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Machine Learning: Intelligent Question Paper Generation System

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ABSTRACT—

For many years, there has been debate concerning the efficacy of remedial mathematics courses in post-secondary education. Since students come from a variety of backgrounds and have varying levels of prior knowledge, it is not always possible for them to have a fundamental comprehension of the subjects that are taught in the first semesters of higher education, which causes many students to struggle in their first courses. The results of students' adoption and learning outcomes from using four MOOCs as an additional study resource in preparation for an on-campus calculus diagnostic exam are presented in this research. Before courses began, more than seven hundred recently admitted college students were required to complete a diagnostic test covering four themes related to calculus.

Keywords— Automatic question generation; Machine learning

I. Introduction

The process of generating question papers is a fundamental yet labor-intensive task in education, requiring significant time and effort from educators to ensure that assessments are fair, balanced, and aligned with curriculum standards. Traditional methods often struggle to keep up with the increasing demand for personalized and adaptive testing. In this context, leveraging machine learning for automated question paper generation emerges as a groundbreaking solution. Machine learning, a subset of artificial intelligence, excels at analyzing large datasets to identify patterns and generate insights. Applied to question paper generation, machine learning algorithms can analyze vast amounts of educational content, past exam papers, and student performance data to create diverse, well-structured, and tailored assessments. This approach not only saves time but also enhances the quality and relevance of the questions, ensuring they meet specific learning objectives and difficulty levels.

The benefits of this technological advancement are manifold. Automated question paper generation can provide a consistent and unbiased means of creating exams, reducing the risk of human error and bias. It can also adapt to the evolving educational standards and individual student needs, offering a more personalized learning experience. Furthermore, the ability to generate high-quality question papers quickly allows educators to focus more on teaching and less on administrative tasks. In summary, a machine-learning approach to automated question paper generation promises to revolutionize the educational assessment landscape. By integrating advanced algorithms and educational data, this method offers an efficient, accurate, and adaptive way to produce question papers, ultimately enhancing the teaching and learning process.

II. SYSTEM ANALYSIS

A. PROPOSED SYSTEM

- The following characteristics of the online exam that was designed for online testing The suggested solution is more efficient and will take less time to implement than the current one.
- The automated nature of the suggested method will make analysis very simple. Because the calculations and evaluations are done by the itself, the results will be very exact and correct and will be announced in a very short amount of time.
- Because the suggested system depends solely on the administrator, there is no possibility of question paper leakage. This makes it extremely secure. The logs of the applicants who appeared and their grades are kept and can be used as a backup in the future.

Advantage

- It is very secure no chances to leakage of question paper as it depending on administrator only.

- It is automated result will be very precise and accurate and will be declared in very short span of time because calculation and evaluation are done by itself.
- To take exam of more candidates and invigilator are required but no need invigilator in case of online exam.
- The online examination is very much time consuming.

B. **EXISTING SYSTEM**

- Up until now, the whole test assignment and post-test score evaluation procedure has been done by hand. When the software was not installed, processing the test paper, that is, examining and allocating the appropriate scores, used to take time.
- The existing procedure takes a long time. The exam is incredibly hard to manually analyse. More invigilators are needed to take exams for more applicants, while online exams do not require invigilators. Because calculations and evaluations are done by hand, the results are not exact.
- Compared to the suggested approach, there is a higher risk of paper leakage in the current system. Because result processing is done by hand, it takes longer.

Disadvantage

- The exam is incredibly hard to manually analyse.

III. METHODOLOGY

System development deals with the operations that are carried out in order to get desired output from software product based on certain design specifications. This Application hold the following modules.

ADMIN

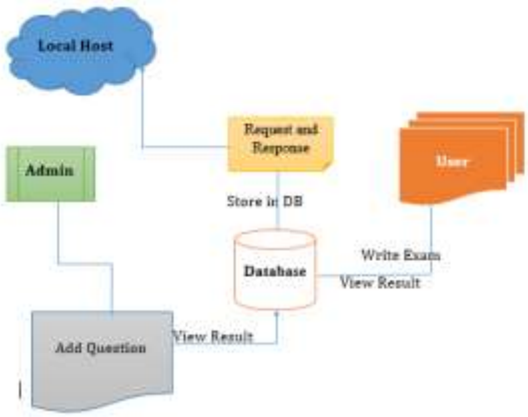
- Admin's First Step is To Login By Given ID And Password , Then View the Home Page.
- After That , Admin View User Result And Add Question's And Then View Question's ,Add Video's.
- These Data's Are Retrieve From The Data Base.

USER

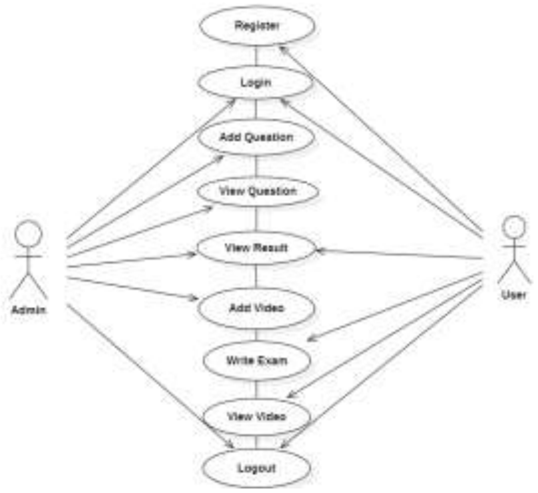
- User First Used To Register By Using Name, Number , Email , Address, Then View the Home Page.
- After That , Admin View Result And View Video's And Then Write Exam.
- These Data's Are Added and Retrieve From The Data Base.

IV. SYSTEM DESIGN

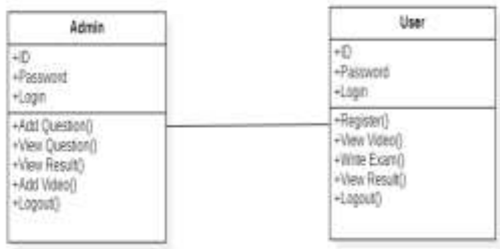
Architecture Diagram



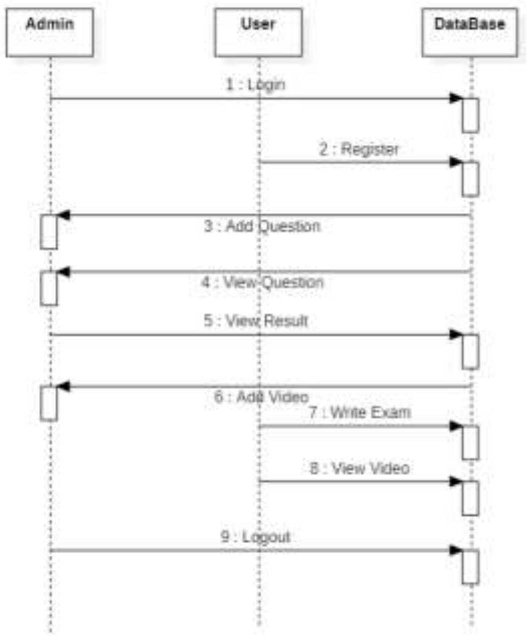
Use Case Diagram



Class Diagram



Sequence Diagram



IMPLEMENTATION AND DATABASE DESIGN

AES Algorithm

AES is an encryption standard chosen by the National Institute of standards and Technology (NIST), USA to protect classified information. It has been accepted worldwide as a desirable algorithm to encrypt sensitive data. It is a block cypher that uses a 128-bit block size for both encryption and decryption. Every Round carries out the same tasks.

AES is working process

- To encrypt data, AES essentially performs 4 major tasks again.
- It takes 128-bit block of data and a key[layman term password] and gives a cipher text as Output. The functions are:
    1. **Sub Bytes**
    2. **Shift Rows**
    3. **Mix Columns**
    4. **Add Key**
- The number of rounds performed by the algorithm strictly depends on the size of key.
- The following tables gives overview of No.of rounds performed with the input of varying key lengths:

Key size(in bits)	Rounds
128	10
192	12
256	14

The data will be more secure the more keys there are. The number of rounds will cause s/w to take longer to encrypt.

For a symmetric block cypher, E=encryption function in this case

m= plaintext message of size 128bits

n= cipher text

K= same 128-bit key used for encryption and decryption.

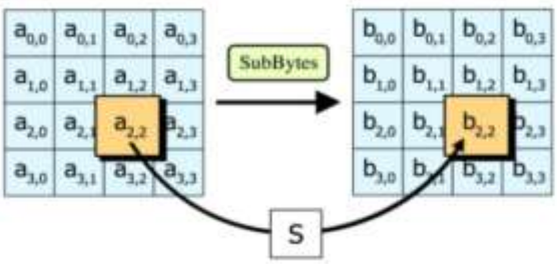
D=Decryption function for symmetric block cipher

Key expansions-In the key Expansion process the given 128 bits cipher key is stored in [4]x[4] bytes matrix (16*8=128 bits) and then the four column words of the key matrix is expanded into a schedule of 44 words (44*4=176) resulting in 11 round keys (176/11=16 bytes or 128 bits).

Number of round keys=Nr+1. In this scenario, the round keys equal 11. Where Nr is the number of rounds (which is 10 in the case of a 128-bit key size).

Sub Bytes

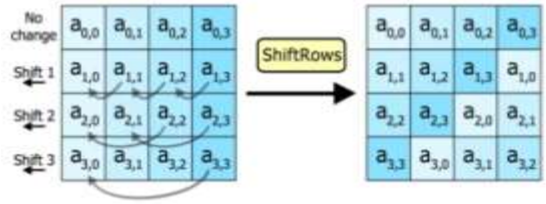
- An S-box matrix element substitutes for each matrix element.



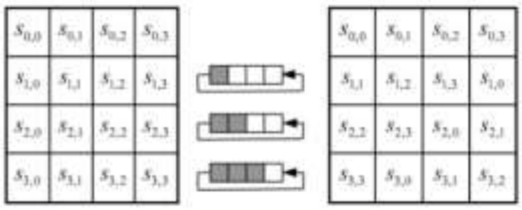
- A unique lookup table made of Galois fields is called an S-box.
- GF(2^8) is the generating function that this algorithm uses.
- i.e 256 values are possible
- The elements of the s-box are written in hexadecimal system

Shift Rows

- The block's rows are cylindrically relocated to the left in this phase.
- The first row is u touched, the second by one shift, third by two and fourth by 3.



• Shift Rows

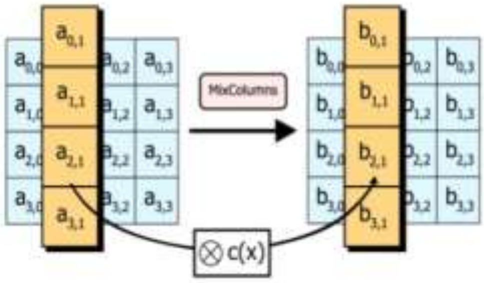


Resulting matrix after shift operation

Mix columns

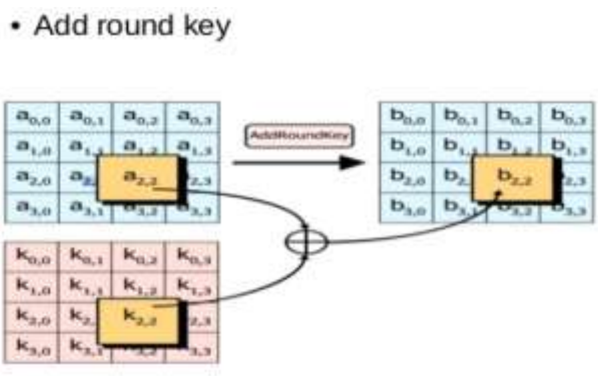
- This is the most important part of the algorithm
- It results in bit flips that disperse throughout the block.
- The block is multiplied by a fixed matrix in this phase.
- For each row there are 16 multiplication in galois field.
- For each row there are 16 multiplication,12 XORs and a 4-byte output.

• Mix Columns



Add round key

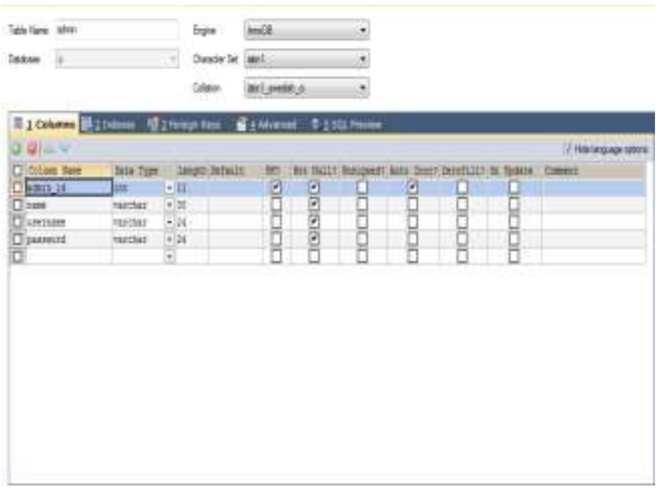
- Each byte is XORed with the matching element of the key matrix in this phase.
- The keys are no longer available for this phase once it is completed. The algorithm will be weakened by using the same key.
- Expanded keys are provided to address this issue.
- In the last round the mix columns step is skipped.
- It is not documented anywhere why this is done but recently a paper was published against this method highlighting the weakening of cipher text.



Advantages of AES

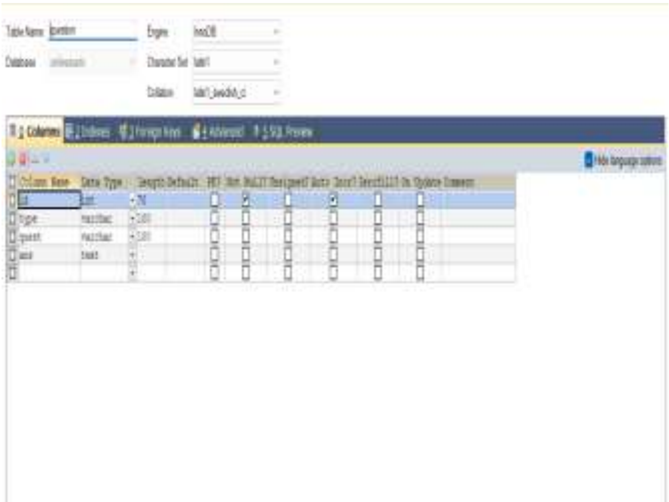
- As it is implemented in both hardware and software, it is most robust security protocol.
- Because it employs longer encryption keys (128, 192, and 256 bits), the AES algorithm is more resistant to hacking.
- It is also the most widely used security protocol, found in a wide range of applications, including financial transactions, wireless communication, e-business, and encrypted data storage.
- It is also one of the most widely used commercial and open source solutions globally.
- Your personal information is safe because it requires approximately 2128 attempts to break (128 bits).

Admin Login Table



User Register Table

Answer Details



Question Details

TEST PLAN ID	TESTING MODULE	TESTING TYPE	DURATION	TEST DESCRIPTION
TP1	Admin Login	Unit Testing	1 hour	Admin correct Login name and Password than Login
TP2	Question Upload	Validation Testing	3 hours	To Upload a Question to Database Storage.
TP3	List out Question	Integration Testing	1 hour	To view a Added Question all data’s
TP4	View all Student information	Block Box Testing	3 hours	Only view for admin side, in overall results

TP5	Admin view Allotted Question	Block Box Testing	4 hours	Admin view form Allotted Question
TP6	User New Registration	Unit Testing	3 hours	User new registration a address and user full details in enter the registration form
TP7	User Receive Result	Unit Testing	2 hours	User first login than Receive Status
TP8	View the result	Integration Testing	1 hours	View the result and details
TP9	User check status	Unit Testing	2 hours	User check status and result

Conclusions

Traditional question paper generation is a labor-intensive process requiring significant time and expertise. A machine-learning approach to automated question paper generation offers a transformative solution, providing efficiency, accuracy, and relevance. By analyzing past exam papers, curriculum guidelines, and student performance data, machine learning systems can create well-balanced and challenging question papers aligned with educational standards. This approach frees educators to focus on teaching, enhances consistency and objectivity in assessments, and reduces human error and bias. Continuous learning from feedback ensures that these systems improve over time, offering increasingly effective question papers. In summary, adopting machine-learning for automated question paper generation not only streamlines the process but also enhances the quality and fairness of educational assessments. Embracing this pedagogical practices, meeting contemporary education demands effectively.

FUTURE ENHANCEMENTS

Future enhancements in machine-learning-driven question paper generation include adaptive algorithms to tailor question difficulty based on real-time student performance, improving integration with Learning Management Systems (LMS) for efficient workflows, and developing multilingual capabilities to support global education standards. Advanced natural language processing (NLP) can diversify questions to include scenario-based and critical-thinking prompts. Real-time feedback mechanisms for educators can continuously refine question generation, while advanced security measures ensure the integrity and confidentiality of question papers. Features for educator collaboration and peer review can further enhance question quality. These advancements will lead to more effective, secure, and customized assessment tools, ultimately improving educational outcomes.

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