# Adaptive Machine Learning For Subjective Assessment

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***Abstract-*** In contemporary educational settings, examinations can be broadly classified into two categories: objective and subjective. While competitive exams commonly adopt the multiple-choice question format, which can be conveniently administered and evaluated online, subjective exams like board exams present a different challenge. Due to their nature, they cannot be effectively conducted through computerized means. Consequently, there is a growing need to integrate Artificial Intelligence (AI) into online examination systems to address this issue [1]. By leveraging AI, the evaluation of subjective answers could be significantly streamlined, leading to faster and more accurate results. Our proposed system aims to replicate the assessment process carried out by human evaluators, ensuring reliability and consistency. This innovative approach holds immense promise for educational institutions seeking to enhance the efficiency of their assessment procedures.

***Keywords*** - Automated answer verifier, answer verifier, theory answer checker, matching answers.

## 1. INTRODUCTION

In today's educational landscape, a variety of examination methods are utilized, including online assessments, multiple-choice question (MCQ) formats, and optical mark recognition (OMR) sheet exams. These assessment modalities are deployed regularly on a global scale. Central to any examination is the crucial task of evaluating students' responses. Traditionally, this responsibility falls on teachers, a process that can become cumbersome, especially when dealing with a large number of students [4]. Consequently, automating the answer checking process holds significant promise. Automating answer evaluation not only alleviates the burden on examiners but also enhances transparency and fairness by mitigating potential biases inherent in manual grading [12].

This project aims to leverage machine learning to develop an adaptive approach for subjective answer evaluation [11]. The resulting solution can be implemented across educational institutions to streamline grading processes [2]. With further refinement, the tool could even support the conduct of online theory examinations.

Upon launching the application, users will be presented with two options: logging in as an admin/college faculty member or as a student [3]. Faculty members will have access to features such as uploading question papers and reviewing student answer sheets, while students can upload their answer sheets and view their allocated marks in real-time.

## 2. LITERATURE SURVEY

**A survey on the techniques, applications, and performance of short text semantic similarity:** The measurement of short text similarity holds significant importance within the realm of natural language processing (NLP), finding applications across various domains. However, due to the inherent limitation of context in short texts, accurately gauging their similarity poses a challenge. The utilization of semantic similarity to assess textual resemblance has garnered considerable attention from both academia and industry, yielding improved outcomes. In this survey, we conduct a thorough and structured analysis of semantic similarity, categorizing it into three main types: corpus-based, knowledge-based, and deep learning (DL)-based approaches [2]. We critically examine the advantages and disadvantages of established and emerging algorithms within each category, also exploring their utilization in diverse NLP contexts. Furthermore, we assess the performance of state-of-the-art DL techniques using four commonly used datasets, demonstrating that DL-based methods excel in addressing challenges like sparse data and complexity inherent in short text similarity tasks. Notably, models like the bidirectional encoder representations from transformers effectively leverage limited information in short texts and semantic nuances, achieving higher accuracy and F1 scores. Lastly, we propose potential future avenues for research in this domain. [2]

**Subjective answer evaluation using machine learning:** The traditional method of evaluating subjective papers faces challenges due to the subjective nature of human assessment, which can lead to inconsistencies. Human emotions and biases can impact the quality and fairness of evaluations. In contrast, our proposed system leverages Machine Learning (ML) and Natural Language Processing (NLP) to provide a more objective and consistent assessment of subjective answers [4]. By employing techniques such as tokenization, part-of-speech tagging, lemmatization, and semantic analysis using resources like WordNet, our algorithm not only evaluates surface-level characteristics but also delves into the semantic meaning of responses, resulting in a more comprehensive evaluation. Our system is structured into two modules: one for efficiently extracting data from scanned images and organizing it, and another for applying ML and NLP techniques to the extracted text to assign marks based on a deeper understanding of the content [4]. This approach ensures that subjective assessments are conducted in a fair, timely, and accurate manner, overcoming the limitations of human-centric evaluation methods [4].

**Automated assessment system for subjective questions based on LSI:** Subjective questions can gauge a student's ability to apply knowledge, but their assessment faces challenges like complexity, synonym usage, and multiple meanings. These issues hinder the effectiveness of subjective questions in online exercises. This paper presents an automated assessment system for subjective questions based on latent semantic indexing [6]. It employs Chinese automatic segmentation methods and subject ontology to convert reference answers into a term-document matrix. This matrix is then transformed into a k-dimensional LSI space using Singular Value Decomposition, addressing synonym and polysemy issues. A reference unit vector is also introduced to mitigate complexity [6]. The system evaluates solution quality based on the similarity between projected vectors. Experimental results validate the practicality of our approach for automated assessment of subjective questions [6].

**Factors affecting sentence similarity and paraphrasing identification:** Sentence similarity assessment assesses whether two sentences are similar in structure and meaning. Various factors, including sentence representation, similarity metrics, and word weighting functions, can influence the detection of sentence similarity [9]. This research evaluates the impact of three such factors on similarity detection and paraphrase identification using clustering algorithms. We experimented with different word embedding models, clustering algorithms, and weighting methods for contextual words to assess their impact. Our experiments were conducted on an Arabic paraphrasing benchmark comprising 1010 pairs of Arabic sentences, created based on Arabic transformation rules and annotated for similarity and paraphrasing. The results of our experiments indicate that using pre-trained embeddings, weighting context words based on part of speech, and labeling sentence pairs with majority expert agreement led to improved recall and precision [9].

**Conceptual graphs based approach for subjective answers:** Automated assessment systems for multiple-choice tests are already in use. However, creating an automated assessment system for subjective tests presents a significant challenge. This paper focuses on evaluating simple text-based subjective responses using Natural Language Processing (NLP) techniques [10]. The evaluation process involves comparing a student's answer to a model answer for the question. Since exact matches are unlikely due to writing variations, researchers develop conceptual graphs for both the student and model answers and use graph similarity measures to determine similarity. Marks are then assigned based on this similarity. The authors of this manuscript also compare the results obtained from human graders to those from the proposed system using the Pearson correlation coefficient. Additionally, they compare the proposed system's results with those of other existing assessment systems. The experimental evaluation of the proposed system demonstrates promising outcomes [10].

**Subjective evaluation: A comparison of several statistical techniques:** Research on evaluating subjective examinations using computerized tools has spanned over four decades, with numerous statistical and mathematical techniques proposed by researchers. This study compares several previously proposed methods such as Latent Semantic Analysis (LSA), Generalized Latent Semantic Analysis (GLSA), Bilingual Evaluation Understudy (BLEU), and Maximum Entropy (Maxent) using common input data. The implementation of these techniques utilizes Java programming language, MATLAB, and other open-source tools. Experimental trials were conducted using a database comprising 4500 responses to around 50 computer science questions [11]. The authors note a lack of existing literature comparing these techniques on a shared database. The database used for testing was derived from examinations administered to graduate-level computer science students. The paper discusses the merits and limitations of each technique based on the outcomes of these experiments [11].

**Automarking: Automatic assessment of open questions:** Several Learning Management Systems (LMSs) are available in today's market, with one of their components dedicated to managing student assessments. In certain assessment formats like open-ended questions, the LMS lacks the capability to assess student responses autonomously, necessitating human involvement. To achieve assessments at higher levels of Bloom's taxonomy, incorporating open-style questions where students respond without the aid of recall cues is essential [12]. The automation of assessing open questions has been a subject of research since the 1960s, initially focusing on statistical or probabilistic methods centered around conceptual comprehension. Recent advancements in Natural Language Processing have shifted the evaluation of free text towards a more linguistic approach, emphasizing factual comprehension [12]. This study aims to capitalize on recent research in Natural Language Processing, Information Extraction, and Information Retrieval to deliver a fair, timely, and accurate assessment of student responses to open questions, considering the semantic meaning of their answers.

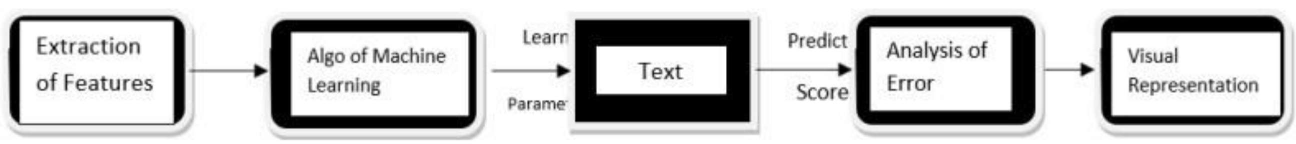
## 3. DATA COLLECTION

Data collection encompasses a structured process aimed at gathering and quantifying information pertinent to specific modifications within a well-defined framework [6]. This systematic approach enables individuals to assess existing conditions and tackle relevant inquiries efficiently [5]. Data collection stands as a cornerstone in research, extending its reach across various domains including physical and social sciences, business, and humanities. Its primary objective revolves around accumulating reliable and substantial evidence to assist in formulating definitive responses to posed questions [10]. It's crucial to highlight that the data employed in this project has been internally generated since the project's inception.

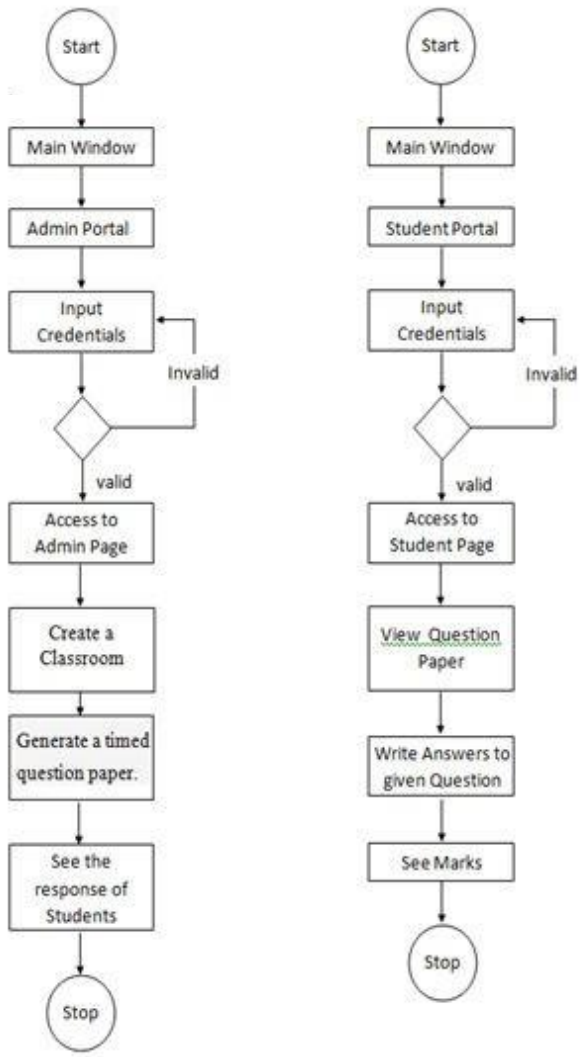
## 4. ALGORITHM

Step I: Start
Step II: Main Window/Page Opens
Step III: Log into the system as Administrator or a Student. If client log in as Student go to the step IV, if client log in as an Administrator go to step VIII.
Step IV: Student window page opens.
Step V: View the available subject question paper.
Step VI: Attempt the paper by answering all questions.
Step VII: submit to view the marks.
Step VIII: Administrator window page opens.
Step IX: Create the classroom which will help to generate the question paper.
Step X: View student responses.

## 5. SYSTEM ARCHITECTUIRE




## 6. FLOW CHART



## 7. FUTURE SCOPE

Within this system, the elimination of notations and symbols during pre-processing enables text overlapping[7]. However, this pre-processing step also results in the removal of essential symbols and features, particularly in the context of mathematical problems. As a consequence, the system's performance is relatively inferior when evaluating mathematical questions compared to textual format questions. Nonetheless, educational institutions can still utilize this system effectively to assess students' coursework, thereby reducing the manual workload for teachers[8]. In future iterations, it is crucial for the system to incorporate the capability to evaluate mathematical content accurately and assign appropriate scores.

## 9. CONCLUSION

The project, titled "Machine Learning Based on an Adaptive Approach for Subjective Answer Evaluation," introduces a virtual platform designed for theory-based question examinations. Notably, the application exhibits robustness, paving the way for diverse opportunities to enhance its functionality in the future. Upcoming efforts will focus on crafting an algorithm specifically tailored to identify and evaluate syntax errors within keywords. Extensive research and testing will be undertaken to ensure optimal performance and fairness in addressing these errors.

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