# CS 5100: Final Project

## *AI Cognitive Classification*


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***Abstract*—This project focused on developing a machine learning-based solution for classifying educational questions according to Bloom's Taxonomy, an essential framework in the educational domain for categorizing educational objectives. Utilizing advanced data preprocessing methods, including Word2Vec embeddings and TF-IDF vectorization, alongside a range of machine learning algorithms (Random Forest, KNN, SVM with linear and RBF kernels, Decision Tree, and Logistic Regression), the study aimed to enhance the accuracy and efficiency of automatic question classification. The results demonstrated high accuracy across most models, with SVM and Logistic Regression showing particularly promising performance. This work not only contributes to the field of educational technology by providing an effective tool for automatic question categorization but also sets a benchmark for future explorations into the application of machine learning in educational data analysis.**


## I. Introduction

In the ever-evolving landscape of education and assessment, the classification and categorization of questions according to their cognitive complexity is a fundamental task with profound implications. Understanding the cognitive demands imposed by different questions allows educators and instructional designers to tailor their teaching strategies to the specific needs of learners, thereby enhancing the effectiveness of educational processes. One established framework for this purpose is Bloom's Taxonomy (Fig.1), which classifies questions into hierarchical levels of cognitive complexity, ranging from the recall of basic facts to the application of knowledge in novel contexts. Traditionally, this categorization has been a time-consuming and subjective task, often reliant on expert judgment.

Recent advances in the field of machine learning have opened up exciting possibilities for automating the categorization of questions according to Bloom's Taxonomy. The use of machine learning algorithms, particularly support vector machines (SVM), has gained significant traction in this domain. These algorithms can be trained to recognize patterns and relationships in question text and other relevant features, allowing for the automated assignment of questions to their appropriate cognitive levels. This not only saves time but also offers a more consistent and objective approach to question classification.

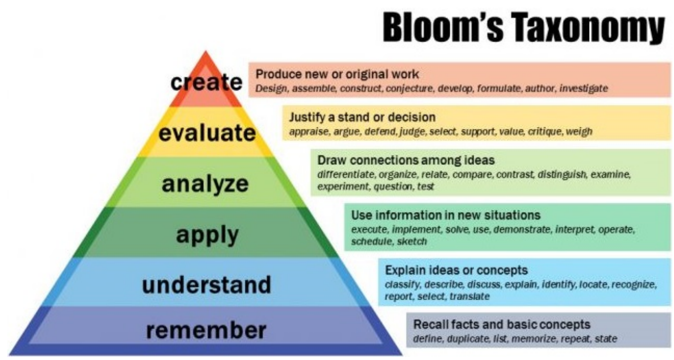


Fig. 1. Bloom's Taxonomy

The synergy between machine learning and educational assessment is not only about efficiency; it holds the promise of transforming the educational landscape. By automating the categorization of questions, educators can better align their teaching materials and assessments with learning objectives and goals. Furthermore, as the volume of educational content grows in the digital age, the ability to categorize and tag questions automatically becomes invaluable in developing adaptive learning systems, personalized learning experiences, and intelligent tutoring systems.

This paper explores the application of machine learning techniques, with a focus on Machine Learning methods, to categorize questions based on their cognitive level according to Bloom's Taxonomy. We investigate the challenges and opportunities associated with this approach, considering the nuances of question text analysis, the choice of feature representations, and the potential impact on educational practices.

As we delve deeper into the realm of machine learning for educational assessment, it becomes evident that the accurate and automated categorization of questions by cognitive level is not only a technological advancement but a pivotal step in enhancing the quality of education itself. This paper presents a comprehensive exploration of this exciting intersection between machine learning and education, shedding light on the possibilities and challenges in the pursuit of more effective and personalized learning experiences.

## II. Literature Review

Our research draws significant inspiration from the earlier work of Suliana Sulaiman and colleagues, particularly their paper on Question Classification Based on Cognitive Levels utilizing Linear Support Vector Classification (SVC) [13]. In their study, the team successfully categorized questions based on Bloom's Taxonomy, achieving an impressive peak accuracy of 91%. The models employed included Linear SVC, Naive Bayes, and KNN. While the project went well, due to the complex nature of NLP classification problem, there still remains room for higher accuracy. Our objective is to replicate Sulaiman's methodology while expanding the scope of our investigation by exploring additional models and engaging in hyperparameter tuning to enhance overall accuracy.

Our research encompasses various models, such as Support Vector Machine (SVM) with both linear and Radial Basis Function (RBF) kernels, Decision Tree, Random Forest, Logistic Regression, and K-Nearest Neighbors (KNN). This diverse model exploration aims to discern the most effective approach for tackling the inherent challenges in the question classification problem.

The choice of SVM with an RBF kernel is grounded in its demonstrated efficacy in handling non-linear and high-dimensional datasets. This model excels in discerning complex decision boundaries and exhibits resilience in scenarios with a substantial number of features. The effectiveness of SVM with RBF kernel has been demonstrated in addressing complex, high-dimensional Computer Vision classification problems [14].

Opting for the Random Forest model is motivated by its status as an ensemble method, leveraging multiple decision trees to enhance overall predictive performance. Renowned for its robustness in handling high-dimensional data, the Random Forest model excels in capturing intricate relationships within the dataset. Additionally, the provision of a feature importance metric by Random Forests proves valuable in comprehending the significance of individual features in the classification process, as detailed in [15].

K-Nearest Neighbors (KNN), a non-parametric method, is chosen for its potential effectiveness in handling high-dimensional data. The KNN methodology involves classifying samples based on the majority class among their nearest neighbors within the feature space. While acknowledging that KNN may face challenges in computational efficiency as the dataset's dimensionality increases, we are exploring opportunities for hyper-parameter tuning to further improve model accuracy, building upon its original implementation in our study.

We are confident by experimenting with all the above we will arrive at a higher accuracy than the one acheived by Sulaiman.

## III. Problem Characterization

Our Machine Leaning model as a rational agent is **fully observable** because the required inputs (text questions) for feature extraction are fully available and accessible to the model. It operates as a **single agent**, as there is no need for it to interact and communicate with other agents to yield a result. The system is **deterministic**, as the next state (better or lower accuracy) of the task problem is entirely determined by the current state and the agent's executed action. It follows an **episodic** nature, where the current decision has no bearing on future decisions. The only elements with the potential to impact the system are the training dataset and the underlying model. The environment remains **static** during the agent's output delivery. Lastly, the problem is inherently **discrete** since the goal is to categorize text inputs into a predefined set of classes, which are distinct and well-defined. Under any circumstance, it only has one goal, assigning the provided question to the closest category.

### State Transition

State transition happens mostly in the training phase and the prediction phase. In the training phase the system undergoes state transitions as it learns to associate input text with corresponding categories or labels. The model adjusts its parameters to minimize errors and optimize classification accuracy. In the prediction phase, when the trained NLP model is applied to new, unseen text, it undergoes a state transition during the inference process. The initial state is the raw text input, and the final state is the predicted category or label assigned by the model.

## IV. Methodology

### Problem-Solving Approach

To address the challenge of classifying questions according to Bloom's Taxonomy, our approach amalgamated advanced NLP techniques with machine learning algorithms. The methodology began with preprocessing, crucial for refining text data into a format suitable for analysis. This step involved lowercasing, removing special characters and punctuation, tokenizing the text, eliminating stopwords, and applying lemmatization for reducing words to their base forms. To capture the semantic richness of language, we integrated Word2Vec embeddings, which map words into high-dimensional vector spaces, reflecting their contextual meanings. Additionally, TF-IDF (Term Frequency-Inverse Document Frequency) was used to weigh the words, emphasizing those that are distinctively frequent in a document but not across all documents, thus highlighting their unique contribution to the semantic content.

### Simulation Setup

The dataset, sourced from a comprehensive collection of educational materials, consisted of a variety of questions tagged with corresponding Bloom's Taxonomy categories. These categories included Analyze, Apply, Create, Evaluate, Remember, and Understand. In the preprocessing phase, we implemented custom Python scripts to clean and structure the data, followed by the application of Word2Vec and TF-IDF transformations. The resulting vectorized representations of the questions formed the input for the machine learning models.

### Data Sources

Our dataset consists of 6458 questions, 600+ of them are gathered from [3], [16], [17] and ChatGPT. They cover a variety of subjects suitable for all educational levels, from kindergarten to PhD. These 600 questions are then fed into ChatGPT to augment more dataset in different styles ranging from formal to informal and fun. This data augmentation process is illustrated in Fig. 2. These diversifying measures are meant to prevent issues like over-fitting.

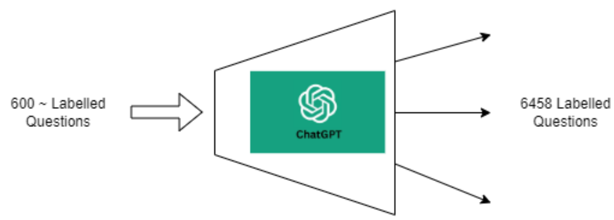


Fig. 2. Data Augmentation

### Algorithm Parameters

For Random Forest, we experimented with different numbers of trees (n_estimators) and tree depths (max_depth) to find the optimal balance between bias and variance. KNN was tested with a range of neighbors (n_neighbors) to determine the best radius for classifying a data point. For SVM (both linear and RBF kernels), we fine-tuned the regularization parameter (C) and the kernel coefficient (gamma), which are critical for controlling the trade-off between a smooth decision boundary and classifying training points correctly. In Decision Trees, parameters like criterion (gini or entropy), max_depth, and min_samples_split were adjusted for optimal tree complexity. Finally, for Logistic Regression, we selected parameters like regularization strength (C) and solver type to ensure robust convergence.

### Modifications and Hypotheses

Our modifications primarily involved adapting the algorithms to handle the high-dimensional feature space created by Word2Vec and TF-IDF. We hypothesized that these feature engineering techniques would enhance the models' ability to understand and categorize text data accurately, based on Bloom's Taxonomy.

### Performance Metrics

To evaluate the models, we employed several performance metrics:

- Accuracy: A fundamental measure of overall correctness across all categories.
- Precision and Recall: These metrics helped in understanding the models' performance in terms of false positives and false negatives, crucial for imbalanced classes.
- F1-Score: As a harmonic mean of precision and recall, it provided a single metric to assess the balance between precision and recall.
- Cohen's Kappa: This was used to measure the agreement between different models, offering insights beyond mere accuracy, especially important in multi-class classification tasks.

These metrics collectively offered a comprehensive assessment of each model's performance and suitability for Bloom's Taxonomy classification.

## V. Results

### Data Presentation

The experimental results were pivotal in evaluating the performance of two distinct approaches used for Bloom's Taxonomy classification. The first approach involved basic data preprocessing and model training, while the second incorporated advanced preprocessing with Word2Vec embeddings and TF-IDF vectorization. Key findings from both approaches include accuracy scores, confusion matrices, ROC curves, and precision-recall curves for each model.

Accuracy Scores: For the first approach, models like SVM Linear and Random Forest displayed high accuracy, while in the second approach, SVM RBF and SVM Linear stood out. Specifically, SVM RBF in the second approach achieved the highest accuracy of 99.69%.
Confusion Matrices: These matrices provide insights into the true positive and false positive rates across different Bloom's Taxonomy categories for each model.

ROC Curves: The ROC curves for each model, particularly in the second approach, show a higher true positive rate against the false positive rate, indicating improved model performance.

Precision-Recall Curves: These curves depict the balance between precision and recall for each category, with the second approach showing more favorable curves, especially for SVM RBF and SVM Linear.

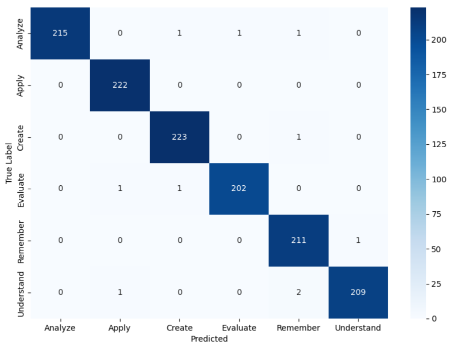


Fig. 3. Random Forest Approach 1 Confusion Matrix

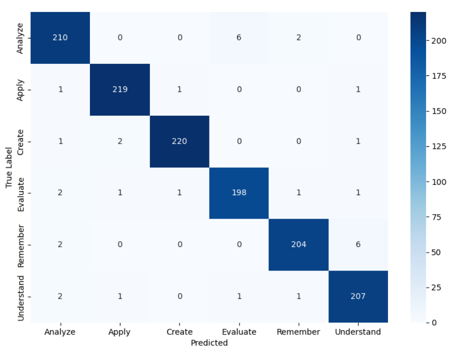


Fig. 4. KNN Approach 1 Confusion Matrix

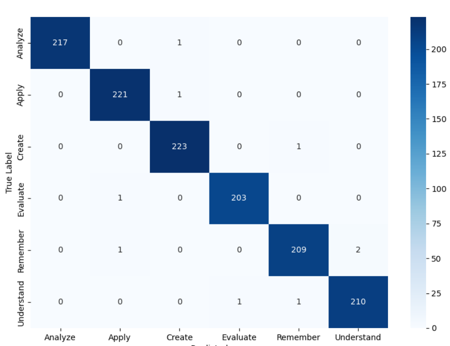


Fig. 5. SVM Linear Approach 1 Confusion Matrix

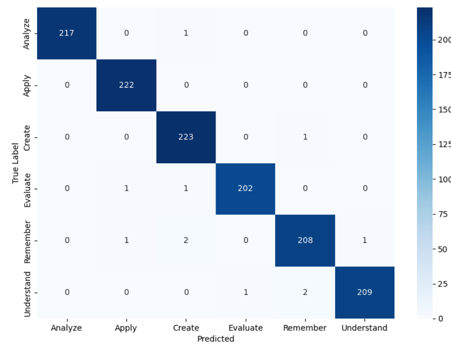


Fig. 6. SVM RBF Approach 1 Confusion Matrix

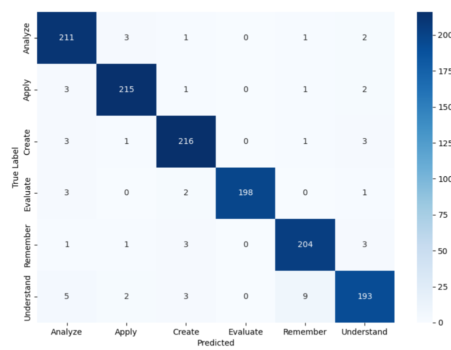


Fig. 7. Decision Tree Approach 1 Confusion Matrix

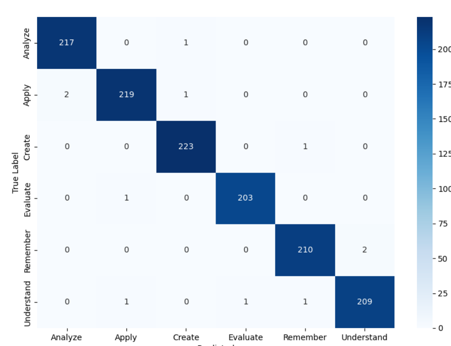


Fig. 8. Logistic Regression Approach 1 Confusion Matrix

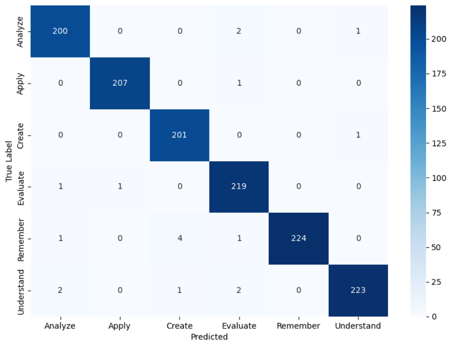


Fig. 9. Random Forest Approach 2 Confusion Matrix

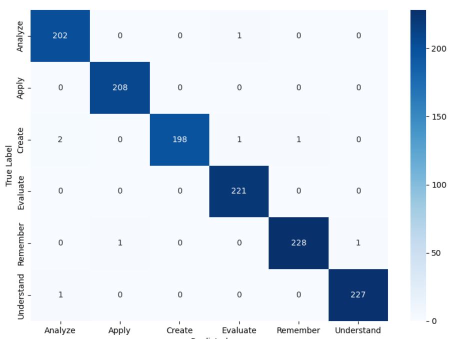


Fig. 10. KNN Approach 2 Confusion Matrix

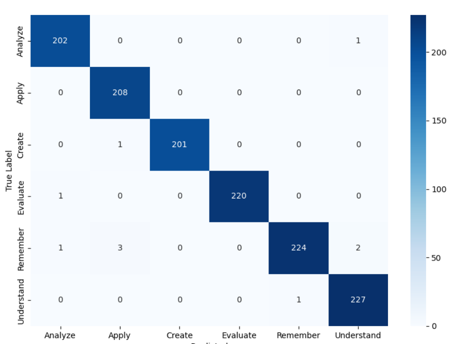


Fig. 11. SVM Linear Approach 2 Confusion Matrix

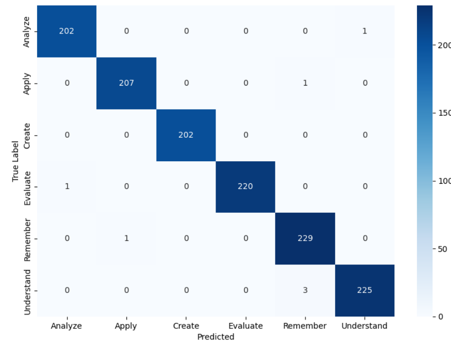


Fig. 12. SVM RBF Approach 2 Confusion Matrix

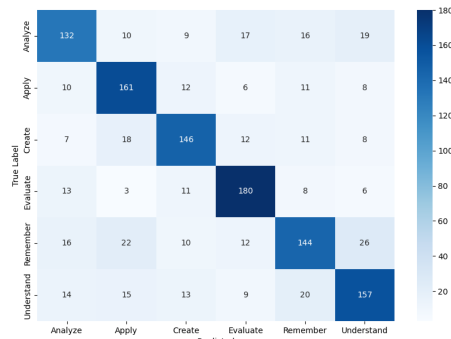


Fig. 13. Decision Tree Approach 2 Confusion Matrix

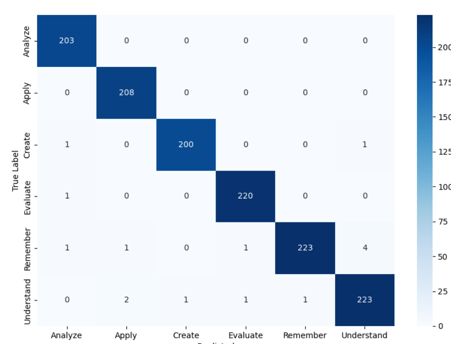


Fig. 14. Logistic regression Approach 2 Confusion Matrix

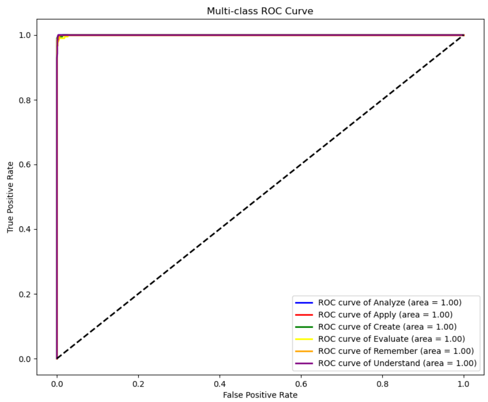


Fig. 15. Random Forest Approach 1 ROC Curve

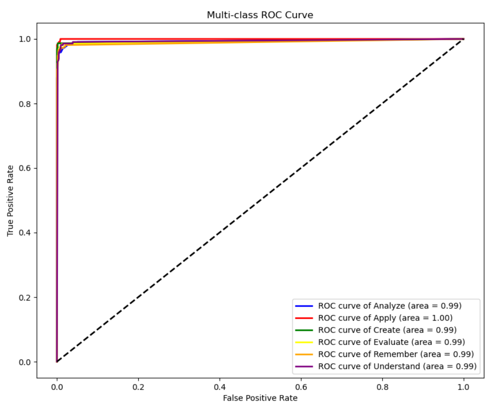


Fig. 16. KNN Approach 1 ROC Curve

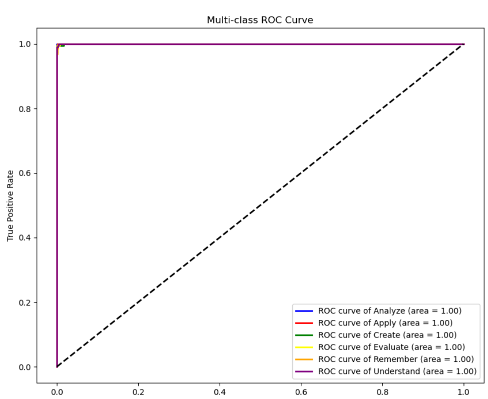


Fig. 17. SVM Linear Approach 1 ROC Curve

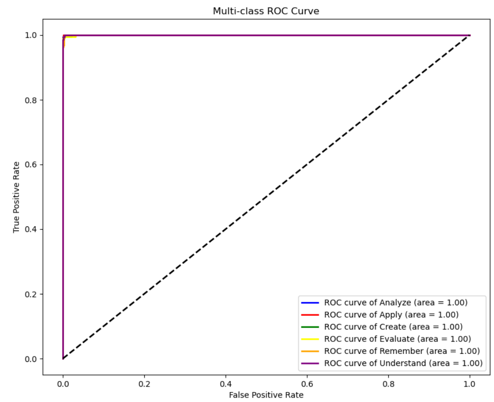


Fig. 18. SVM RBF Approach 1 ROC Curve

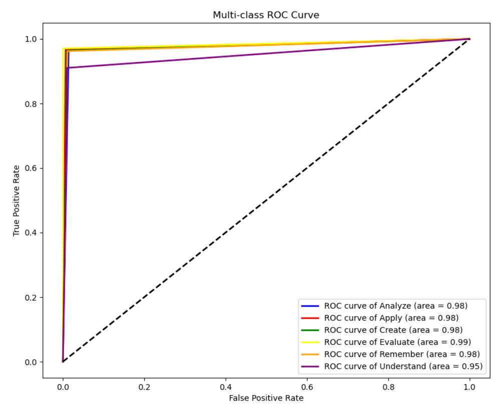


Fig. 19. Decision Tree Approach 1 ROC Curve

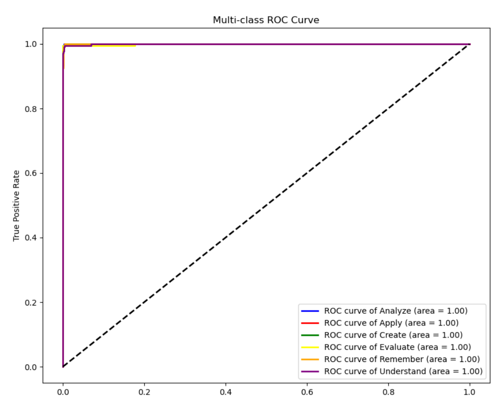


Fig. 20. Logistic Regression Approach 1 ROC Curve

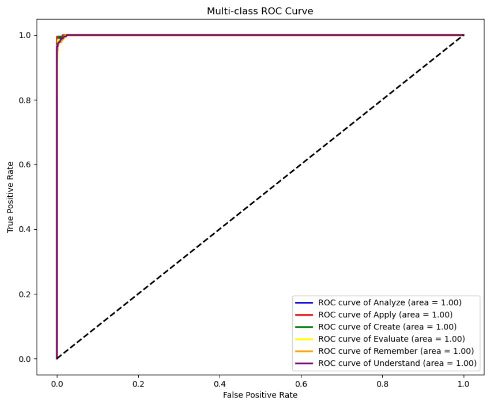


Fig. 21. Random Forest Approach 2 ROC Curve

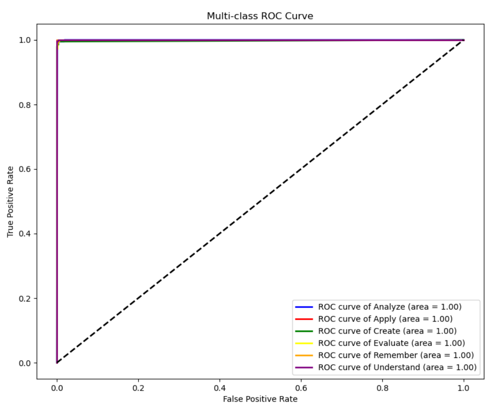


Fig. 22. KNN Approach 2 ROC Curve

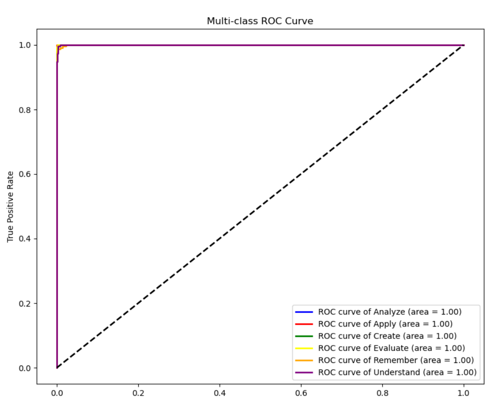


Fig. 23. SVM Linear Approach 2 ROC Curve

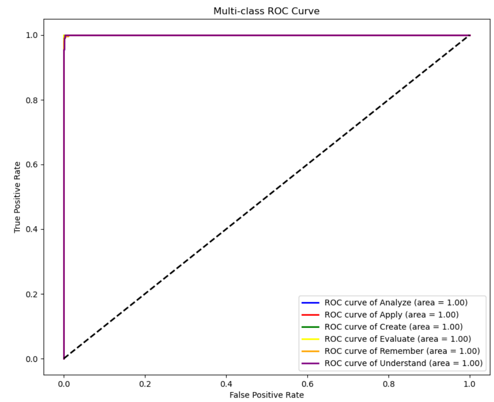


Fig. 24. SVM RBF Approach 2 ROC Curve

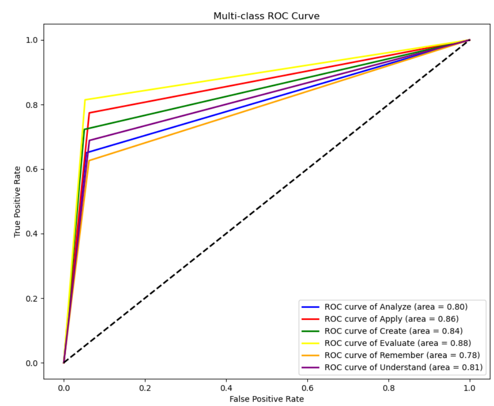


Fig. 25. Decision Tree Approach 2 ROC Curve

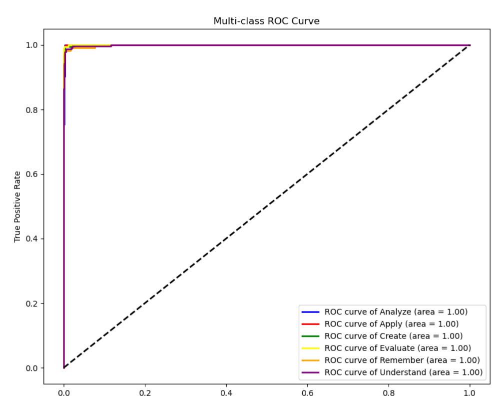


Fig. 26. Logistic Regression Approach 2 ROC Curve

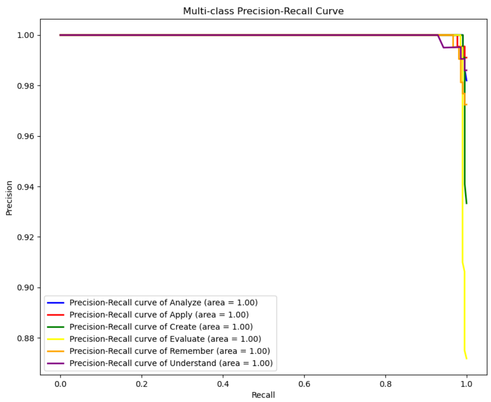


Fig. 27. Random Forest Approach 1 Precision-Recall Curve

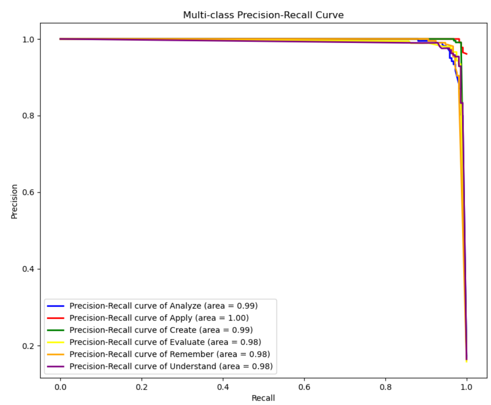


Fig. 28. KNN Approach 1 Precision-Recall Curve

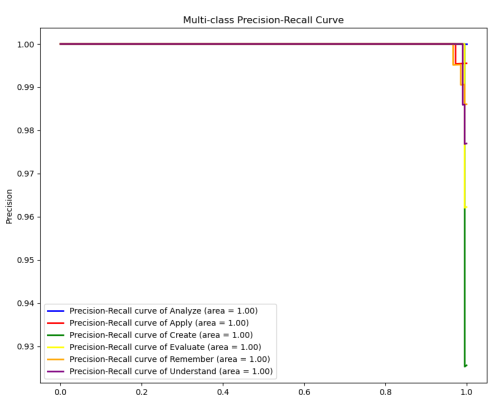


Fig. 29. SVM Linear Approach 1 Precision-Recall Curve

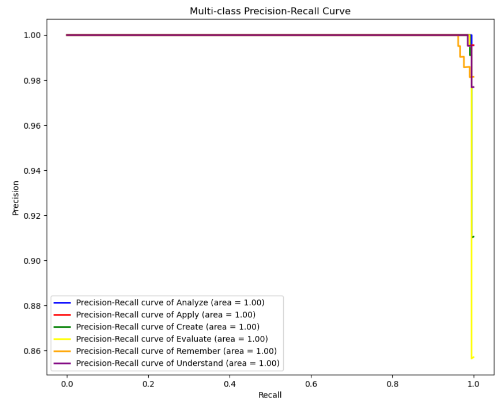


Fig. 30. SVM RBF Approach 1 Precision-Recall Curve

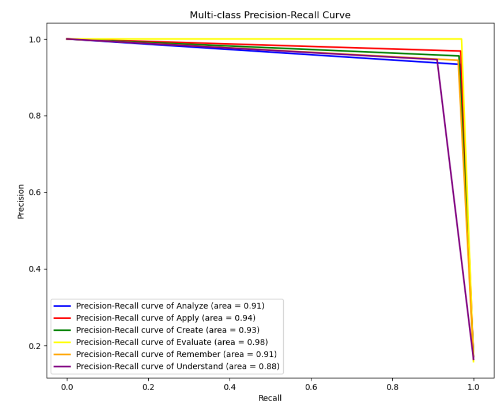


Fig. 31. Decision Tree Approach 1 Precision-Recall Curve

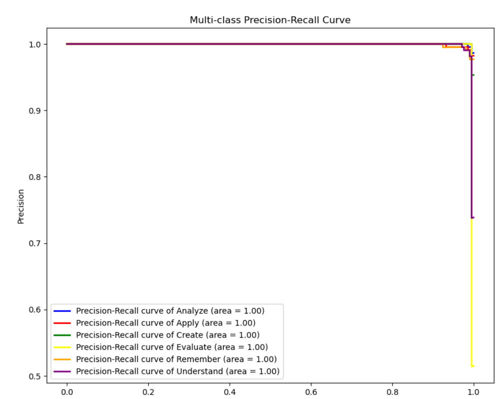


Fig. 32. KNN Approach 1 Precision-Recall Curve

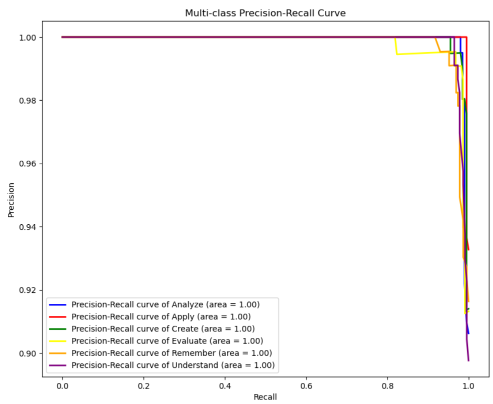


Fig. 33. Random Forest Approach 2 Precision-Recall Curve

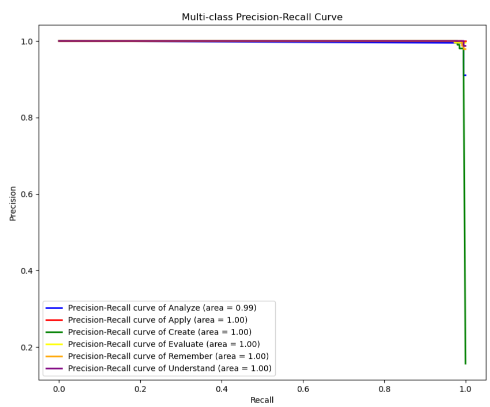


Fig. 34. KNN Approach 2 Precision-Recall Curve

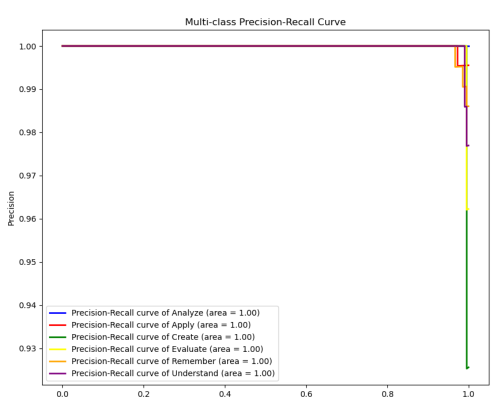


Fig. 35. SVM Linear Approach 2 Precision-Recall Curve

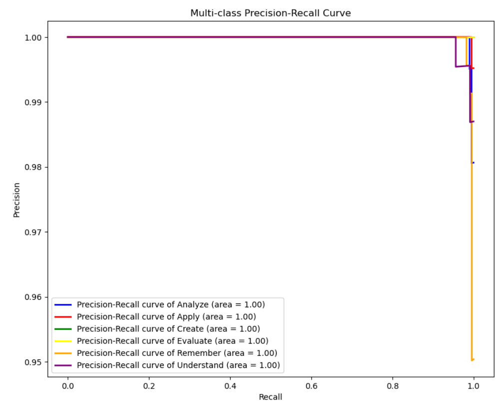


Fig. 36. SVM RBF Approach 2 Precision-Recall Curve

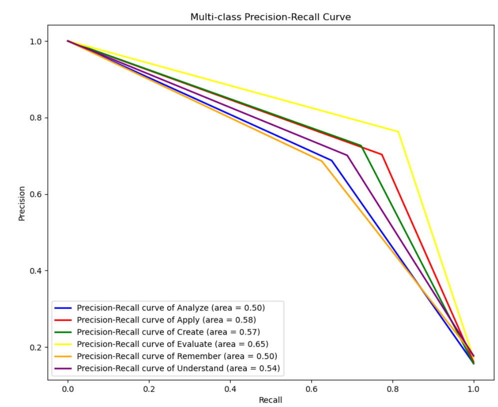


Fig. 37. Decision Tree Approach 2 Precision-Recall Curve

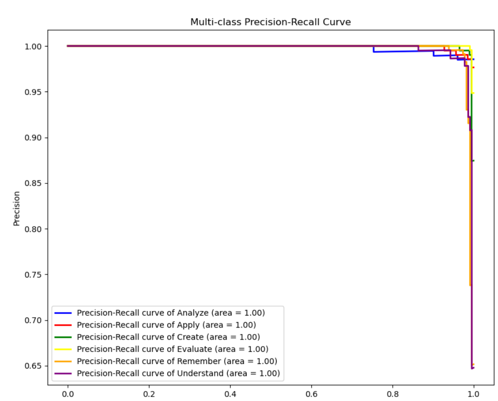


Fig. 38. Logistic Regression Approach 2 Precision-Recall Curve

## VI. Discussions

We employed two techniques to pre-process the datasets into organized vector structures required for further processing. One involves completely extracting features from scratch, while the other utilizes external TF-IDF. Both methods yielded similar results; however, the completely customized method took seven times as long as the one using external TF-IDF ( 10 mins vs  75 mins). This result is expected because the customized method extracts features without compacting, resulting in a large feature vector set.

The Decision Tree algorithm yielded the lowest accuracy among the six models employed. This is especially true in the second approach, illustrated in Fig. 40. This outcome was anticipated due to the complexity of educational question datasets, characterized by various linguistic nuances and contextual subtleties. Decision Trees make binary decisions based on individual features, and they may struggle to effectively capture complex relationships among features. Moreover, Decision Trees are prone to overfitting, especially when the tree depth is not properly controlled. Overfitting occurs when the model captures noise and specific patterns in the training data that do not generalize well to new, unseen data. In Bloom's Taxonomy classification, where the goal is to categorize diverse educational questions, overfitting may lead to poor generalization and reduced accuracy on test data.

In contrast, other algorithms performed better, as expected. The high performance of models, especially SVM RBF in the second approach, highlights the effectiveness of Word2Vec embeddings in capturing semantic meaning, which is crucial for accurate classification in Bloom's Taxonomy. The consistent performance of SVM models across both approaches suggests their suitability for high-dimensional text data. Their effectiveness can be attributed to their ability to handle large feature spaces and complex decision boundaries efficiently, which is vital in text classification tasks. Random Forest and KNN models also performed well, but their inability to outperform SVM models might be due to their less effective handling of the high-dimensional and sparse data typical of text.

High Cohen's Kappa scores, particularly between SVM Linear and SVM RBF in both approaches (illustrated in Fig. 41 and Fig. 42), indicate strong agreement in their classification decisions, reaffirming their reliability for this task.

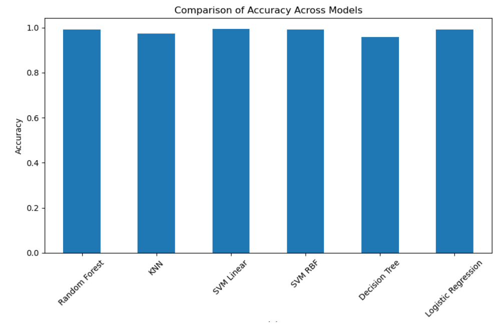


Fig. 39. Accuracy Comparison Approach 1

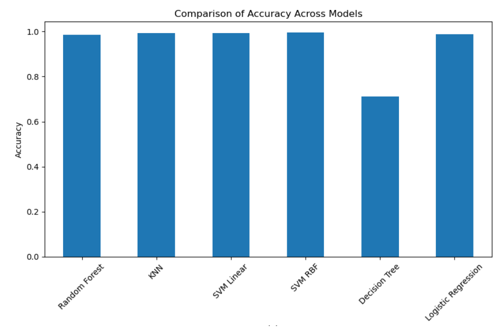


Fig. 40. Accuracy Comparison Approach 2

## VII. Conclusion

In summary, this research project has successfully developed a robust machine learning-based solution for the classification of educational questions according to Bloom's Taxonomy. Leveraging advanced data preprocessing techniques, such as Word2Vec embeddings and TF-IDF vectorization, in conjunction with a diverse set of machine learning algorithms, the study exceeded expectations by achieving high accuracy levels across most models.

Notably, the SVM and Logistic Regression models exhibited particularly promising performance, showcasing the effectiveness of the chosen methodology. The outcomes of this research not only fulfill the primary objective of providing an efficient tool for automatic question categorization in the educational domain but also establish a benchmark for future investigations into the application of machine learning in educational data analysis.

In conclusion our result exceeded our expectation laid out in the problem statement. Sulaiman's work result yielded an accuracy of 91% and ours resulted in around 99%. However there are some areas we would like to work on in the future.

The current iteration of the project focuses on the classification of questions into a single category. However, to enhance the versatility and granularity of the system, there are plans to extend its functionality to assign questions into two or more categories. This expansion aims to capture the diverse nature of questions that may encompass multiple topics, themes, or aspects. By accommodating multiple categories for a single question, the system becomes more flexible and capable of handling a broader range of user queries.

In the future, the project envisions incorporating Ensemble Methods to enhance the overall performance of the classification model. Ensemble methods involve combining predictions from multiple models to leverage their individual strengths, compensating for weaknesses, and improving overall accuracy. By integrating ensemble techniques, the project aims to create a holistic model that provides more robust and reliable categorization results. This approach is likely to enhance the model's generalization capabilities and effectiveness across a diverse set of questions.

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Cohen's Kappa between RandomForest and SVM Linear: 0.9897809431703379
Cohen's Kappa between RandomForest and SVM RBF: 0.9916386468816784
Cohen's Kappa between KNN and RandomForest: 0.9721310874268495
Cohen's Kappa between KNN and SVM Linear: 0.9674858478593651
Cohen's Kappa between KNN and SVM RBF: 0.9656271548640337
Cohen's Kappa between KNN and Logistic Regression: 0.9684152324170962
Cohen's Kappa between SVM Linear and SVM RBF: 0.9934967767914604
Cohen's Kappa between Decision Tree and RandomForest: 0.9498296445763119
Cohen's Kappa between Decision Tree and KNN: 0.9321826716213574
Cohen's Kappa between Decision Tree and SVM Linear: 0.9470434688814583
Cohen's Kappa between Decision Tree and SVM RBF: 0.9479699866674529
Cohen's Kappa between Decision Tree and Logistic Regression: 0.947971782573366
Cohen's Kappa between Logistic Regression and RandomForest: 0.9897810386928473
Cohen's Kappa between Logistic Regression and SVM Linear: 0.9962840274297449
Cohen's Kappa between Logistic Regression and SVM RBF: 0.990709767974298
```

Fig. 41. Cohen's Kappa Approach 1

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Cohen's Kappa between RandomForest and SVM Linear: 0.9767708788806296
Cohen's Kappa between RandomForest and SVM RBF: 0.9795574619147691
Cohen's Kappa between KNN and RandomForest: 0.978627932851606
Cohen's Kappa between KNN and SVM Linear: 0.9842021185157587
Cohen's Kappa between KNN and SVM RBF: 0.9860599207616548
Cohen's Kappa between KNN and Logistic Regression: 0.9786269798058188
Cohen's Kappa between SVM Linear and SVM RBF: 0.9897781060726479
Cohen's Kappa between Decision Tree and RandomForest: 0.6552852965585487
Cohen's Kappa between Decision Tree and KNN: 0.6524821011827064
Cohen's Kappa between Decision Tree and SVM Linear: 0.6506242192315188
Cohen's Kappa between Decision Tree and SVM RBF: 0.6497260136058336
Cohen's Kappa between Decision Tree and Logistic Regression: 0.6506320083308881
Cohen's Kappa between Logistic Regression and RandomForest: 0.975842131001352
Cohen's Kappa between Logistic Regression and SVM Linear: 0.9842034137714529
Cohen's Kappa between Logistic Regression and SVM RBF: 0.9804861348853132
```

Fig. 42. Cohen's Kappa Approach 2

Recognizing the dynamic nature of user needs and the evolving nature of language use, another area of improvement is that the project intends to implement a User Feedback Loop in the classification process. This feedback loop is designed to collect user input, including corrections or additional context related to the model's predictions. By actively involving users in the refinement process, the model can adjust itself based on real-world user feedback. This two-way interaction ensures that the model continuously learns from its application in different contexts, making it more adaptive and accurate over time. User feedback, whether indicating correct or incorrect labels, serves as valuable data for model improvement and adaptation to changing user requirements.

The results of our study demonstrate result of the different ML technologies in automating the categorization of educational questions. This has broad implications for educators, e-learning platforms, and content creators by facilitating the creation of adaptive learning materials and assessments. Furthermore, this research provides insights into the evolving intersection of machine learning and education, addressing the demand for more efficient and accurate methods of question categorization in educational contexts.

Since this is a Natural Language Processing problem, the solution developed and methodologies utilized are not confined just to the realm of this very issue, but can be extended to address similar challenges in different contexts.

In conclusion, this project serves as more than an opportunity for us to apply class knowledge; it is a profound gateway for us to delve into practical applications and endless possibilities in the sea of Artificial Intelligence.

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