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A

PROJECT REPORT

ON

VOICE BASED ANSWER DETECTION AND EVALUATION SYSTEM USING NLP & ML

SUBMITTED IN PARTIAL FULFILMENT OF

THE REQUIREMENTS FOR THE DEGREE OF

BACHELOR OF ENGINEERING IN

INFORMATION TECHNOLOGY

UNDER

SAVITRIBAI PHULE PUNE UNIVERSITY, PUNE

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DEPARTMENT OF INFORMATION TECHNOLOGY

ALL INDIA SHRI SHIVAJI MEMORIAL SOCIETY'S

INSTITUTE OF INFORMATION TECHNOLOGY

PUNE– 411001

APRIL 2022

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Department of Information Technology

Certificate

This is to certify that the Project Report entitled

Voice Based Answer Detection and Evaluation System Using Natural Language Processing and Machine Learning

Submitted by

Abhishek Zade, Mansi Kuwadia, Sarang Chambhare and Sourav Shinde

is a record of bona-fide work carried out by them, in the partial fulfilment of the requirement for the award of Degree of Bachelor of Engineering in Information Technology at All India Shri Shivaji Memorial Societies' Institute of Information Technology, Pune under the Savitribai Phule Pune University, Pune. This work is completed during academic year 2021-22, under our guidance.

Dr. Meenakshi A. Thalor	Dr. Meenakshi A. Thalor	Dr. P. B. Mane
Project Guide	Head of Department	Principal

Examiner 1: - - - - - - -

Examiner 2: - - - - - - -

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Acknowledgement

There is always a sense of gratitude that people express towards others for their help and supervision in achieving the goals. This formal piece of acknowledgment is an attempt to express the feeling of gratitude towards people who helped us in completing our presentation.

We would like to express our deep and sincere gratitude to our seminar guide, **Dr. Meenakshi A.Thalor** for allowing us to do this work and providing invaluable guidance. We would like to express our deep gratitude to **Dr. P. B. Mane**, Principal, **Dr. Meenakshi A. Thalor**, Head of Department, and **Prof. Reshma Y. Totare**, Project Coordinator for their constant co-operation. They were always there with competent guidance and valuable suggestions throughout the pursuance of this presentation.

We would like to convey my sincere gratitude to **Technikien Technologies Pvt. Ltd.** for sponsoring my project and also for providing all the necessary information. We would also like to appreciate all the respondents and group members whose responses and coordination were of utmost importance for the presentation and who helped me a lot in collecting necessary information.

Above all, no words can express my feelings to my parents, friends, and all those people who supported me during my seminar.

Abhishek Zade, Mansi Kuwadia,

Sarang Chambhare and Sourav Shinde

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Abstract

As the globe evolves toward automation in our modern age, there is a need for automation in answer evaluation systems. When analysing theory solutions, the checker's job becomes even more difficult since only mcq-based questions are now eligible for online answer evaluation. The teacher examines the answer thoroughly before assigning the proper grade. In order to examine the response, the existing method necessitates the hiring of additional personnel and the allocation of additional time. This paper describes a machine learning-based application that evaluates answers. Because manual answer evaluation involves much more personnel and time, the purpose of this paper is to reduce labour and time utilisation. Furthermore, with the manual process, two identical solutions may obtain different marks. This application approach enables for the automatic evaluation of replies based on the moderator's keyword input into the computer, ensuring that marks are distributed fairly and saving time and resources.

Keywords: Natural Language Processing (NLP), Machine Learning, Speech to Text, Text to Speech, Naive Bayes, Word2vec, Cosine Similarity.

Sponsorship Certificate

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TECHNIKIEN
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Ref: TTL/PRO/22/01/21/01

Date: 21-01-2022

To,
The Principal,
AISSMS,
Institute of Information Technology,
Kennedy Road, Near R.T.O,
Pune – 411001

Subject: Permission for Student Project Sponsorship

Dear Sir/Madam,

Our Organization agrees to guide and do the Student Project work in our office for following students of final year B.E IT

1) Sarang Chambhare 2) Abhishek Zade 3) Mansi Kuwadia 4) Sourav Shinde

Project Name: **Voice Based Subjective Answer Detection and Evaluation Using NLP and ML.**

Guided By Dr. Meenakshi Thalor

After completion of the work, it may please to ensure that one copy of project report will be submitted to our organization. The project developed by the student will be used for demonstration purpose during the examination time. We are ready to provide technical support and mentor to the students for academic year 2021-22

It is expected that student will obey rules and regulation for the organization during the project work. Please note that student will not be granted any stipend and any allowance during work in the organization.

Please acknowledge the receipt of the letter.

With regards,

Shaikh Ahmed
Director

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Chapter 1

INTRODUCTION

1.1 Introduction:

- In general, students' academic achievement is evaluated through examinations, which might be subjective or objective.
- Manually evaluating subjective responses is a time-consuming and labor-intensive operation that requires a large number of people.
- Many handicap people or blind people are facing issues like getting a proper device and using it.
- To make their task somewhat easier we are implementing this project.
- The project's goal is to use machine learning and natural language processing to automate the evaluation process for subjective answers.

1.2 Motivation:

In today's modern era, education system's evaluation system is still is offline. The students are needed to go in centers to give exams and also teachers are given burden to evaluate each and all students answer sheet separately. Due to overload of evaluation burden on teachers, it may happen that two identical answers which should be given same marks gets different marks. It is also difficult task for evaluators to identify copied answers. Also, when the topic of physically disabled students come, then for them it is more difficult and tedious task to give examination because initially it is very difficult for them to reach to the exam centers and also, they need some other person to write the paper on their behalf.

So, basically to deal with the above problems, idea of NLP and Machine Learning for Voice Based Answer Detection and Evaluation comes into existence. Voice based answer detection for physically disabled students and evaluation system for teachers will try to reduce the efforts of students and teachers by making evaluation process fast, secure and easy to use.

1.3 Related Theory:

Voice activity detection (VAD), also known as speech activity detection or speech detection, is a speech processing technique that detects the presence or absence of human speech. The major applications of VAD are voice coding and recognition. It can help with speech processing and can also be used to turn off some processes during non-speech sections of an audio session: for example, in Voice over Internet Protocol (VoIP) applications, it can prevent unnecessary coding and transmission of silence packets, saving time and network bandwidth.

VAD is a critical enabler for a wide range of speech-based applications. As a result, a variety of VAD algorithms have been created, each with its own set of features and trade-offs between latency, sensitivity, accuracy, and computing cost. Some VAD algorithms go much further, determining if the speech is spoken, unvoiced, or sustained. The detection of voice activity is usually independent of language. It was first looked into for usage in TASI (time-assignment speech interpolation) systems.

1.4 Need of the topic:

- To reduce the tedious task of teachers from checking answer sheet of every student.
- To make a system which can help handicapped and blind students which will be user friendly for both students and teachers.

Chapter 2

LITERATURE SURVEY

The existing grading system for subjective papers is inefficient. It's crucial to understand how difficult it is to judge subjective answers. When a person evaluates anything, their emotions may influence the quality of the evaluation. As a result, a slew of automated subjective response evaluation systems has popped up. We briefly examined some of the current research articles that are relevant to our work in this part. Refer table 2.1 for brief review of studied literature.

TABLE 2.1: Literature Survey

Sr. No.	Title	Conclusion	Limitations
1.	Subjective Answer Evaluation using Natural Language Processing and Machine Learning.	The length, keyword matching, grammatical check, cosine similarity, and contextual likeness of a subjective question to the faculty's model answer and the student's answer are used to grade it.	The grade is determined by the length of the answer, which varies from person to person.
2.	Answer Evaluation Using Machine Learning	The proposed technique is 75-87.5 percent accurate when compared to a manual system. The proposed method eliminates all human effort and time spent on response analysis.	The proposed system can only recognise printed text, not handwritten text.
3.	Evaluating Student Descriptive Answers Using Natural Language Processing.	The main goal of this newly proposed method is to determine the semantic meaning of student responses, which is difficult because students can react to questions in a variety of ways.	The suggested system considers the meaning of group utterances, which may differ from the meaning of students' responses.
4.	Automatic Answer Evaluation Using Machine Learning	The proposed system will combine optical character recognition (OCR) with a back propagation method and an artificial neural network. Based on the scanned answer sheet, the moderator's keywords, and the length provided, the algorithm will evaluate the response. The following elements are used to determine the grade: a. the number of keywords that were	Synonyms or similar words are not suitable substitutes for the exact keyword.

		matched; and b. the length of the answer.	
5.	Design Engineering Automated Explanatory Answer Evaluation Using Machine Learning Approach	Using Natural Language Processing, the programme evaluates the responses by extracting keywords from the students' responses and the teacher answer key. To verify that the student's answer and the answer key are similar, cosine similarity metrics are used.	For grading reasons, the technique largely uses cosine similarity.
6.	Automatic Online Subjective Text Evaluation using Text Mining	Similar data that a human would examine when analysing, such as answer length, keyword presence, and keyword context, drives the project. To find keywords and answer specific inquiries, Natural Language Processing is used with categorization algorithms.	For model training, greater computing power is required.
7.	Evaluating Students Descriptive Answers Using Natural Language Processing And Artificial Neural Networks.	After the text mining process is completed, the student answer is compared to the correct answer using the ANN algorithm, and the student answer is checked for spelling and grammatical errors using the NLP algorithm. When the text mining method is finished, the result is automatically calculated using the NLP and ANN results.	There is no way for students to provide comments or recommend improvements.
8.	Computerized Evaluation of Subjective Answers Using Hybrid Technique.	The use of a combination of LSA and BLEU for evaluation is complementary. Because WordNet finds synonyms for the supplied keywords, it minimises the number of keywords required. This ensures that the student is free to use whichever language he desires.	For evaluation, models (LSA and BLEU) are necessary. Working with a single model is impossible.
9.	Subjective Answer Grader System Based on Machine Learning	The correctness of LSA and IG algorithms can be determined by comparing the computed scores of the replies to the human evaluation scores. When LSA and IG were augmented using WordNet, their accuracy increased from less than 40% to more than 75%.	The system does not support formulas or diagrams.
10	A Keyword Based	The keywords are used by the	Erroneous evaluations

	Technique to Evaluate Broad Question Answer Script.	algorithm to evaluate the student's response. Based on the sample answer and the student's response, the student will be given a grade.	will come from teachers' mistakes in providing answer keys.
11	Text Similarity Analysis for Evaluation of Descriptive Answers	Natural language processing (NLP), data mining, and an LSTM are all used in the system (recurrent neural network). The distribution of marks is extremely consistent. The technology also checks for plagiarism to avoid unethical practises.	Students must type their answers into the system. There is no feedback given after the evaluation.
12	ASSESS - Automated Subjective Answer Evaluation Using Semantic Learning.	The suggested system uses NLP, semantic learning, and Google's USE algorithm to generate system embedding. It removes the need for the user to type more responses and provides suitable feedback.	Two elements are used to assign grades: similarity and keywords. A synonym module is not included.
13	Computer Application For Assessing Subjective Answers Using Artificial Intelligence.	Machine learning, natural language processing, and artificial intelligence are all used in the system, as are methods like HMM, RNN, STS, and CFG. The core elements of evaluation are sequencing, watchword planning, and summarization.	There is no feedback given after the evaluation. Answers with equations, graphs, or formulas are impossible to evaluate.
14	Subjective Answer Grader System Based on machine learning.	Algorithms like LSA and IG are used in the system, while WordNet is used to improve their evaluation. It can be as accurate as 83 percent of the time. The time required for review is reasonable.	There is no evaluation for equations or graphs. Algorithms require WordNet for better outcomes.
15	Speech To a Text Translation Enabling Multilingualism.	This solution uses Google's Speech Recognition software and uses NLP with pre-existing data. It is suitable for folks with no prior computer expertise. It is not necessary to have internet connectivity. Speech can be translated into a number of other languages.	A preloaded Speech Recognition application is required for this model. It only converts a few words at a time.
16	Subjective Answer Evaluation Using Machine Learning.	Machine learning and natural language processing are used in the proposed method, with Naive Bayes as the underlying	There is no input from the system. Teachers must manually enter the appropriate keywords.

		classifier. It assesses swiftly and effectively. The accuracy rate of the system is 90%.	
17	Speech to text conversion using GRU And one hot vector encoding.	An RNN-based model with a gated recurrent unit is used in this system. It has an accuracy rate of 87 percent. The technology can distinguish between different audios. There is also a noise cancellation option.	There is only one language accessible. It only converts a few words at a time.
18	A focus on code mixing and code switching in Tamil speech to text.	The solution makes use of Google's cloud conversion API and Google's Speech to Text paradigm. The technology allows two or more languages to be spoken at the same time, as well as the composition of words using two or more languages.	Requires a quiet environment. Only a few accents are accepted. There is no output if the pronunciation is incorrect.
19	Virtual assistant for the visually impaired.	Google's STT for Python module and selenium are used for automation. The precision of the system is up to 96.25 percent. It also features audio tempo and accent altering.	Only one language can be used. A few websites are accessible to me. Speech to text conversion accuracy can be increased.
20	A Spell-checker Integrated Machine Learning Based Solution for Speech to Text Conversion.	To convert voice, the proposed system employs Deep-Voice, machine learning, and natural language processing. The model is really precise.	Access to the internet is necessary. More cycles are necessary to train the model. Long sentences are impossible to process.
21	Evaluating Student's Descriptive Answers using Natural Language Processing and Artificial Neural Networks.	This research employed natural language processing and artificial neural networks. They developed their own algorithm based on NLP and ANN to analyse responses. They've developed algorithms specifically for detecting grammatical errors.	They didn't use vectorization to assess similarity, instead depending on keywords, which is insufficient because students use similar terms outside of keywords.
22	Speech to text and text to speech recognition systems-A review.	HMM is a better speech signal to text converter in STT. The finest converter in TTS systems is formant synthesis, which uses parallel and cascade synthesis. Because it incorporates the benefits of both rule-based and statistical machine translation systems, hybrid machine translation is frequently	The main downside of HMM is that, while converting sound to text is ideal, it is not always practicable. Their computational efficiency is a drawback.

		employed.	
23	Speech to Text Conversion for Multilingual.	The goal of this system is to extract, characterise, and recognise speech data. The suggested system for speech classification employs the Mel-frequency Cepstral Coefficient (MFCC) feature extraction approach, as well as the Minimum Distance Classifier and Support Vector Machine (SVM) methodologies.	This system was created and taught solely for the purpose of converting Marathi to English speech to text.
24	Automated Explanatory Answer Evaluation Using Machine Learning Approach.	This paper's author defined tokenization and lemmatization, as well as how they work and are applied in systems. This study also looked into spell checking.	The system prioritises keywords over all other considerations.
25	Development of GUI for Text-to-Speech Recognition using Natural Language Processing.	Text-to-Speech synthesis was developed by the authors of this research study, which translates text into spoken words by analysing and processing audio using Natural language processing and then turning the processed text into synthesised speech representation of the text.	The planned user interface was not up to date. It's quite difficult to work with.

Chapter 3

PROPOSED WORK

3.1 Proposed Definition:

In the education field, exams are conducted regularly in different locations. However, these assessments are currently time-consuming and manual. This is why the need for automatic answer scoring systems is so important. The assessment process usually takes a long time to prepare and conduct. It also needs more human resources to carry out the tasks and assess the results of the tests. The score can also vary depending on the answer given by the other students. This can create conflict between the instructor and the student. It is also possible that the student's score is different from that of other students. This study aims to identify the difficulties in processing subjective answers in different languages. Due to the differences in the way natural language processing is done in each language, the results of subjective answers are different.

3.2 Project Scope:

- Main focus of this topic is it will be the option for the exam portal for blind and handicapped students
- Since it will minimize the human efforts and automate the process of evaluating the answer and the result.

3.3 Project Objectives:

- To provide an easy-to-use and accessible system for blind and disabled pupils. Reducing teacher's workload for evaluating exams.
- To provide an easy-to-use and accessible system for blind and disabled pupils.
- Proposed system will provide voice assistant for visually impaired students.
- In a nutshell, the goal is to improve the efficiency of the evaluation process while minimising human labour.

3.4 Project Constraints:

- Once an answer has been recorded by student, it cannot be changed.
- Distortion in the environment can lead to misspell in the answer.
- It requires a stable internet connection.

Chapter 4

RESEARCH METHODOLOGY

4.1 System Architecture:

The given below diagram is the system architecture. This diagram is divided into two-parts. The first part is the voice detection part. On the Exam webpage, students will be given questions and Answers will be detected using the speech of the student. Speech is converted into text. The answer can be given just using text also this is an alternative way to get answers from students. These answers are then pre-processed and stored in the database. In Fig. 4.1, the workflow of our proposed system in shown.

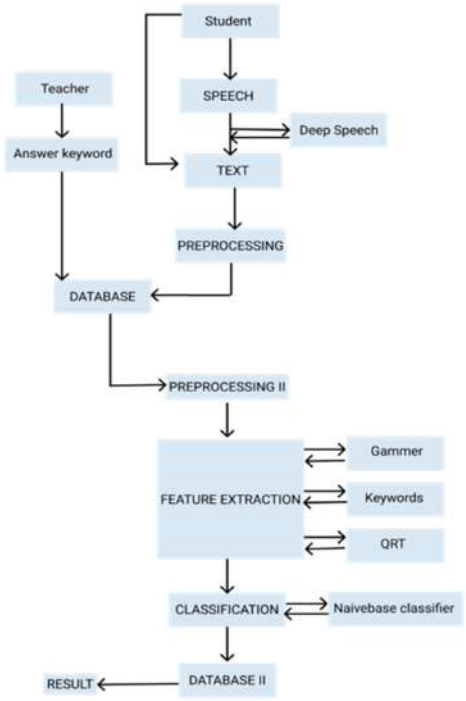

Figure 4.1 System Architecture

Now coming to the second part of the diagram i.e., answer evaluation. The answers are again pre-processed and feature extraction is done. In feature extraction, we are features such as grammar of answers, keywords, and question-related things. After feature extraction we are going to classification whether the student is pass or fail for this we are going to the naive base classifier and the result is going to be stored in the database and the result will be shown on the result page.

4.2 Methodology / Algorithm:

4.2.1 Methodology:

To analyse voice-based answers, the proposed methodology employs natural language processing and machine learning. As inputs, all of the students' responses are used, as well as one standard answer to each question. The final grades of the students are the product. To begin, input is pre-processed in order to make it ready for evaluation. Students' and standard responses have been tokenized, searched for synonyms, stopped, and stemmed completed. The proposed method is intended to assess exam outcomes for pupils who cannot write but can speak. The proposed method will be used to evaluate exam results for students who are unable to write but can talk. The stages of the assessment technique are depicted in Figure 4.1. The suggested system has two components:

1. Conversion of speech to text and text to speech
2. Evaluation of the response.

4.2.2 Algorithm:

Naïve Bayes

The Naive Bayes method is a supervised learning algorithm that uses the Bayes theorem to solve classification problems. It's typically employed in text classification issues where a big training dataset is required. The Naive Bayes Classifier is a simple and effective classification method for quickly developing machine learning models that can generate accurate predictions. It's a probabilistic classifier, meaning it makes predictions based on the probability of an object. Please see Fig. 4.2.1 for the Bayes Theorem formula.

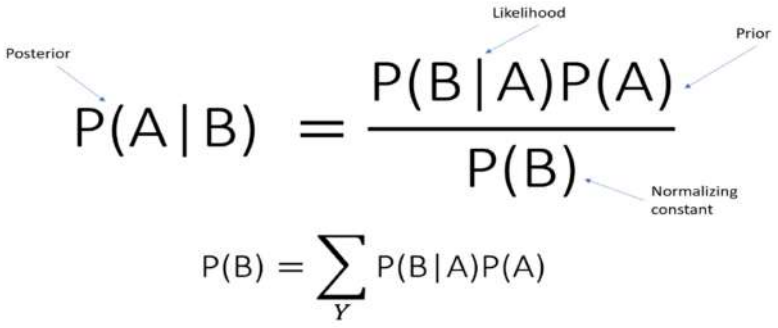

Figure 4.2.1: Bayes Theorem Formula

Where,

- The probability of a hypothesis on the observed event B is called posterior probability (P(A|B)).
- P(B|A) stands for Likelihood, which is the probability of the evidence if the probability of a hypothesis is true.
- The likelihood of a hypothesis before looking at the evidence is known as prior probability (P(A)).
- P(B) stands for Marginal Probability of Evidence.

It's a very popular and effective classification algorithm.

Chapter 5

PROJECT DESIGN

5.1 Hardware Requirements:

- Processor: Intel Dual Core or higher.
- Ram: 2GB or higher.
- Disk Space: Varies according to the number of questions and answers.
- Good system or external mic.
- Stable Internet Connection.

5.2 Software Requirements:

- Python.
- Django.
- Python Libraries like NLTK Library.
- Compatible browser.

5.3 Risk Analysis:

- If more than one person talks while giving answer, system will take both the voices as input.
- If there is any network failure, the test will be submitted automatically.
- If the pronunciation is not clear, then it will affect the results.

5.4 Data Flow Diagrams:

This part of report shows various diagrams related to the project .It includes Sequence Flow Diagram i.e. the actual flow, System Flow Diagram i.e. the direction in which the data is transferred in the system.

5.4.1. Sequence Flow diagram:

A sequence diagram shows object interactions arranged in the time sequence in the field of software engineering. The following diagram shows how the sequence of the system works and the data flow. Interprets the object involved in the scenario and the sequence of messages exchanged between the objects needed to carry out the functionality of scenario. Fig 5.4.1 shows the sequence flow diagram of the system.

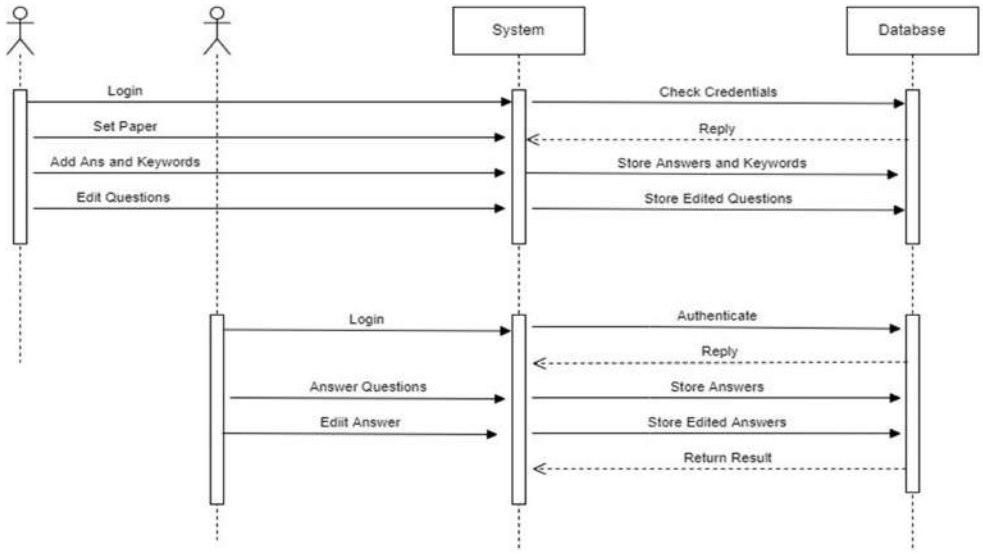

Figure 5.4.1 Sequence Flow Diagram

5.4.2 System flow diagram:

Fig 5.4.2 is the flow chart of the system, which shows the proper flow of how system works.

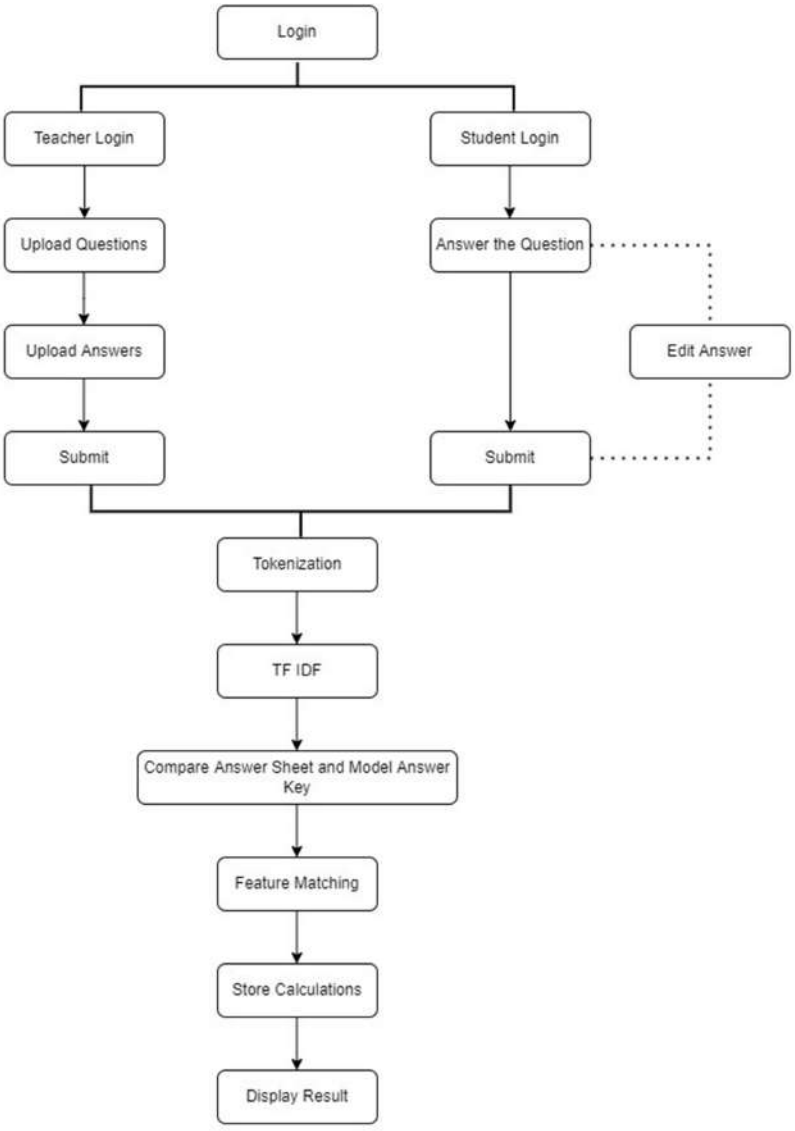

Figure 5.4.2 System Flow Chart

5.5 Project Schedules:

Preliminary Survey Introduction and Problem Statement, Literature Survey, Project Statement, Software Requirement and Specification, System Design, Partial Report Submission, Architecture Design, Implementation, and Deployment will all be covered in this chapter. Testing, publication of papers, submission of reports, and so on. This chapter also focuses on the stakeholder list, which includes information about the project type, the proposed system's customer, the user, and the project member who designed the system. The Table 5.5.1 gives the information about the project schedule.

TABLE 5.5.1: Project Schedule

		Sem 1					Sem 2				
	Task	**Aug**	**Sep**	**Oct**	**Nov**	**Dec**	**Jan**	**Feb**	**Mar**	**Apr**	**May**
1.	Topic Finalization										
3.	Base Paper Submission										
4.	Review 1										
5.	Literature survey										
6.	Review 2										
7.	Preparation of Review 3										
8.	Review 3										
9.	Paper publication										
10.	Preparation of Review 4										
11.	Review 4										

5.6 UML Design and Documentation:

Use case Diagram:

In this use case diagram, there are 3 actors i.e., teacher, student and admin. Fig 5.6.1 gives us a brief idea about use case diagram of our system.

Some of the scenarios of the system are as follow:

- Admin has the right to add both the teacher and student to the system. Adding to admin right, he/she can manage other outputs of system and has access to data uploaded by teacher and student.
- To enter the best portal all the 3 actors have to login through with all the credentials provided.
- Teachers are allowed to upload the test on the system, they can also update it. If they want specific set of keywords / answer they can upload sample.

- Answer paper in order to give the best students have to login and select the mode in which they want to answer. Answers can be vocal or in the form of image copy of written or query.
- If student find some issue or query with the paper they can comment. The comments will be shared with the teacher to take necessary actions.
- Students can also check their results after the teacher uploads the result on the portal.

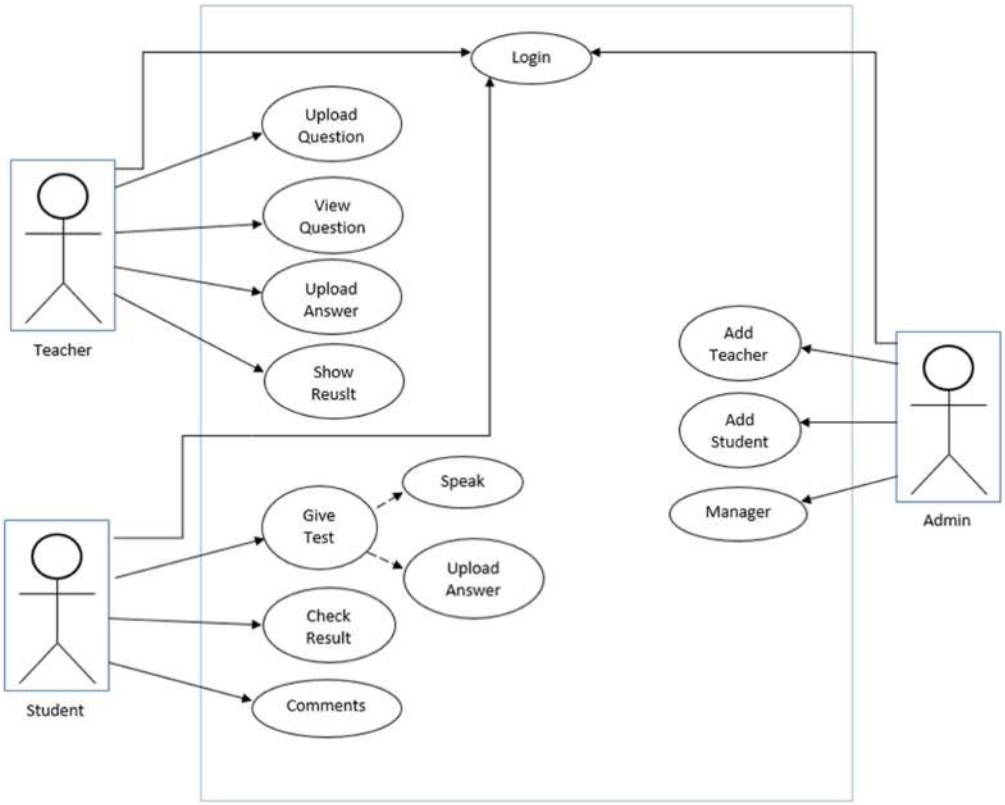

Figure 5.6.1 Use Case Diagram

Class Diagram:

The below class diagram Fig. 5.6.2 describes the structure of the system by showing the system's classes, their attributes, operations, and the relationships among objects.

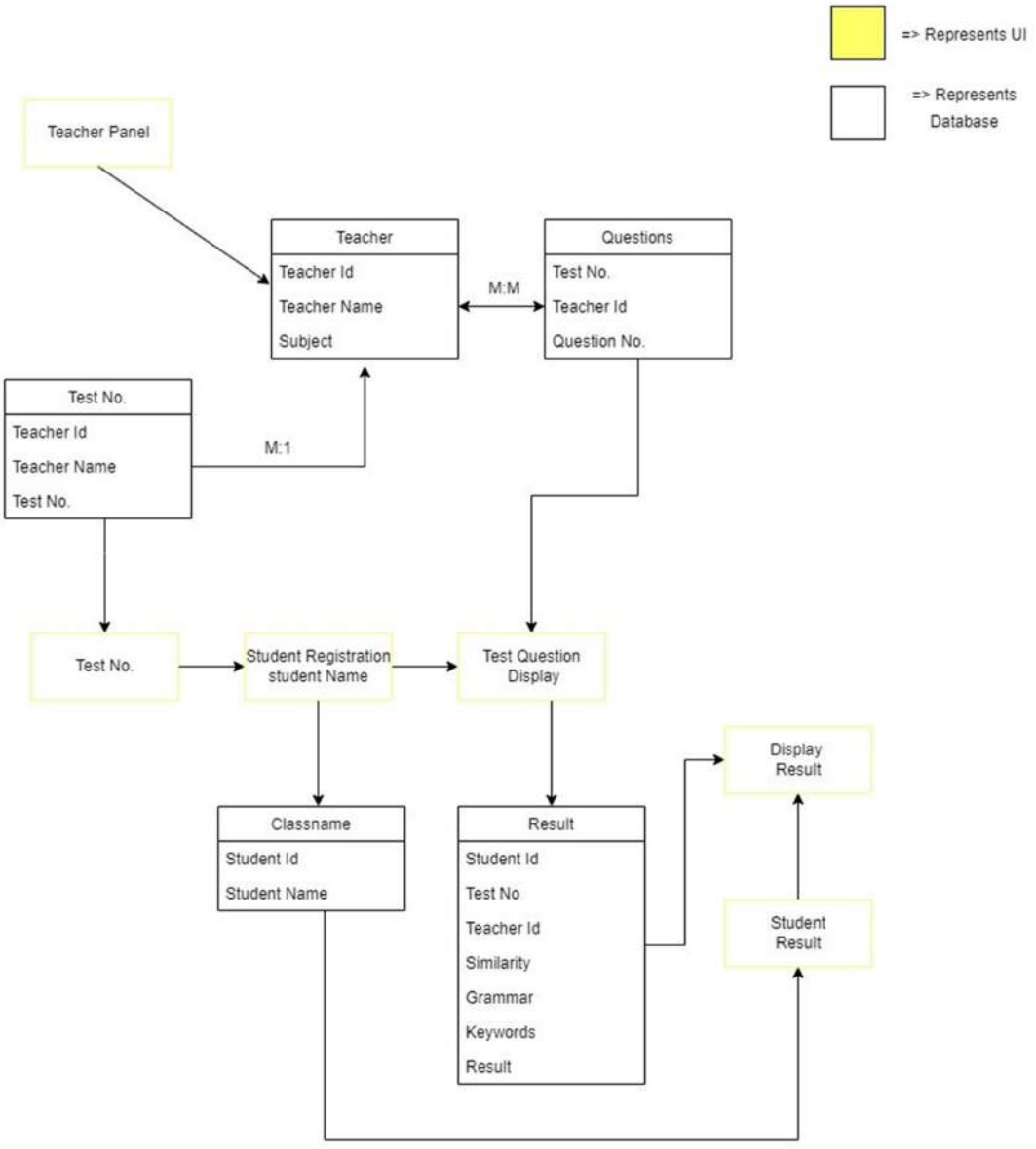

Figure 5.6.2 Class Diagram

Chapter 6

SYSTEM IMPLEMENTATIONS

6.1 Important Libraries /Packages:

- Speechrecognition
- gtts
- nltk
- gensim
- numpy
- pandas
- cdifflib
- rake-nltk
- gingerit
- django
- django-livereload-servee

6.2 Important Functions:

- Vector Similarity check
- Grammar evaluation
- Keyword Check

6.3 Important Algorithms:

- Naive Bayes algorithm
- Natural Language Processing

6.4 Graphics User Interface Screenshots:

Fig 6.4.1 shows the login page where student can login to the exam window.

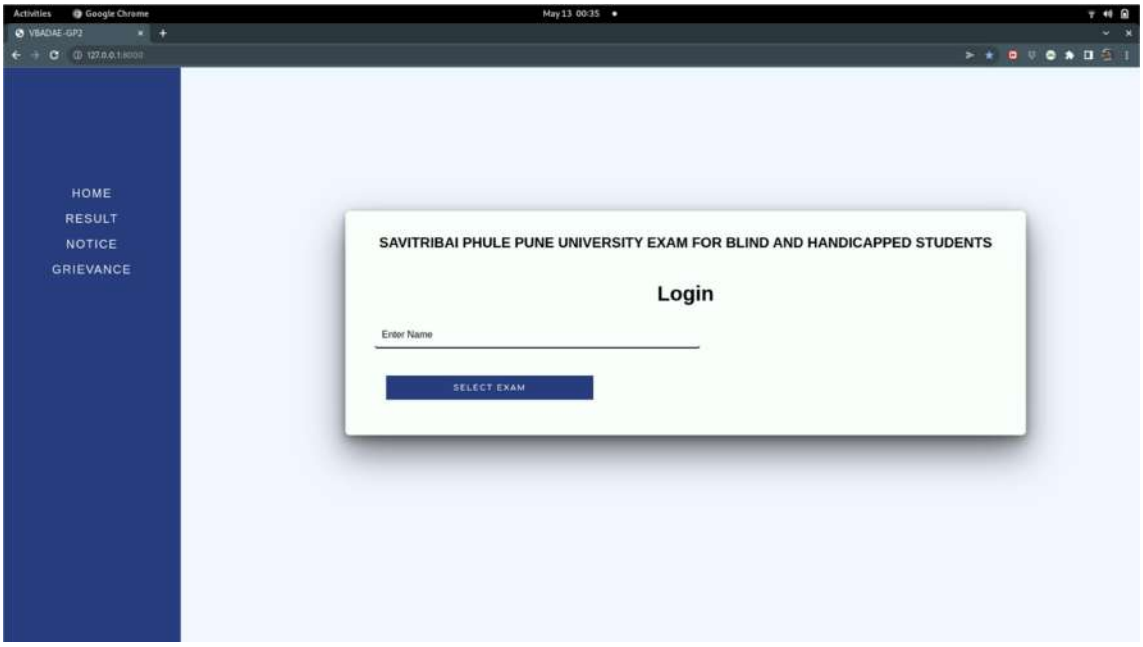

Figure 6.4.1: User Interface(Login Page)

Fig 6.4.2 shows the exam window from where student can select their scheduled exam.

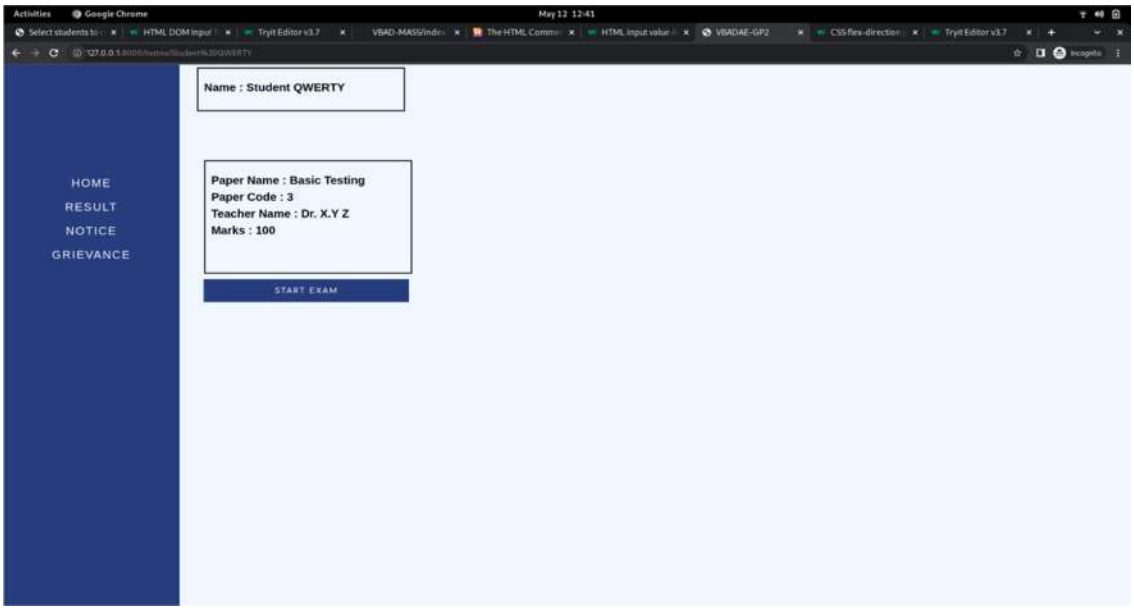

Figure 6.4.2: User Interface (Home Page)

Fig 6.4.3 shows the exam window from where student answers the question.

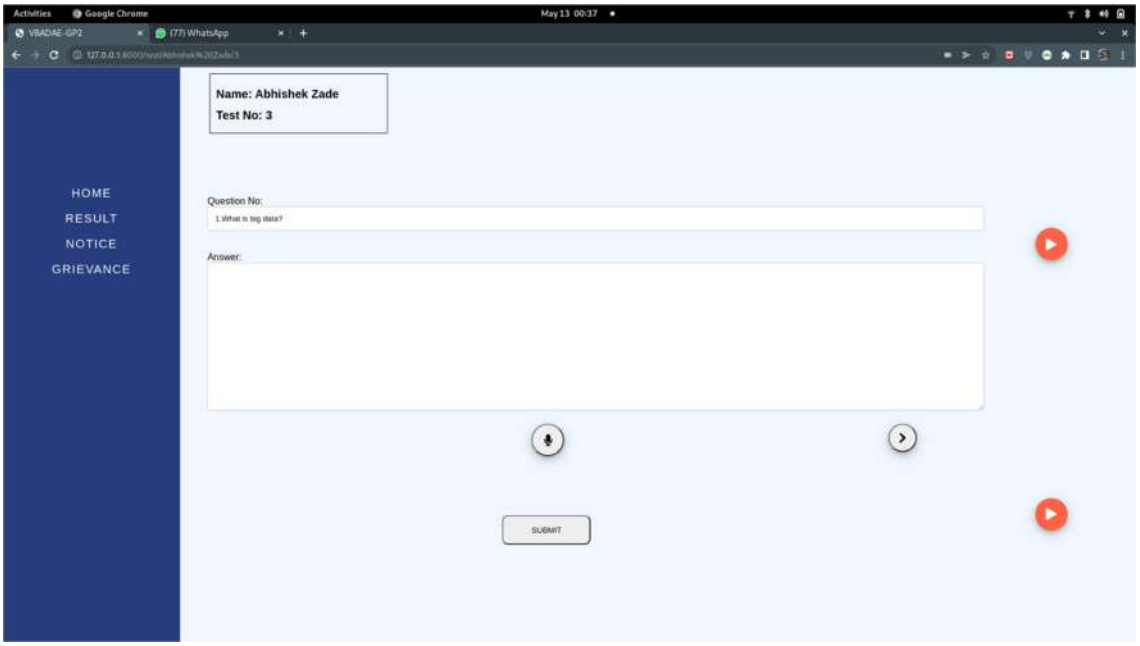

Figure 6.4.3: User Interface (Question Panel)

Fig 6.4.4 show the result of an individual student.

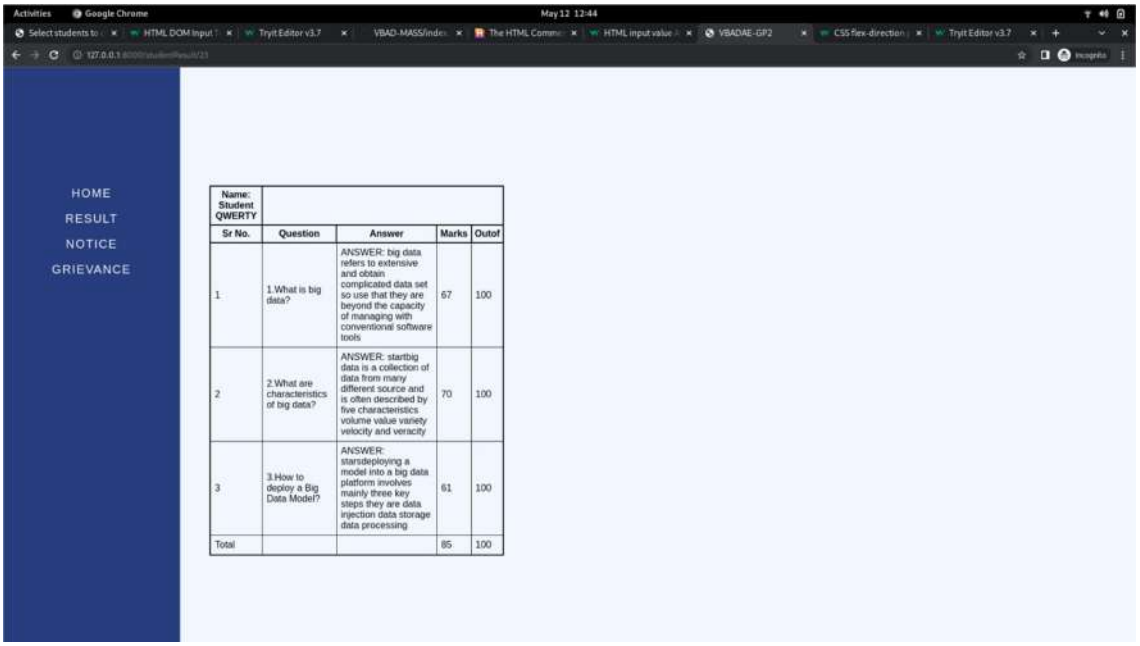

Figure 6.4.4: Result Page

Figure 6.4.5 shows the comparison of student and teachers answer to the teacher.

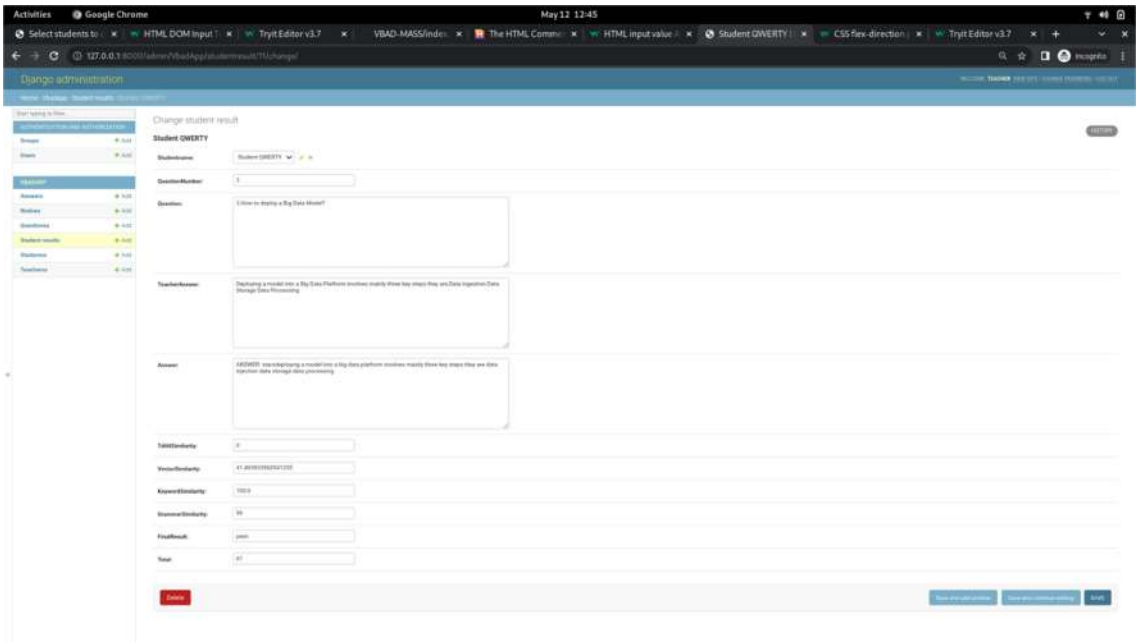

Figure 6.4.5: Teachers Result Page

Figure 6.4.6 gives information about the exams scheduled, announcements and important notices.

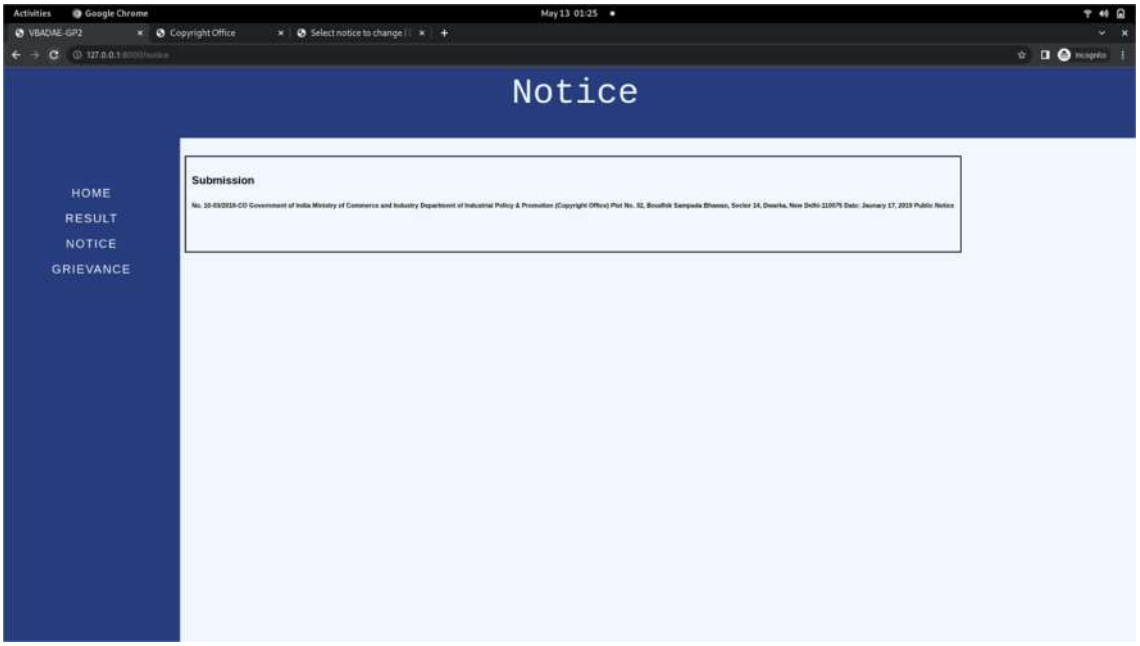

Figure 6.4.6: Notice Page.

Chapter 7

SYSTEM TESTING

System Testing is a level of testing that validates the complete and fully integrated software product. The purpose of a system test is to evaluate the end-to-end system specifications. The following Table 7.1 depicts manual testing of proposed system.

TABLE 7.1: System Testing Results

Description	Testing procedure	Input	Output
Login Page	Enter username	Username will be issued	Proceed to the next page
Home Page	User selects the exam scheduled	Click on the scheduled exam	Scheduled exam will start

Chapter 8

EXPERIMENTAL RESULTS

The experimental results show the student's overall outcome based on aspects such as grammar check, keyword check, tf–idf, tokenization, and vector similarity. To deal with the aforementioned issues, the notion of NLP and Machine Learning for Voice Based Answer Detection and Evaluation was born. Voice-based answer detection for physically challenged students and a teacher evaluation system will attempt to reduce student and instructor effort by making the evaluation process quick, secure, and simple to use. As a result of these findings, the proposed system can execute with an accuracy of up to 85%. Refer Fig. 8.1 for sample of results page screenshot of the proposed system.

Figure 8.1.1 gives the detail information about the students and teachers answer, as well as the final evaluation scheme.

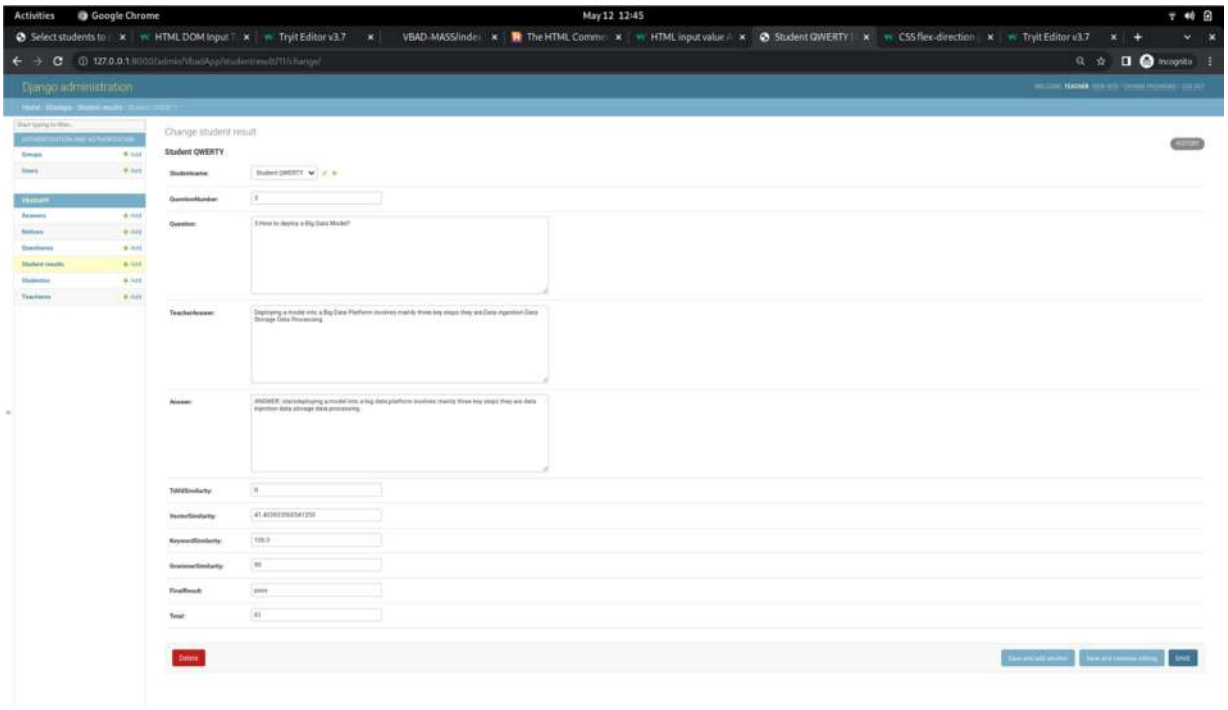

Figure 8.1.1: Experimental Results Screenshot

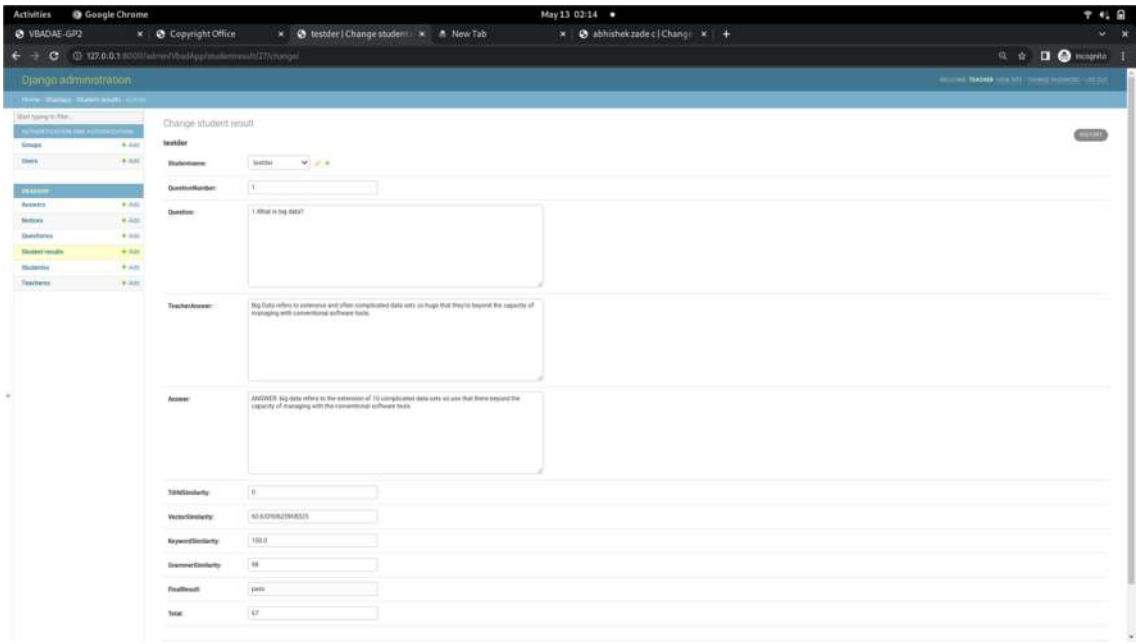

Figure 8.1.2: Question no 01

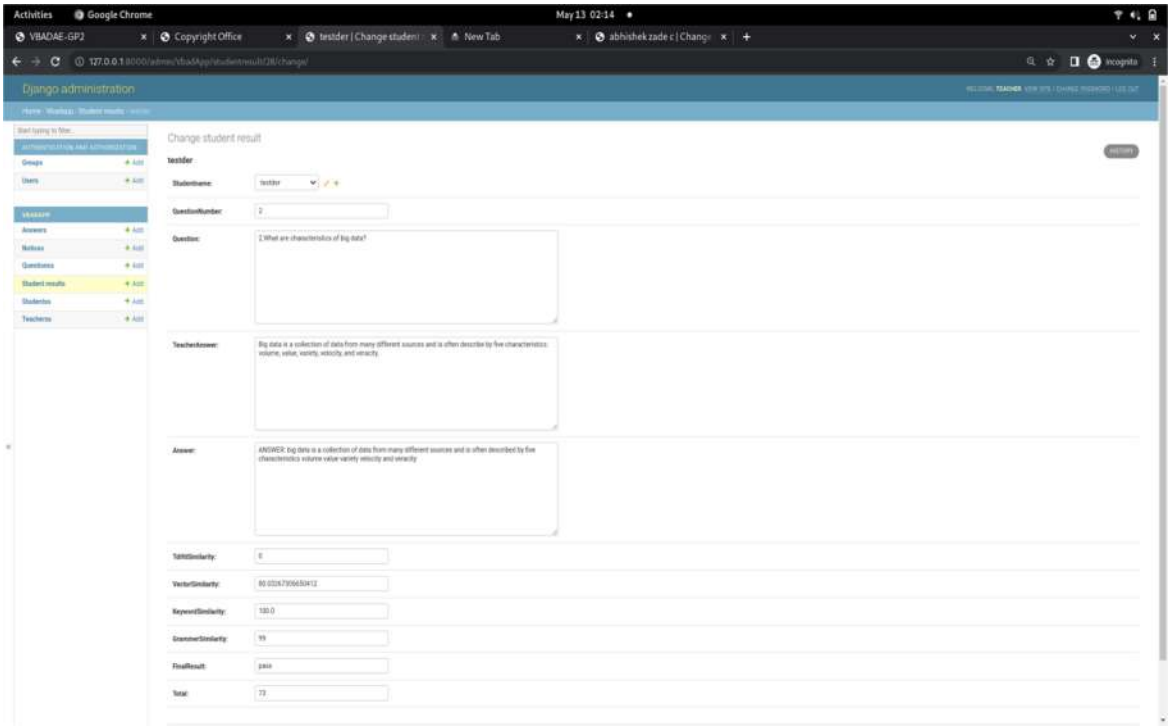

Figure 8.1.3: Question no 02

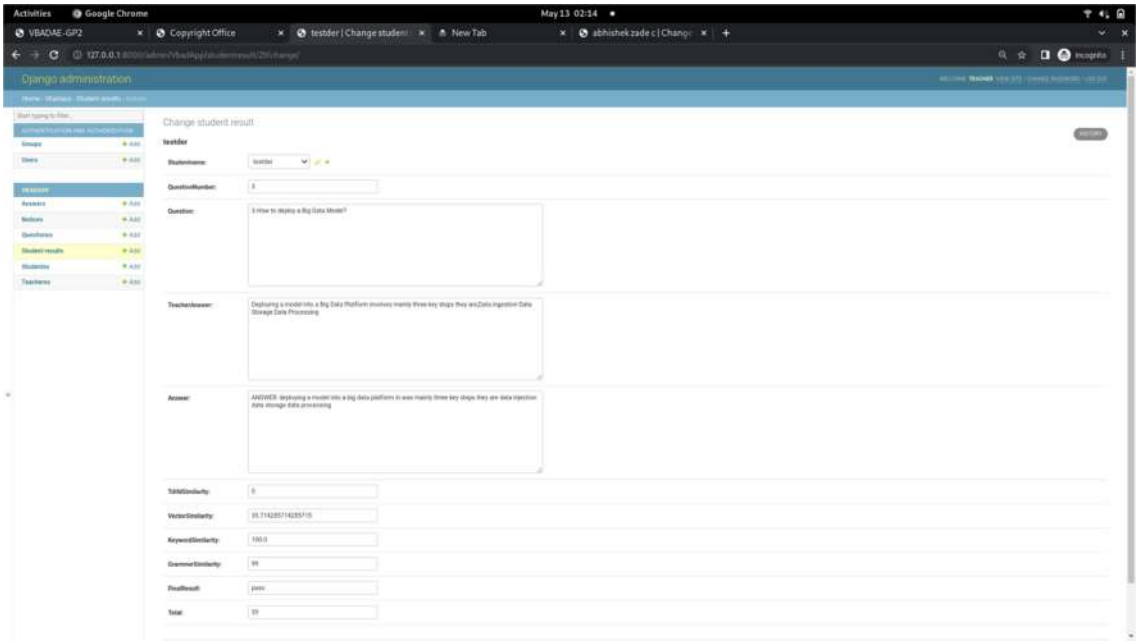

Figure 8.1.4: Question no 03

The above screenshots fig 8.1.2, fig 8.1.3, fig 8.1.4 represents the question and answers of students as well as teacher and their respective results.

The below table 8.1 shows the detail experimental results obtained by the system. The evaluation is based on the components like tdifid, vector similarity, keyword similarity and grammar similarity.

Table 8.1 System Experimental Results

Question	Teacher's Answer	Student's Answer	Tdifid similarity	Vector Similarity	Keyword similarity	Grammar Similarity	Final Result	Total
1.What is big data?	Big Data refers to extensive and often complicated data sets so huge that they're beyond the capacity of managing with conventional software tools.	Big Data refers to the extension of ten complicated data sets so used that they are beyond the capacity of managing with the conventional software tools	0	60.63	100	98	Pass	67
2.What are characteristics of big data?	Big data is a collection of data from many different sources and is often describe by five characteristics: volume, value, variety, velocity, and veracity.	Big data is a collection of data from many different sources is often describe five characteristics: volume, value, variety, velocity, and veracity.	0	80.03	100	99	Pass	73
3.How to deploy a Big Data Model?	Deploying a model into a Big Data Platform involves mainly three key steps they are, Data ingestion Data Storage Data Processing	Deploying a model into a Big Data Platform involves three key steps they are, Data ingestion Data Storage Data Processing	0	35.7	100	99	Pass	59

Chapter 9

CONCLUSION

The project is driven by data that a human would check when analysing, such as answer length, keyword presence, and keyword context. A Python voice recognizer is also used in the proposed system to convert speech to text and text to speech. Natural Language Processing is combined with classification algorithms to locate keywords and respond to specific enquiries. Students will have a lot of discretion in composing the response because the algorithm looks for keywords, synonyms, correct word context, and covering of all subjects. The robust evaluation system has determined that using machine learning methodologies produces satisfactory outcomes. By supplying a large and accurate training dataset, the evaluation's accuracy can be increased. We want to construct a voice-based answer evaluation system for physically challenged students that uses natural language processing and machine learning. According to the literature review, speech recognition is the best alternative for our suggested system. Finally, we may use the naive Bayes classifiers technique to classify the findings.

Chapter 10

FUTURE SCOPE

- It can be Replacement for human based exam system.
- It decides the time of evaluation.
- It will help to build an educational programme, assess its achievements and improve upon its effectiveness.
- It will be highly secure, easy to use, an environment friendly.

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DEPARTMENT OF INFORMATION TECHNOLOGY

SEMESTER - I

Weekly Planning Sheet

Week No.	Activity Planned	Activity Completed Status	Student Signature	Guide Signature
Week 1	Study for selecting project topic.	Completed.		
Week 2	Research of papers needed for the project topic.	Completed.		
Week 3	Prepared synopsis for presentation of idea of project topic before mentor.	Completed.		
Week 4	Did literature survey for base paper and deeply studied each paper.	Completed.		

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Week 5	Took approval of our guide for base paper.	Completed.		
Week 6	Project Review I	Completed.		
Week 7	Searched for the proper technologies that can be used	Completed.		
Week 8	Studied the technologies that we are using	Completed.		
Week 9	Designed a architecture for the system	Completed.		

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Week 10	Developed a basic prototype	Completed.		
Week 11	Testing and improvised the basic prototype	Completed.		
Week 12	Project Review II.	Completed.		

Dr. Jaydeep Patil
(Project Coordinator)

Dr. M. A. Thalor
(Internal Guide)

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SEMESTER - II

Weekly Planning Sheet

Week No.	Activity Planned	Activity Completed Status	Student Signature	Guide Signature
Week 13	Planned to add extra feature to the system	Completed.		
Week 14	Designed architecture with the extra features	Completed.		
Week 15	Developed prototype with extra features	Completed.		
Week 16	Testing of system	Completed.		

Week 17	Designing UI.	Completed.		
Week 18	Project Review III.	Completed.		
Week 19	Paper writing for project.	Completed.		
Week 20	Implementing changes to evaluate the full result of individual student	Completed.		
Week 21	Testing of Project	Completed.		

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Week 22	Paper with Experimental Results submitted.	Completed.		
Week 23	Project Report.	Completed.		
Week 24	Project Review IV.	Completed.		

Prof. R. Y. Totare
Project Coordinator

Dr. M. A. Thalor
Internal Guide

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Voice based Answer Detection and Evaluation System using NLP and ML

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ABSTRACT

As the globe evolves toward automation, there is a need for automation in answer evaluation systems in our modern age. Because online answer evaluation is now only available for mcq-based questions, the checker's job is made more difficult when evaluating theory answers. The teacher carefully checks the answer and assigns the appropriate grade. The existing system necessitates additional staff and time in order to assess the response. An application based on the evaluation of answers using machine learning is presented in this publication. The goal of this paper is to reduce labor and time usage in particular because manual answer evaluation requires significantly more people and time. Also, with the manual approach, it's possible that two identical responses will receive different marks. This application system enables an automatic evaluation of answers based on the keyword provided to the application in the form of an input by the moderator, ensuring that marks are distributed evenly and saving time and personnel.

KEYWORDS: Natural Language Processing, Machine Learning, Speech to Text, Text to Speech, Naive Bayes, Word2vec, Cosine Similarity.

1. INTRODUCTION

In general, students' academic success is evaluated based on their examination results, which might be subjective or objective. There are a number of systems that can swiftly evaluate objective or multiple-choice questions. After providing pre-defined accurate responses, these strategies are evaluated in machines. However, it is only useful for evaluating competitive or objective exams. Subjective examinations provide the foundation of all university and board-level exams. The moderator will know how much knowledge the student has obtained during his academic career based on the descriptive answer, on which the moderator will allocate marks. Manually evaluating subjective responses is a time-consuming and labor-intensive operation that requires a large number of people. According to their method of evaluation, the mood at the moment of evaluation, and interrelationship between student and moderator, answer evaluation varies from moderator to moderator. This has an impact on the student's grade. The goal of the research is to use machine learning and natural language processing to automate the evaluation process for subjective answers.

The mapping, succession, linear sequence matching, quantitative identification, and semantic research methods are utilized to evaluate student answers utilizing natural language processing and machine learning. The major goals of this research are to review student descriptive type responses using NLP and ANN algorithms, as well as to build a tool for evaluating student descriptive type replies using NLP for Grammatical checking, keywords and evaluation of marks, and ANN for normal answer comparison and producing marks. Also, the proposed system aims to provide voice assistant for visually impaired students. This project aims for the exam evaluation for students who can't write but are able to speak by providing speech-to-text and text-to-speech technology.

2. LITERATURE SURVEY

The existing method of evaluating subjective papers is ineffective. The challenge of evaluating subjective answers is crucial. When a human being evaluates anything, the quality of the evaluation can vary depending on the person's emotions. As a result, a plethora of automated subjective answer evaluation systems has emerged. We have briefly discussed some of the existing research articles that are connected to our work in this part. For details on related research publications refer Table I.

Table I. Literature Review

Sr. No.	Title	Conclusion	Limitations
1.	Subjective Answer Evaluation using Natural Language Processing and Machine Learning [1]	Subjective Answer Evaluation software assigns a grade to a subjective question based on the length of the answer, keyword matching, grammar check, cosine similarity, and contextual resemblance to the faculty's model answer and the student's answer.	The length of the answer determines the grade, although the length varies from person to person.
2.	Answer Evaluation Using Machine Learning [2]	When compared to a manual system, the proposed technique is around 75-87.5 percent accurate. The proposed approach eliminates all human effort and time required to analyze a response.	Only printed text can be recognized by the proposed technology, not handwritten text.
3.	Evaluating Student Descriptive Answers Using Natural Language Processing [3]	The main goal of this newly proposed method is to determine the semantic meaning of student responses, taking into account that students can respond to questions in a variety of ways.	The proposed system takes into account the meaning of collective utterances, which may conflict with the meaning of students' responses.
4.	Automatic Answer Evaluation Using Machine Learning [4]	The suggested system will use OCR with a backpropagation method and an artificial neural network. The algorithm will assess the response based on the scanned answer sheet, the moderator's keywords, and the length provided. The marks are given out based on the following factors: a. the number of keywords that were matched; and b. the length of the answer.	Exact keyword is required; synonyms or similar words are not acceptable.
5.	Design Engineering Automated Explanatory Answer Evaluation Using Machine Learning Approach [5]	Using Natural Language Processing, the system assesses the responses by extracting keywords from the students' replies and the tutor answer key. The cosine similarity metrics are used to verify for similarity between the student's answer and the answer key.	The technique primarily relies on cosine similarity for grading purposes.
6.	Automatic Online Subjective Text Evaluation using Text Mining [6]	The project is driven by similar data that a human would consider when analyzing, such as answer length, keyword presence, and keyword context. Natural Language Processing, in combination with categorization algorithms, is used to look for keywords and answer specific questions.	For model training, greater computing power is required.
7.	Evaluating Students Descriptive Answers Using Natural Language Processing and Artificial Neural Networks [7]	After the text mining process is completed, the student answer is compared to the correct answer using the ANN algorithm, and the student answer is checked for spelling and grammatical errors using the NLP algorithm.	No feedback option for students to suggest any improvements.
8.	Computerized Evaluation of Subjective Answers Using Hybrid Technique [8]	The methods of evaluation utilized the combination of LSA and BLEU is complimentary. The usage of WordNet reduces the number of keywords required because it finds synonyms for the specified keywords. This assures that the student can use any language he wants.	Models (LSA & BLEU) are required for evaluation. It is impossible to work with a single model.

Sr. No.	Title	Conclusion	Limitations
9.	Subjective Answer Grader System Based on Machine Learning.[9]	By comparing the computed scores of the replies with the human evaluation scores, the accuracy of LSA and IG algorithms may be determined. The accuracy of LSA and IG has grown from less than 40% to more than 75% once they were enhanced using WordNet.	Formulas and diagrams are not supported by the system.
10.	A Keyword Based Technique to Evaluate Broad Question Answer Script [10]	The system assesses the student's response using the keywords. The student will be assigned marks based on the sample answer and the student's answer.	Teachers' errors in submitting answer keys will result in erroneous evaluations.
11.	Text Similarity Analysis for Evaluation of Descriptive Answers [11]	The system employs natural language processing (NLP) and data mining, as well as an LSTM (recurrent neural network). Marks are distributed in a highly regular manner.	Answers must be typed into the system by the students. After the evaluation, no feedback is given.
12.	ASSESS-Automated Subjective Answer Evaluation Using Semantic Learning [12]	To generate system embedding, the proposed system employs NLP, semantic learning, and Google's USE algorithm. It eliminates the need for the user to write further answers and gives appropriate feedback.	Marks are assigned based on two factors: similarity and keywords. There is no synonym module included.
13.	Computer Application for Assessing Subjective Answers Using Artificial Intelligence [13]	The system is based on machine learning, natural language processing, and artificial intelligence, as well as methods such as HMM, RNN, STS, and CFG. Sequencing, watchword planning, and summarization are the basic concepts of evaluation.	After the evaluation, no feedback is given. It is impossible to evaluate answers that include equations, graphs, or formulas.
14.	Subjective Answer Grader System Based on machine learning [14]	In the system, algorithms such as LSA and IG are used, and WordNet is used to improve their evaluation. It has an accuracy of up to 83 percent.	For equations and graphs, there is no evaluation. For improved results, algorithms require WordNet.
15.	Speech To a Text Translation Enabling Multilingualism [15]	NLP with pre-existing data This method makes use of Google's Speech Recognition software. It can be used by people who have no prior computer experience. It is not necessary to have access to the internet. Speech can be translated into a variety of languages.	This model requires a pre-installed Speech Recognition program. Converts a small number of words at a time.
16.	Subjective Answer Evaluation Using Machine Learning [16]	The proposed approach employs machine learning and natural language processing, utilizing Naive Bayes as the underlying classifier. It evaluates quickly and efficiently. The system has a 90 percent accuracy rate.	The system does not provide feedback. Teachers must provide required keywords manually.
17.	Speech to text conversion using GRU And one hot vector encoding [17]	This system employs an RNN-based model with a gated recurrent unit. It is capable of achieving an accuracy of 87 percent.	It is only available in a single language. Converts a small number of words at a time.
18.	A focus on code mixing and code switching in Tamil speech to text [18]	Google's cloud conversion API and Google's Speech to Text model are used by the system. The technology allows for two or more languages to be spoken simultaneously, as well as the usage of two or more languages to compose a word.	Requires a quiet setting. Few accents are supported. For improper pronunciation, no output is produced.

3. METHODOLGY

The proposed model uses natural language processing and machine learning to evaluate voice-based answers. All of the student replies, as well as one standard answer each question, are used as inputs. The output is the pupils' final grades. To begin, input is pre-processed to prepare it for usage in the review process. Tokenization, synonym search, stop words, and stemming of student and standard replies have been completed. The proposed technique is designed to evaluate exam results for students who are unable to write but can talk. The proposed technique is designed to evaluate exam results for students who are unable to write but can talk. **Fig. 1** shows how the assessment technique is executed in a sequence of phases.

There are two aspects to the proposed system:

- Conversion of speech to text and text to speech
- Evaluation of the responses.

3.1 Text Extraction

Text extraction, often known as audio extraction, is a method of automatically scanning text and extracting relevant or core words and phrases from unstructured data using machine learning. This section focuses primarily on speech-to-text conversion. As we all know, speech-to-text conversion is part of natural language processing. We record the sound, process it, and then output it as text. We can utilize two alternative natural language processing modules to convert speech to text:

1. Deep Speech: Deep Speech is an open-source speech-to-text library that converts text to speech in real time. However, based on the examined literature, we may conclude that Deep Speech outcomes are good, albeit at the cost of the module's enormous file size.
2. Python Speech recognizer: The speech recognizer package in Python is used to do voice recognition with a variety of engines and APIs. The Recognizer class in Python speech recognizer utilizes seven different methods for recognizing speech for audio sources.

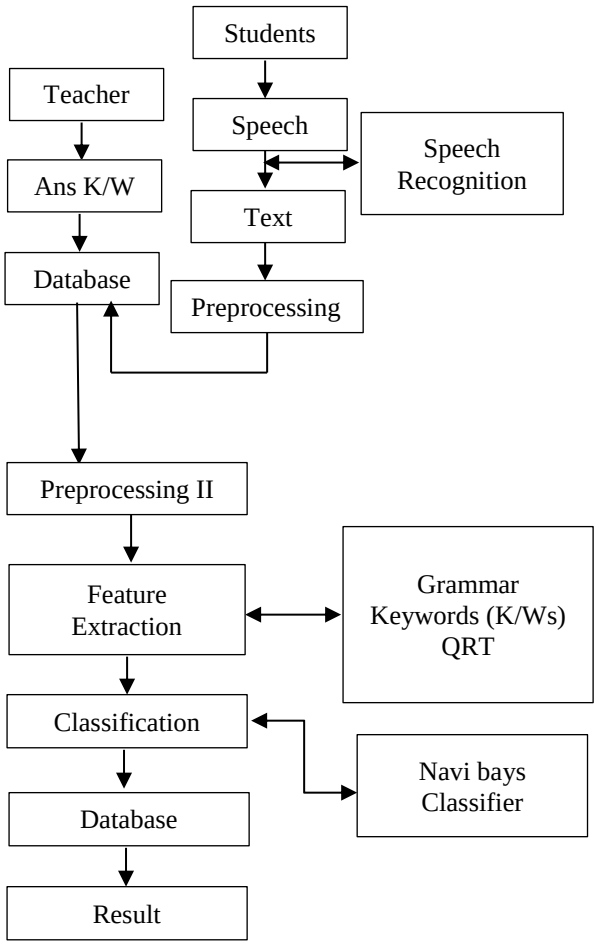

Fig. 1. System Architecture

3.2 Answer Evaluation

The following step is the answer evaluation, which comes after the text extraction procedure. There are three elements to the answer evaluation:

- The pre-processing stage
- Extraction of features
- Classification of Scores.

3.2.1The Pre-Processing Stage

Text pre-processing is a common stage in Natural Language Processing (NLP). It converts material into a more digestible format, allowing machine learning algorithms to perform the rest of the work more efficiently. As a result, we must pre-process the instructor and student data before evaluating them. We don't need some features in data because we're going to compare them, for example, we don't require punctuation or stop words. Pre-processing begins with the removal of punctuation, followed by word tokenization to convert the entire work into tokens, and finally the removal of stop words. The stop words are essentially "the," "and," and so on. Following the removal of stop words, stemming is used to eliminate all distinct versions of the same word, such as move and moving. All other phases in feature extraction, with the exception of grammar assessment, are pre-processed.

3.2.2. Feature Extraction

Because document data cannot be computed, it must be converted to numerical data, such as a vector space model. Feature extraction of document data is the common term for this transformation activity. Feature extraction is divided into three stages. These three components are an important feature of the suggested assessment method since they serve as the foundation for our evaluation.

a) Checking for similarity

In this exercise, we will compare the similarity of teacher and student responses and calculate the percentage of similarity. We are going to calculate Tf-IDF (Term frequency and inverse document frequency) of terms that are included in teacher and student

answers, and then we will calculate percentage similarity using cosine similarity.

b) Extraction of Keywords

As we receive essential keywords connected to teacher responses. To extract relevant terms from the answer, we use the Rake-NLTK module. This is done to cut down on the length of the answer and to allow for quick and efficient comparison. After extracting essential terms from student responses, we'll compare them to keywords used by professors. To compare keywords, we'll use a sequence matcher from difflib, which compares two strings and returns a ratio, such as the ratio of similarity between the words "abc" and "abc123." We've detected the keywords if the similarity ratio is 0.8 or higher. Following the comparison, the proportion of keywords for each category is found.

c) Grammar Evaluation

We need to evaluate the grammar because we want the response to have meaning. If we don't assess grammar, some pupils may rely solely on keywords and pass the exam. This is done to ensure a fair assessment. We don't need to perform pre-processing for grammar evaluation because punctuation is required to complete the sentence's meaning. We're sentencing, which involves tokenizing paragraphs, then words tokenizing sentences, chunking and chinking, and lastly calculating sentence mistakes. If there is no problem in the sentence, it is grammatically correct; if there is, it is grammatically incorrect. Finally, we will calculate the average accurate percentage in this manner.

3.2.3. Classification of Scores

Now that we have all of the percentages, we must assess them. We'll categories using a Naïve Bayes classification machine learning technique to figure out which group our answer belongs to.

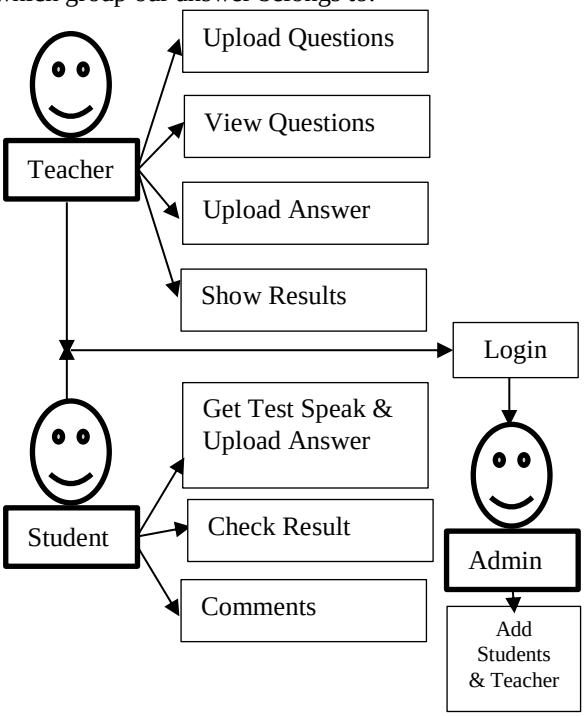

Fig. 2. Use Case Diagram

We'll train some example datasets and put our findings to the test. As a result, we'll come to a conclusion about the end result. Refer **Fig. 3** for use case diagram.

4 ALGORITHMS

4.1 Naïve Bayes

The Naive Bayes method is a supervised learning algorithm for addressing classification issues that is based on the Bayes theorem. It is mostly utilized in text classification tasks that require a large training dataset. The Naive Bayes Classifier is a simple and effective classification method that aids in the development of fast machine learning models capable of making quick predictions. It's a probabilistic classifier, which means it makes predictions based on an object's probability. Bayes Theorem is given in Equation (1).

$$P(A/B) = \frac{P(A/B)\,P(A)}{P(B)} \quad (1)$$

Where,

- Posterior probability (P(A|B)) is the probability of a hypothesis on the observed event B.
- P(B|A) stands for Likelihood, which is the probability of the evidence provided that a hypothesis' probability is true.
- Prior Probability (P(A)) is the probability of a hypothesis before looking at the evidence.
- P(B) stands for Probability of Evidence Marginal Probability.

It's a popular and effective classification algorithm.

4.2 Natural Language Processing

Natural language processing (NLP) is a branch of linguistics, computer science, and artificial intelligence that studies how computers interact with human language, particularly how to design computers to process and analyze massive amounts of natural language data. The goal is to create a computer that can "understand" the contents of papers, including the nuances of language in context. The system can then extract accurate information and insights from the papers, as well as categories and organize them.

Natural language processing techniques and approaches:

Natural language processing employs two basic techniques: syntax and semantic analysis. The arranging of words in a phrase to make grammatical sense is known as syntax. NLP analyses a language's meaning using syntax and grammatical rules. Syntax techniques include the following:

Parsing: This is a sentence's grammatical analysis. The text "The dog barked" is supplied to a natural language processing system as an example. Parsing is the process of breaking down a sentence into its constituent components of speech, such as dog = noun and barked

= verb. This is beneficial for activities that require more complex downstream processing.

Segmentation of words: This is the process of deriving word formations from a string of text. A person scans a handwritten paper into a computer, for example. The program would be able to examine the page and detect the presence of white spaces between the text.

Sentence Breaking: In lengthy texts, this creates sentence borders. The text is fed through a natural language processing system, for example, "The dog let out a bark. I became aware of my surroundings." The algorithm is able to distinguish the period that is used to break up the phrases.

Segmentation morphologically: This breaks down words into smaller units known as morphemes. The word untestable, for example, would be broken down into [[un[[test]able]]ly, where the algorithm recognizes the morphemes "un," "test," "able," and "ly." This is very important in speech recognition and machine translation.

Stemming: This separates words that have inflections into root forms. For example, the algorithm would be able to determine that the root of the word "barked" is "bark" in the sentence "The dog barked." If a user was looking for all instances of the word bark, as well as all of its conjugations, this would be handy. Even if the letters are different, the algorithm recognizes that they are basically the same term.

Semantics is the study of how words are used and what they mean. Algorithms are used in natural language processing to understand the meaning and structure of sentences. Figure 4 shows semantic similarity-based technique. Techniques used in semantics include:

Disambiguation of word meanings: This method uses context to determine the meaning of a word. Consider the following sentence: "The pig is in the pen." The term "pen" has a variety of meanings. This approach allows an algorithm to grasp that the term "pen" refers to a fenced-in region rather than a writing implement.

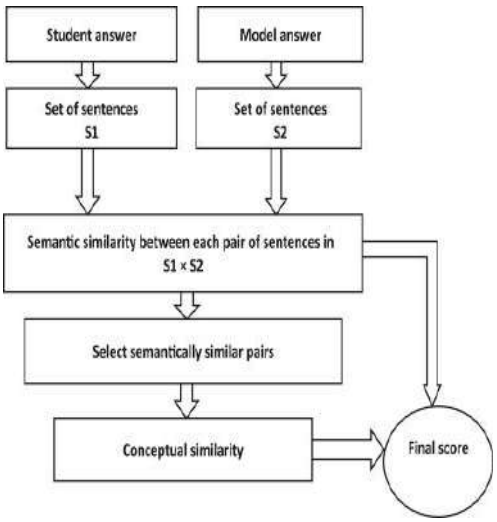

Fig. 4. Semantic Similarity based Subjective Answer Evaluation Model

Recognition of named entities: This defines which words can be grouped together. For example, using this strategy, an algorithm could evaluate a news story and find all mentions of a specific firm or product. It would be able to distinguish between visually similar entities using the semantics of the text. The system might detect the two instances of "McDonald's" in the line "Daniel McDonald's son went to McDonald's and ordered a Happy Meal," for example, as two unique entities one a restaurant and the other a person.

Generating natural language: The semantics behind words is determined using a database, and fresh text is generated. For instance, an algorithm may generate a summary of findings from a business intelligence platform automatically, connecting particular terms and phrases to elements of the BI platform's data. Another example would be creating news stories or tweets automatically based on a body of content used for training.

5 CONCLUSION

The project is driven by similar data that a human would consider when analyzing, such as answer length, keyword presence, and keyword context. Also, the proposed system uses Python speech recognizer for speech to text and text to speech conversion. Natural Language Processing, in combination with categorization algorithms, is used to look for keywords and answer specific questions. Because the system analyses for the occurrence of keywords, synonyms, correct word context, and coverage of all subjects, students will have a lot of leeway while crafting the answer. As a result of the robust evaluation system, it can be determined that applying ML approaches yields satisfactory results. The accuracy of the evaluation can be improved by providing it a big and accurate training dataset. We aim to create a Voice-based answer evaluation system using natural language processing and machine learning for physically disabled students. From the literature survey, for our proposed system speech recognizer is the best option available. And finally, we can classify results using the naive Bayes classifiers algorithm.

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VOICE BASED ANSWER EVALUATION SYSTEM USING NATURAL LANGUAGE PROCESSING AND MACHINE LEARNING

Abstract: In our modern age, as the world moves toward automation, there is a need for automation in answer evaluation systems. The checker's task is made more harder when analysing theory answers because online answer evaluation is now only available for mcq-based questions. The teacher examines the answer thoroughly before assigning the proper grade. In order to examine the answer, the current approach requires additional employees and time. This publication presents an application based on the evaluation of answers using machine learning. Because manual answer evaluation involves much more personnel and time, the purpose of this paper is to reduce labor and time utilization. It's also possible that two identical solutions will obtain different grades if you use the manual way.

Keywords: Natural Language Processing (NLP), Machine Learning, Speech to Text, Text to Speech, Naive Bayes, Word2vec, Cosine Similarity.

1. Introduction:

Students' academic achievement is generally measured by their examination scores, which might be subjective or objective. A variety of methods exist that can quickly assess objective or multiple-choice questions. These tactics are tested in machines after producing pre-defined accurate responses. It is, however, only applicable to judging competitive or objective exams. All university and board level exams are built on the foundation of subjective examinations. Based on the detailed answer, the moderator will determine how much knowledge the student has acquired during his academic career and assign marks accordingly. Manually assessing subjective replies is a time-consuming and labor-intensive process that necessitates the participation of a large number of people. Answer evaluation differs from moderator to moderator depending on their style of evaluation, mood at the time of evaluation, and interrelationship between student and moderator. The student's grade is affected as a result of this. The research's purpose is to automate the evaluation procedure for subjective answers using machine learning and natural language processing. Natural language processing and machine learning are used to analyse student replies using

mapping, succession, linear sequence matching, quantitative identification, and semantic research methodologies. The main objectives of this study are to examine student descriptive type responses using NLP and ANN algorithms, as well as to develop a tool for evaluating student descriptive type responses that uses NLP for grammatical checking, keywords, and mark evaluation, and ANN for normal answer comparison and mark production. The suggested technology also includes a voice aid for visually challenged students. This initiative uses speech-to-text and text-to-speech technology to provide exam evaluation for students who cannot write but can speak. The current system for grading subjective papers is ineffective. The difficulty of judging subjective responses is critical. When a person examines anything, the quality of the evaluation might be affected by their emotions. As a result, there have been a slew of automated subjective answer evaluation systems developed. In "Subjective Answer Evaluation using Natural Language Processing and Machine Learning", the system was assigning grade to a subjective question based on the length of the answer, keyword matching, grammar check, cosine similarity, and contextual resemblance to the faculty's model answer and the student's answer [1]. Similarly, in the "Evaluating Student Descriptive Answers Using Natural Language Processing", the authors proposed a new system to determine the semantic meaning of student responses, taking into account that students can respond to questions in a variety of ways [2]. While in "Automatic Online Subjective Text Evaluation using Text Mining", the project was driven by similar data that a human would consider when analyzing, such as answer length, keyword presence, and keyword context. Natural Language Processing, in combination with categorization algorithms, was used to look for keywords and answer specific questions [7].

2. Methodology:

To analyze voice-based answers, the proposed methodology employs natural language processing and machine learning. As inputs, all of the student responses are used, as well as one standard answer for each question. The final grades of the students are the product. To begin, input is pre-processed in order to make it ready for evaluation. Student and standard responses have been tokenized, searched for synonyms, stopped, and stemmed. The proposed method is intended to assess exam outcomes for pupils who cannot write but can speak. The proposed method is intended to assess exam outcomes for pupils who cannot write but can speak. The

assessment technique is depicted in Figure 1 as a series of phases.

There are two aspects to the proposed system:

1. Conversion of speech to text and text to speech

2. Evaluation of the responses.

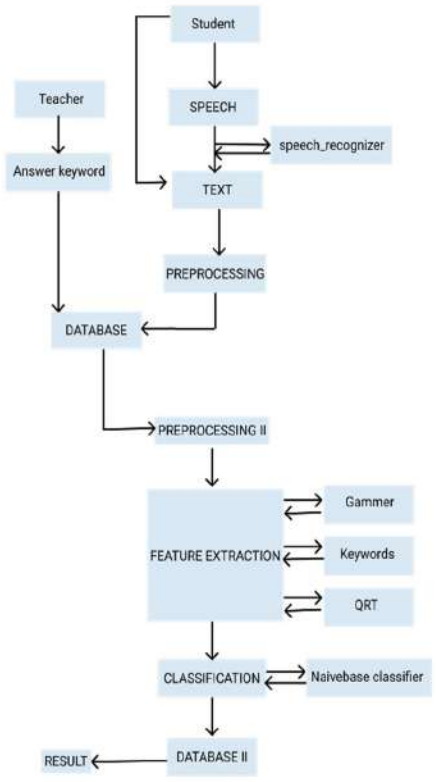

Figure 1: System Architecture

2.1 Text Extraction:

Text extraction, also known as audio extraction, is a way of employing machine learning to automatically scan text and extract relevant or core words and phrases from unstructured data. The main topic of this section is speech-to-text conversion. Natural language processing includes speech-to-text conversion, as we all know. We record the sound, then process it before converting it to text. To convert speech to text, we can use one of two natural language processing modules:

1. DeepSpeech is a term that refers to a type of speech that DeepSpeech is a free, open-source voice-to-text engine that translates text into speech in real time. However, based on the research, we can infer that DeepSpeech produces good results, but at the expense of the module's massive file size.

2. Python Speech Recognizer: The Python Speech Recognizer module is used to recognize voices using a number of engines and APIs. For recognizing speech for audio sources, the Recognizer class in Python uses seven different techniques.

3.2 Answer Evaluation:

The following step is the answer evaluation, which comes after the text extraction procedure. There are three elements to the answer evaluation:

3.2.1. The pre-processing stage

3.2.2. Extraction of features

3.2.3. Classification of Scores.

3.2.1 The Pre-Processing Stage:

In Natural Language Processing, text pre-processing is a common stage (NLP). It transforms data into a more readable format, allowing machine learning algorithms to complete the remaining tasks more quickly. As a result, before reviewing the instructor and student data, we must pre-process them. We don't need some data attributes because we're going to compare them; for example, punctuation and stop words aren't required. The elimination of punctuation is the first step in pre-processing, followed by word tokenization, which converts the entire work into tokens, and ultimately the removal of stop words. "The," "and," and so on are examples of stop words. After the stop words have been removed, stemming is used to delete all different variants of the same word, such as move and moving. With the exception of grammar assessment, all other aspects of feature extraction are pre-processed.

3.2.2 Feature Extraction:

Due to the inability to compute document data, it must be translated to numerical data, such as a vector space model. This transformation operation is known as feature extraction of document data. There are three phases to feature extraction. These three elements are crucial to the proposed assessment approach since they serve as the foundation for our assessment.

a) Checking for similarity:

We'll examine the similarity of teacher and student responses and compute the percentage of similarity in this exercise. We'll calculate Tf-IDF (Term frequency and inverse document frequency) of terms found in teacher and student responses, and then use cosine similarity to calculate percentage similarity.

b) Extraction of Keywords:

As we receive key terms associated with teacher responses. The Rake-NLTK module is used to extract relevant terms from the answer. This is done to shorten the answer and enable for faster and more efficient comparison. We'll compare essential terms extracted from student responses to keywords utilised by professors. We'll use a sequence matcher from difflib to compare keywords, which compares two strings and produces a ratio, such as the similarity ratio between the words "abc" and "abc123." If the similarity ratio is 0.8 or above, we've found the keywords. The fraction of keywords for each category is determined after the comparison.

c) Grammar Evaluation:

We must assess the grammar in order for the response to be meaningful. If we don't analyze grammar, some students may pass the exam simply on the basis of keywords.

This is done to ensure a balanced evaluation. Because punctuation is necessary to complete the sentence's meaning, we don't need to undertake any pre-processing for grammar evaluation. We're in the process of sentencing, which entails tokenizing paragraphs, words tokenizing sentences, chunking and chinking, and finally computing sentence errors. If the sentence contains no errors, it is grammatically correct; if it contains errors, it is grammatically incorrect. Finally, we'll use this method to calculate the average accurate percentage.

3.2.3 Classification of Scores:

We must now evaluate all of the percentages that we have. To figure out which group our answer belongs to, we'll use a Nave Bayes classification machine learning algorithm. We'll use some sample datasets to train our algorithms and put our conclusions to the test. As a consequence, we'll reach a decision about the final product.

The use case diagram is shown in Figure 2.

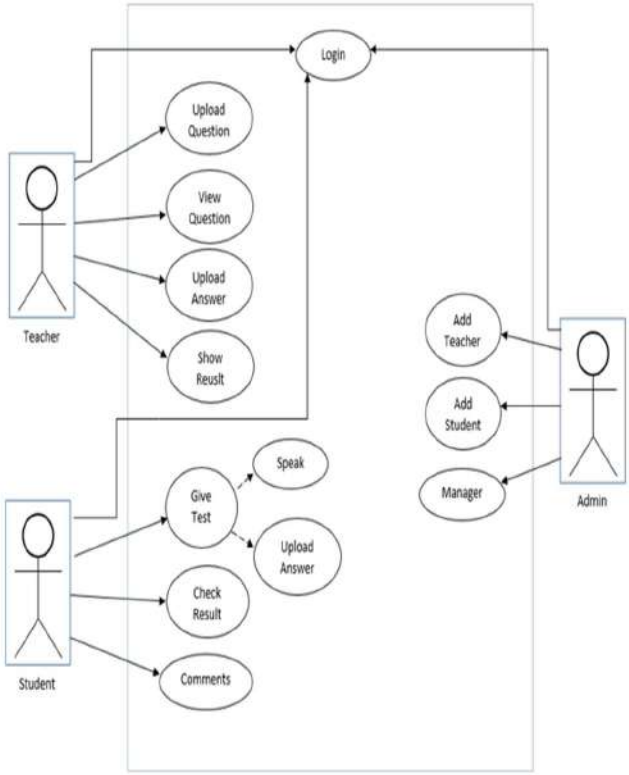

Figure 2: Use Case Diagram

3. Algorithms:

The following section gives detailed information about the algorithms used for implementation of proposed system.

3.1 Naïve Bayes:

The Naive Bayes method is a supervised learning algorithm that uses the Bayes theorem to solve classification problems. It is mostly used in text classification problems that necessitate a large training dataset. The Naive Bayes Classifier is a basic and effective classification method for developing fast machine learning models that can make quick predictions. It's a probabilistic classifier, meaning it makes predictions based on the probability of an object. The Bayes Theorem formula is shown in Figure 3.

$$P(A|B) = \frac{P(B|A)\ P(A)}{P(B)}$$

Figure 3: Bayes Theorem Formula

Where,

- Posterior probability (P(A|B)) is the probability of a hypothesis on the observed event B.
- P(B|A) stands for Likelihood, which is the probability of the evidence provided that a hypothesis' probability is true.
- Prior Probability (P(A)) is the probability of a hypothesis before looking at the evidence.
- P(B) stands for Probability of Evidence Marginal Probability.

It's a popular and effective classification algorithm.

4.2 Natural Language Processing:

Natural language processing (NLP) is an area of linguistics, computer science, and artificial intelligence that examines how computers interact with human language, especially how to construct computers that can process and analyze large amounts of natural language data. The goal is to develop a computer that can "understand" the contents of documents, including language nuances in context. After that, the system can extract correct data and insights from the articles, as well as categories and organize them.

Syntax and semantic analysis are the two primary strategies used in natural language processing. Syntax is the process of organizing words in a phrase so that they make grammatical sense. Using syntax and grammatical rules, NLP examines the meaning of a language. The following are examples of syntax techniques:

A] Parsing: This is a grammatical examination of a sentence. As an example, the text "The dog barked" is sent to a natural language processing system. The process of breaking down a sentence into its basic parts of speech, such as dog = noun and barked = verb, is known as parsing. This is advantageous for operations that necessitate more sophisticated downstream processing.

B] Segmentation of Words: The process of extracting word forms from a string of text is known as derivation. A person, for example, scans a handwritten piece of paper into a computer. The application would be able to scan the page for white spaces between the text and detect them.

C] Sentence Breaking: This generates sentence borders in long texts. For example, the text is given into a natural language processing system "A bark came from the dog. I became more conscious of my surroundings." The system can tell if a period is being used to break up the phrases.

D] Segmentation Morphology: This breaks words down into morphemes, which are smaller units. The word untestably, for example, would be broken down into [[un[[test]able]]ly, with the morphemes "un," "test," "able," and "ly" recognized by the algorithm. In speech recognition and machine translation, this is critical.

E] Stemming: This divide inflection-affected words into root forms. For example, in the line "The dog barked," the algorithm may figure out that the root of the word "barked" is "bark." This would be useful if a user was seeking for all instances of the word bark, as well as all of its conjugations. Despite the fact that the letters are different, the algorithm identifies that the terms are essentially the same.

The study of how words are used and what they mean is known as semantics. Natural language processing employs algorithms to decipher the meaning and structure of texts. The semantic similarity-based method is shown in Figure 4.

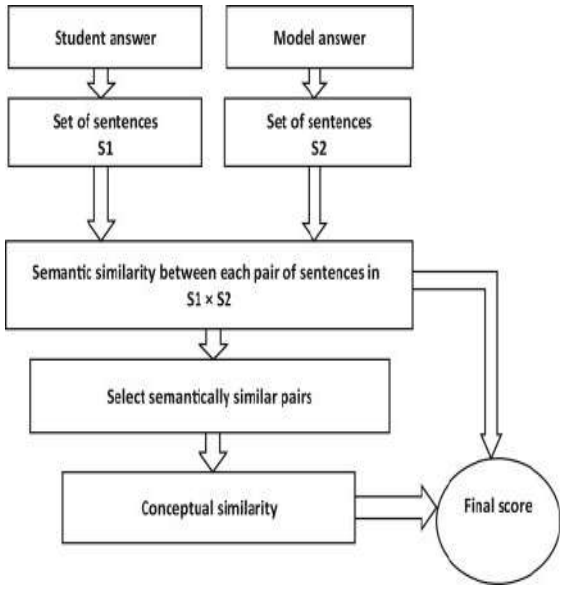

Figure 4: Semantic Similarity based Subjective Answer Evaluation Model

Techniques used in semantics include:

i. Disambiguation of word meanings: This approach determines the meaning of a word based on its context. Take this sentence for example: "The pig is in the pen." The word "pen" has several different connotations. This method enables an algorithm to understand that the term "pen" refers to a fenced-in area rather than a writing tool.

ii. Recognition of named entities: This determines which words can be combined. An algorithm may, for example, analyze a news piece and discover all mentions of a given corporation or product using this method. Using the semantics of the text, it would be able to discern between visually similar items. For example, the system might recognize the two

"McDonald's" in the line "Daniel McDonald's son went to McDonald's and ordered a Happy Meal" as two distinct entities, one a restaurant and the other a person.

Natural language generation: The semantics behind words are determined using a database, and fresh text is generated. For example, an algorithm may automatically write a summary of findings from a business intelligence platform, correlating specific terms and phrases to data items in the BI platform. Another example is automatically making news items or tweets from a corpus of content used for training.

4. Experimental Results:

Every student's performance is evaluated in any educational system around the world through a series of tests. After doing some investigation, we discovered that there are many methods for evaluating objective type answers, but just a few for evaluating descriptive answers. Professors keep several crucial keywords in mind while evaluating descriptive answers, so we provide keywords of the answer in our system to assess whether the answer is correct. Our method extracts keywords from the responses given by students, and then compares the extracted and given keywords from the answer sheet using cosine similarity. We have also implemented voice recording feature to record answers orally and get evaluated by the proposed system.

5. Conclusion:

Similar data that a human would examine when evaluating, such as answer length, keyword presence, and keyword context, drives the project. In addition, for speech to text and text to speech conversion, the proposed system employs a Python speech recognizer. To hunt for keywords and answer particular inquiries, Natural Language Processing is utilized in conjunction with categorization algorithms. Students will have a lot of discretion in composing the response because the algorithm looks for keywords, synonyms, correct word context, and covering of all subjects. The robust evaluation system has determined that using machine learning methodologies produces satisfactory outcomes. By supplying a large and accurate training dataset, the evaluation's accuracy can be increased. We want to construct a voice-based answer evaluation system for physically challenged students that uses natural language processing and machine learning. According to the literature review, speech recognition is the best alternative for our suggested system. Finally, we may use the naive Bayes

classifiers algorithm to classify the findings.

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A PROJECT REPORT ON VOICE BASED ANSWER DETECTION AND EVALUATION SYSTEM USING NATURAL LANGUAGE PROCESSING AND

MACHINE LEARNING

SUBMITTED

IN

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UNDER SAVITRIBAI PHULE PUNE UNIVERSITY, PUNE

BY

ABHISHEK ZADE (B150258576)

MANSI KUWADIA (B150258539) SARANG CHAMBHARE (B150258515) SOURAV SHINDE (

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UNDER

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is a record of bona-fide

work carried out by them,

in

the partial fulfilment of the requirement

for the award of Degree of Bachelor of Engineering

in Information Technology

at

All India Shri Shivaji Memorial Societies' Institute of Information Technology, Pune under the Savitribai Phule Pune University,

Pune. This work is completed during academic year 2021-22, under our guidance.

Dr. Meenakshi A. Thalor Dr. Meenakshi A. Thalor

Dr. P.B.Mane Project Guide

Head of Department Principal Examiner 1: - - - - - - -

Examiner 2: - - - - - - -

Contents

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Abhishek Zade, Mansi Kuwdia, Sarang Chambhare and Sourav Shinde

AISSMS IOIT, Pune.

When analysing theory solutions, the checker's

job becomes even more difficult since only mcq-based questions are now eligible for online answer evaluation.

The teacher examines the answer thoroughly before assigning the proper grade. In order to examine the response, the

existing method necessitates the hiring of additional personnel and the allocation of additional time. This paper describes a machine learning-based application that evaluates answers.

Because manual answer evaluation involves much more personnel and time, the purpose of this paper is to reduce labour and time utilisation. Furthermore, with the manual process, two identical solutions may obtain different marks. This application approach enables for the

automatic evaluation of replies based on the moderator's keyword input into the computer, ensuring that marks are distributed fairly and saving time and resources.

Keywords: Natural Language Processing (NLP), Machine Learning, Speech to Text, Text to Speech, Naive Bayes, Word2vec, Cosine Similarity.

List of Tables

Manually evaluating subjective responses is a time-consuming and labor-intensive operation that requires a large number

of people.

•

Many handicap people or blind people are facing issues like getting a proper device and using it.

• To make their task somewhat easier we are implementing this project.

• The project'

s goal

is to use machine learning and natural language processing to automate the

evaluation

process for subjective answers.

1.2

Motivation: In today's modern era, education system's evaluation system is still is offline. The students are needed to go in centers to give exams and also teachers are given burden to evaluate each and all students answer sheet separately. Due to overload of evaluation burden on teachers, it may happen that two identical answers which should be given same marks gets different marks. It is also difficult task for evaluators to identify copied answers. Also, when the topic of physically disabled students come, then for them it is more difficult and tedious task to give examination because initially it is very difficult for them to reach to the exam centers and also, they need some other person to write the paper on their behalf. So, basically to deal with the above problems, idea of

NLP and Machine Learning for

Voice Based Answer Detection

and Evaluation comes into existence. Voice based answer detection for physically disabled students and evaluation system for teachers will try to reduce the efforts of students and teachers by making evaluation process fast, secure and easy to use.

1.3 Related Theory: Voice activity detection (VAD), also known as speech activity detection or speech detection, is

a speech processing technique that detects

the presence or absence of human speech. The major applications of VAD are voice coding and recognition. It can help with speech processing and can also be used to turn off some processes during non-speech sections of an audio session: for example, in Voice over Internet Protocol (VoIP) applications,

it can prevent unnecessary coding and transmission of silence packets, saving time and network bandwidth. VAD is a critical enabler for a wide range of speech-based applications. As a result, a variety of VAD algorithms have been created, each with its own set of features and trade-offs

between latency, sensitivity, accuracy, and computing cost. Some VAD algorithms go much further, determining if the speech is spoken, unvoiced, or sustained.

The detection of

voice activity is usually independent of language. It was first looked into for usage in TASI (time-assignment speech interpolation) systems.

1.4 Need of the topic:

• To reduce the tedious task of teachers from checking answer sheet of every student. • To make a system which can help handicapped and blind students which will be user friendly for both students and teachers.

Chapter 2

literature survey

The existing

grading system for subjective papers is inefficient. It's crucial to understand how difficult it is to judge

subjective answers. When a person evaluates anything, their emotions may influence

the quality of the evaluation. As a result, a slew of automated subjective response evaluation systems have popped up. We briefly examined some of the current research articles that are relevant to our work in this part. TABLE 1: Literature Survey

Sr. No.

Title Conclusion Limitations

1. Subjective Answer Evaluation using Natural Language Processing and Machine Learning.

The length, keyword matching, grammatical check, cosine similarity, and contextual likeness of a subjective question

spent on response analysis. The proposed system can only recognise printed text,

algorithm will evaluate the response. The following elements are used to determine the grade:

suitable substitutes for the exact keyword.

5.

Design Engineering Automated Explanatory Answer Evaluation Using Machine Learning Approach

Using Natural Language Processing,

the programme evaluates the responses by extracting keywords from the students' responses and the

teacher answer key.

To verify that the student's answer and the answer key are similar,

cosine similarity metrics

are used. For grading reasons, the technique largely uses cosine similarity.

6. Automatic Online Subjective Text Evaluation using Text Mining Similar data that a human would examine when analysing, such as answer length, keyword presence, and keyword context,

drives the project. To find keywords and answer specific inquiries, Natural Language Processing is used with categorization algorithms.

For model training, greater computing power is required.

7. Evaluating Students Descriptive Answers Using Natural Language Processing And Artificial Neural Networks. After the

text mining process is completed,

the student answer is compared to the correct answer using the ANN algorithm, and the student answer is checked for spelling and grammatical errors using the NLP algorithm.

When the text mining method is finished, the result is automatically calculated using the NLP and ANN results.

There is no way

for evaluation is complementary. Because WordNet finds synonyms for the supplied keywords, it minimises the number of keywords required. This ensures that the student is free to use whichever language he desires. For evaluation, models (LSA and BLEU) are necessary. Working with a single model is impossible.

9. Subjective Answer Grader System Based on Machine Learning The correctness of LSA and IG algorithms can be determined

were augmented using WordNet, their accuracy increased from less than 40% to more than 75%. The system does not support formulas or diagrams.

10.

response, the student will be given a grade. Erroneous evaluations will come from

are all used in the system (recurrent neural network). The distribution of marks is extremely consistent. The technology also checks for plagiarism to avoid unethical practises. Students must type their answers

into the system. There is no feedback given

after the evaluation.

12. ASSESS - Automated Subjective Answer Evaluation Using Semantic Learning. The suggested system uses NLP, semantic learning, and Google's USE algorithm

to generate system embedding. It removes the need for the user to type more responses and provides suitable feedback. Two elements are used to assign grades:

63%	MATCHING BLOCK 10/24	W	https://aissmsioitresearch.com/wp-content/uplo ...

similarity and keywords. A synonym module is not included. 13. Computer Application For Assessing Subjective Answers Using Artificial Intelligence. Machine learning, natural language processing, and artificial intelligence

are all used in the system, as are methods like HMM, RNN, STS, and CFG. The core elements of evaluation are sequencing, watchword planning, and summarization. There is no feedback given after the evaluation. Answers with equations, graphs, or formulas are impossible to evaluate.

14.

76%	MATCHING BLOCK 11/24	W	https://aissmsioitresearch.com/wp-content/uplo ...

Subjective Answer Grader System Based on machine learning. Algorithms like LSA and IG are used

in the system, while WordNet is used to improve their evaluation. It can be as accurate as 83 percent of the time. The time required for review is reasonable. There is no evaluation for equations or graphs. Algorithms require WordNet for better outcomes.

15. Speech To a Text Translation Enabling Multilingualism. This solution uses Google's Speech Recognition software and uses NLP with pre-existing data. It is suitable for folks with

no prior computer expertise. It is not necessary to have internet connectivity. Speech can be translated into a number of

other languages. A preloaded Speech Recognition

application is required for this model. It only

76%	MATCHING BLOCK 12/24	W	https://aissmsioitresearch.com/wp-content/uplo ...

converts a few words at a time. 16. Subjective Answer Evaluation Using Machine Learning. Machine learning and natural language processing

are used in the proposed method, with Naive Bayes as the underlying classifier. It assesses swiftly and effectively. The accuracy rate of the system is 90%. There is no input from the system. Teachers must manually enter the appropriate

88%	MATCHING BLOCK 13/24	W	https://aissmsioitresearch.com/wp-content/uplo ...

keywords. 17. Speech to text conversion using GRU And one hot vector encoding. An RNN-based model with a gated recurrent unit is

used in this system. It has an accuracy rate of 87 percent. The technology can distinguish between different audios. There is also a noise cancellation option. There is only one language accessible. It only

87%	MATCHING BLOCK 14/24	W	https://aissmsioitresearch.com/wp-content/uplo ...

converts a few words at a time. 18. A focus on code mixing and code switching in Tamil speech to text.

The solution makes use of

at the same time, as well as the composition of words using two or more languages. Requires a quiet environment. Only a few accents are accepted. There is no output if the pronunciation

is incorrect.

19. Virtual assistant for the visually impaired. Google's STT for Python module and selenium are

used for automation. The precision of the system is

up to 96.25 percent. It also features audio tempo and accent altering. Only one language

can be used. A few websites are accessible to me. Speech to text conversion accuracy can be increased.

20.

A Spell-checker Integrated Machine Learning Based Solution for Speech to Text Conversion.

To convert voice,

the proposed system employs Deep-Voice, machine learning, and natural language processing.

The model is really precise. Access to the internet is necessary. More cycles are necessary to train the model. Long sentences are impossible to process.

21.

Evaluating Student's

Descriptive Answers using Natural Language Processing and Artificial Neural Networks.

This research employed

natural language processing and artificial neural networks. They developed their own algorithm based on NLP and ANN

to analyse responses. They've developed algorithms specifically for detecting grammatical errors. They didn't use

vectorization to assess similarity, instead depending on keywords, which is insufficient because students use similar terms outside of keywords.

22. Speech to text and text to speech recognition systems-A review. HMM is a better speech signal to text converter in

STT. The finest converter in TTS systems is

formant synthesis, which uses parallel and cascade synthesis. Because it incorporates the benefits of both rule-based and statistical machine translation systems,

hybrid machine translation is frequently employed.

The main downside of HMM is that, while converting sound to text is ideal, it is not always practicable. Their computational efficiency is a drawback.

23. Speech to Text Conversion for Multilingual.

The goal of this system is to extract, characterise, and recognise speech data. The suggested system

for speech classification

employs

the Mel-frequency Cepstral Coefficient (MFCC) feature extraction approach, as well as the Minimum Distance Classifier and Support Vector Machine (SVM) methodologies. This

system was created and taught solely for the purpose of converting

Marathi to English speech to text.

24. Automated Explanatory Answer Evaluation Using Machine Learning Approach. This paper's author defined tokenization and lemmatization, as well as how they work and are applied in systems. This study also looked into spell checking. The system prioritises keywords over all other considerations.

25. Development of GUI for Text-to-Speech Recognition using Natural Language Processing. Text-to-Speech synthesis

was developed by

the authors of this research study, which translates text into spoken words by analysing and processing audio using Natural language processing and then

turning the

processed text into synthesised speech representation of the text.

The planned user interface was not up to date. It's quite difficult to work with.

Chapter 3

PROPOSED WORK

3.1 Proposed Definition: In the education field, exams are conducted regularly in different locations. However, these assessments are currently time-consuming and manual. This is why the need for automatic answer scoring systems is so important. The assessment process usually takes a long time to prepare and conduct. It also needs more human resources to carry out the tasks and assess the results of the tests. The score can also vary depending on the answer given by the other students. This can create conflict between the instructor and the student. It is also possible that the student's score is different from that of other students. This study aims to identify the difficulties in processing subjective answers in different languages. Due to the differences in the way natural language processing is done in each language, the results of subjective answers are different.

3.2 Project Scope: • Main focus of this topic is it will be the option for the exam portal for blind and handicapped students • Since it will minimize the human efforts and automate the process of evaluating the answer and the result.

3.3 Project Objectives:

• To

provide an easy-to-use and accessible system for blind and disabled pupils. Reducing teacher's workload for evaluating exams. • To provide an easy-to-use and accessible system for blind and disabled pupils. •

Proposed system will provide voice assistant for visually impaired students. • In a nutshell, the goal is to improve the efficiency of the evaluation process while minimising human labour.

3.4 Project Constraints:

• Once an answer has been recorded by student, it cannot be changed. •

Distortion in the environment can lead to misspell in the answer. • It requires a stable internet connection.

Chapter 4

RESEARCH METHODOLOGY

4.1 System Architecture:

The given below diagram is the system architecture. This diagram is divided into two-parts. The first part is the voice detection part. On the Exam webpage, students will be given questions and Answers will be detected using the speech of the student. Speech is converted into text. The answer can be given just using text also this is an alternative way to get answers from students. These answers are then pre-processed and stored in the database. In Fig. 4.1, the workflow of our proposed system in shown.

Figure 4.11 System Architecture

Now coming to the second part of the diagram i.e., answer evaluation. The answers are again pre-processed and feature extraction is done. In feature extraction, we are features such as grammar of answers, keywords, and question-related things. After feature extraction we are going to classification whether the student is pass or fail for this we are going to the naive base classifier and the result is going to be stored in the database and the result will be shown on the result page.

4.2 Methodology / Algorithm:

4.2.1 Methodology:

To analyse voice-based answers,

to each question. The final grades of the students are the product. To begin, input is pre-processed in order to make it ready for evaluation. Students' and standard responses have been tokenized, searched for synonyms, stopped, and stemmed

The stages of

the assessment technique are depicted in Figure 4.1.The suggested system has two components: 1.

Conversion of speech to text and text to speech 2. Evaluation of the

response.

4.2.2 Algorithm:

Naïve Bayes The Naive Bayes method is a supervised learning algorithm that uses the Bayes theorem

to solve classification problems. It's typically employed in text classification issues where a big training dataset

is required.

for quickly developing machine learning models that can generate accurate

the probability of an object. Please see

Fig. 4.2

for the Bayes Theorem formula.

Figure 4.22 Bayes Theorem Formula

Where, •

The probability of a hypothesis on the observed event B

is called posterior probability (P(A|

is known as prior probability (P(A)). • P(B) stands for Marginal Probability

Probability of Evidence. It's a very popular and effective classification algorithm.

Chapter 5

PROJECT DESIGN

5.1 Hardware Requirements:

• Processor: Intel Dual Core or higher. • Ram: 2GB or higher. • Disk Space: Varies according to

the number of questions and answers. • Good system or external mic. • Stable Internet Connection.

5.2 Software Requirements:

• Python. • Django. • Python Libraries like NLTK Library. • Compatible browser.

5.3 Risk Analysis: • If more than one person talks while giving answer, system will take both the voices as input. • If there is any network failure, the test will be submitted automatically. • Pronunciation must be clear.

5.4 Data Flow Diagrams:

5.4.1. Sequence Flow diagram:

Figure 5.4.1 Sequence Flow Diagram Fig 5.4.1 shows the sequence flow diagram of the system.

This diagram shows how the sequence of the system works and the data flow. A sequence diagram shows object interactions arranged in the time sequence in the field of software engineering .Interprets the object involved in the scenario and the sequence of messages exchanged between the objects needed to carry out the functionality of scenario.

5.4.2 System flow diagram:

Figure 5.4.2 System Flow Chart Fig 5.4.2 is the flow chart of the system, which shows the proper flow of how system works.

5.5 Project Schedules:

and Deployment will all be covered in this chapter. Testing, publication of papers, submission of reports, and so on. This chapter also focuses on the stakeholder list, which includes information about the project type, the proposed system's customer, the user, and the project member who designed the system.

The following table II gives the information about the project schedule. TABLE III:

Project Schedule

Sem 1 Sem 2

Task Aug Sep Oct Nov Dec Jan Feb Mar Apr May 1. Topic Finalization 3. Base Paper Submission 4. Review 1 5. Literature survey 6. Review 2 7. Preparation of Review 3 8. Review 3 9. Paper publication 10. Preparation of Review 4 11. Review 4

5.6 UML Design and Documentation: Use case Diagram:

In this use case diagram, there are 3 actors i.e., teacher, student and admin. Fig 5.1 gives us a brief idea about use case diagram of our system.

Figure 5.33 Use Case Diagram Some of the scenarios of the system are as follow:

• Admin has the right to add both the teacher and student to the system. Adding to admin right, he/she can manage other outputs of system and has access to data uploaded by teacher and student. • To enter the best portal all the 3 actors have to login through with all the credentials provided. • Teachers are allowed to upload the test on the system, they can also update it. If they want specific set of keywords / answer they can upload sample. • Answer paper in order to give the best students have to login and select the mode in which they want to answer. Answers can be vocal or in the form of image copy of written or query. • If student find some issue or query with the paper they can comment. The comments will be shared with the teacher to take necessary actions. • Students can also check their results after the teacher uploads the result on the portal.

Class Diagram:

Figure 5.44 Class Diagram

Chapter 6

SYSTEM IMPLEMENTATIONS

6.1 Important Libraries /Packages: • Speechrecognition • gtts • nltk • gensim • numpy • pandas • cdifflib • rake-nltk • gingerit • django • django-livereload-servee

6.2 Important Functions: • Vector Similarity check • Grammar evaluation • Keyword Check

6.3 Important Algorithms: • Naive Bayes algorithm • Natural Language Processing

6.4

Graphics User Interface Screenshots:

In this section, user interface screenshots are added for reference.

Chapter 7

SYSTEM TESTING

The following table depicts manual testing of proposed system. Refer Table 7.1 for testing results.

TABLE 7.1:

System Testing Results

Teacher's Question Teacher's Answer Student's Answer Keywords Extracted Keywords detected

Grammar check Manual Evaluation By Teacher System Evaluation

1.What is AI? Artificial intelligence (AI) refers to the simulation of human intelligence in machines. AI refers to the machines with human intelligence. Artificial, Intelligence, simulation, human, machines

Machines , Human, intelligence

4.5/5

4/5

3/5

2.What is DBMS? Database Management System is a software for storing and retrieving users' data. DBMS is used to store and retrieve. Database, management , system, software, retrieving, user

Store, Retrieve

4/5

2.5/5

2/5

Chapter 8

EXPERIMENTAL RESULTS

The following experimental results show the student's overall outcome based on aspects such as grammar check, keyword check, tf–idf, tokenization, and vetor similarity. To deal with the aforementioned issues, the notion of NLP and Machine Learning for

Voice Based Answer Detection and Evaluation was born. Voice-based answer detection for physically challenged students and a teacher evaluation system will attempt to reduce

student and instructor effort by making the evaluation process quick, secure, and simple to use. As a result of these findings, the proposed system can execute with an accuracy of up to 85%.

Chapter 9

A Python voice recognizer is also used in

respond to specific enquiries.

Students will have a lot of discretion in composing the response because the algorithm looks for keywords, synonyms, correct word context, and covering of all subjects. The robust evaluation system has determined that using machine learning methodologies produces satisfactory outcomes. By supplying a large and accurate training dataset, the evaluation's accuracy can be increased. We want to construct a voice-based answer evaluation system for physically challenged students that uses natural language processing and machine learning. According to the literature review, speech recognition is the best alternative for our suggested system. Finally, we may use the naive Bayes classifiers technique to classify the findings.

Chapter 10

future scope

• It can be Replacement for human based exam system. • It decides the time of evaluation • It will helps to build an educational programme, assess its achievements and improve upon its effectiveness • It will be highly secure, easy to use, an environment friendly.

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Curiginal

Hit and source - focused comparison, Side by Side

Submitted text As student entered the text in the submitted document.

Matching text As the text appears in the source.

1/24	SUBMITTED TEXT	21 WORDS	71%	MATCHING TEXT	21 WORDS

Abstract As the globe evolves toward automation in our modern age, there is a need for automation in answer evaluation systems.

SA 2565-4997-1-SM.docx (D112694950)

2/24	SUBMITTED TEXT	39 WORDS	71%	MATCHING TEXT	39 WORDS

Introduction: • In general, students' academic achievement is evaluated through examinations, which might be subjective or objective. •

INTRODUCTION In general, students' academic success is evaluated based their examination results, which might be subjective or objective.

W https://aissmsioitresearch.com/wp-content/uploads/2022/02/1-IJTEAMS-1-2-4.pdf

17/24	SUBMITTED TEXT	42 WORDS	50%	MATCHING TEXT	42 WORDS

to the faculty's model answer and the student's answer are used to grade it. The grade is determined by the length of the answer, which varies from person to person. 2. Answer Evaluation Using Machine Learning The proposed technique is 75-87.5 percent accurate

to the faculty's model answer and the student's answer. The length of the answer the grade, the length varies from person to person. 2. Answer Evaluation Using Learning [2] compared to a manual system, the proposed technique is around 75-87.5 percent accurate.

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3/24	SUBMITTED TEXT	16 WORDS	66%	MATCHING TEXT	16 WORDS

when compared to a manual system. The proposed method eliminates all human effort and time

When compared to a manual system, the proposed technique is around 75-87.5 percent accurate. The proposed approach eliminates all human effort and time

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Curiginal

4/24	SUBMITTED TEXT	99 WORDS	66%	MATCHING TEXT	99 WORDS

not handwritten text. 3. Evaluating Student Descriptive Answers Using Natural Language Processing. The main goal of this newly proposed method is to determine the semantic meaning of student responses, which is difficult because students can react to questions in a variety of ways. The suggested system considers the meaning of group utterances, which may differ from the meaning of students' responses. 4. Automatic Answer Evaluation Using Machine Learning The proposed system will combine optical character recognition (OCR) with a back propagation method and an artificial neural network. Based on the scanned answer sheet, the moderator's keywords, and the length provided, the

not handwritten text. 3. Evaluating Student Descriptive Answers Using Natural Language Processing [3] The main goal of this newly proposed method is to determine the semantic meaning of student responses, taking into account students can respond to questions in a variety of ways. The proposed system takes into account the meaning of collective utterances, which may conflict with the meaning of students' responses. 4. Automatic Answer Evaluation Using Machine Learning [4] The suggested system will OCR with a backpropagation method and an artificial neural network. The algorithm will assess the response based on the scanned answer sheet, the moderator's keywords, and the length provided. The

W https://aissmsioitresearch.com/wp-content/uploads/2022/02/1-IJTEAMS-1-2-4.pdf

5/24	SUBMITTED TEXT	21 WORDS	90%	MATCHING TEXT	21 WORDS

a. the number of keywords that were matched; and b. the length of the answer. Synonyms or similar words are not

a. the number of keywords that were matched; and b. the length of the answer. Exact keyword is required; synonyms or similar words are not

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6/24	SUBMITTED TEXT	26 WORDS	60%	MATCHING TEXT	26 WORDS

for students to provide comments or recommend improvements. 8. Computerized Evaluation of Subjective Answers Using Hybrid Technique. The use of a combination of LSA and BLEU

for students to suggest improvements. 8. Computerized Evaluation of Subjective Answers Using Hybrid Technique [8] The methods of evaluation utilized the combination of LSA and BLEU

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7/24	SUBMITTED TEXT	18 WORDS	76%	MATCHING TEXT	18 WORDS

by comparing the computed scores of the replies to the human evaluation scores. When LSA and IG

By comparing the computed scores of the replies with the human evaluation scores, the accuracy of LSA and IG

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8/24	SUBMITTED TEXT	30 WORDS	50%	MATCHING TEXT	30 WORDS

A Keyword Based Technique to Evaluate Broad Question Answer Script. The keywords are used by the algorithm to evaluate the student's response. Based on the sample answer and the student's

A Keyword Based Technique to Evaluate Broad Question Answer Script [10] The system assesses the student's response using the keywords. The student will be assigned marks based on the sample answer and the student's

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9/24	SUBMITTED TEXT	24 WORDS	56%	MATCHING TEXT	24 WORDS

teachers' mistakes in providing answer keys. 11. Text Similarity Analysis for Evaluation of Descriptive Answers Natural language processing (NLP), data mining, and an LSTM

Teachers' errors in submitting answer keys will in erroneous Text Similarity Analysis for Evaluation of Descriptive Answers [11] The system employs natural language processing (NLP) and data mining, as well as an LSTM (

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10/24	SUBMITTED TEXT	27 WORDS	63%	MATCHING TEXT	27 WORDS

similarity and keywords. A synonym module is not included. 13. Computer Application For Assessing Subjective Answers Using Artificial Intelligence. Machine learning, natural language processing, and artificial intelligence

similarity and keywords. There is synonym module Computer Application for Assessing Subjective Answers Using Artificial Intelligence [13] The system is based on machine learning, natural language processing, and artificial intelligence,

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11/24	SUBMITTED TEXT	15 WORDS	76%	MATCHING TEXT	15 WORDS

Subjective Answer Grader System Based on machine learning. Algorithms like LSA and IG are used

Subjective Answer Grader System Based on machine learning [14] In the system, algorithms such as LSA and IG are used,

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12/24	SUBMITTED TEXT	20 WORDS	76%	MATCHING TEXT	20 WORDS

converts a few words at a time. 16. Subjective Answer Evaluation Using Machine Learning. Machine learning and natural language processing

Converts a small number of words at a time. 16. Subjective Answer Evaluation Using Machine Learning [16] The proposed approach employs machine learning and natural language processing,

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13/24	SUBMITTED TEXT	22 WORDS	88%	MATCHING TEXT	22 WORDS

keywords. 17. Speech to text conversion using GRU And one hot vector encoding. An RNN-based model with a gated recurrent unit is

keywords Speech to text conversion using GRU And one hot vector encoding [17] This system employs an RNN-based model with a gated recurrent unit. It is

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14/24	SUBMITTED TEXT	21 WORDS	87%	MATCHING TEXT	21 WORDS

converts a few words at a time. 18. A focus on code mixing and code switching in Tamil speech to text.

Converts a small number of words at a time. 18. A focus on code mixing and code switching in Tamil speech to text [18]

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15/24	SUBMITTED TEXT	21 WORDS	79%	MATCHING TEXT	21 WORDS

Google's cloud conversion API and Google's Speech to Text paradigm. The technology allows two or more languages to be spoken

Google's cloud conversion API and Google's Speech to Text model are used by the system. The technology allows for two or more languages to be spoken

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16/24	SUBMITTED TEXT	26 WORDS	46%	MATCHING TEXT	26 WORDS

the proposed methodology employs natural language processing and machine learning. As inputs, all of the students' responses are used, as well as one standard answer

The proposed model uses natural language processing and machine learning to evaluate voice-based answers. All of the student replies, as well as one standard answer

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18/24	SUBMITTED TEXT	39 WORDS	53%	MATCHING TEXT	39 WORDS

completed. The proposed method is intended to assess exam outcomes for pupils who cannot write but can speak. The proposed method will be used to evaluate exam results for students who are unable to write but can talk.

completed. The proposed technique is designed to evaluate exam results for students who are unable to write but can talk. The proposed technique is designed to evaluate exam results for students who are unable to write but can talk.

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19/24	SUBMITTED TEXT	12 WORDS	100%	MATCHING TEXT	12 WORDS

The Naive Bayes Classifier is a simple and effective classification method

The Naive Bayes Classifier is a simple and effective classification method

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20/24	SUBMITTED TEXT	12 WORDS	83%	MATCHING TEXT	12 WORDS

predictions. It's a probabilistic classifier, meaning it makes predictions based on

predictions. It's a probabilistic classifier, which means it makes predictions based on

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21/24	SUBMITTED TEXT	57 WORDS	67%	MATCHING TEXT	57 WORDS

B)). • P(B|A) stands for Likelihood, which is the probability of the evidence if the probability of a hypothesis is true. • The likelihood of a hypothesis before looking at the evidence

B. ? P(B|A) stands for Likelihood, which is the probability of the evidence provided that a hypothesis' probability is true. ? Prior Probability (P(A)) is the probability of a hypothesis before looking at the evidence. ?

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24/24	SUBMITTED TEXT	23 WORDS	100%	MATCHING TEXT	23 WORDS

Preliminary Survey Introduction and Problem Statement, Literature Survey, Project Statement, Software Requirement and Specification, System Design, Partial Report Submission, Architecture Design, Implementation,

Preliminary Survey Introduction and Problem Statement, Literature Survey, Project Statement, Software Requirement and Specification, System Design, Partial Report Submission, Architecture Design, Implementation,

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22/24	SUBMITTED TEXT	23 WORDS	84%	MATCHING TEXT	23 WORDS

CONCLusion The project is driven by data that a human would check when analysing, such as answer length, keyword presence, and keyword context.

CONCLUSION The project is driven by data that a human would consider when analyzing, such as answer length, keyword presence, and keyword context.

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23/24	SUBMITTED TEXT	25 WORDS	47%	MATCHING TEXT	25 WORDS

the proposed system to convert speech to text and text to speech. Natural Language Processing is combined with classification algorithms to locate keywords and

the proposed system uses Python recognizer for speech to text and text to speech conversion. Natural Language Processing, in combination with categorization algorithms, is to look for keywords and

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