

Group 25 Final Project Report:

AI Essay Detector

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1 Introduction

The widespread and accessible nature of Generative AI (GenAI) tools, such as ChatGPT and Gemini, has created a significant shift in the educational landscape. While these tools are valuable for quick information retrieval, their rapid adoption precedes the necessary adaptations in academic practices. The core issue is that unchecked reliance on GenAI for academic work can have long-term developmental consequences for students. It prevents them from engaging in the process of formulating original thoughts and arguments, which is critical for developing their unique intellectual voice. A reliable AI Text Detector, integrated within the education system, would allow educators to foster responsible use of GenAI as an educational aid rather than a replacement for student effort.

Developing an effective detector is challenging for several reasons:

- Low Accuracy of Existing Models: Current models are not accurate enough for real-world academic use.
- Evolving Realism: GenAI systems are constantly improving, generating increasingly human-like text, requiring the detector to be dynamically updated.
- Critical False Positive Rate: The model must achieve a near-zero false positive rate to ensure no student is wrongfully accused of plagiarism while maintaining high accuracy in identifying genuine misuse.

Detecting AI-generated text is closely connected to research in text classification. An overview of how methods such as TF-IDF have been used in traditional machine-learning models before the development of deep-learning techniques as seen in the survey “A Survey on Text Classification: From Traditional to Deep Learning” (Li et al., 2022).

In practical applications, AI text detection has been explored through competitions, such as the kaggle AI Text Detection Competition ([Al-Ahmadi](#)). Public notebooks from the competition show examples of baseline systems that use TF-IDF combined with classifiers such as Logistic Regression or SVM. Two examples are the notebooks by Faris Al-Ahmadi ([Al-Ahmadi](#)) and Jasmine Mohamed ([Mohammad](#)), where TF-IDF is used to represent essays numerically before training classification models.

More recent work focuses on neural network approaches. LSTM models are often used for text classification tasks because they can process text as a sequence and keep track of earlier context in the input. An example of this is shown in an LSTM text-classification notebook ([Khotijah](#)). Transformer-based models such as DistilBERT have also been applied to similar classification problems. The KerasNLP starter notebook from the same Kaggle competition shows how DistilBERT can be fine-tuned for detecting AI-generated text ([Audevert](#)).

There is also research specifically focused on identifying patterns unique to AI-generated writing. The “DetectGPT” paper ([Mitchell et al., 2023](#)) shows that AI-generated text often has different patterns in how words are used compared to human writing and discusses ways to detect those differences.

2 Dataset

We will be using the DAIGT V2 Train Dataset from Kaggle ([Kleczeck](#)) to train the model, as well as adding a new, manually compiled dataset with AI generated and human written essays to evaluate the trained models performance on.

2.1 DAIGT V2 Train Dataset

To start, the DAIGT V2 Train Dataset is a comprehensive dataset containing a collection of other

datasets. One of the sub datasets contain argumentative essays written by grade 6 to 12 students. The remaining sub datasets contain AI-generated essays from numerous models as seen in Table 1. The dataset is prelabelled and additional columns include prompt_name (original persuade prompt), source (original dataset), text (actual text content), and RDizzl3_seven (Classifier built for a previous Kaggle competition, indicating whether the essays were written in response to one of the seven essay prompts for the competition).

Our team has dropped all the features other than text and the label.

2.1.1 Preprocessing

Using the text feature, we have extracted additional features. These include:

Word Statistics

The features include the total number of words in the text/document, the sum of words that repeat frequently (greater or equal to 5 times), and the sum of words that appear infrequently (less than 5 times). All these features are integers.

Punctuations Statistics

The features include the number and ratios of the following punctuations: [', -, ;, :, ., !, ?, (,), [,], {, }, /, ", ', _]. The model incorporates the percentage of characters that are one of the 17 different punctuation marks shown above. These features are integers. It also includes the total punctuation percentage, which is the sum of these individual percentages. These values are between 0 and 1.

TF-IDF Vectorizer

The model uses the TF-IDF vectorizer provided by ski-kit as another feature set. Term frequency (TF) measures how often a word appears in a specific document as shown in Equation 1. A higher frequency suggests greater importance within that document. Inverse document frequency (IDF) captures the term popularity as an inverse of the overall corpus as shown in Equation 2. Our TF-IDF matrix has a max of 10000 features.

2.2 New Dataset

The new dataset contains 15 AI generated essays using ChatGPT 5.1 and 13 human written essays. This dataset is put through the same preprocessing steps as the DAIGT V2 Train Dataset and evaluated using the trained model. The table of the prompts used for the essay can be found in Table 2. The human essays were sourced from multiple websites,

which can be found in Table 3. The essays vary in quality, with some being used as examples of excellent essays, while others scored low in their respective rubric.

3 Features

Describe your model inputs. What feature engineering or representation learning was performed? Why did you add these features? Why does it make sense to include them? Did you perform any feature selection or augmentation? One good way to vary your experiments is to try different kinds of features as inputs. How did you vary the features used for your experiments

4 Implementation

Describe the model implementation. You should have several models or versions of your model that you have run on your data. You should have a simple baseline to compare it to (likely majority vote), and may have other baselines from related work. Your model should outperform your simple baseline. For most of you, your model should also outperform at least one other trained model baseline. If it does not outperform this baseline and you expected it to, why doesn't it? You should be able to provide an explanation. This explanation can also be part of your error analysis section. You do not have to outperform all models from previous work, but you should have an approach you implement for comparison. What was your loss function? Describe the optimization technique. If you implemented a complex model with many parts, you should consider providing ablations. This means different experiments where you only include one feature at a time so you can tell what feature is contributing more to the performance that you see.

5 Evaluation

The total training dataset [see 2.1] was split into 80/10/10 for training, validation, and test respectively. Cross-validation was not used as we had sufficient datapoints, almost 45 thousand, to adequately train the model. Cross-validation in this case would've been too computationally expensive for relatively small benefits to reduce variance of the training sets. For the test set, we use the same evaluation methods as our progress report, where we evaluate the accuracy, precision, recall and f1-score of both the validation and test sets after training. However, since we are still only evaluating

from the training dataset, the results have become less relevant, as most of our models would have almost 100% accuracy and F1 scores. Following the restructuring of our model to allow us to pass in data frames and predict our model on new data. Our model evaluation strategy evolved to testing the model against the new dataset [see 2.2] while using the same metrics of accuracy, precision, recall and F1-score. The metrics were adequate, as the results would vary significantly against the new dataset, allowing us to accurately access the performance of our models against each other.

6 Progress

We followed through 50% of our plan from the progress report. We brought in new data [see 2.2] to further test our model’s accuracy. This helped the team identify model performance, as our earlier evaluation strategy was proving irrelevant, as all models scored over 98% accuracy from the test set [see 2.1]. We ended up not implementing k-fold cross validation as it would be too computationally expensive for relatively limited improvements as we had an adequate dataset size. Moving to the model itself, we ended up not implementing a Neural Network. Although we did test using a Neural Network, we used Multi-layer Perceptron (MLP) instead of Long Short Term Memory (LSTM). The main cause of that was due to our TF-IDF vectorization, LSTM requires a sequence input, however our current model preprocessing converts that into a un-sequenced vector. This distinction makes our current structure incompatible with LSTM, we would’ve had to completely rebuild our model’s preprocessing, pipeline and feature sets. However, even with MLP, the training time was extremely long, and the resulting accuracy was very similar to the model we ended up going with the Linear Support Vector Classification (SVC) model since we were using TF-IDF and the accuracy was almost identical to MLP while being much faster, which is what we ended up with.

7 Error Analysis

We systematically examined the model’s errors in two stages, using accuracy, precision, recall, F1-score and Confusion Matrix. Initially, the Linear SVC model was tested on its original training distribution (DAIGT V2), where it achieved 99.7% accuracy [see Table 4 and Table 5]. This result signaled overfitting. To expose its true limitations,

a critical second stage involved testing on a new external dataset, designed to simulate Data Drift, featuring essays from the advanced ChatGPT 5.1 (GPT-5) and authentic human essays. This external test caused the model’s performance to plummet to 61.8% [see Table 6], highlighting the profound difference between its in-distribution and real-world generalization capabilities.

The model’s strength lies in its specialized ability to detect the specific statistical signatures and stylistic artifacts of older AI texts that were present in the DAIGT V2 training data. It excelled at separating those initial AI generations from the original human essays. However, its profound weakness is a complete inability to generalize to newer, more sophisticated LLM output.

The core error pattern identified was a catastrophic bias towards classifying all text as AI-generated [see Figure 3]. This pattern is supported by key figures from the external evaluation: the model produced 13 False Positives (FP) and 0 True Negatives (TN). This means the model incorrectly flagged every single human-written essay in the new dataset as being AI-generated. This occurred because the decision boundary, relying on fragile TF-IDF and punctuation features, was pushed so far by the highly human-like GPT-5 text that authentic human essays now fell on the misclassified AI side of the boundary.

To specifically address the fragility of the TF-IDF and punctuation features and the model’s poor generalization, future development should focus on two key areas:

1. **Update Database:** Incorporating text generated by the latest, most sophisticated LLMs (GPT-5) to teach the detector their new statistical and stylistic signatures.
2. **Implement Deep Neural Networks with Dropout Regularization:** Given the complexity of distinguishing advanced AI from human text, we must move beyond linear models. Implementing a deep Neural Network architecture (such as an LSTM or Transformer) combined with Dropout is essential. This prevents complex co-adaptations on the training data, effectively mitigating the severe overfitting observed in the current model and promoting generalization across diverse writing styles.

8 Team Contributions

Fei: Restructured the model to allow users to pass in new datasets and predict using trained model. Created the new dataset used in the new evaluation strategy. Wrote sections Evaluation and Progress. Updated sections Introduction and Dataset.

Haniye:

Ghena: Implemented MLPClassifier and tried to implement and tried to implement KerasClassifier with dropout, however there wasn't enough CPU space and couldn't run. Wrote the Error Analysis section.

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Tables and figures

See Table 1, Table 2, and Table 3.

Equations

$$TF(w, d) = \frac{\text{count}(w, d)}{\text{total words in } d} \quad (1)$$

$$IDF(w, C) = \log \left(\frac{|C|}{|\{d \in C : w \in d\}|} \right) \quad (2)$$

Dataset Name	Description
Persuade Corpus 2.0 (Broad, 2023b)	Provides argumentative essays produced by 6 to 12 grade students. It was created by The Learning Agency and Vanderbilt University, originally pulled from the following GitHub repository.
ChatGPT (Paullier, 2023)	Contains 2.5k student written texts sourced from the FeedBack Prize 3 Competition, and 2.5k AI-generated texts using ChatGPT. The compiled dataset includes only AI-generated texts and prompts.
Llama 70b + GPT-4 (Broad, 2023a)	Contains 9k essays generated by Llama 70b and Falcon 180b. Prompts come from the Persuade Corpus and GPT4, using a total of 35 prompts for generation.
LLM Generated Essays (Osmulski, 2023)	Contains 700 essays generated by LLMs 500 from GPT3.5Turbo and 200 from GPT4.
Claude Essays (Hanley, 2023)	Contains 1000 essays generated by Claude-Instant-1 using 15 prompts from the Persuade Corpus. Prompts were sourced from the competition discussion.
PaLM Essays (Rizqi, 2023)	Contains 1384 essays generated by PaLM. Prompts were sourced from a Kaggle competition notebook.

Table 1: Summary of Datasets Used in the DAIGT V2 Train Dataset

Model	Prompt
GPT 5.1	Write an argumentative essay about cars and transportation, in the style of a 6th–12th grader, using the following essay prompt: “Today the majority of humans own and operate cell phones on a daily basis. In essay form, explain if drivers should or should not be able to use cell phones in any capacity while operating a vehicle.”
GPT 5.1	Write five argumentative essay about cars and transportation, in the style of a 6th-12th grader with the following essay prompt: "Some schools require students to complete summer projects to assure they continue learning during their break. Should these summer projects be teacher-designed or student-designed? Take a position on this question. Support your response with reasons and specific examples. "
GPT 5.1	Write five argumentative essay about cars and transportation, in the style of a 6th-12th grader with the following essay prompt: "Your principal has decided that all students must participate in at least one extracurricular activity. For example, students could participate in sports, work on the yearbook, or serve on the student council. Do you agree or disagree with this decision? Use specific details and examples to convince others to support your position. "

Table 2: Prompts Used to Generate Argumentative Essays, 5 essays were generated from each

Source	Essays Used
PrepScholar (pre)	3
Skyline College (sky)	1
Government of British Columbia (bce)	9

Table 3: Sources of Human written essays

Class	Precision	Recall	F1-Score	Support
0 (Human)	1.00	1.00	1.00	2735
1 (AI)	1.00	0.99	1.00	1748
<i>Accuracy: 0.996877091233549</i>				
<i>F1 Score: 0.995983935742972</i>				
Macro Avg	1.00	1.00	1.00	4483
Weighted Avg	1.00	1.00	1.00	4483

Table 4: Validation Evaluation Metrics

Class	Precision	Recall	F1-Score	Support
0 (Human)	1.00	1.00	1.00	2737
1 (AI)	1.00	0.99	1.00	1750
<i>Test Accuracy: 0.9973256073100066</i>				
<i>Test F1 Score: 0.9965616045845271</i>				
Macro Avg	1.00	1.00	1.00	4487
Weighted Avg	1.00	1.00	1.00	4487

Table 5: Test Evaluation Metrics (In-Distribution)

Class	Precision	Recall	F1-Score	Support
0 (Human)	0.00	0.00	0.00	13
1 (AI)	0.72	0.81	0.76	42
<i>Test Accuracy: 0.6181818181818182</i>				
<i>Test F1 Score: 0.7640449438202246</i>				
Macro Avg	0.36	0.40	0.38	55
Weighted Avg	0.55	0.62	0.58	55

Table 6: External Data Drift Evaluation Metrics (Critical Failure)

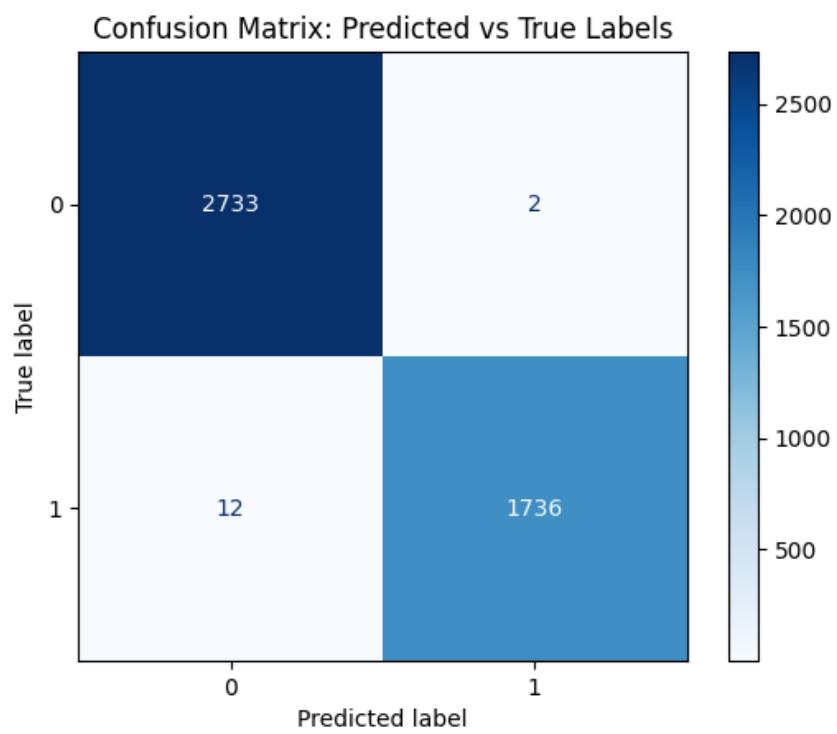


Figure 1: Confusion Matrix of the Validation Data

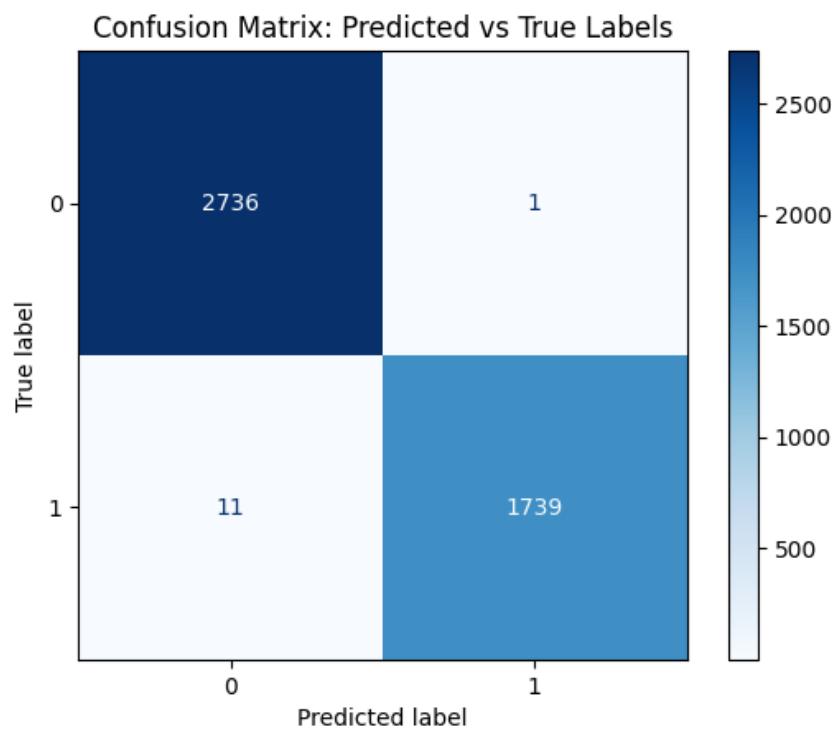


Figure 2: Confusion Matrix of the Test Data

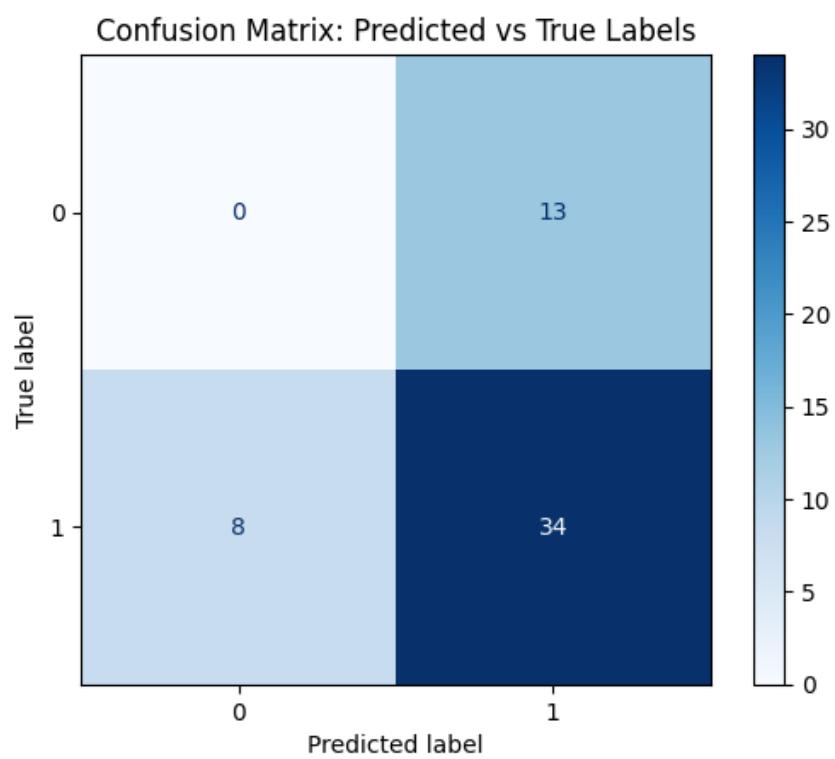


Figure 3: Confusion Matrix of the External Data Drift