

# A Survey on Automated Assessment Questions Generation System using Supervised Algorithms

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**Abstract:** *Assessment is the sole way to determine whether a teacher's lessons are effective and whether pupils are learning what they are supposed to. When test questions are manually generated, they are first created and then assigned at random to the exam. Manually producing test papers that adhere to the standards of a good test paper requires a lot of time and work. Assessments that are created expressly to evaluate students' technical abilities require more time to develop, and trainers are constantly looking for methods to learn more about their candidates by asking them questions on technical concepts. With the help of our technology, questions regarding numerous technological topics and domains may be automatically generated from a database. We use classification and supervised algorithms like the Naive Bayes Classifier, Random Forest Classifier, and Decision Tree to generate test papers depending on the predicted skill of the applicant. The supervised algorithms Naive Bayes, Random forest, and Decision tree are all examples. Instead of assessing the candidate's knowledge in a completely unrelated field, test questions based on the candidate's talents will efficiently evaluate the candidate's knowledge in the skills that they know. The opportunity for the recruiters to fully comprehend a candidate's capabilities will also allow them to make greater use of their talents and assign tasks to applicants based on how well they do in a specific skill.*

**Keywords:** Automated questions generation, Naive Bayes classifier, MYSQL, Random Forest Classifier, Decision Tree Algorithm

## I. INTRODUCTION

In recent years, the field of education has witnessed a significant shift towards technology-driven solutions. One such area of innovation is the automated generation of assessment questions using supervised algorithms. This approach shows the power of machine learning to create a system that can generate a wide range of assessment questions for various domains.

The goal of an automated assessment question generation system is to alleviate the burden on educators and instructors by automating the process of creating high-quality questions. By employing supervised algorithms, which learn from labeled training data, this system can effectively mimic the expertise and knowledge of human question creators.

The use of supervised algorithms enables the system to analyze and understand patterns in existing assessment questions, including their structure, content, and associated correct answers. Through this process, the system learns to generate questions that adhere to the same patterns and standards as those found in the training data.

This approach offers several advantages. Firstly, it provides a scalable solution, enabling the generation of a large volume of questions in a short period. Additionally, it ensures consistency in question quality and difficulty level, reducing potential biases and variations that may arise from manual question creation.

While these systems offer significant benefits, it's important to note that they are not intended to replace human instructors or domain experts. Rather, they serve as a valuable tool to enhance the efficiency and effectiveness of the question creation process, allowing educators to focus more on other critical aspects of teaching and assessment.

In conclusion, an automated assessment question generation system using supervised algorithms represents a promising advancement in the field of education. By harnessing the capabilities of machine learning, it enables the generation of diverse and high-quality assessment questions, streamlining the assessment process and enhancing educational outcomes.

## II. EXISTING SYSTEM

Many systems which are in existence to generate the questions in the assessment automatically using the concept of Bloom's Taxonomy which deals with the difficulty levels of the questions that need to be given in the assessment or test. These systems are designed using the algorithms like fuzzy and Apriori algorithms, Utility based and Learning agents, Ant colony algorithm and Genetic algorithm.

Using the complex algorithms like fuzzy algorithms, makes the system immutable to make any future updates.

The Apriori algorithm primarily handles categorical or binary data, as it relies on itemsets and frequent itemset generation. It does not directly handle continuous attributes, which are common in many real-world datasets. In contrast, supervised learning algorithms can handle both categorical and continuous attributes and are more versatile in terms of data types.

Supervised learning algorithms rely on labeled training data, where each input instance is associated with a corresponding target or class label. In contrast, learning agents, particularly in reinforcement learning, often operate in environments where the desired outcomes or optimal actions are not explicitly known or easily obtainable. This lack of labeled data can make training and evaluation more challenging.

## III. PROPOSED SYSTEM

This system aids in the automatic generation of assessment questions based on the skills and capabilities of the candidate, which in turn aids recruiters or examiners in effectively determining the strength of the particular candidate and aids them in making decisions based on the results and performance of the candidate in the assessment. Our system can overcome the drawbacks of the current system by focusing on the automatic generation of the questions along with the randomness and the difficulty levels of the questions that need to be generated in the assessment. In our system, the skills of the candidate are classified using the supervised classification algorithms of the Machine Learning with the good accuracy. In our system, we are also providing a user-friendly web application and user interface to communicate with users efficiently. Users may perform assessments using the offered application, and results are automatically saved in the database for further processing.

## IV. MODULES

### IMPORTING NECESSARY DEEP LEARNING MODULES

Numpy, Pandas, Sklearn, Matplotlib, Seaborn

### DATA COLLECTION

Gather a dataset that includes information about students which is more relevant to the system, such as the name, their CGPA and the level of understanding of different skills. You can obtain this dataset from sources like Kaggle or public datasets.

### DATA PREPROCESSING

Explore the dataset to understand its structure and features.

Handle missing values by imputing or removing them.

Split the dataset into training and testing sets.

### FEATURE ENGINEERING

Identify the most relevant features that contribute to the target variable and remove irrelevant or redundant features. Techniques for feature selection include univariate selection, recursive feature elimination, or feature importance using tree-based models.

### MODEL SELECTION AND TRAINING

Split the training data into further training and testing sets.

Train the chosen classification model on the training set using appropriate algorithms and techniques.

**MODEL EVALUATION**

However, in general, higher values of certain metrics indicate better performance, while lower values indicate poorer performance. Here's a general guideline for commonly used performance evaluation metrics:

**Accuracy:** This parameter assesses the general accuracy of the model's or technique's predictions. It is measured as the proportion between the number of occurrences that were properly categorised and the overall number of instances.

**Precision:** The ratio of accurate positive predictions to all positive forecasts is measured. True positives divided by the total of true positives and false positives is how it is determined.

**Recall (Sensitivity):** This statistic depicts the percentage of accurate positive predictions among all positive examples. It is determined by dividing the total of true positives and false negatives by the number of true positives.

**F1 Score:** This represents the harmonic mean of recall and accuracy. It offers a mix between recall and accuracy. As  $2 * (precision * recall) / (precision + recall)$ , it is computed.

**Confusion Matrix:** It offers a tabular representation of a classification algorithm's performance. The numbers of true positives, true negatives, false positives, and false negatives are displayed.

**MODEL DEPLOYMENT**

Once the model is trained and evaluated, deploy it for real-world use.

Create a user-friendly interface (web application, API, etc.) to interact with the model.

Continuously monitor and update the model as new data becomes available.


**QUESTION GENERATION**

Once the model is trained and validated, use it to generate new assessment questions. Provide it with relevant input, such as the desired topic or subject area and the type of question required (e.g., multiple-choice). The model will generate questions based on the patterns it learned from the training data.

**V. OUTPUT SCREENS**

```
importing
['poojitha', 'we', 21, 'poojitha@gmail.com', 'f', 'CSE', 2023, 7.5, 2, 1, 1, 0, 1, 2, 1, 3, 3]
backend_developer
advanced
['harini', 'er', 22, 'harini@gmail.com', 'f', 'ECE', 2023, 7.3, 1, 0, 1, 1, 1, 2, 1, 1, 0]
frontend_developer
intermediate
['sourav', 'ru', 12, 'sourav@gmail.com', 'm', 'CSE', 2023, 8.1, 3, 2, 2, 1, 1, 2, 1, 2, 1]
programmer
advanced
['ganesh ', 'bt', 20, 'ganesh@gmail.com', 'm', 'ECE', 2023, 7.6, 0, 0, 1, 0, 2, 3, 3, 1, 0]
frontend_developer
advanced
['kiran', 'ace', 34, 'kiran@gmail.com', 'm', 'CSE', 2023, 8.1, 1, 1, 1, 1, 1, 1, 1, 1, 1]
programmer
basic
```

name	mail	password	c	java	python	cplusplus	js	html	css	mysql	dbms	category	tag
poojitha	poojitha@gmail.com	Pooji	2	1	1	0	1	2	1	3	3	backend_developer	advanced
harini	harini@gmail.com	Test@123	1	0	1	1	1	2	1	1	0	frontend_developer	intermediate
sourav	sourav@gmail.com	Test@123	3	2	2	1	1	2	1	2	1	programmer	advanced
ganesh	ganesh@gmail.com	Test@123	0	0	1	0	2	3	3	1	0	frontend_developer	advanced
kiran	kiran@gmail.com	Test@123	1	1	1	1	1	1	1	1	1	programmer	basic



**LOGIN WITH YOUR USERNAME**

SOURAV@GMAIL.COM, Welcome to ASSESSMENT

you have to select only one option out of 4. Best of Luck

CATEGORY: programmer  
LEVEL: advanced

3What is the output of the following code snippet?

```
int main() {
int a[] = {1, 2, 3, 4};
int sum = 0;
for(int i = 0; i < 4; i++) {
sum += a[i];
}
printf("%d", sum);
return 0; }
```

1  
 4  
 20  
 10

					id	username	level	category	totalques	answercorrect
<input type="checkbox"/>					1	poojitha@gmail.com	basic	backend_developer	15	2
<input type="checkbox"/>					2	poojitha@gmail.com	intermediate	backend_developer	15	2
<input type="checkbox"/>					3	poojitha@gmail.com	advanced	backend_developer	15	2
<input type="checkbox"/>					4	harini@gmail.com	basic	frontend_developer	15	1
<input type="checkbox"/>					5	harini@gmail.com	intermediate	frontend_developer	15	1
<input type="checkbox"/>					6	kiran@gmail.com	basic	programmer	15	4
<input type="checkbox"/>					7	poojitha@gmail.com	basic	backend_developer	15	1
<input type="checkbox"/>					8	poojitha@gmail.com	intermediate	backend_developer	15	4
<input type="checkbox"/>					9	poojitha@gmail.com	advanced	backend_developer	15	2

### VI. PERFORMANCE EVALUATION

The particular metric and the issue at hand determine how performance assessment metrics results for supervised learning algorithms should be interpreted. However, in general, greater values of some measures imply better performance, while lower ones suggest inferior performance.

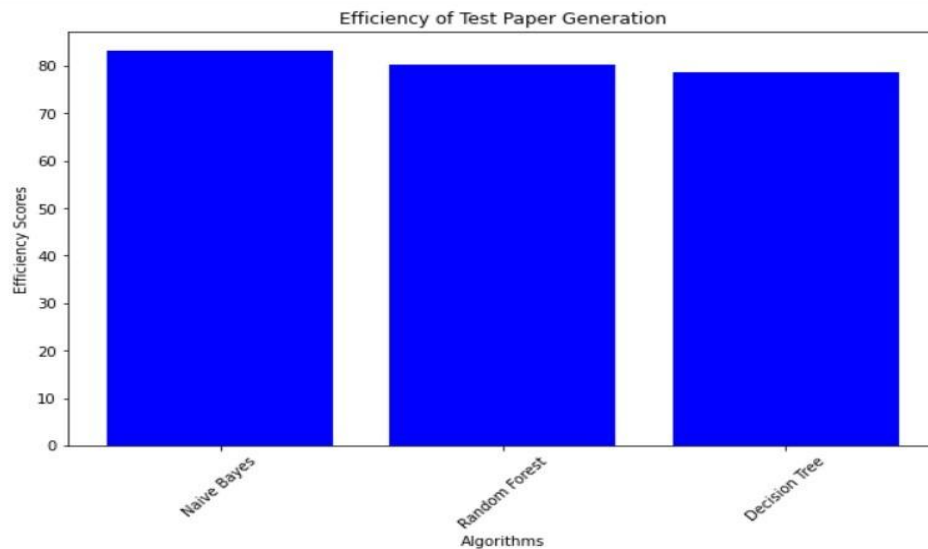
Here are some frequently used performance evaluation measures and their corresponding formulas:

1. Accuracy: Accuracy is the percentage of cases that are properly categorised relative to the total number of occurrences. Accuracy is calculated as  $(TP + TN) / (TP + TN + FP + FN)$ .
2. Precision: Out of all positive forecasts, precision estimates the percentage of real positive predictions. Precision is TP divided by  $(TP + FP)$ .
3. Recall (Sensitivity or True Positive Rate): Recall calculates the percentage of predictions that came true out of all occurrences of real positive outcomes. Recall equals TP divided by  $(TP + FN)$ .

- F1 Score: The F1 score combines recall and precision into one statistic to provide a fair assessment of a classifier's performance. Formula:  $F1 \text{ Score} = \frac{Precision + Recall}{2 * (Precision * Recall)}$ .
- Confusion matrix: A confusion matrix is a table that displays the counts of true positive (TP), true negative (TN), false positive (FP), and false negative (FN) predictions for a classification model on a set of test data. The formula for creating a confusion matrix is as follows:

		Predicted Class	
		Positive	Negative
Actual Class	Positive	TP	FN
	Negative	FP	TN

### VII. PERFORMANCE EVALUATION OF THE SYTEM USING VARIOUS ALGORITHMS



### VIII. CONCLUSION

The main goal of the proposed system is to automatically generate test questions based on the abilities of the candidates, and we are providing a user interface that is very easy to use where candidates can assess themselves and scores are recorded in the database for later use. With high accuracy, we categorise the pupils based on their talents using a variety of algorithms.

### IX. FUTURE ENHANCEMENT

In the future, we can also increase the system's strength and security by introducing more assessment functions like automated proctoring and live proctoring ideas. Automated proctoring uses AI and machine learning to track and examine the test-taker's behaviour throughout the evaluation. Using several methods like facial recognition, eye monitoring, or keystroke analysis, it can find patterns of cheating, unapproved assistance, or questionable activity. A live proctor is a person who uses video conferencing to watch the test-takers in real time. Throughout the assessment, the proctor keeps an eye on the test-taker's conduct, confirms their identification, and makes sure all exam requirements are followed. Data security and privacy should be given top priority in proctoring systems. Measures should be in place to protect the confidentiality and integrity of test-taker data, ensuring compliance with relevant data protection regulations.

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