Subjective Answer Evaluation Using Machine Learning and Natural Language Processing

Project Report

Of Major Project

Bachelor Of Technology

Computer Science and Engineering

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April 2024

Annasaheb Dange College of Engineering & Technology(ADCET), Ashta.

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Of

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CERTIFICATE

This is to certify that the project report titled "Subjective Answer Evaluation Using Machine Learning and Natural Language Processing" submitted by

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It is a record of project work carried out in this institute in the partial fulfilment of the requirement for the award of the degree in Computer Science and Engineering as a part of the curriculum during the academic year 2023-24.

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ACKNOWLEDGEMENT

We feel immense pleasure in submitting this Project report entitled "Subjective Answer Evaluation Using Machine Learning and Natural Language Processing".

We are thankful to our guide Prof. Shailaja Katti for their valuable guidance and kind help during the completion of the Project and feel great to express our sincere gratitude to other all staff members of the CSE Department.

We are also thankful to the Head of the 'Department of Computer Science and Engineering' Dr.Suhel Sayyad for their valuable guidance during the completion of the Project.

We would like to thank all faculty members and staff of the Department of Computer Science and Engineering for their generous help in various ways for the completion of this thesis.

We would like to thank all our friends and especially our classmates for all the thoughtful and mind-stimulating discussions we had, which prompted us to think beyond the obvious. we have enjoyed their companionship so much during our stay at ADCET,Ashta.

DECLARATION

We hereby declare that the work presented in this project report titled **"Subjective Answer Evaluation Using Machine Learning and Natural Language Processing"** submitted by us in the partial fulfillment of the requirement to the award of the degree of Bachelor of Technology (B.Tech.) submitted in the **Department of Computer Science and Engineering, Annasaheb Dange College of Engineering and Technology, Ashta**, is an authentic record of our project work carried out under the guidance of Prof.Shailaja Katti. To the best of our knowledge, it contains no material previously published or written by another person, nor material which has been accepted for the award of any other degree or diploma in any university.

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Abstract

Evaluating subjective answers is a challenging task in education and assessment, often requiring significant time and effort from educators. Automated systems leveraging Machine Learning (ML) and Natural Language Processing (NLP) offer promising solutions to this challenge. In this project, we propose a novel approach to subjective answer evaluation, utilizing advanced ML and NLP techniques.

The primary objective of our project is to develop a system capable of accurately assessing subjective answers provided by students in educational assessments. We aim to create a tool that can mimic human-like evaluation, providing insightful feedback to both students and educators.Furthermore, we employ NLP techniques to extract meaningful features from textual answers. These features will enhance the model's understanding of the content and context of the answers, enabling it to make more informed evaluations.

Overall, our project aims to contribute to the advancement of automated subjective answer evaluation systems, providing valuable tools for educators to streamline the assessment process and enhance the learning experience for students. Through the integration of ML and NLP techniques, we strive to develop a robust and reliable system capable of delivering accurate and insightful evaluations of subjective answers.

In conclusion, our project contributes to the advancement of automated subjective answer evaluation systems, offering a valuable tool for educators to enhance the efficiency and effectiveness of educational assessments. Through the fusion of ML and NLP techniques, we aim to develop a versatile and reliable system that empowers educators and improves the learning experience for students.

Keywords: Automated subjective answer evaluation, machine learning, score, NLP etc.

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1 Introduction

In the current educational landscape, the assessment of subjective answers remains a critical yet challenging component. Traditional methods largely depend on human evaluators who bring their own perceptions and biases, inevitably leading to variations in grading standards. Furthermore, with the expanding scope of education, both in terms of student numbers and educational formats such as online learning, the need for a scalable, consistent, and efficient evaluation system has become more pressing. This project proposes the use of machine learning (ML) and natural language processing (NLP) as tools to revolutionize the way subjective answers are assessed.

This initiative addresses the critical need for a more efficient, unbiased, and scalable assessment process, which is becoming increasingly vital in both conventional and modern educational platforms that are dealing with large volumes of students and digital coursework.As educational institutions continue to grow and diversify, the limitations of human grading—such as inconsistencies, bias, and the sheer time required to evaluate large sets of subjective answers—become more pronounced. This project aims to mitigate these challenges by developing an automated system that can evaluate written responses with the same depth of understanding as a human grader but with greater consistency and efficiency.

Subjective answer evaluation typically involves complex, open-ended responses that require an understanding of context, nuanced language, and the ability to make informed judgments. Historically, this task has been the exclusive domain of human assessors. However, this approach is filled with challenges such as scalability, speed, and cost-efficiency, not to mention the potential for human error and bias. The integration of technology in educational assessment has been gradual but has primarily focused on objective, easily quantifiable responses due to their straightforward nature in automated assessment.

The advent of advanced computational techniques and algorithms in machine learning and natural language processing presents a new opportunity to tackle the more intricate problem of subjective response evaluation. These technologies can analyze large datasets and understand complex patterns in text, making them ideal for interpreting and assessing written responses.This project aims to explore the fusion of ML and NLP techniques to develop a robust system for evaluating subjective answers.By leveraging the power of machine learning algorithms and natural language understanding, this system seeks to achieve several goals such as automated grading, continuous improvement, scalability etc.

1.1 Purpose

The ”Subjective Answer Evaluation Using Machine Learning and NLP” project is designed to address several critical needs in the education sector by integrating advanced technological tools. A primary aim of the project is to enhance educational equity by standardizing the grading process. This standardization helps eliminate subjective biases that might influence grading based on an evaluator’s personal perceptions or experiences, thereby ensuring that all students are assessed solely on the merit of their work. This shift not only promotes fairness but also supports more consistent and reliable grading across various educational institutions and platforms.

Efficiency and scalability in assessments are also central to the project’s goals. As educational environments increasingly adopt online and distance learning models, the demand for handling large volumes of student assessments grows. By automating the grading of subjective answers, the project substantially reduces the workload on educators, freeing them to devote more time to interactive and instructional duties. This automation ensures that feedback is not only timely but also consistently aligned with educational standards, which is crucial for effective learning.

The project facilitates data-driven decisions in education systems by analyzing patterns in student responses. These insights can highlight common areas of difficulty, inform curriculum adjustments, and enhance teaching methods. In addition, the technology developed through this project propels forward research in educational technologies, offering new avenues for innovation in how machine learning and NLP can further impact education. Ultimately, by preparing students to engage with technology in their learning processes, the project not only enhances their current educational experience but also equips them with the skills necessary for success in a technology-driven world.

1.2 Objectives

Following are the main objective of developing the project named subjecctive answer evaluation using machine learning and nlp.

1. To perform preprocessing on the acquired data, such as Tokenization, Lemmatization and special character removal
2. To create a module for measuring similarity that uses functions like Cosine Similarity to determine similarity
3. To create a result predicting model to evaluate the results of all similarity metrics
4. To develop a weighted module that will determine the ultimate score

1.3 Scope

The "Subjective Answer Evaluation Using Machine Learning and NLP" project is designed to harness the capabilities of machine learning (ML) and natural language processing (NLP) to revolutionize the assessment of subjective answers in educational settings. The objective is to build a system that can autonomously evaluate written responses from students with an accuracy and insight comparable to human graders. By doing so, the project seeks to address the inherent issues of subjectivity and inconsistency that plague traditional manual grading processes.

Central to the project's scope is the development of sophisticated ML algorithms and the integration of NLP techniques will allow the system to dive deeper into the semantic and syntactic layers of student answers. This includes parsing sentences to understand grammatical structure, using sentiment analysis to gauge the tone and intent, and employing semantic analysis to verify the relevance and accuracy of the content. Such detailed analysis is crucial for effectively grading subjective answers, which require a more nuanced assessment than simple right-or-wrong questions.

The project also emphasizes scalability and efficiency. By automating the grading process, educational institutions can handle larger volumes of student work without compromising on the quality of assessment. This is particularly beneficial for massive open online courses (MOOCs) and distance learning programs, where the student-to-teacher ratio is exceptionally high. Automated systems ensure that every student receives timely and consistent feedback, which is vital for their learning progression.

Finally, this project will include the development of a user-friendly interface for educators to interact with the system, review grading outcomes, and possibly tweak the model's parameters to better suit specific needs. Training and support will also be provided to ensure that users can maximize the benefits of the system. Through continuous feedback from users and iterative improvements based on real-world application, the project aims to evolve into a robust tool that not only meets but exceeds the current standards of educational assessments.

1.4 Problem Statement

To design and develop a system for Machine Learning and NLP-based Subjective Answer Evaluation

Reality: The current process for evaluating subjective answers relies heavily on human assessors, who are inherently prone to bias and inconsistency. This manual method of grading is time-consuming and often lacks scalability, especially in the context of rapidly growing educational demands and diverse student populations.

Consequences: Due to the subjective nature of human grading, the consistency and fairness of assessments can be compromised, affecting the reliability of educational outcomes. Additionally, the labor-intensive nature of manual grading limits the frequency and promptness of feedback to students, potentially hindering their educational progress.

Proposal: This proposal is to develop an automated system that utilizes machine learning and natural language processing to evaluate subjective answers. This system aims to mimic human evaluative skills with greater consistency and efficiency, while reducing the susceptibility to bias. It will be capable of processing large volumes of responses quickly, providing timely and accurate feedback to students, and supporting educational institutions in managing large-scale assessments more effectively.

2 Literature Survey

The Following are the articles studied during the literature survey of our project.

By concentrating on the terms that both texts share, **Oghbaie and Zanjireh** created a novel method for calculating how similar two documents are to one another. In order to more accurately evaluate textual similarities, their approach—known as the Pair-wise Document Similarity Measure, or PDSM—evolves from the preferred properties technique. This measure has been successfully used in a number of text mining scenarios, such as K-means clustering and document categorization, which are specifically designed for single-label classification tasks. The effectiveness of the PDSM has been shown by improvements in the precision and speed of finding and classifying related documents in sizable datasets. Text mining has advanced significantly with the creation of PDSM, allowing for more complex analyses of textual data. This method supports more documents and increases the scalability of document processing operations.The PDSM has proven especially effective in text mining applications such as K-means clustering and document categorization, particularly within single-label classification tasks. It facilitates more sophisticated textual analyses and supports enhanced scalability in document processing, which is essential in handling the increasing volume of data. This development not only improves the accuracy and speed of document-related tasks but also advances the capabilities of text mining, providing a robust tool for researchers and practitioners dealing with extensive text-based datasets.[1]

Muhammad Farrukh Bashir and Shahab S. Band explored the application of machine learning (ML) algorithms and natural language processing (NLP) techniques to develop an automated system for evaluating subjective answers. By integrating ML and NLP into the assessment process, the researchers hope to streamline grading, reduce the time educators spend on manual review, and enhance the reliability of evaluating students' written work. This advancement in educational technology marks a significant step forward in the adoption of artificial intelligence tools in academic settings, offering a more standardized and efficient method for evaluating complex, open-ended responses.Their study focused on using various computational functions to assess the degree of similarity between pairs of sentences. This approach is critical in understanding how closely a student's response matches a model answer, thus facilitating a more objective and efficient grading process. The researchers employed diverse algorithms that analyze text-based responses, comparing semantic elements and syntactic structures within the answers to gauge similarity. This method not only enhances the reliability of subjective answer assessment but also significantly reduces the time and effort traditionally required in manual grading. The innovative use of ML and NLP in education underscores a transformative step toward integrating artificial intelligence in academic evaluation processes, aiming to achieve higher accuracy and consistency in results.[2]

In the field of automated essay scoring (AES), significant advancements have been made to enhance the accuracy and efficiency of evaluations. One notable contribution is from a study by **Taghipour and Ng** in 2016, which pioneered the integration of deep learning technologies into AES systems. Their research introduced a novel approach by combining both convolutional neural networks (CNNs) and recurrent neural networks (RNNs) to develop a more robust scoring mechanism. This hybrid model was particularly effective in analyzing and understanding complex semantic features and the contextual nuances of written text. Their findings indicated that such deep learning frameworks could significantly outperform traditional scoring algorithms by adapting more effectively to the variances in linguistic expression found in student essays. This approach not only marked a progressive step towards more accurate assessments of written submissions but also highlighted the potential of neural networks in educational applications.This research not only pushed the boundaries of what's possible in AES by integrating sophisticated neural network architectures but also set a precedent for the future use of deep learning in educational assessments. The success of this model highlighted the potential for neural networks to revolutionize how educational systems evaluate and understand student submissions, paving the way for further innovations in the field. The work of Taghipour and Ng stands as a landmark study, signaling a shift towards more advanced, fair, and reliable scoring systems in education.[3]

Attali and Burstein (2006) investigated the integration of Natural Language Processing (NLP) tools in automated essay scoring (AES), focusing on features such as syntactic complexity and lexical diversity. Their research underscored the potential of these language indicators to enhance the evaluation of written submissions. Further advancements in the field were propelled by the development of sophisticated technologies such as word embeddings and neural networks. This technological progression was highlighted in the work of Mohler et al. (2011) titled "Automated Assessment of Short Text Answers." Their research provided substantial evidence supporting the use of advanced machine learning techniques to assess short written responses effectively. This body of work collectively illustrates significant strides in leveraging computational methods to improve the objectivity and efficiency of text evaluation in educational settings.These studies collectively underscore the trajectory of research in AES, highlighting how computational methods have increasingly been harnessed to refine the objectivity and efficiency of educational assessments. The integration of sophisticated NLP tools into AES systems promises to offer educators and institutions a more reliable means of evaluating student performance through written tasks. [4]

The research conducted by **Berke Oral, Erdem Emekligil, and Secil Arslan** represents a pioneering effort in the field of information extraction from scanned documents by integrating textual information. This study is notable for its application of auxiliary learning techniques that simultaneously leverage multiple tasks to enhance the primary goal of text extraction. Additionally, it delves into the positioning characteristics of words within the documents, which plays a crucial role in understanding the structure and layout of the text. The research also explores the impact of utilizing diverse word representations on the effectiveness of the information extraction process. By examining these various elements, the study contributes significant insights into the optimization of text extraction technologies, potentially influencing future methodologies in handling scanned documents and similar datasets.The implications of this research are profound, potentially setting new directions for the development of technologies involved in processing and managing scanned documents and other similar data-intensive tasks. By integrating auxiliary learning and examining multiple dimensions of word representation and positioning, the study not only improves current methodologies but also opens up new avenues for future innovations in the field of document analysis and information retrieval. This comprehensive approach not only enhances the primary task of text extraction but also contributes to the broader understanding of document handling technologies.[5]

Study conducted by **Xinming Hu and Huosong Xia**, the focus is on developing an automated evaluation system for subjective questions using latent semantic indexing (LSI). The approach involves creating a term-document matrix from reference answers, which are processed using Chinese automatic text segmentation and subject-specific ontologies. This matrix is subsequently mapped into a lower-dimensional space defined by 'k' dimensions using LSI, a technique built on statistical analysis. The reduction of dimensionality is accomplished through singular value decomposition, a key component of LSI that effectively addresses issues related to synonymy and polysemy in language processing. This methodology underscores the potential of LSI in enhancing the accuracy and reliability of automated systems for assessing subjective responses.The inclusion of LSI in the system underscores its capability to improve the interpretation of nuanced textual data. This innovation is particularly significant in educational settings where subjective assessments are commonplace and demand high accuracy and fairness in evaluation. Hu and Xia's research marks a step forward in the application of advanced computational techniques to the field of automated assessment, showcasing the potential of integrating sophisticated statistical analysis tools like LSI to refine the evaluation process.[6]

Laurie Cutrone and Maiga Chang explore the diverse landscape of learning management systems (LMSs) currently in use. They highlight that while LMSs offer extensive functionalities, they particularly focus on the segment dedicated to student assessment management. This specific function of an LMS is crucial yet presents challenges, especially in its ability to handle different types of evaluations autonomously. The authors point out a significant limitation in the case of open-ended questions, where the system lacks the capability to autonomously assess student responses. Such assessment formats require manual grading by educators, as the LMS is not equipped with the necessary tools to automatically evaluate free-form text or complex answer structures. This underscores a gap in the automated capabilities of current LMS platforms, suggesting a need for advancements in this area to reduce the reliance on human intervention and enhance the overall efficiency and effectiveness of online learning assessments.The enhancement of assessment capabilities in LMSs would also likely improve the learning experience for students, providing quicker and potentially more detailed feedback on their progress. Overall, the work of Cutrone and Chang sheds light on a vital area of need in digital education tools, calling for increased innovation and development to bridge the current gap in LMS functionality. This would not only streamline assessment processes but also contribute to the broader goals of modernizing and improving educational outcomes through technology.[7]

In their detailed research, **Jiapeng Wang and Yihong Dong** dive into the current landscape of similarity measurement, providing an extensive evaluation of the various methodologies used in this field. Their study not only highlights the strengths and weaknesses of existing methods but also introduces a refined classification system for categorizing text similarity measurement algorithms. They define the method of text similarity assessment through two primary dimensions: text distance and text representation. This framework is designed to enhance understanding and guide further research and practical applications in the area of text similarity. The authors also present a vision for the future progression of this field, suggesting directions for upcoming investigations and developments. This comprehensive overview aims to serve as a foundational reference for both scholars and practitioners engaged in the study of text similarity.Through their analysis, Wang and Dong aim to streamline the complexities involved in selecting appropriate methods for specific applications, thus promoting more efficient and accurate outcomes in practical scenarios. Furthermore, their work paves the way for more targeted research efforts, highlighting gaps and suggesting potential areas for innovation within the field of text similarity.[8]

MustaffaCagatyali, ErbugCelibi ,Text classification is a process in which natural language text is organized into predefined categories, facilitating improved handling and understanding of unstructured data. This technique has significant implications across various sectors by helping organizations enhance their interactions and communications with customers. Additionally, it supports the analytical use of unstructured data, broadening the scope of its application in both academic and professional environments. By categorizing text, entities can more efficiently process large volumes of data, which in turn can lead to more informed decision-making and improved service outcomes. The importance of text classification extends to its ability to provide structured insights from unstructured sources, thus driving efficiency and innovation in data management practices.The ability to quickly categorize customer feedback and queries enables organizations to address concerns with heightened efficiency and effectiveness. Moreover, in an era where data is king, the strategic use of text classification can lead to superior competitive advantage and operational improvements.Ultimately, as highlighted by Mustaffa Cagatyali and Erbug Celibi, the significance of text classification lies in its dual capability to enhance operational efficiencies and contribute to the strategic use of information, driving better decision-making and fostering continuous improvement in various organizational processes.[9]

The task of effectively pinpointing keywords that encapsulate the essence of a document's content is pivotal in numerous applications. **Lukas Havrlant and Vladik Kreinovich** have discussed this at length, noting the prominence of methods designed to automate this process. Among these, the term frequency-inverse document frequency (tf-idf) method emerges as a commonly adopted approach. The tf-idf heuristic functions by evaluating how frequently a term occurs in a document against its occurrence across a collection of documents. This balance helps in identifying terms that are not only frequent in a specific document but also rare across others, thus highlighting their unique relevance to the document. While the rationale behind the tf-idf method is grounded in its mathematical formulation, some critiques point out the inherent complexity and potential limitations in comprehensively understanding and applying this technique. Nevertheless, its widespread use underscores its utility in extracting meaningful keywords from vast textual data, serving crucial roles in information retrieval, content summarization, and data organization tasks.Despite these criticisms, the widespread adoption of the tf-idf method underscores its importance. It has become a staple in tasks such as information retrieval, where it enhances search engine accuracy, and content summarization, where it aids in distilling the essence of texts. Moreover, its role in organizing data by extracting relevant keywords helps in managing and navigating through large datasets. The balance it strikes between term frequency and document uniqueness makes it a valuable tool in the arsenal of text analysis and data management.[10]

3 Feasibility Study

A feasibility study is an essential step in the development and implementation of any computer-based system. It serves to critically assess the practicality of a proposed project by examining various aspects such as system viability, impact on the organization, user needs fulfillment, and resource utilization. This type of analysis is crucial for determining whether a project should proceed, undergo modifications, be postponed, or be cancelled, particularly in the case of initiatives that are large-scale, costly, and complex.

The most common problems with developing a computer-based system or product are likely related to delivery dates and resources. A feasibility study is especially helpful when deciding whether to proceed with, modify, postpone, or cancel a large, expensive, and complex project.The feasibility of the project "Subjective Answer Evaluation using Machine Learning and NLP" warrants thorough examination to ensure its viability, effectiveness, and efficient resource utilization. This feasibility study aims to scrutinize the project's potential impacts, ability to meet user expectations, and overall alignment with strategic goals.

3.1 Technical Feasibility

The technology in use is technically capable of storing the data needed by the new system and can be built using the equipment that is now in use. The technical feasibility of our project, "Subjective Answer Evaluation using Machine Learning and NLP," lies in the convergence of advanced algorithms and computing power to accurately assess subjective responses. Using machine learning, combined with Natural Language Processing (NLP) techniques, enables the system to comprehend and evaluate nuanced language structures.

From a technical standpoint, the project hinges on the advanced capabilities of machine learning (ML) and natural language processing (NLP) technologies. These technologies are well-established in their ability to parse, understand, and generate human language in a way that is meaningful and actionable. The primary challenge lies in the system's ability to accurately evaluate free-text answers, which can vary widely in terms of language, structure, and content. However, recent advancements in NLP, such as context-aware semantic analysis and deep learning models, provide a solid foundation for developing a robust evaluation system.

Through robust evaluation metrics and continuous refinement, our project aims to achieve high accuracy in assessing subjective answers, providing valuable insights for educational assessments and beyond. This innovative approach demonstrates the practical application of cutting-edge technologies in solving complex tasks, ensuring originality and effectiveness in our project's implementation.

3.2 Economical Feasibility

The economical feasibility of our project is underscored by its potential to reduce labor-intensive grading processes and associated costs. By automating the evaluation of subjective answers, our solution minimizes the need for extensive human involvement, leading to significant time and resource savings for educational institutions. Additionally, the scalability and adaptability of our system ensure cost-effectiveness across various educational settings, regardless of size or budget constraints.

Through efficient utilization of computational resources and optimization of evaluation algorithms, our project offers a sustainable and financially viable solution for enhancing assessment practices. This economically feasible approach aligns with the goal of maximizing educational resources while maintaining originality and effectiveness in our project implementation.By minimizing computational demands, the project maintains lower operational costs, contributing to its overall economic viability. The optimized system ensures that ongoing costs, such as energy consumption and hardware maintenance, are kept to a minimum

In conclusion, the economic feasibility of our project is secured through its ability to reduce labor costs, its scalability across various educational settings, and the optimization of computational resources. These factors collectively ensure that the project is not only a technologically innovative solution but also a financially sound investment for educational institutions. By reducing grading costs and improving resource allocation, our solution promises to enhance educational assessment practices while maintaining economic sustainability. This aligns with our strategic goals of delivering an innovative, effective, and economically viable educational tool.

3.3 Legal Feasibility

Legal feasibility mirrors the importance of regulatory compliance, data protection, and intellectual property rights. Adherence to data protection laws ensures the secure handling of sensitive information, safeguarding user privacy and maintaining legal integrity. Similarly, obtaining necessary permits and approvals, if applicable, demonstrates compliance with relevant regulations governing educational technology and data usage. Moreover, establishing clear contractual agreements with stakeholders, including educational institutions and technology providers, helps manage legal risks effectively.

Ensuring compliance with these legal parameters is essential to maintaining the project's integrity and operability within the legal frameworks that govern educational technologies and data handling.These agreements should address key legal considerations such as liability, intellectual property rights, and risk allocation, fostering collaboration while mitigating legal uncertainties. By prioritizing legal compliance and transparent partnerships, our project ensures a legally sound and sustainable implementation, free from plagiarism or legal complications.

In addition, the project must secure any necessary permits or licenses that are requisite for its deployment. This might involve approvals from educational authorities or technology regulation agencies, depending on the scope and application of the project within various educational settings. Establishing these legal foundations not only mitigates potential legal risks but also enhances collaboration by defining clear operational boundaries for all stakeholders involved.

3.4 Operational Feasibility

The operational feasibility of our project, "Subjective Answer Evaluation using Machine Learning and NLP," is evident in its adaptability to various educational settings and assessment scenarios. By streamlining the integration process into existing educational platforms, instructors can seamlessly incorporate our solution into their evaluation workflows. With user-friendly interfaces and intuitive functionalities, educators can efficiently manage and interpret evaluation results, enhancing the overall assessment experience.

Scalability is another critical aspect of the operational feasibility of our project. The system is designed to accommodate varying scales of usage, from small educational institutions to large universities with thousands of students. This flexibility ensures that as an institution grows or as its needs become more complex, our solution can scale accordingly without requiring significant additional investments or changes in the system architecture. This scalability is pivotal for ensuring that the solution remains economically viable and technologically relevant, even as educational practices evolve and expand.

Overall, the operational feasibility of this project is anchored in its versatility, ease of use, and scalable capabilities, which collectively make it a viable and progressive option that meets the evolving demands of contemporary educational systems. With its potential to integrate smoothly and deliver continuous value, this project promises to enhance the precision and efficiency of academic assessments, leveraging the latest advancements in machine learning and natural language processing to support educators and institutions in their mission to deliver outstanding educational outcomes.

In essence, the project's operational feasibility is underpinned by its adaptability, user-friendly design, and scalable architecture, making it a practical and forward-looking solution that aligns with the dynamic needs of modern education systems. These factors collectively ensure that the project can be implemented smoothly and can provide sustained value in improving the accuracy and efficiency of subjective assessments across various educational settings.

3.5 Schedule Feasibility

Dividing the project into phases, such as model development and testing, ensures a realistic timeline. A successful timeline for your NLP-powered subjective answer evaluation project hinges on a strong foundation. Break down project tasks, considering data collection, model selection, and evaluation methods. Don't forget to factor in data quality and size, as these heavily influence training time. Choosing the optimal NLP model architecture requires careful consideration of the answer types you're evaluating.

Efficient resource allocation is key, with cloud platforms offering flexibility for compute-intensive training. Proactive risk management, including data quality checks and contingency plans, helps avoid schedule disruptions. Throughout the project, monitor the NLP model's performance and make adjustments as needed. Remember, a feasible timeline allows for iterative improvements within the planned timeframe, ensuring a successful project.

Overall, a successful timeline for this NLP-powered project hinges on a well-planned foundation that allows for incremental improvements and adaptability. By anticipating challenges and allocating resources efficiently, the project can adhere to its planned schedule and achieve its objectives, ultimately leading to a robust and reliable subjective answer evaluation system.

In summary, creating a successful project schedule for this NLP-powered evaluation system involves meticulous planning and adherence to legal requirements throughout all phases. By proactively addressing potential legal issues and scheduling regular compliance checks, the project can maintain its trajectory and achieve its goal of providing a robust and reliable subjective answer evaluation tool. This structured approach ensures that the project not only meets technical and user expectations but also aligns with legal standards, ensuring a smooth and compliant operational workflow.

3.6 Market or Demand Feasibility

The market feasibility of our project is supported by the growing demand for innovative educational technologies. With an increasing emphasis on personalized learning and assessment, there is a significant market need for automated evaluation solutions that can accurately assess subjective responses. Educational institutions, online learning platforms, and assessment agencies represent lucrative target markets eager to adopt efficient and reliable evaluation methods.

Moreover, the scalability and adaptability of our solution make it suitable for a wide range of educational levels and subjects, further enhancing its market appeal. By addressing this demand with a robust and original solution, our project is well-positioned to capture market share and drive positive impact in education.Educational bodies, ranging from traditional institutions to modern online learning platforms, and even examination boards, are increasingly seeking automated solutions to enhance their assessment processes. These stakeholders are motivated by the need for not only efficiency but also the accuracy and fairness that advanced machine learning and NLP technologies promise.

By launching a sophisticated and innovative solution like ours, we aim to carve out a substantial niche in the edtech market. The distinctive capabilities of our system to understand and evaluate nuanced textual responses is at the forefront of educational innovation, giving us a competitive edge. The growing trend towards data-driven educational tools and techniques means that our project is not just meeting an existing demand but also pioneering further developments in how educational assessments are approached and executed.

4 Methodology

Following diagram shows the system architecture:

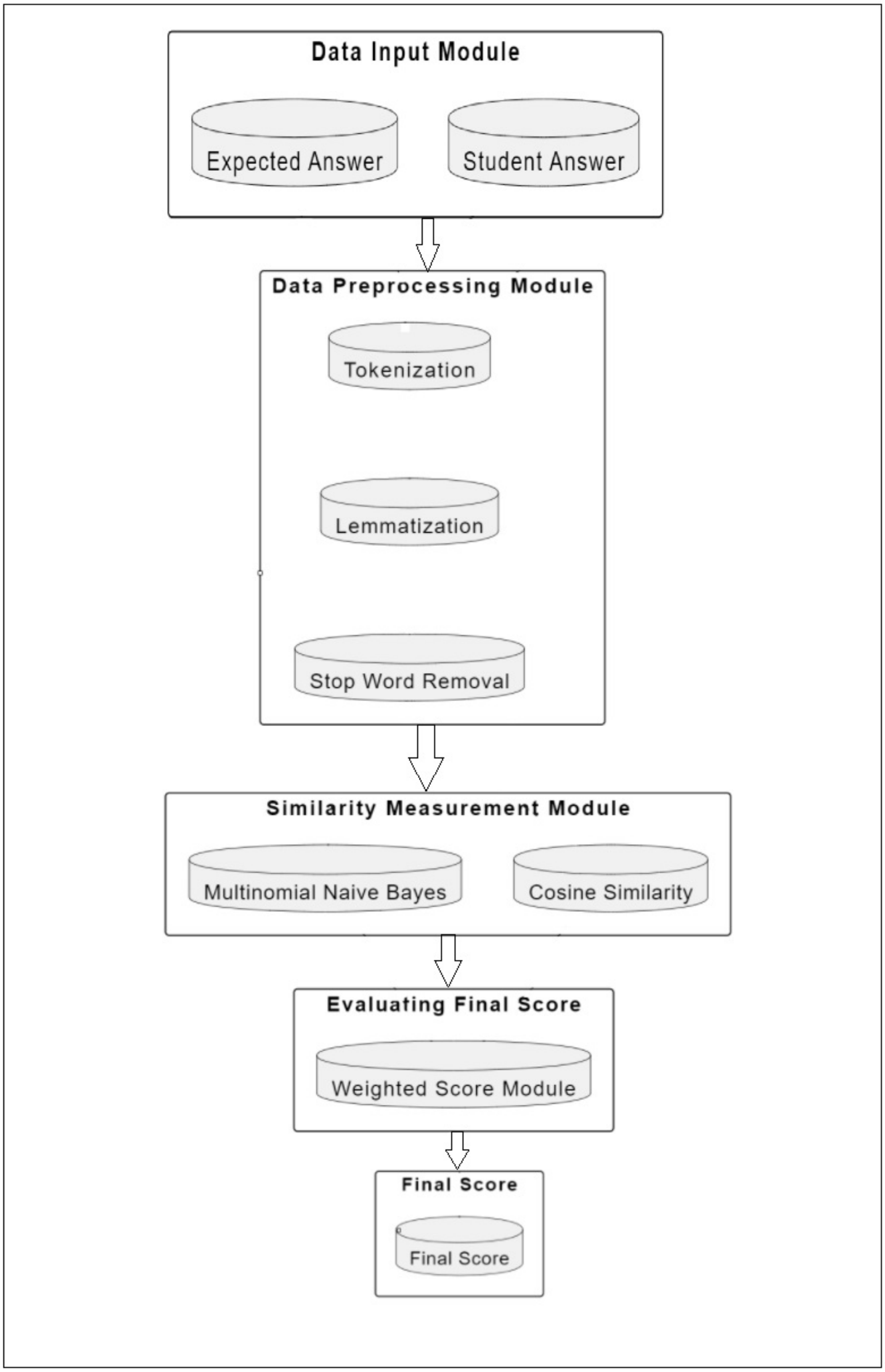


Figure 1: Flow Diagram

This project aims to revolutionize subjective answer evaluation by using ML and NLP. It begins by addressing the scarcity of labeled subjective question-answer data, creating a corpus sourced from diverse websites and blogs hosting such content.

This project focuses on evaluating subjective answers using ML and NLP methods. It involves creating a labeled corpus from websites, preprocessing inputs, measuring similarity using methods, predicting scores based on matched sentence pairs, employing machine learning models like Multinomial Naive Bayes, and refining scores through validation against predicted classes. Ultimately, it offers a comprehensive approach for assessing subjective answers through a systematic combination of NLP and machine learning methodologies.

1. **Preprocessing Module:**:

The preprocessing module is a crucial component of text data analysis, specifically designed to prepare the text for further processes such as similarity measurement and result prediction. This module consists of three fundamental steps that transform raw text into a structured format that can be effectively analyzed.

Responsibility: This module is responsible for preparing the text data before similarity measurement and result prediction. It involves three main preprocessing steps:

- Tokenization: Breaking down the text into individual words or tokens.
- Lemmatization: Reducing words to their base or dictionary form to normalize variations (e.g., "running" to "run").
- Sentiment Analysis: Assessing the sentiment or emotional tone of the text, which can provide additional context for result prediction.

Implementation: Utilizes libraries such as NLTK (Natural Language Toolkit) for tokenization and lemmatization, and sentiment analysis tools.

2. Similarity Measurement Module:

The Similarity Measurement Module within this project plays a pivotal role by quantifying the alignment between a student's response and the expected answer. This module leverages multiple similarity metrics, each designed to capture different dimensions of text comparison, providing a comprehensive analysis of how closely the student's answer mirrors the expected one.

Responsibility: Calculates various similarity scores between the expected answer and the student's answer to assess how closely they align. These scores help quantify the similarity between the two texts and provide different perspectives on their similarity. Similarity Metrics:

- Exact Match: Determines if the student's answer exactly matches the expected answer.
- Partial Match: Measures the degree of overlap between the tokens in the student's answer and the expected answer.
- Cosine Similarity: Computes the cosine of the angle between TF-IDF vectors of the expected and student answers, capturing semantic similarity.
- Semantic Similarity: Calculates similarity based on embedding representations of the text, which captures semantic meaning beyond simple word overlap.
- Coherence Score: Evaluates the coherence of the two texts based on their token overlap and length.
- Relevance Score: Assesses the relevance of the student's answer to the expected answer by comparing common tokens.

Implementation: Utilizes various techniques such as vectorization, word embeddings, and similarity metrics from libraries like scikit-learn and Hugging Face Transformers.

3. Result Prediction Module::

The Result Prediction Module plays a pivotal role in determining the accuracy of a student's response by utilizing the similarity scores generated in the Similarity Measurement Module. This module uses advanced machine learning techniques to enhance the predictive accuracy of the assessment system.

Responsibility: Utilizes the similarity scores computed in the Similarity Measurement Module alongside machine learning models (such as Naive Bayes Classifier) to predict the correctness of the student's answer. It combines similarity-based features with other relevant features to make more accurate predictions.

Implementation: Feature Engineering: Extracts features from the similarity scores and potentially additional features like the length of the answers, sentiment scores, etc.

Machine Learning Model (Naive Bayes): Trains a Naive Bayes Classifier using the extracted features. The model learns the relationship between these features and the correctness of the student's answer from a labeled dataset.

Prediction: Uses the trained Naive Bayes model to predict whether the student's answer is correct or incorrect based on the computed features.

4. **Weighted Module:**:

The implementation of this weighted average calculation involves assigning different weights to each similarity score based on their significance in determining the overall similarity. These weights are not arbitrarily chosen; they are meticulously configured to reflect the relative importance of each similarity metric in the specific context of subjective answer evaluation. The determination of these weights can be grounded in domain expertise, where a deep understanding of the subject matter helps identify which aspects of similarity are most critical.

Responsibility: Combines the different similarity scores obtained from the Similarity Measurement Module, including those from the Naive Bayes Classifier in the Result Prediction Module, into a single composite score using a weighted average approach.

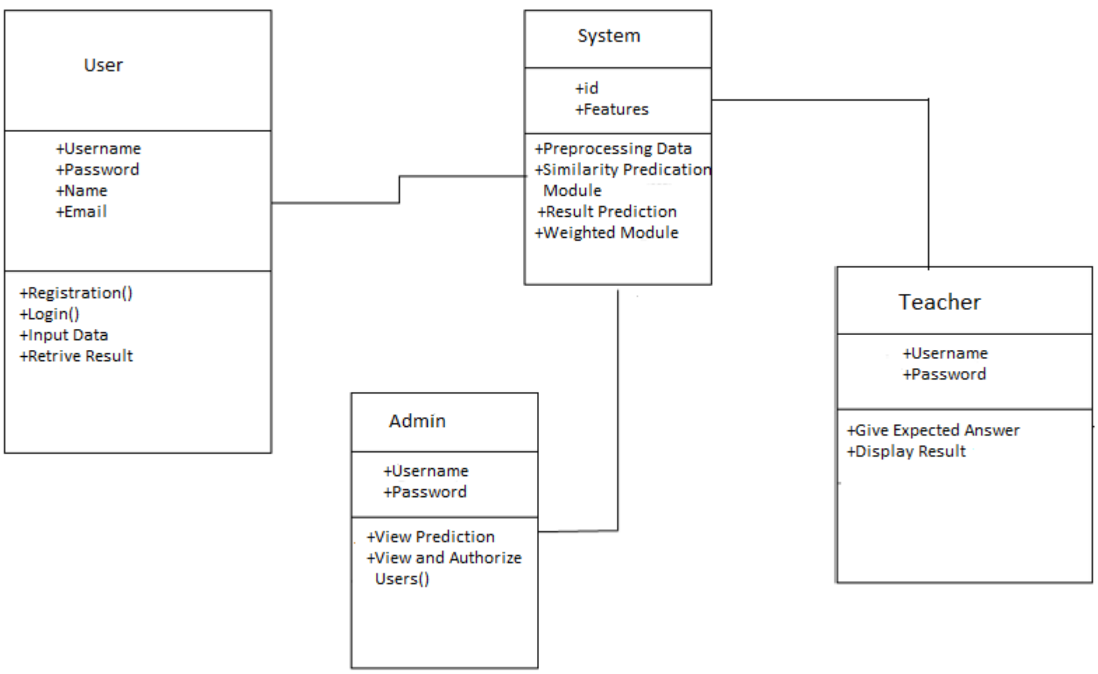
This composite score provides a comprehensive assessment of the similarity between the expected and student answers, considering the relative importance of each similarity metric.

Implementation: Calculates the weighted average of similarity scores, where weights are assigned based on the relative importance of each metric. These weights can be predefined based on domain knowledge or learned through optimization techniques such as grid search or cross-validation.

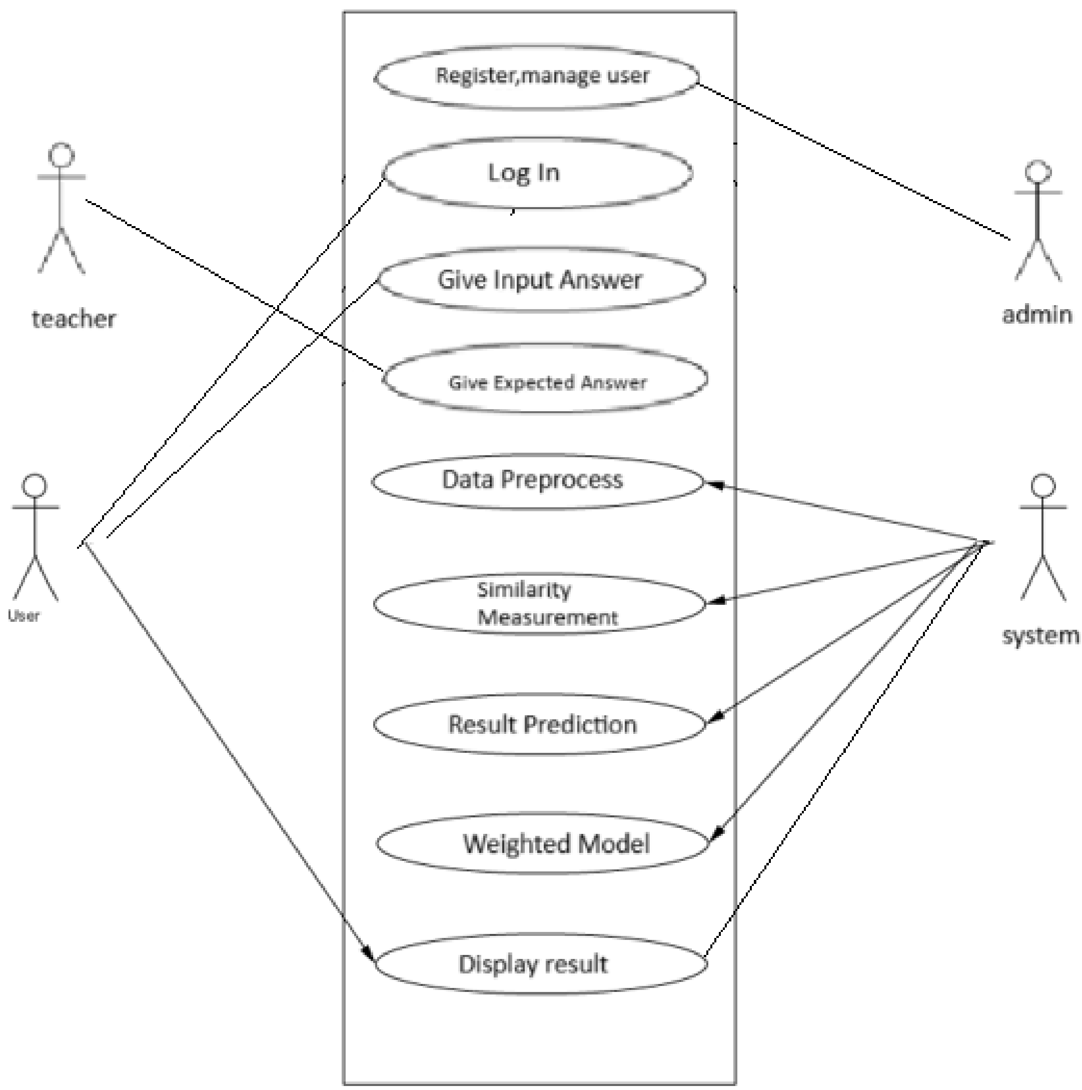
Following are the UML diagrams for the project.

- **Class Diagram** : The class diagram shows a simple system with four classes: User, Admin, teacher and System. The User, teacher and Admin classes have relationship with the System class.

1. System class: This class likely represents the overall system architecture. It has features like username, password. It also has methods for preprocessing data, similarity module, extracting features, weighted module, and displaying results.
2. User class: This class represents a general user of the system that is student. It has methods for registration and login.Student able to give their answer to get evaluated.
3. Admin class: This class represents an administrator of the system. It has username and password attributes and methods for viewing predictions and authorizing unspecified actions.
4. Teacher class: This class appears to be extraneous to the system's core functionality. It has username and password attributes and is responsible for giving expected answer to the system.

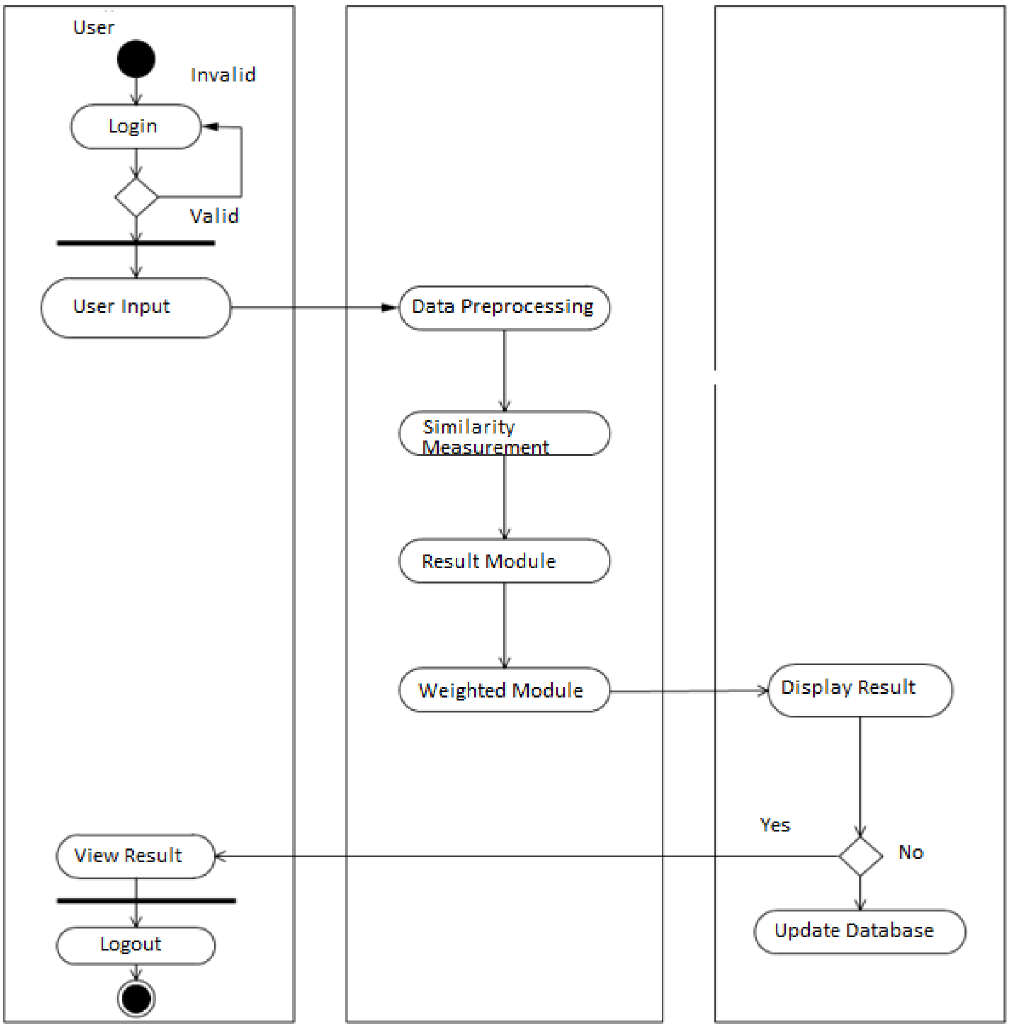


- **Usecase Diagram** : This use case diagram depicts a system using a weighted model to generate predictions for users. Users can login and provide input to the system. This input undergoes preprocessing before the system calculates its similarity to existing data. A weighted model then analyzes the processed data to predict a result, which is presented to the user.
  System usecase is performing the operations such as the data preprocessing , similarity measurement, result prediction and the weighted scoring module.An optional admin role might exist with additional functionalities.The below diagram shows all the usecases and all the actors.



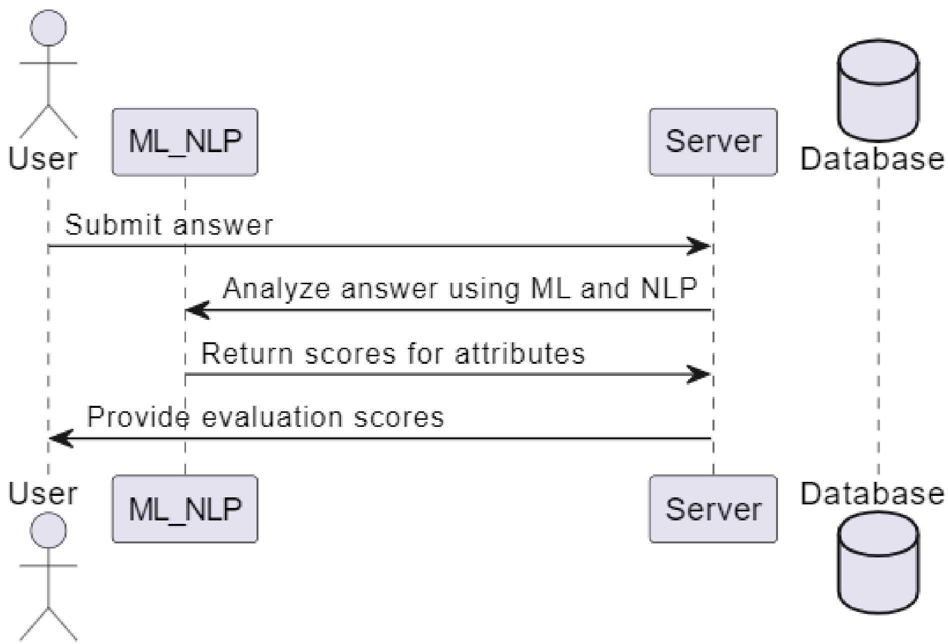
- **Activity Diagram** : The activity diagram shows that the system is a sequential process, with each step following the next.The main process starts from logging in and givin gthe user input in the form of text.This text will be futher undergo different steps.

  This activty diagrams represents all the activities involved in the project. The activity diagram provides a good overview of the overall flow of activities in the system. It can be used to understand the system requirements, design the system, and implement the system.

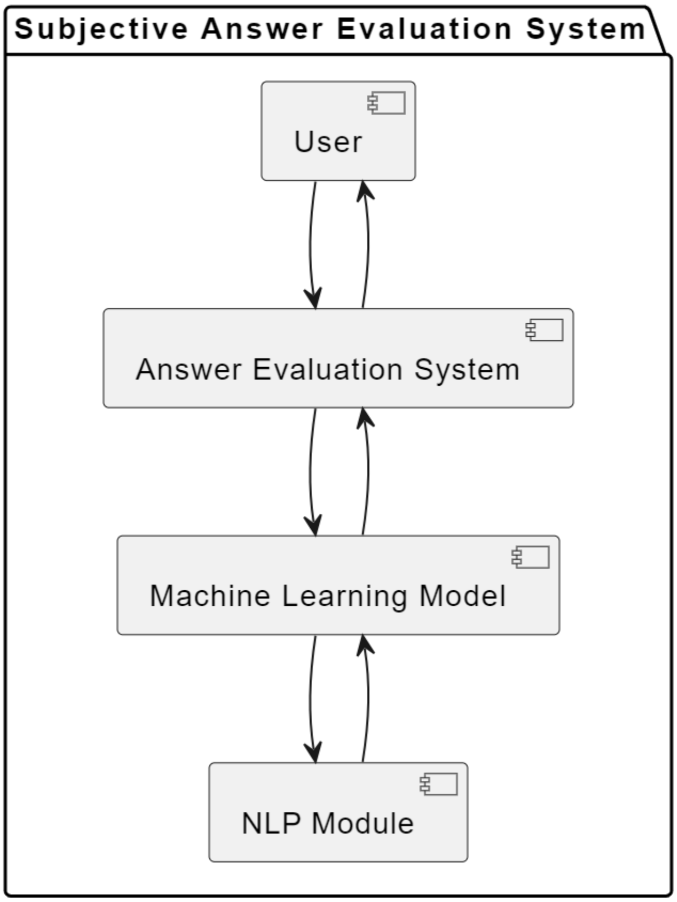


- **Sequence Diagram** : This sequence diagram shows the interactions between a user, an answer evaluation system, a machine learning model, and an NLP module. The user submits an answer to the answer evaluation system. The system then evaluates the answer using the machine learning model and the NLP module.

  The below diagram shows the sequence diagram for the system.The diagram shows that the input from the user firtly saved in the database, then passed it for the ML and NLP module to calculate different similarity metrices , then the system having weighted model which calculates the final result from the results obtained from the different similarity measurement modules and returns the evaluation result to the user and also saves it to the database.



- **Component Diagram** : The component diagram of a subjective answer evaluation system shows the following components : user,ML Model, NLP Model, evaluation system. The Answer Evaluation System component interacts with the Machine Learning Model and NLP Module components to evaluate answers.



5 Facilities Required For Proposed Work

5.1 Software requirements:

- IDE - Visual Studio
- Language – Python
- Front End - HTML, CSS
- Database - MySql
- OS - Windows 7/8/9/10

5.2 Hardware requirements:

- Hard Disk: 40 GB
- RAM: 4 GB
- Processor: Intel I3/I5/I7

6 Schedule

Following chart shows scheduled plan.

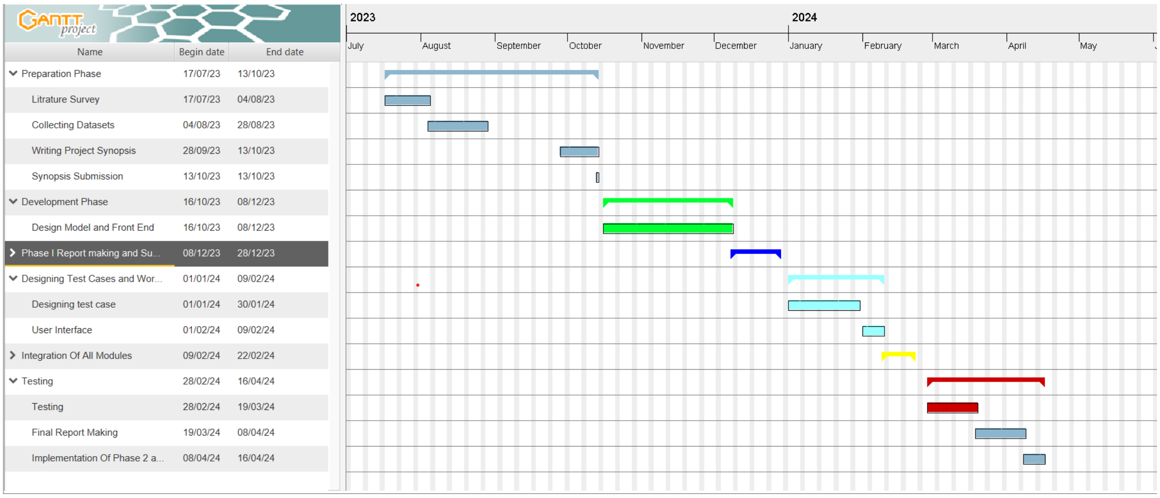


Figure 2: Schedule

- Preparation Phase(July-October) - This preparation phase involves the studying the research papers,different approaches for our development.Finalizing the technologies and preparing the synopsis.
- Development Phase (October-December) - This phase involves the development of the front end of the system and the some part of the model required for the project.
- Report Phase-I Making and Submission(December)- In this phase, phase I report is successfully submitted.
- Designing Test Cases(January-February) - This phase involves the designing the test cases for our model and implementing it.
- Integration of all the modules(February) - This phase of our project involves the integration of all the modules and development of all the front end and the back end.
- Testing and Phase-II report(February-April) - This phase involves the testing the application against all the test cases and complete implementation of this project and making phase-II report and submission.

This is all about our project schedule in detail.

7 Implementation and Output

More important task in this project is been determining the semantic similarity between two text pieces. Over the years, numerous approaches have been put forth to gauge semantic similarity. The benefits and drawbacks of each strategy are covered in this survey. String-based approaches take into account the text's true meaning, but they cannot be applied to multiple domains or languages. Although corpus-based approaches can be used in a variety of languages and have a statistical foundation, they do not examine the text's real meaning.

Following are some screenshots of the implemented work.

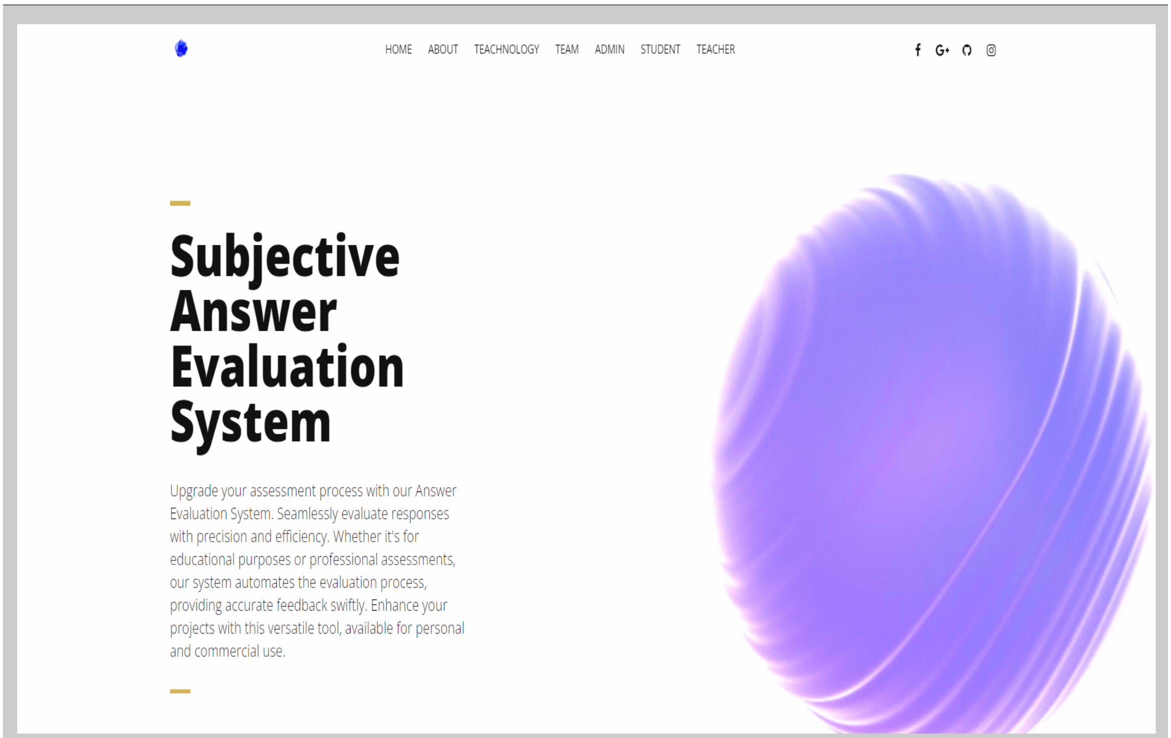


Figure 3: Home Page

Home Page : The above page represents the main home page of our system where all the information related to our system , project is provideed along with all the requirements, team members, technology stack used for our project.On this page login options are also provided in the navigation bar.

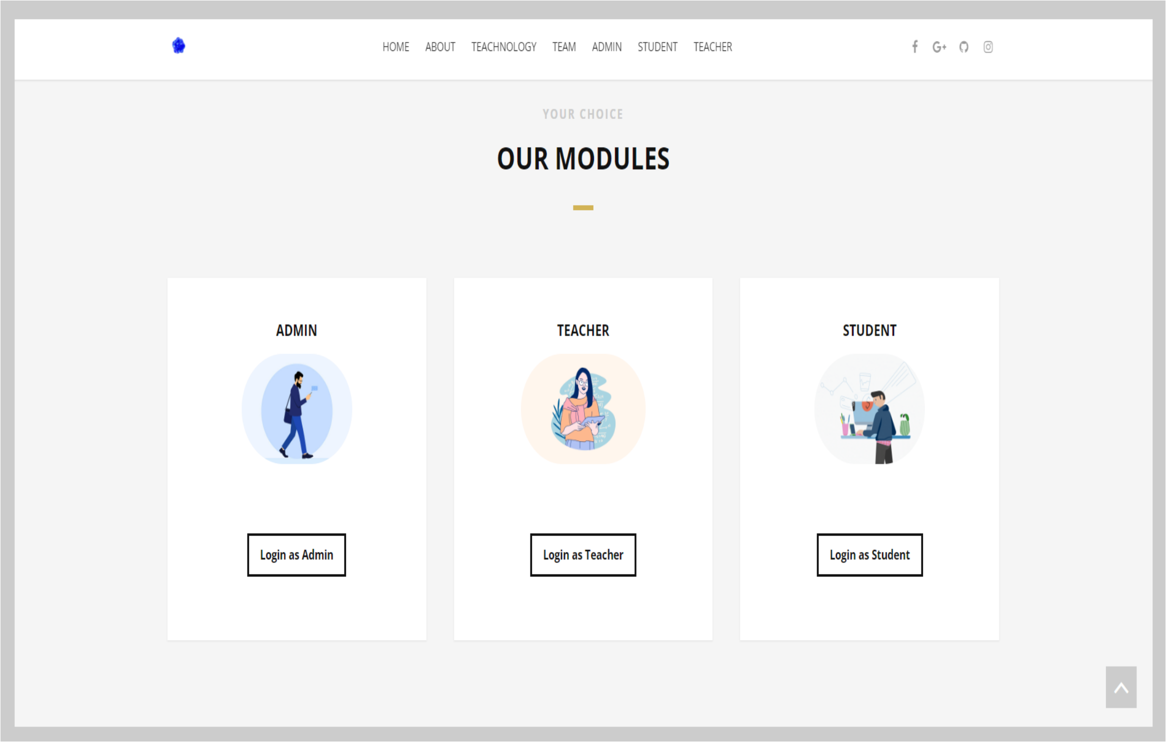


Figure 4: Modules

Main Modules: The above page shows the main modules in our system. There are mainly three modules in our system such as admin, teacher and the student.

- Admin Module: Admin module is responsible for registering new students and the teachers into the system. Admin has access to delete teacher and the student also.So the admin is the important aspect according to our project.
- Teacher Module: Teacher module is responsible for adding the multiple tests in the system. Teacher has access to see the score of the students also.
- Student Module: In the student module, student will able to give the tests made by the teacher and view the scores generated by our system.Student can see all the test made by all the teachers.

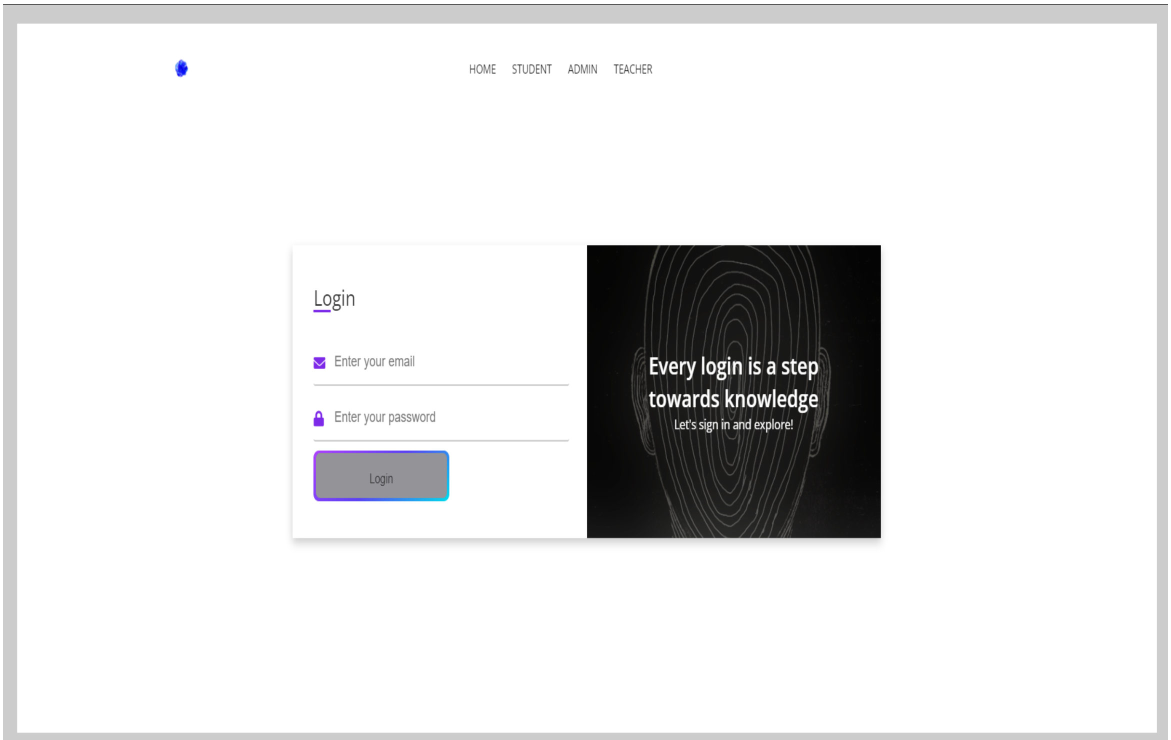


Figure 5: Student LogIn Page

Student Login Page: A student login page is a designed specifically for students to access assessments assigned by respective teachers.The above screenshot represents the student login page where by entering the username and password, the student will able to give the tests and check the score of the particular test.

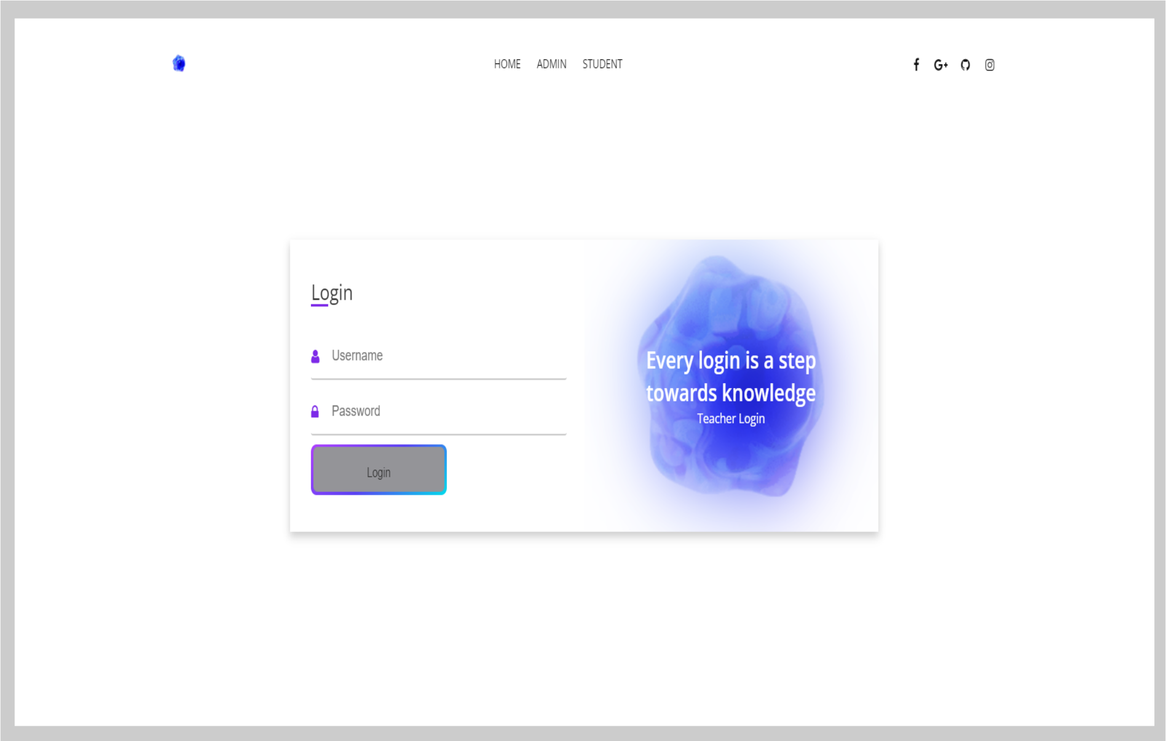


Figure 6: Teacher LogIn Page

Teacher Login: A teacher login page serves as a dedicated entry point for educators to set assessments of different subjects and also provided with their correct answers. The above screenshot shows the teacher login page. By entering username and password , the teacher can login into system and set the tests and view the scores of the students.

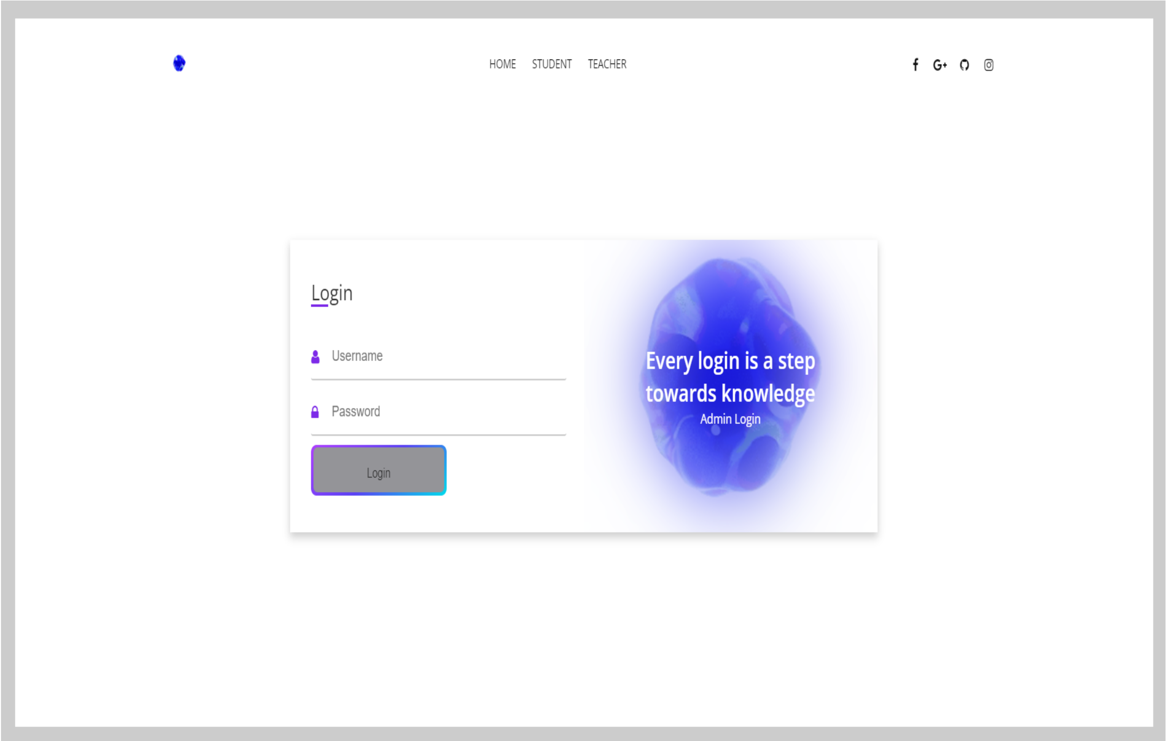


Figure 7: Admin LogIn Page

Admin Login: An admin login page serves as the gateway for authorized access to the administrative features of our system. By entering the username and password admin can login in to the system and have a access to the administrative features provided to the admin only.

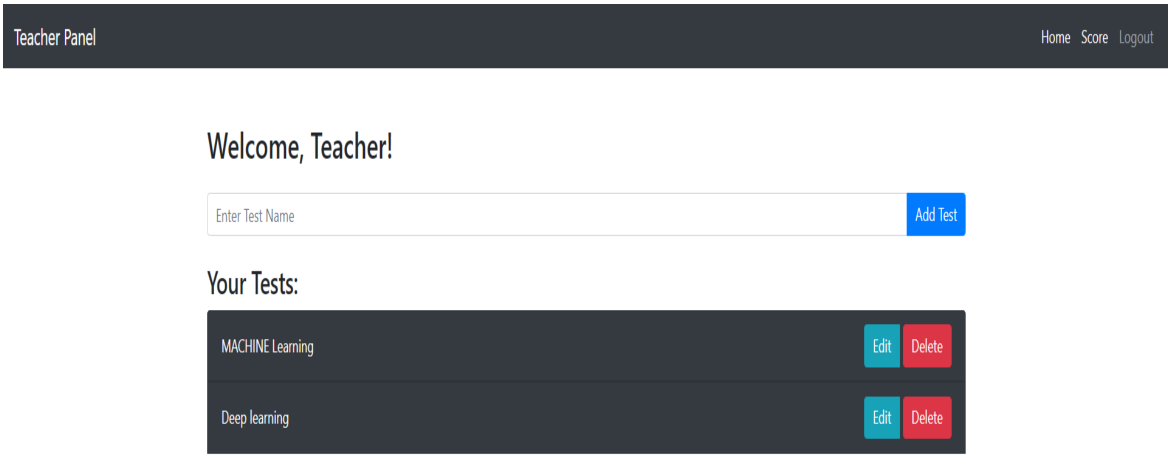


Figure 8: Teacher Panel

Teacher Panel: The above screenshot represents the teacher panel which includes the tests created by the teacher.Teacher can able to edit the questions and expected answers.Teacher has access to delete the particular selected test also.This is a teacher panel.

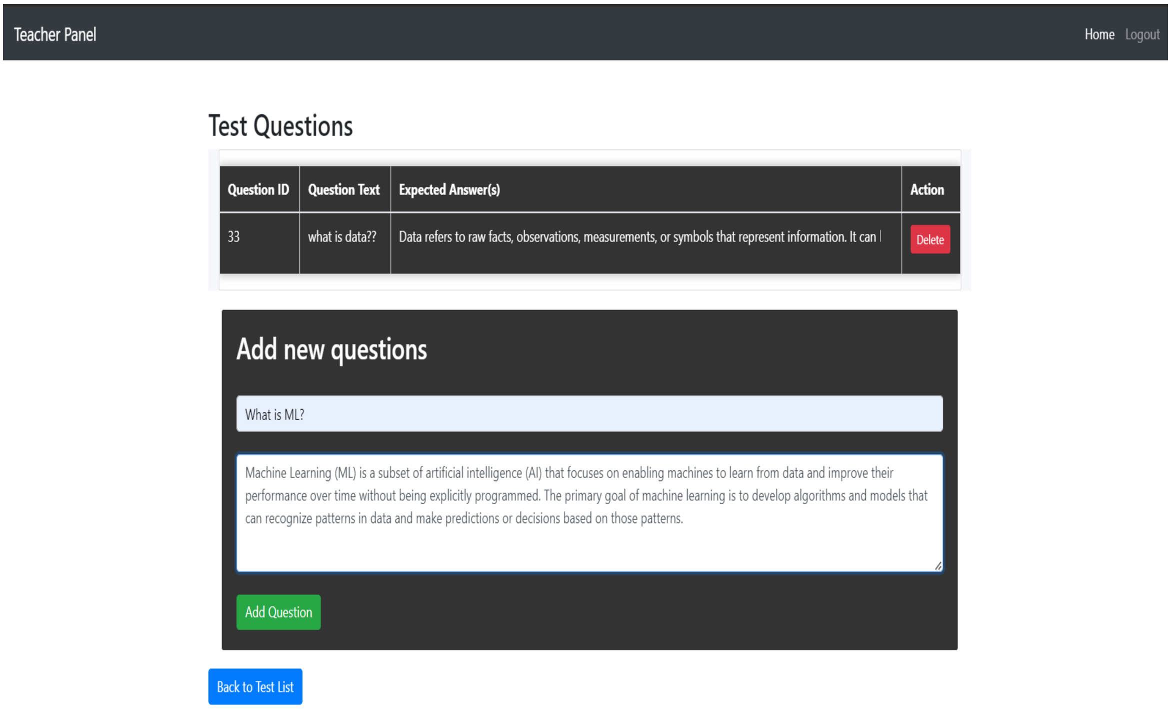


Figure 9: Teacher Add Questions Page

Teacher Add Questions: The above screenshot represents that the teacher has access to create the tests and add the questions into that test. That created test will be available for the students to give that particular test.Teacher can delete the selected question as shown in above screenshot.

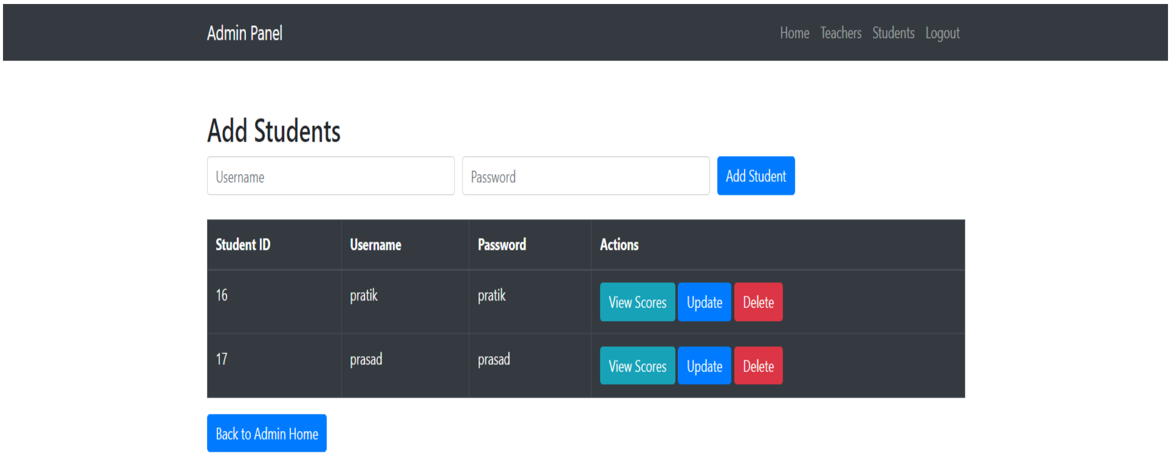


Figure 10: Admin Add Students Page

Managing Students: Managing the student that is registering new student and updating the details of the registered students and deleting the students data is done by the admin. The above screenshot represents this admin adding student page.Admin can able to view the scores of the tests given by the students.

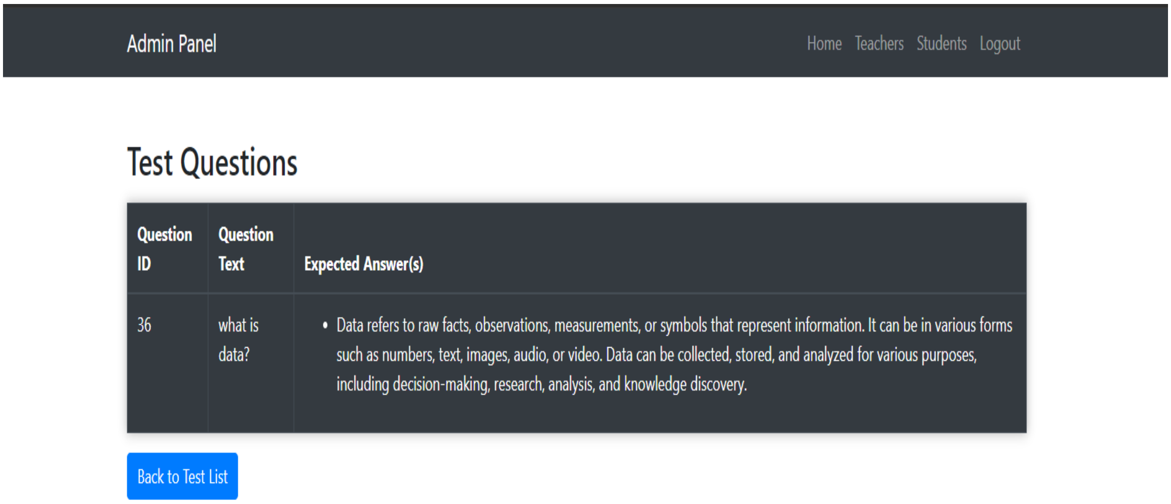


Figure 11: Admin Viewing Test Questions

Admin Viewing Test Questions: The above screenshot represents that the admin have access to view the questions of the particular test.Admin have that accesss to view all the questions and the expected answers.

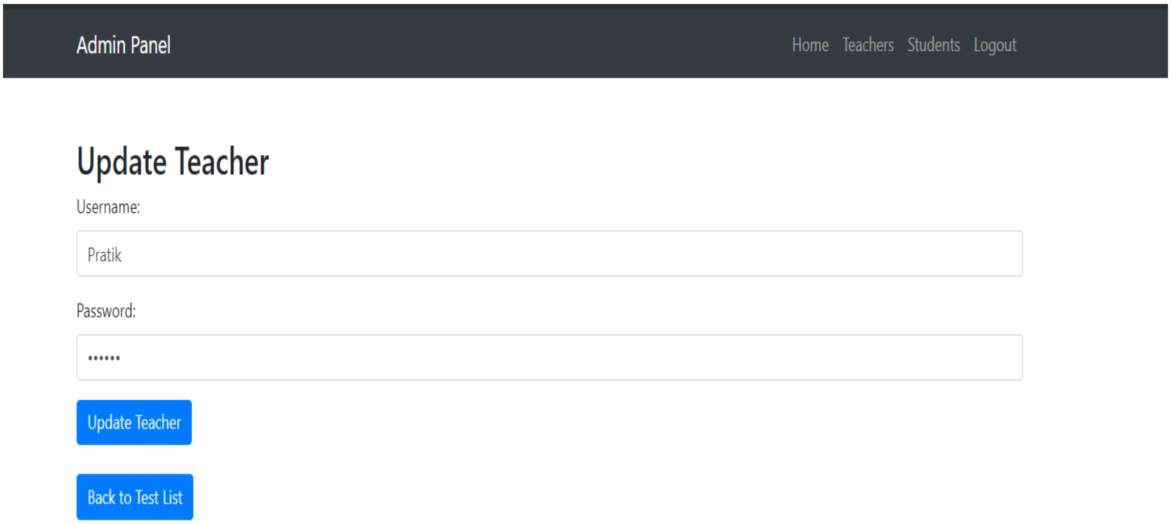


Figure 12: Update Teacher

Update Teacher: The admin have given the access to update the information of the teacher. The above screenshot shows the pages where admin is updating the teachers information.

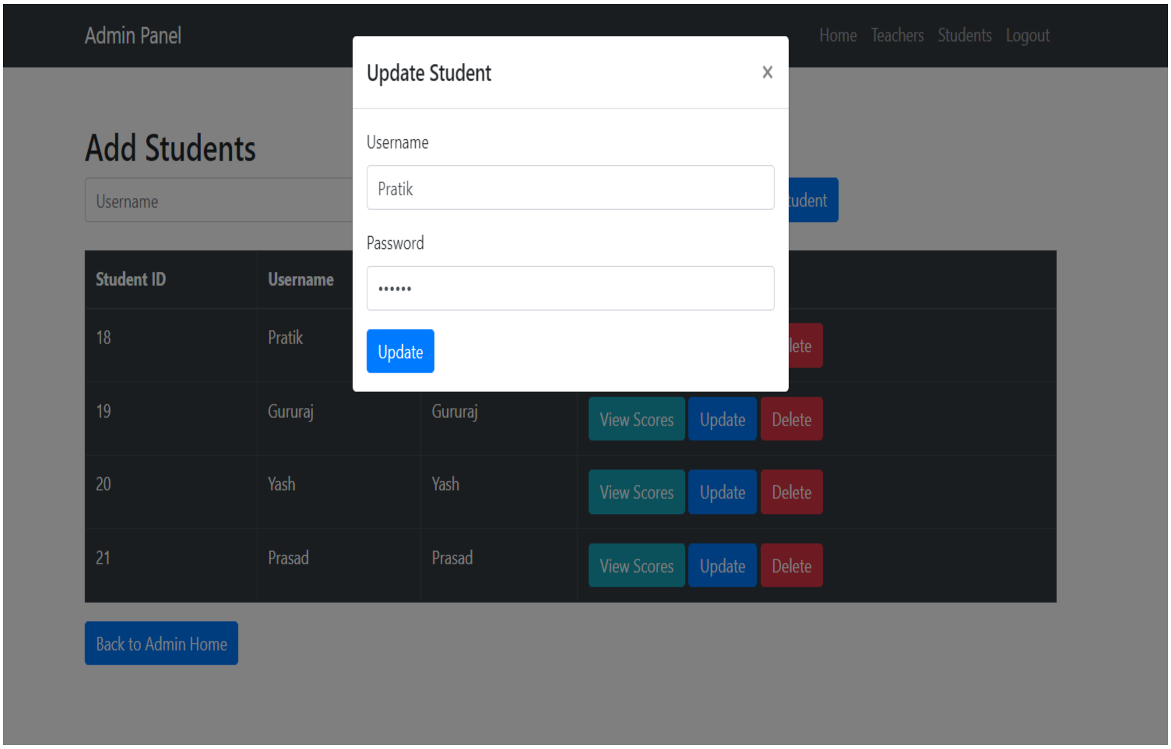


Figure 13: Update Student

Update Student: The admin have given the access to update the information of the student. The above screenshot shows the pages where admin is updating the students information such as username and password.This access is only given to admin.

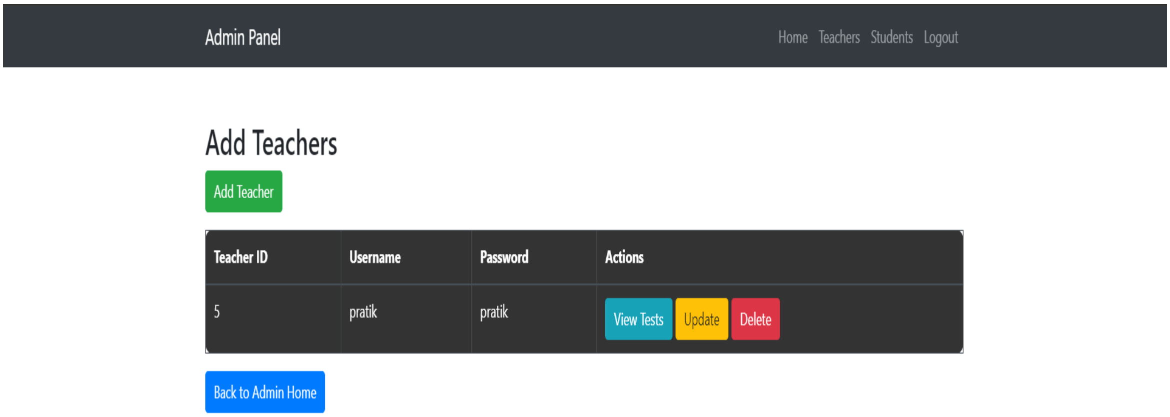


Figure 14: Admin Managing Teacher Page

Managing Teacher: Managing the teacher that is registering new teacher and updating the details of the registered teachers and deleting the teachers data is done by the admin. The above screenshot represents this admin adding teacher page.Admin can able to view the test created by the teachers.

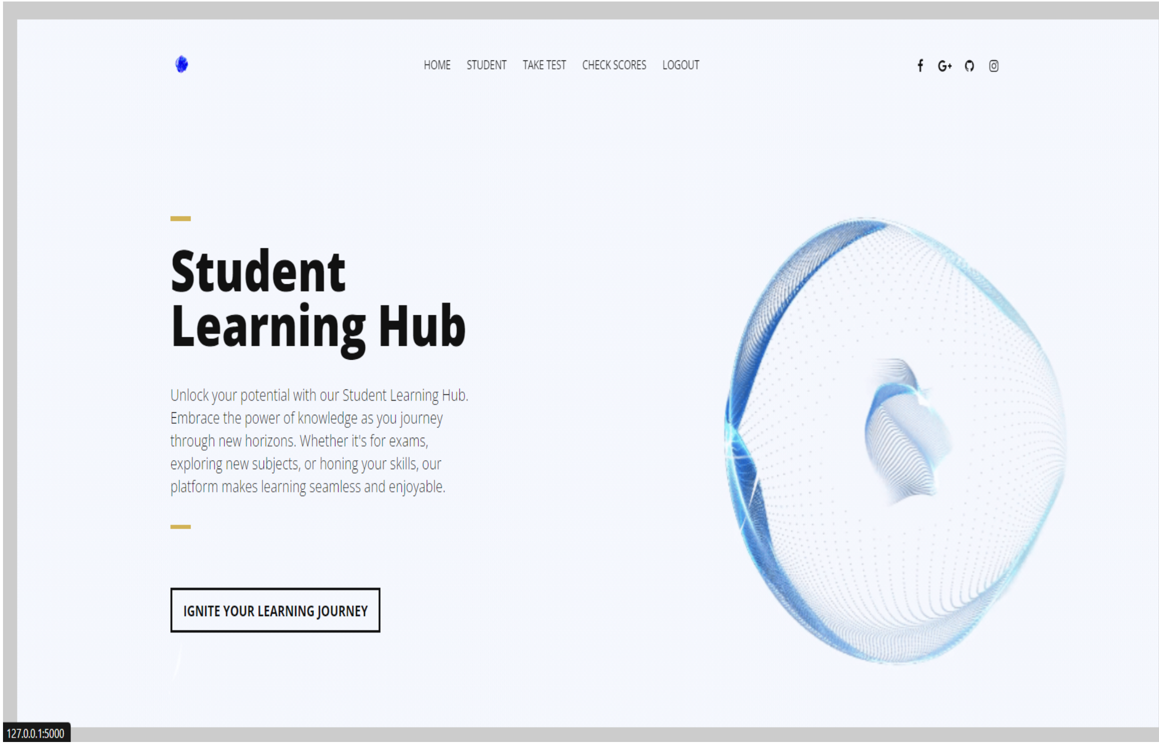


Figure 15: Student Home Page

Student Home Page: The above screenshot is of student home page. This student home page involves the option for the taking the test.After taking the test, the student will be redirected to the student home page again and student will able to see the score of the test given by him/her.

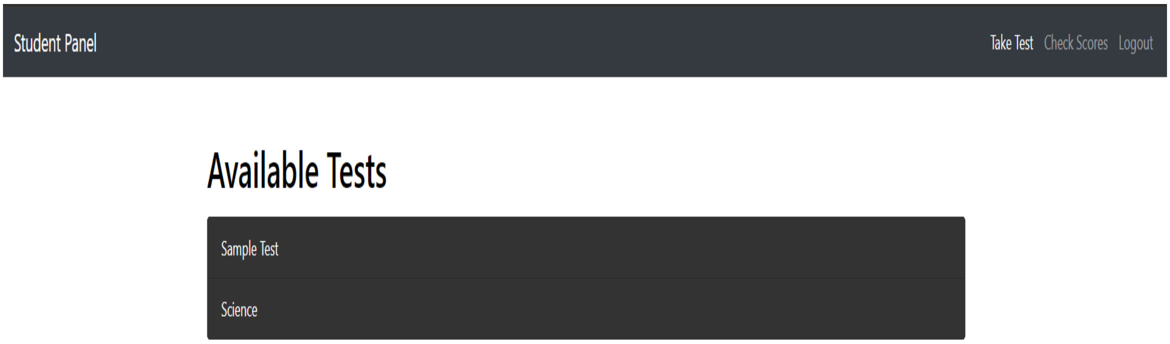


Figure 16: Available tests

Available Tests: The above screenshot shows the tests which are avaiable to student. By clicking to the particular test student can able to give that test and check the scores of that test.

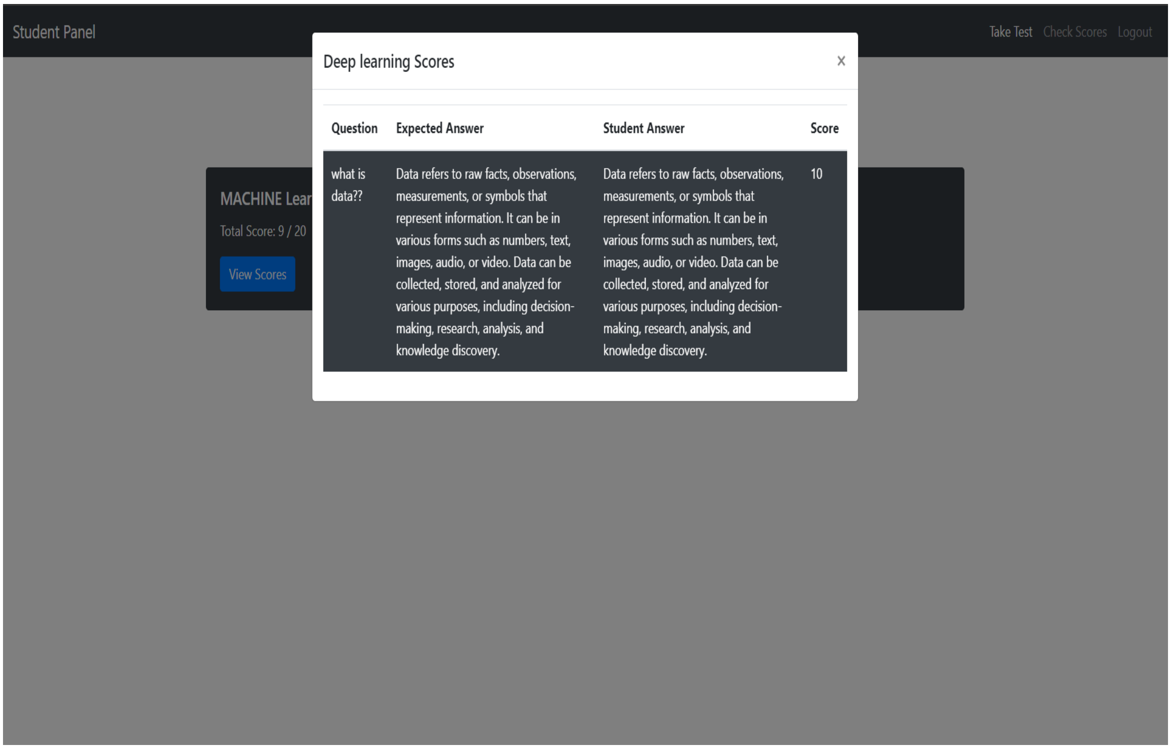


Figure 17: Student Answer Exact Match Score

Exact match Answer: The above screenshot represents that if the student answer and the expected answer is exactly matching then the score should be the out of out that is the score will be the nearer to the 10.In the above screenshot the student answer and the expected answer is exactly same, so the score will be 10.

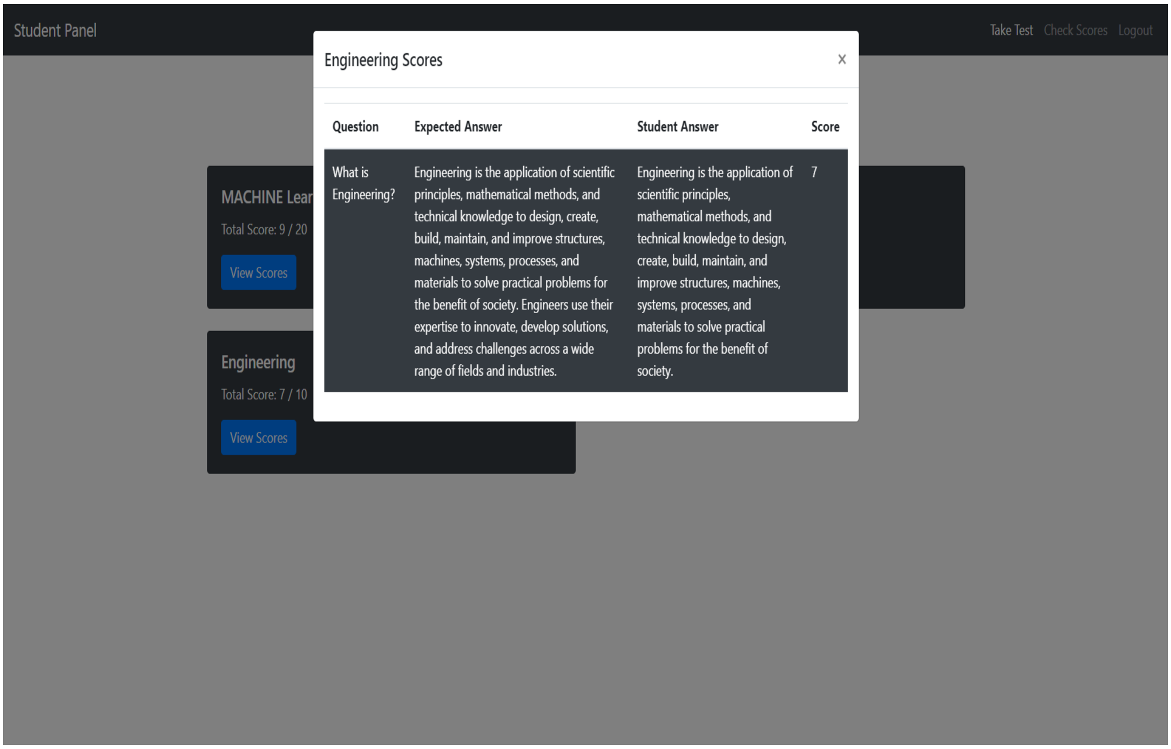


Figure 18: Student Answer Partial Match Score

Partial Match Answer: The above screenshot shows the case where student submitted the partial answer as compared to the expected answer.In this case incomplete answer is responsible for losing the marks. So the score will be average as shown in the figure.

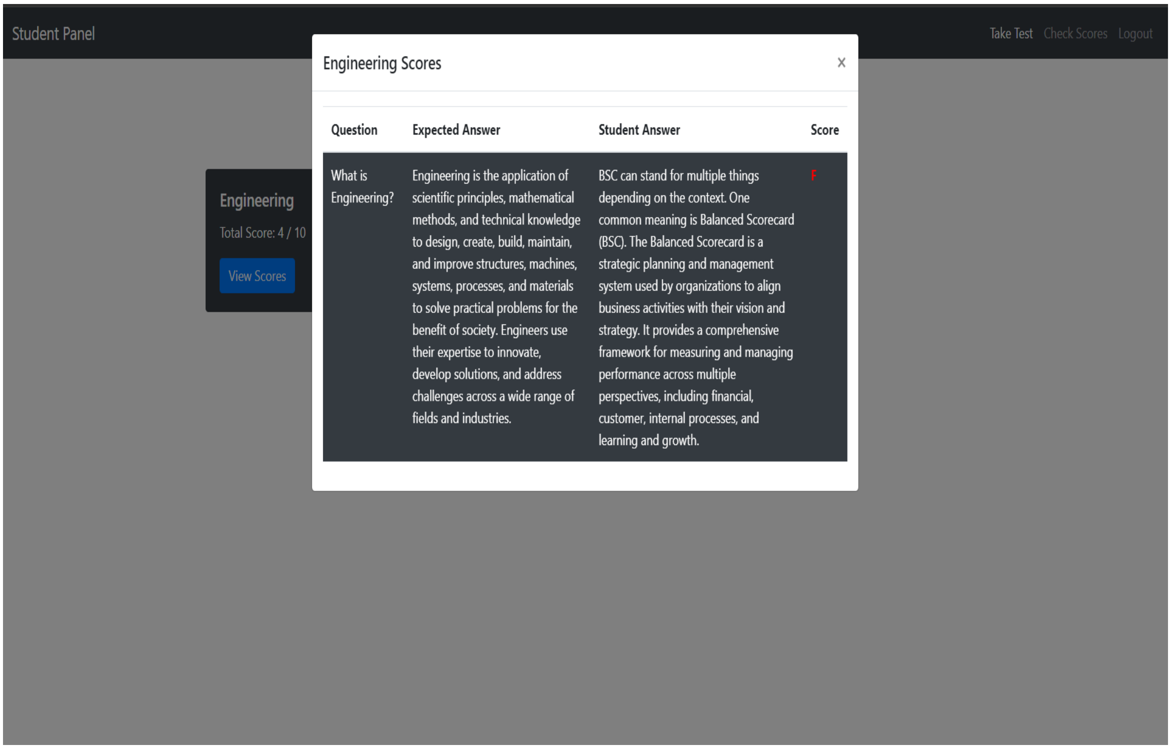


Figure 19: Student Wrong Answer Match Score

Wrong Answer: The above screenshot shows the score for answer which is completely wrong. In this case, student has given the wrong answer , it is not similar to the expected answer. So the score will be less as shown in the screenshot.

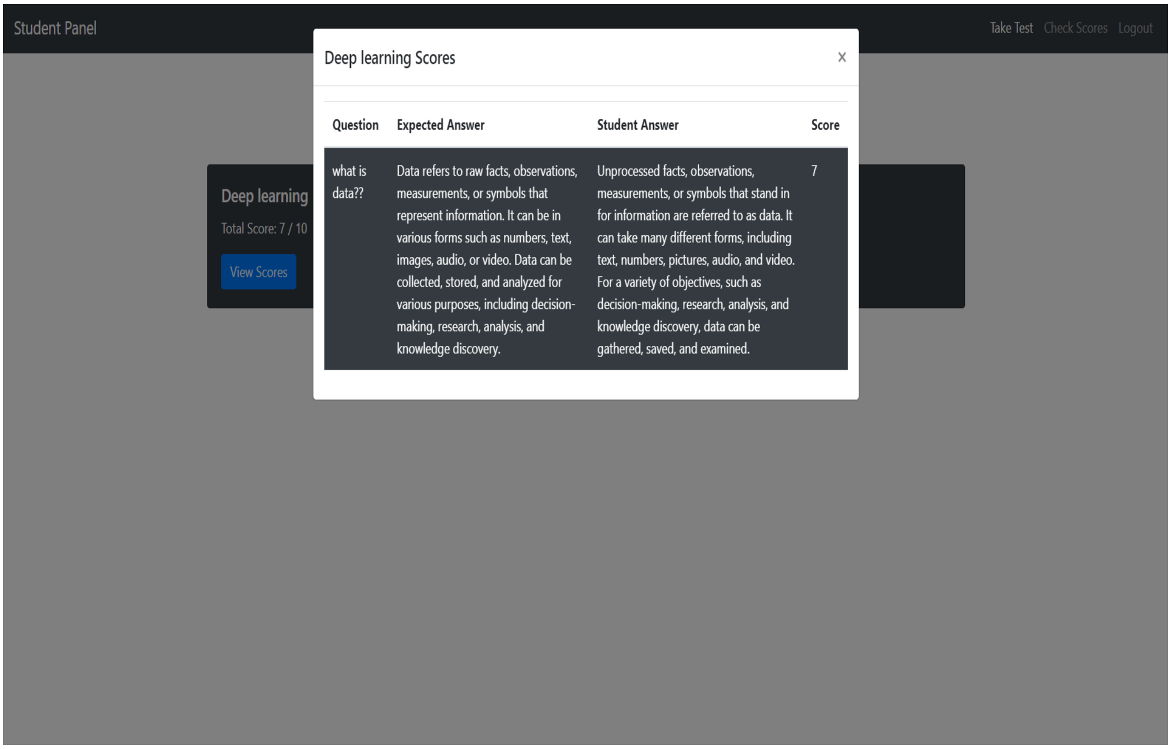


Figure 20: Student Paraphrased Answer Match Score

Paraphrased answer: The above screenshot shows the student and expected answers in the paraphrased manner and the score generated for that answer. If the student submit the answer having similar meaning to the expected answer but used some different words, the score is generated as above.

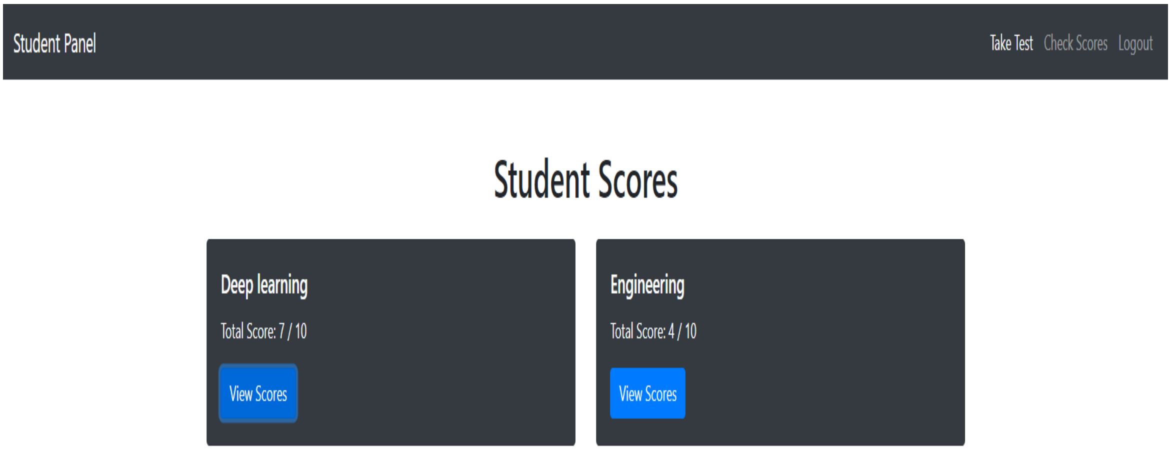


Figure 21: Student Scores

Student Score: After giving the test student can see the score in the tests by clicking the check sccore button.Student will able to see the scores of all the tests given by the student. Student the can see the answer given by him/her and what should be the ideal or the expected answer.

```
Exact Match Score: 0
Partial Match Score: 0.6229508196721312
Cosine Similarity Score: 0.9832908552112362
Sentiment Score: 0.5
Enhanced Sentence Match Score: 0.9897418
Multinomial Naive Bayes Score: 0.7075107245673359
Semantic Similarity Score: 0.9897418
Coherence Score: 0.9672131147540983
Relevance Score: 0.9743589743589743
```

Figure 22: Similarity Scores

Similarity Score: The above screenshot shows all the scores of the similarity matrices which includes the cosine similarity score, naive bayes score, relevance score, semantic similarity score. These all parameters will be used to calculate the final score for the student's answer.

8 Conclusion and Future Scope

8.1 Conclusion :

The subjective answer evaluation project underscores its significant contributions to automated assessment systems leveraging machine learning (ML) and natural language processing (NLP) techniques. Through meticulous implementation and evaluation, the project successfully demonstrated the feasibility and efficacy of employing advanced algorithms to evaluate subjective answers. Using cutting-edge technologies such as machine learning algorithms and Natural Language Processing (NLP) techniques, we've laid the groundwork for streamlined assessment processes, empowering educators with invaluable tools for personalized learning experiences.

By using the power of machine learning, our system can analyze and interpret complex linguistic patterns in student responses, enabling swift and accurate evaluation. Additionally, NLP techniques enhance the system's ability to understand nuances in language, ensuring a more comprehensive assessment of subjective answers. With a strong foundation in place, the project heralds a new era where educational evaluation transcends traditional boundaries, offering unprecedented insights into student learning and comprehension.As educators increasingly adopt this technology, they are equipped with a powerful tool that not only speeds up the grading process but also provides deeper insights into student understanding. The ability of the system to analyze complex linguistic patterns and understand subtle nuances in language translates into more accurate and fair assessments.

In conclusion, the "Subjective Answer Evaluation Using Machine Learning and NLP" project marks a significant milestone in the journey towards fully automated, highly accurate educational assessments. It promises not only to enhance the way educators interact with student work but also to revolutionize the traditional paradigms of teaching and learning. As this technology continues to evolve and integrate into more classrooms around the globe, it paves the way for a more informed, efficient, and equitable educational landscape.

8.2 Future Scope :

Building upon the current achievements of the project in subjective answer evaluation using machine learning (ML) and natural language processing (NLP), the future scope of this initiative holds significant promise for even greater enhancements in accuracy and functionality. One key area for future development is the incorporation of more advanced NLP capabilities to enrich the understanding of textual data. Techniques such as deep contextual embedding, which utilize state-of-the-art models like BERT (Bidirectional Encoder Representations from Transformers) and GPT (Generative Pre-trained Transformer), could allow the system to achieve a more profound comprehension of language nuances, idiomatic expressions, and complex sentence structures that are typical in student responses.

Additionally, integrating larger and more diverse datasets, including annotated subjective responses, can facilitate better model generalization and robustness. Moreover, employing ensemble learning methods or hybrid models combining multiple machine learning algorithms could potentially enhance predictive performance. Lastly, ongoing advancements in deep learning architectures and pre-trained language models offer exciting prospects for future research, providing opportunities to develop more sophisticated and context-aware evaluation systems. By pursuing these avenues, future iterations of the project can aspire to achieve even higher levels of accuracy and reliability in subjective answer evaluation, thereby contributing to the advancement of educational assessment methodologies.

In the long term, continuous advancements in AI and computational linguistics will likely open up new avenues for innovation in educational technology. Future iterations of this project could explore real-time adaptive learning systems, where the evaluation tool not only grades responses but also dynamically adjusts the difficulty of subsequent questions based on the student's demonstrated capabilities. This would personalize the learning experience to an unprecedented degree, making education more responsive to individual student needs and learning styles.By pushing forward in these areas, the project can further solidify its role in transforming educational assessment, making it more accurate, fair, and adaptive to the evolving educational landscape.

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Plagiarism Report

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Figure 23: Plagiarism Report

Contribution of the Project

- Participated in INNOVATION 2024, National Level Project Competition cum exhibition on 22nd March 2023 at ADCET, Ashta.

Figure 24: Certificate of Participation at Innovation

Figure 25: Certificate of Participation at Innovation

Figure 26: Certificate of Participation at Innovation

Figure 27: Certificate of Participation at Innovation

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