of an Automated Question Paper Generator System that employs Fuzzy and Apriority approaches. It is designed to allow universities to quickly generate question papers with random but even questions that cover most chapters of a topic at various levels and mail them to colleges. [13].

The researchers Ashok Immanuel and et al, 2015. They have proposed "Framework for Automatic Examination Paper Generation System," depended on an evaluation system where a university produces an exam every year.

The framework is dependent on the client- server architecture, it would be a three-tier model including the question gathering which would be the question bank, Question Paper Generation Algorithm which would extend logical tier, bank interface and interface for the user. This framework provides a platform to aggregate questions; classify questions, and associate questions with the syllabus of the course. This supports the build of a system that would simplify the standardization of assessment to a greater extent. It also attempts to provide flexibility in defining the classification criteria which could be distinct for every educational institution [14].

Table 1. Comparison between literature reviews

Researchers	Objectives	Techniques
Abd Rahim , 2020	Produced an automated examquestion set of generator.	Using utility based agent & Learning GA to optimize the generation of exam.
Paul, Dimple Valayil,2020	Focus on the question paper template generation.	GA Educational taxonomies.
Bangera Shanika,et al ,2019	Generation paper on GA.	GA Blooms cognitive scope.
Ashraf Amria, and et al , 2018	Educators can use this framework to map questions to methods. Bloom's cognitive theory is the base of the learning results.	Learning management system Naïve Bayes , support Vector , K-nearest neighbor.
Song , Wanli ,2018	Online test paper.	GA.
Abd Rahim, Tengku Nurrlhude Tengku , et al , 2017	Present an automated exam question generation of multiple choice exam questions.	GA Educational taxonomies.

Havan, Aishwarya, et al, 2016	Present the answer in the form of a system that generates automated question papers.	Fuzzy algorithm.
Ashok Immanuel and et al, 2015	Proposed framework for automatic examination paper generation system depended on an evaluation system.	Pattern composer Syllabus engine.

Most of the previous studies used Genetic Algorithms to generate the exam paper, and the most difficult challenge was to generate an exam paper without repeating the questions taking into account the six levels of Blooms. The scientific contribution of the research is to introduce an improved framework based on Bloom's levels by combining genetic algorithms with unsupervised learning methods, where the unsupervised learning methods can collect each group of questions that have the same characteristics (time, degree of difficulty, class...etc.) in one group. This reduces the presence of questions that have the same characteristics and not to be repeated in the exam paper. It facilitates the work of the genetic algorithm in choosing the best exam based on levels of Blooms. also increases the accuracy of the genetic algorithm. Thus, will get a high-quality exam paper covering the six levels of knowledge.

3. THE PROPOSED FRAMEWORK

In this section, present the proposed framework in detail. divided the proposed framework into four sequential stages, the first stage is the question bank, the second stage is the application of the algorithm of assembly, then in the third stage, the application of the Genetic algorithm, and in the final stage the examination paper. As shown in Figure 1.

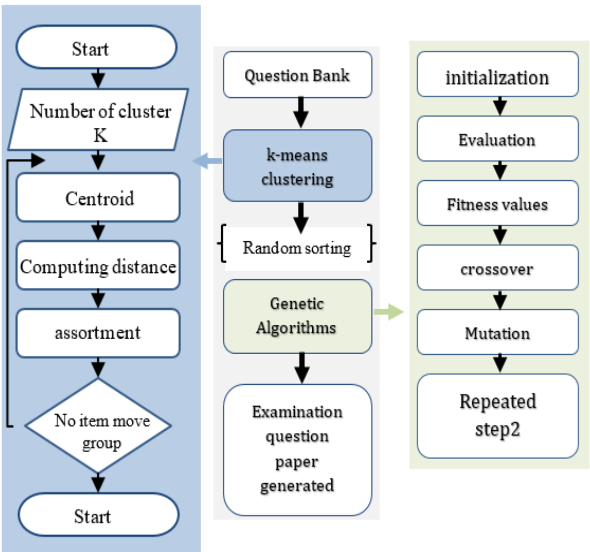

Figure 1. The Proposed Framework

3.1 Question bank

Previous exam questions will be processed and saved in the questions bank as input for the Automated Exam Questions Generator during this phase. In addition, the educator can develop new exam questions and save them in a question bank for later use. The Automated Exam Questions Generator creates new exam questions based on Bloom's Taxonomy's six levels.

The data set was obtained from EGI. Department of Information Systems. Course title in the database, the dataset consists of 800 rows for four consecutive years, and 9 features. As shown in Table 2.

Table 2. Description of dataset

factor	Description
Question id	ID is a unique number for every question that is not repeated Such that (2L_2020_1_30%) (level_year_serial_quality)
course code	A Course Code is a 5-digit letters and numbers code that is produced and assigned to the courses generated by institutions.
Mark	Refer to score every question
Chapter	Refer to number of chapters
Question type	Refer to the question's type. Multiple choice, true or false, short answer, and essay are examples of question types.
Course title	Refer to name of course such as (database, programming . . . etc.)
CLO	Refer to course learning outcomes
Difficult level	The Bloom taxonomy cognitive level is used to determine the difficulty level. In the OBE documents for each course, there is a predefined cognitive level.
Time	Reflect the total time required to complete the question

3.2 K-means algorithm

The K-means clustering method is a partition clustering algorithm that optimizes a criterion function to group a set of objects into k clusters. [15].

At this stage, used the k mean technique to divide the question bank into groups that have similar properties in terms of the type of question, the time, the degree of difficulty of the question, the separation ... etc., so that get similar groups in these features to facilitate the generation of an exam paper after that through the genetic algorithm.

There are three basic steps to the technique:

(1) Choosing k objects as cluster centroids: In this phase, chose six centroids (k=6) based on SSE, as shown in figure 3. (2) Objects are assigned to the closest cluster based on means, and (3) centroids are updated based on the assigned data. Steps 2 and 3 are repeated until no item joins a cluster or the criteria function improves after a certain number of iterations [16]. The goal of the traditional K-means clustering technique is to find a set C of K clusters CJ with cluster mean cj in order to reduce the number of squared errors [16]. Equation 1 demonstrates this.

$$E= \sum_j^k =1 \sum xi \ \in cj \ ||cj - xi||^2 \qquad (1)$$

||... || is the distance metric between a cluster mean and a data point *xi Cj*; E is the addition of square error *(SSE)* of objects with cluster means for K cluster; ||... || is the distance metric between a cluster mean and a data point *xi* Cj. Equation 2 demonstrates this.

$$||x - y|| = \sqrt{\sum_{i=1}^{v} |xi - yi|^2} \qquad (2)$$

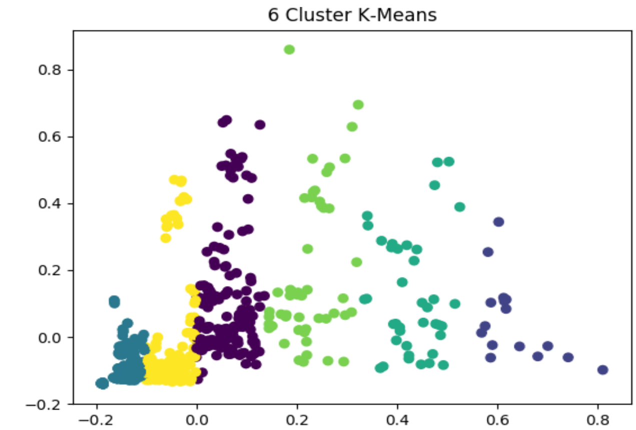

Figure 2. Example of visualization segmentation of questions bank

The following is a vector of cluster mean Ci. As show in Equation 3

$$cj = \frac{1}{|cj|}\sum_{i\in cj} xi \qquad (3)$$

A flowchart of K-means clustering has been depicted, which includes six key stages. To begin, let's look at the preliminary value of centroids: Let (C1, C2...) be the centroids that harmonize. Second, the object-centroid distance is calculated, which is the distance between the cluster centroid and all objects. After that, the distance matrix at iteration 0 is constructed using the Euclidean distance. Every item is represented by a column in the distance matrix. The distance of every object in the first row corresponds to the distance of every object in the second row, and the distance of every object in the second centroid corresponds to the distance of every object in the second centroid. Object clustering in the third row: Assign each object to the location with the shortest distance. Determining the centroids at iteration 1 of the 4th row: by identifying the components of all groups, the new centroid of every set is computed on the basis of these new memberships. Repeat step 2 for the fifth row. The last iteration grouping is compared in the sixth row, and this iteration states that groups are not shifted by objects. As a result, K-means clustering algorithm has become stable, and iteration is no longer required. [17].

$$SSE = \sum_{i=1}^{n}(X_I - \bar{X})^2 \qquad (4)$$

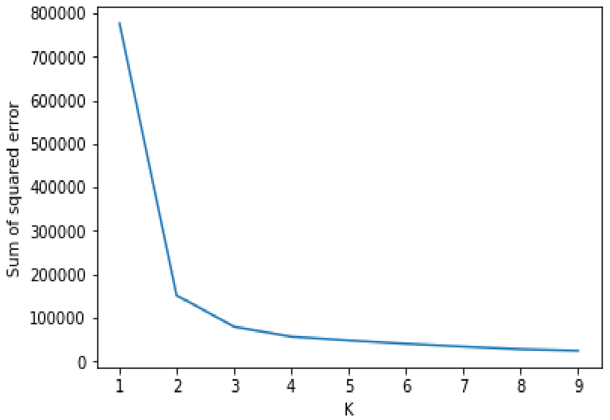

Figure 3. Results of Evaluation k-means cluster using SSE

3.3 Random sorting

The output of the previous assembly stage is that got 6 sets of clusters. Each cluster has a set of similar questions in its own features, at this stage, use the random sorting function to randomly arrange each cluster to ensure that it is not repeated when choosing a set of random solutions.

3.4 Genetic algorithm

Initialization, Evaluation, Selection, Crossover, Mutation, and Repeat are the generic processes of Genetic Algorithm [19] [20].

1) Initialization: Three initial populations will be established by picking questions at random from the questions bank. It was then separated into a number of clusters. To avoid predicting question patterns, a simple query was run beforehand to filter all of the questions in the bank, resulting in the development of new exam questions containing only questions from selected chapters and excluding previous questions from two consecutive years.

level	2L	5L	5L	6L	2L	4L
Chromosome 1	40	90	90	100	30	80
level	2L	4L	2L	4L	5L	2L
Chromosome 2	40	60	30	80	90	30
level	2L	6L	2L	1L	4L	5L
Chromosome 3	40	100	30	20	80	90
level	2L	6L	2L	1L	4L	5L
Chromosome 4	50	100	70	80	80	80
level	2L	2L	3L	6L	6L	5L
Chromosome 5	40	40	70	100	100	90
level	2L	3L	6L	2L	5L	5L
Chromosome 6	20	70	100	30	90	90

Figure 4. Initialization of population

Each population is made up of chromosomes, and each chromosome is made up of genes. Each gene represents a question in the test set, and each chromosome represents the entire set [21].

2) Evaluation (fitness values): Just when new population is generated or population is initialized, evaluation of the fitness values of the candidate solutions are carried out. Each chromosome in the population will be examined, and a fitness value for each chromosome will be calculated. The fitness value will be derived using Bloom's Taxonomy (the six levels of cognitive domains with varying degrees of ability) and the weightage percentage of quality exam questions as given in Table 3 below [2][3].

Table 3 shows the weighted average of exam question quality

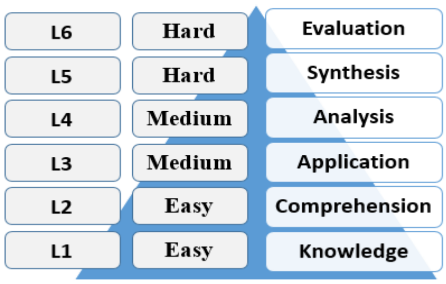

Figure 5. The Six Level BLOOM'S

The weighted average of exam question quality is determined in table 3 below based on the Bloom's taxonomy classification coverage, where Knowledge and Comprehension levels are grouped as Easy; Application and Analysis levels are grouped as the good quality of exam questions covers all three Bloom's taxonomy classifications, i.e. Easy, Medium, and Hard.

Exam questions of medium grade contain at least two Bloom's taxonomy classifications: Easy and Medium combined, Medium and Hard combined, or Easy and Hard combined. Only one of Bloom's taxonomy classifications is covered by the poor quality of exam questions [2].

$$\textbf{Fitness value} = 1/Q \qquad (5)$$

$$Q = \frac{\sum weightage}{number\ of\ genes}$$

Table 3. Fitness value for each chromosome

Chromosome	Fitness values
1	0.014
2	0.018
3	0.016

Chromosome	Fitness values
4	0.013
5	0.013
6	0.015

5) Selection: more copies solutions are allocated by means of selection with high-level fitness and the idea of survival possibilities of being fittest is imposed on the solutions of the candidates. The main notion choice is to choose the solutions which are better and favoring them over other ones. Therefore, many procedures of selection were suggested to accomplish this notion. Based on the fitness value or quality of questions.

Table 4. Quality of Exam Questions Weightage Percentage

Good	6Level	100%	e.g. Knowledge, Comprehension, Application, Analysis, Synthesis and Evaluation
	5Level	90%	e.g. Knowledge, Comprehension, Application, Analysis and Evaluation
	4Level	80%	e.g. Knowledge, Comprehension, Analysis and Synthesis
	3Level	70%	e.g. Comprehension, Analysis and Synthesis
Medium	4Level	60%	e.g. Comprehension, Application, Analysis and Evaluation
	3Level	50%	e.g. Knowledge, Application and Evaluation
	2Level	40%	e.g. Analysis and Synthesis
Bad	2Level	30%	e.g. Application and Analysis
	1Level	20%	e.g. Synthesis

The best population is determined by the fitness function with the lowest value among the six original populations, and it is chosen using the Roulette Wheel [22] [23].

Parent 1	40	90	90	100	30	80
Parent 2	40	90	90	100	30	80

Figure 6. Show the parent based on lowest values of fitness function

3) Crossover: Combining parts of two or more of the main solutions to have new and better solutions (i.e. offspring) [21]. There are several ways to achieve this and the efficient performance relies on the recombination mechanism which should be properly designed.

To improve the fitness value of the created chromosome, a single crossover approach is used, with the crossover point chosen at random. Figure 6 illustrates the situation.

Parent 1	40	90	90	80	80	80
Parent 2	50	100	70	100	100	90
Parent 3	40	40	70	100	30	80

Figure 7. Show mating pool for the parents

4) Mutation: Depending on the mutation rate, a mutation process will replace a few genes with new genes. In other words, questions that appear on the exam more than once will be removed and replaced with new questions based on the mutation rate.

Finally, the procedure will be repeated from step 2 (**assessment**) through step 5 (**mutation**) until the best solution or complete loop is discovered. By comparing all fitness values, the lowest fitness value can be found. To assess optimal fitness, the coverage of Bloom's Taxonomy levels in created exam questions is used.

4. EXAMINATION QUESTION PAPER

According to the results of the trial, the weighted average of exam questions is 84%. The highest weighted exam question percentage is 95%, while the lowest is 60%. Since there are fewer questions for each Bloom's Taxonomy stage in the issue bank, the final outcome of this study is influenced.

Table 5. Comparison between results of literature review

Studies	Highest Weightage Rate	Least Weightage Rate
Bangera Shanika Ashok Shanthi,2019	The weightage rate of exam questions is normally estimated to be 70%.	The lowest percentage of exam questions that are weighted is 40%.
Tengku Nurulhuda Tengku Abd Rahim,2017	It achieves a score of 90% for the most weighted exam questions.	Exam question weightage percentage has an average value of 70%.
This Research	The greatest percentage of weighted exam questions is 95%.	Exam question weighted average is 84 percent, while the lowest is 60 percent.

Table 5 compares two studies; the findings indicate that the suggested framework outperforms the first and second studies in terms of weighted percentage of test questions and marginally outperforms the weighted average of exam questions, owing to the adoption of the k-means technique and function. Random order, which aided in reducing question frequency by selecting a random population from the questionbank.

5. CONCLUSION

The generator will auto-prepare novel exam questions dependent on the Genetic Algorithm (GA), as well as assess different levels of learners based on Bloom's cognitive domains and educator-selected chapters.

Question banks consist of 800 questions. They were divided into six groups with identical characteristics using the k means in the first step, and then each group was randomly arranged using a random sorting function to ensure that the questions were not replicated when the initial population was generated. After that, the genetic algorithm was used to obtain the best exam results.

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