

GenAI Content Detection Task 2: AI vs. Human – Academic Essay Authenticity Challenge

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Abstract

This paper presents a comprehensive overview of the first edition of the *Academic Essay Authenticity Challenge*, organized as part of the GenAI Content Detection shared tasks collocated with COLING 2025. This challenge focuses on detecting machine-generated *vs* human-authored essays for academic purposes. The task is defined as follows: “*Given an essay, identify whether it is generated by a machine or authored by a human.*” The challenge involves two languages: English and Arabic. During the evaluation phase, 25 teams submitted systems for English and 21 teams for Arabic, reflecting substantial interest in the task. Finally, seven teams submitted system description papers. The majority of submissions utilized fine-tuned transformer-based models, with one team employing Large Language Models (LLMs) such as Llama 2 and Llama 3. This paper outlines the task formulation, details the dataset construction process, and explains the evaluation framework. Additionally, we present a summary of the approaches adopted by participating teams. Nearly all submitted systems outperformed the n-gram-based baseline, with the top-performing systems achieving F1 scores exceeding 0.98 for both languages, indicating significant progress in the detection of machine-generated text.

1 Introduction

The rapid progress in Artificial Intelligence (AI) and the proliferation of generative content produced by LLMs have introduced transformative opportunities across various domains — yet they also pose profound challenges (Wu et al., 2023). One such challenge lies in the detection and prevention of misuse of LLMs in contexts such as fake news, misinformation, disinformation, and academic dishonesty (Tang et al., 2024). For instance, the volume of AI-generated news on misinformation-prone websites surged by 457% between January

1, 2022, and May 1, 2023, with a corresponding increase of 57.3% on mainstream platforms (Hanley and Durumeric, 2024). These issues pose substantial barriers to the broader adoption of LLMs, thereby limiting their potential across various applications. Effectively detecting LLM-generated content is crucial for leveraging the capabilities of these models while mitigating associated risks.

Researchers have responded to these challenges through a variety of approaches. Previous methods include classification algorithms designed to distinguish between AI-generated and human-authored text (Guo et al., 2023), as well as watermarking techniques (Szylter et al., 2021; He et al., 2022; Kirchenbauer et al., 2023). These watermarking approaches strategically embed imperceptible signatures within generated texts, enabling model-specific identification while maintaining human-indistinguishable quality. Other recent efforts have focused on the creation of question-answering datasets such as M4 (Wang et al., 2024b), generated by humans and ChatGPT in both English and Chinese and the associated shared task (Wang et al., 2024a).

Within academic settings, concerns surrounding the potential misuse of LLMs have intensified, particularly regarding academic dishonesty involving AI-assisted essay writing and problem-solving. Recent research has made considerable progress in the development of datasets and benchmarking efforts to address these issues. For instance, Yu et al. (2023) introduced the CHEAT dataset, which focuses on abstracts from IEEE Xplore, while Wang et al. (2024b) developed a comprehensive multilingual dataset. Additionally, Dugan et al. (2024) presented a robust dataset designed to address the challenge of detecting machine-generated text.

Despite these efforts, large-scale initiatives in academic contexts remain limited. Hence, this shared task aims to bridge this gap by tackling the task of distinguishing AI-generated essays from

human-authored ones. The challenge attracted substantial interest, with 99 teams registered to access the dataset and 56 teams actively participating in the development and evaluation phases. In the evaluation phase, 25 teams submitted systems for English, and 21 teams participated for Arabic. Furthermore, seven teams submitted system description papers. The majority of participating systems employed transformer-based models, while one team utilized state-of-the-art LLMs such as Llama 2 and Llama 3. Notably, most submissions outperformed the traditional n-gram-based baseline, signaling substantial progress in AI-generated content detection methodologies.

The subsequent sections of this paper are structured as follows: Section 2 provides a comprehensive review of related work. Section 3 presents the task formulation and dataset setup. Section 4 presents empirical results and offers a comprehensive overview of participating systems. Finally, Section 5 concludes with a summary of findings and future directions.

2 Related Work

The detection of AI-generated text relies on analyzing statistical patterns and linguistic features that distinguish human and machine writing styles. [Zaitsu and Jin \(2023\)](#) highlight that AI-generated text tends to use repetitive sentence patterns and a limited vocabulary, prioritizing clarity over the nuanced variations of human writing. Similarly, [Weber-Wulff et al. \(2023\)](#) report that such texts often exhibit lower syntactic complexity and reduced lexical diversity, making them identifiable through these markers. Additionally, [Gallé et al. \(2021\)](#) report that higher predictability in word n -gram is a key indicator of machine generated text.

Machine learning approaches have become central to AI-generated text detection. [Darda et al. \(2023\)](#) explored traditional classification algorithms such as Support Vector Machines (SVM) and Random Forest. [Vora et al. \(2023\)](#) propose a multimodal approach that uses BERT to analyze syntactic and semantic features of text and CNN architectures for image. [Mikros et al. \(2023\)](#) investigated using stylometric features and transformer-based models. Their findings showed that ensemble techniques, particularly those employing majority voting, outperformed individual classifiers.

There has also been effort to combine different machine learning approaches. For instance, deep

learning architectures can extract features from text, while traditional classifiers make predictions based on these features, leveraging the strengths of both techniques ([Bhattacharjee et al., 2023](#)). Incorporating user feedback further enhances hybrid models, enabling them to adapt to real-world usage patterns ([Rashidi et al., 2023](#)).

Despite advancements in detection methodologies, significant limitations persist. [Weber-Wulff et al. \(2023\)](#) reveal that many detection tools struggle with high rates of false positives and false negatives, indicating a need for further refinement. According to [Perkins et al. \(2024\)](#), humans naturally incorporate varying sentence lengths and structures in their writing, creating what researchers call “burstiness”—a key feature that distinguishes human-authored content from AI-generated text. This variation in writing style, along with occasional grammatical inconsistencies and stylistic irregularities, represents the natural “imperfections” that make human writing unique. Interestingly, [Liang et al. \(2023\)](#) found that texts with lower levels of perplexity and coherence—characteristics often found in writing by non-native English speakers—are more likely to be flagged as human-authored.

Another challenge in AI-generated content detection is the lack of transparency in models’ predictions, reducing their applicability in real-life scenarios, particularly in high-stakes contexts such as academia and forensic applications. Thus, a number of researchers worked on developing explainable AI (XAI) methods for AI generated text detection. For instance, [Shah et al. \(2023\)](#) develop an XAI model using stylistic features. [Wu and Flanagan \(2023\)](#) proposes a hybrid approach that combine statistical analysis with machine learning techniques. Additionally, the integration of user feedback into hybrid models may facilitate the development of more adaptive systems that can learn from usage patterns ([Rashidi et al., 2023](#)).

3 Task and Dataset

3.1 Task Definition

The main objective of the task is to detect whether the given candidate essay is AI-generated or human-written. Given the input essay e , the task is to design a text detector $\mathcal{D}(e)$, such that the model outputs label indicating AI-generated or Human-authored content. For this edition, we designed the task as binary classification problem.

System Prompt	You are a <code>{study_level}</code> student from <code>{country}</code> , preparing for the TOEFL exam. Your English proficiency level is <code>{proficiency_level}</code> . Your task is to write a well-structured TOEFL essay in response to the given prompt. Ensure your essay is clear and coherent, following the standard essay format: an introduction, body paragraphs, and a conclusion. Focus on presenting your ideas logically, using appropriate language, and providing relevant examples to support your arguments. Aim to demonstrate your proficiency in English through organized thought and effective communication.
User Prompt	Do you agree or disagree with the following statement: " <code>{statement}</code> " Write a well-structured essay expressing your opinion. Be sure to use specific reasons and examples to support your viewpoint. The essay should be between <code>{min_length}</code> and <code>{max_length}</code> words in length. Please provide only an essay and in a JSON object. No additional text or explanation. <code>{"essay": "your essay"}</code>

Table 1: Example of *System* and *User Prompts* for training and validation in English essay generation. Similar prompts were used for Arabic essays. Variables include `study_level` ={'pre-university', 'university'}, `proficiency_levels`={‘low’, ‘medium’, ‘high’}, `country_list`={‘Arabic’, ‘German’, ‘French’, ‘Hindi’, ‘Italian’, ‘Japanese’, ‘Korean’, ‘Spanish’, ‘Telugu’, ‘Turkish’, ‘Chinese’}. For Arabic prompts, an additional variable, `nativity`={‘native’, ‘non-native’} is used.

3.2 Datasets

The task aims to develop a system specifically designed for detecting AI generated text in academic essays. The dataset comprises essays authored by both native and non-native speakers, alongside AI-generated content. A significant challenge in this task was collecting authentic human-authored academic essays while addressing the following considerations:

- Ensuring author privacy, obtaining informed consent, and ethically sourcing the content.
- Verifying that the collected essays were genuinely authored by humans, free from any AI interference or plagiarism.
- Acquiring a diverse set of essays representing different academic levels and cultural backgrounds to ensure inclusivity in the dataset.

For the task, we focused on two languages: English and Arabic. For each language, we provided training, validation, dev-test, and the final test sets, which included human-authored and AI-generated texts. We released these data splits in two phases – *(i) Development phase* – we released the training, validation, and mock test data (dev-test); *(ii) Evaluation phase* – we released the final test set which

is used to rank the submitted system. Below, we discuss the dataset design for the development and final evaluation phases, respectively.

3.3 Development Phase

During the development phase we have released training, validation, and dev-test. For this phase, we first collected human-authored essays and essay topics. To create the data splits, we carefully designed each set to ensure unique essay topics, avoiding overlap between training, validation, and dev-test datasets.

Furthermore, within each split, we manually categorized the essay topics based on their thematic similarity. This classification is used to assign topics for generating essays using LLMs, and the rest is reserved exclusively for selecting human-authored essays from various existing datasets mentioned below. The final statistics of the dataset released in this phases are presented in Table 5.

Human-authored Essay The human-authored data was sourced from different language assessment datasets, including examinations like IELTS, and TOEFL among others. To ensure the authenticity of human-authored content, we selected essays that were either handwritten or composed in a supervised classroom setting, explicitly to make

sure that none of the texts were created with the assistance of generative technologies or online articles. This approach was designed to maintain the integrity of the datasets and accurately represent human academic writing.

For the English, we collected essay statements (essay prompt) and essays from:

- **IELTS Writing Scored Essays Dataset**¹ contains 1200 academic essays for varieties of prompts. Each essays are accompanied by the examiners' feedback along with scores
- **ETS Corpus of Non-Native Written English corpus**² contains 12,100 academic essays, written addressing eight different prompts, by non-native speakers from 11 different countries, as part TOEFL English proficiency exam. The dataset includes the speaker's native language along with scores they obtained for the corresponding essays. While the dataset was originally designed for native language identification tasks, its rich collection of academic essays, makes it highly suitable for supporting our AI-generated text detection efforts.

As for the Arabic subtask, the datasets we use are the following:

- **Arabic Learner Corpus (ALC)**³ ([Alfaifi and Atwell, 2013](#)) includes 1,197 essays written by both native and non-native Arabic pre-university/university speakers from 67 nationalities. The dataset includes speakers' nationality along with the information if the essay was written in class or as homework. For the task, we only selected in-class essays, manually excluded off-topic essays, and reviewed the essays for any corrections.
- **Qatari Corpus of Argumentative Writing (QCAW) dataset**⁴ ([Zaghouani et al., 2024](#)) is a collection of 195 argumentative essays written by native Arabic undergraduate students. The prompts given to the student were inspired by TOEFL writing exercises ([Ahmed et al., 2023](#)).

- **The CERCLL corpus**⁵ includes ≈ 270 essays written by non-native (L2) and heritage Arabic speakers.⁶ The dataset includes information about the speakers' proficiency, along with the type – L2 vs heritage speakers. The dataset covers a wide range of topics and multiple genres, including description, narration, and instruction essays.

AI-generated Essay The generated essays, for both languages, utilized seven state-of-the art LLMs including: GPT-3.5-Turbo (2023-03-15-preview), GPT-4o (2024-08-06), GPT-4o-mini (2024-07-18) ([OpenAI, 2024](#)), Gemini-1.5 ([Team, 2024](#)), phi3.5,⁷ Llama-3.1 (8B) ([Abdin et al., 2024](#)), and Claude-3.5.⁸ To produce these essays, we designed the prompts by utilizing a selected subset of essay statements from the aforementioned datasets. The designed prompts included detailed instructions to emulate human writing styles, specify essay length requirements, and incorporate predefined personas reflecting various factors such as nativity and/or language proficiency, following the metadata and statistics obtained from the human-authored essay collections. This approach ensured the generation of essays that closely resemble real-world human writing in both style and content. An example of such a prompt is shown in Table 1.

3.4 Evaluation Phase

For the evaluation, we designed and developed a novel dataset, the **Generated and Real Academic Corpus for Evaluation (GRACE)**, which includes both human-authored and AI-generated essays in English and Arabic.

3.4.1 Data Collection

For designing the human-authored portion of the dataset, we began by carefully designing test set essay statements aligned with those used in development phase topics. We selected five different essay types, and under each type, we created several essay statements (see Table 4 for examples). The topics include social influence & technology, lifestyle choices & preferences, cultural & global perspective, environmental & societal responsibility, and personal growth & experience.

¹<https://www.kaggle.com/datasets/mazlumi/ielts-writing-scored-essays-dataset>

²<https://catalog.ldc.upenn.edu/LDC2014T06>

³<https://www.arabiclearnercorpus.com>

⁴<https://catalog.ldc.upenn.edu/LDC2022T04>

⁵<https://cercll.arizona.edu/arabic-corpus/>

⁶The original dataset is available in pdf format.

⁷<https://huggingface.co/microsoft/Phi-3-5-mini-instruct>

⁸<https://www.anthropic.com/news/claude-3-5-sonnet>

You are tasked with generating creative and rigorous academic essays.

Here's how:

- 1) Topics Selection: You are provided with a set of topics: «<20 random topics»». First, choose one topic at random from this list.
- 2) Generate Related Topics: Based on the chosen topic, create 10 new topic ideas. These should be different from the chosen topic but related in a way that someone interested in the initial topic might also find these new ideas engaging.
- 3) Select Final Topic: From the 10 new topics, pick one at random to focus on.
- 4) Choose a Profession: List 10 random professions that are entirely unrelated to the final topic, ensuring that they come from different fields or disciplines. These professions should be distinct enough that their practitioners would not typically engage with or have knowledge about the topic. Then, select one profession at random from this list.
- 5) Choose a Writing Style: List 10 distinct writing styles (e.g., persuasive, narrative, descriptive) and choose one at random.
- 6) Essay Writing: Write an academic and creative essay on the chosen topic. This essay should be written from the perspective of someone in the chosen profession and in the selected writing style. Do not ever mention the chosen profession or writing style in the essay itself. Do not include any personal opinions or experiences with regarding to the profession in the essay. Do not mention anything about the chosen profession whatsoever.

Your output should be in JSON format, structured as follows:

```
{ "selected_topic": "<randomly selected topic from the given topics>", "generated_topics": [ "<generated topic 1>", "<generated topic 2>", "...", "<generated topic 10>" ], "final_topic": "<randomly selected topic from generated_topics>", "professions": [ "<profession 1>", "<profession 2>", "...", "<profession 10>" ], "selected_profession": "<randomly selected profession from professions>", "writing_styles": [ "<style 1>", "<style 2>", "...", "<style 10>" ], "selected_writing_style": "<randomly selected style from writing_styles>", "essay": "<generated essay>" }
```

Please proceed with this format to generate a fully structured JSON output. Remember to keep the content diverse and creative throughout the process. The essay should be comprehensive, detailed, and reflective of rigorous academic standards. The essay must be multiple paragraphs long (at least 1 page's worth). Return only the valid JSON output and nothing else. Good luck!

Table 2: **Freehand prompt** used to generate AI generated essays for the final test set.

Essay Writing by Recruited Participants: We then recruited⁹ university students, both monolingual and bilingual, contribute to the essay writing. The participants were provided with a list of essay statements in their respective languages (either English or Arabic) and were asked to complete each essay within 30 minutes. They were instructed to limit the essays to 350–500 words and ensure they included an introduction, main arguments, and a conclusion. The essays must be written in Modern Standard Arabic (MSA) for Arabic, or in formal English for the English essays.

Collected Essay Assignments: Additionally, we collected previously submitted English *essay assignments* from university students to enrich the dataset.

Anonymization of Personal Information In the collected *essay assignments* we noticed that there were some information containing mentions of entities. Therefore, we anonymized them to ensure the removal of any information that could directly or indirectly identify the author or reveal any private infor-

mation about an entity that is not publicly known. This process was essential to uphold privacy standards and ethical considerations.

To achieve this, we followed these guidelines:

- **Author Identification Removal:** Any mention of names, addresses, affiliations, or specific details that could identify the essay's author was redacted.
- **Private Entity Information:** Any references to non-public entities, such as organizations, businesses, or private individuals mentioned in the essays, were removed or replaced with generic terms.
- **Sensitive Content:** Sensitive information, such as health conditions, financial details, or other personal data, was also removed to ensure privacy.
- **Consistency:** Replacement terms were standardized (e.g., “[NAME]”, “[ADDRESS]”, “[ORGANIZATION]”) to maintain consistency throughout the dataset.

⁹We use a third-party company for the reward money. The amount was decided based on the standard local rate for data annotation.

Thoroughly rewrite the provided academic essay to enhance clarity, diversity in sentence structure, and vocabulary richness, all while maintaining the original meaning and intent. Your goal is to produce a refined and nuanced version of the text.

Aim to increase the essay's length by adding substantial elaborations, exploring various perspectives, and providing comprehensive explanations that will offer a deeply layered and extensive output. Deliver the output exclusively in JSON format with a single key "text" as shown below, ensuring that no additional information or comments are included:

```
{} "text": "<rewritten_and_greatly_expanded_academic_essay>" }}
```

Here is the passage to rewrite and extensively expand:

```
<<original_passage_start>> {the passage to be paraphrased} <<original_passage_end>>
```

Table 3: **Paraphrasing prompt** used to generate AI generated essays for the final test set.

Question Type	Example Statements
Agree or Disagree	Do you agree or disagree with the following statement? People should be encouraged to take risks, even if there is a chance of failure. Use specific reasons and examples to support your answer.
Preference	Some people prefer to spend their money on experiences, such as travel or concerts, while others prefer to save for physical possessions, such as a car or a home. Which approach do you prefer, and why? Use specific reasons and examples to support your choice.
If/Imaginary Situations	If you could have any superpower, such as the ability to fly or become invisible, which one would you choose, and why? Use specific reasons and examples to explain your answer.
Advan. and Disadvan.	What are the advantages and disadvantages of living in a large city? Use specific reasons and examples to support your answer.
Descriptive	Describe a memorable trip you have taken and explain what made it special. Use specific details to support your response.

Table 4: Examples of different question types and corresponding essay statements (prompts).

Label	Train	Valid	Dev-Test	Total
English				
AI	925	299	712	1,936
Human	1,145	182	174	1,501
Total	2,070	481	886	3,437
Arabic				
AI	1,467	391	369	2,227
Human	629	1,235	500	2,364
Total	2096	1,626	869	4,591

Table 5: Development phase: dataset and label distribution

to carry out this task. Each annotator was provided with clear anonymization guidelines and examples to ensure consistency and accuracy. Such anonymization steps ensure that the dataset meets ethical standards for research.

3.4.2 Data Generation

For the AI-generated essays, we followed two distinct methodologies:

- *Freehand Generation*: An instruct-tuned LLM, namely gpt-4o, independently generated essays using the *Freehand Generation Prompt* shown in Table 2. The prompt was de-

signed to ensure diverse outputs. We were inspired by the prompting techniques proposed by Chen et al. (2024).

- *Paraphrasing Human-Written Text*: Using the *Paraphrasing Prompt* shown in Table 3, human-authored essays were rephrased by an instruct-tuned LLM, namely claude-3.5 to generate stylistically varied yet semantically equivalent AI-written versions. The resulting text comprises a mix of human-written and AI-generated content, designed to challenge the effectiveness of detection methods.

Category	English	Arabic	Total
AI (Free)	400	100	500
AI (Para)	365	98	463
Human	365	95	460
Total	1,130	293	1,423

Table 6: Distribution of essays by *category* and *language* across the test set. Free - freehand generation, Para - paraphrasing-based generation.

The final GRACE dataset comprises a balanced distribution of human-written and AI-generated essays. Table 6 provides a detailed breakdown across languages and generation methods.

3.5 Baseline and Evaluation Setup

3.5.1 Baseline

For all languages, we train an n-gram (unigram, $n = 1$) based baseline model. We transformed the textual content of the essays into a TF-IDF (Term Frequency-Inverse Document Frequency) representation with a maximum of 10k features. A Support Vector Machine (SVM) classifier is then trained on this feature representation to evaluate its performance.

3.5.2 Evaluation Setup

The task was organized into two phases, corresponding to the previously described dataset development process:

- **Development phase:** We released the train and validation subsets, and participants submitted runs on the dev-test set through a competition on Codalab.¹⁰
- **Evaluation phase:** We released the official test subset – GRACE, and the participants were given four days to submit their final predictions through the same Codalab competition URL. Only the latest submission from each team was considered official and was used for the final team ranking.

3.5.3 Evaluation Measure:

We measure the performance of the participating systems using accuracy, macro- precision, recall and F1 measure. However, official ranking was based on macro-F1.

4 Results and Overview of the Systems

In Table 7, we present the results of participants’ systems for both Arabic and English including baseline. For Arabic, all systems outperformed the n-gram baseline, whereas, for English, three teams performed below the baseline. The task generated significant interest, with 56 teams registering to participate. However, the number of system submissions was nearly halved, and ultimately, only five teams submitted system description papers. In Table 8, we provide an overview of the participating systems for which a description paper was submitted. For Arabic top team, **IntegrityAI** (AL-Smadi, 2025), fine-tuned Electra model. For English top team, **CMI-AIGCX** (Kaijie et al., 2025), used LLMs (Llama 2 and 3) and also fine-tuned XLM-roberta model.

Team **IntegrityAI** (AL-Smadi, 2025) fine-tuned ELECTRA-small for English and AraELECTRA-base for Arabic to balance high performance with computational efficiency. Stylistic features, including word count, sentence length, and vocabulary richness, were incorporated to enhance detection capabilities. The lightweight models achieved F1-scores of 0.985 for English and 0.984 for Arabic, demonstrating the effectiveness of combining transformer-based architectures with stylistic analysis. The system was further optimized for deployment on GPUs with moderate memory capacity, ensuring both efficiency and accessibility. Larger models, such as ELECTRA-large, were also tested, achieving an F1-score of 0.997 for English, demonstrating the potential for even greater accuracy with additional computational resources.

Team **CMI-AIGCX** (Kaijie et al., 2025) proposed a method leveraging the Llama-3.1-8B model as a proxy to capture the semantic feature of each token in the text. These token representations were subsequently used to train a model. Instead of fine-tuning an LLM, they leveraged multilingual knowledge and trained a model to enhance detection performance. Their approach demonstrated that using a proxy model with diverse multilingual knowledge can effectively detect machine-generated text across multiple languages, regardless of model size. For English, an F1 score of 0.999 was achieved, securing first place out of 25 teams. For Arabic, an F1 score of 0.965 was obtained, which ranked fourth among 21 teams.

Team **Tesla** (Indurthi and Varma, 2025) extracted a comprehensive set of features encompassing style, language complexity, bias, subjectivity, and emotion. These features were used to train four machine learning algorithms: Logistic Regression, Random Forest, Randomized Decision Trees (Extra Trees), and XGBoost, leveraging diverse approaches to optimize detection performance. Their methods ranked 6th on the leaderboard for the English subtask, achieving an F1-score of 0.986.

Team **EssayDetect** (Agrahari et al., 2025) proposed a fusion model by integrating pre-trained language model embeddings with stylistic and linguistic features to improve classification accuracy. The contributions were threefold: (i) LIME was utilized to identify and highlight highly discriminative features, (ii) focal loss was employed to address class imbalance, and (iii) layer-wise freezing was implemented during fine-tuning to preserve core linguistic representations in the lower layers while

¹⁰<https://codalab.lisn.upsaclay.fr/competitions/20118>

Arabic						English					
Team	Acc	P	R	F1	Rank	Team	Acc	P	R	F1	Rank
IntegrityAI	0.986	0.990	0.979	0.984	1	CMI-AIGCX	0.999	0.999	0.999	0.999	1
USTC-BUPT	0.976	0.983	0.963	0.972	2	starlight	0.997	0.998	0.996	0.997	2
starlight	0.969	0.964	0.966	0.965	3	saehyunMa	0.994	0.995	0.990	0.993	3
CMI-AIGCX	0.969	0.966	0.964	0.965	4	Fsf	0.994	0.995	0.990	0.993	4
apricity	0.966	0.969	0.953	0.960	5	1-800	0.991	0.987	0.993	0.990	5
RA	0.962	0.956	0.959	0.957	6	Tesla	0.988	0.983	0.989	0.986	6
1-800	0.959	0.961	0.945	0.952	7	apricity	0.988	0.983	0.989	0.986	7
Lkminnow	0.956	0.943	0.959	0.950	8	small	0.984	0.981	0.983	0.982	8
alpaca0000001	0.949	0.937	0.948	0.942	9	jojoc	0.982	0.975	0.985	0.980	9
jojoc	0.949	0.939	0.946	0.942	10	EssayDetect	0.978	0.968	0.984	0.975	10
small	0.945	0.938	0.938	0.938	11	ShixuanMa	0.976	0.968	0.979	0.973	11
jebish7	0.945	0.945	0.929	0.937	12	RA	0.973	0.975	0.964	0.969	12
EssayDetect	0.942	0.949	0.919	0.932	13	alpaca0000001	0.956	0.940	0.967	0.951	13
nits_teja_srikar	0.922	0.943	0.882	0.904	14	Lkminnow	0.932	0.913	0.943	0.925	14
Mashixuan	0.898	0.877	0.911	0.889	15	IntegrityAI	0.880	0.864	0.911	0.873	15
Sinai	0.829	0.821	0.866	0.822	16	USTC-BUPT	0.878	0.922	0.812	0.842	16
Vasudha	0.816	0.796	0.831	0.804	17	jebish7	0.847	0.908	0.763	0.794	17
ShixuanMa	0.758	0.783	0.818	0.754	18	CNLP-NITS-PP	0.777	0.784	0.825	0.771	18
gaoyf	0.608	0.720	0.707	0.607	19	Mashixuan	0.742	0.778	0.809	0.739	19
CNLP-NITS-PP	0.590	0.557	0.563	0.557	20	nits_teja_srikar	0.773	0.875	0.649	0.658	20
halcyonized	0.495	0.488	0.487	0.475	21	Vasudha	0.517	0.700	0.643	0.509	21
<i>Baseline</i>	0.474	0.480	0.477	0.461	-	Mahavir_IITA	0.512	0.683	0.634	0.504	22

Table 7: The official results for Arabic and English are ranked based on the official metric: macro-F1. Teams that submitted a system description paper are indicated in bold.

Team	Lang.	Models						Misc							
		Arabic	English	LLama2	LLama3	BERT	RoBERTa	XLM-r	ALBERT	DistiBERT	DeBERTa	Electra	AraBERT	Prep.	Info.
IntegrityAI	1	15													
CMI-AIGCX	4	1	✓	✓				✓					✓	✓	
Tesla															6
EssayDetect	13	10			✓	✓	✓	✓	✓						
RA	6	12				✓				✓		✓			

Table 8: Overview of the approaches. The numbers in the language box refer to the position of the team in the official ranking. Prep.: Preprocessing. Info.: Info. Extraction.

enabling the higher layers to capture task-specific stylistic differences in essays.

Team **RA** (Gharib and Elgendi, 2025) fine-tuned several models for English, including RoBERTa, XLM-RoBERTa, mBERT, and DeBERTa. Similar performance was observed across all models on the validation set, except for mBERT, which exhibited slightly lower performance. For Arabic, AraBERT,

ArBERT, and MarBERT were fine-tuned on the full dataset. AraBERT consistently demonstrated superior performance in terms of F1-score across both languages. The models consistently exceeded both the mean and median scores across tasks, achieving an F1-score of 0.969 in classifying AI-generated essays in English and 0.957 in Arabic.

5 Conclusion and Future Work

We presented an overview of the shared task on the *Academic Essay Challenge*. The task attracted significant attention, with a total of 56 teams registering to participate in the development and evaluation phases. Of these, 21 teams submitted official results on the test set for Arabic, and 25 teams did so for English. Finally, seven teams submitted task description papers. Most systems fine-tuned transformer-based language models; however, several teams also incorporated additional features, such as style, language complexity, bias, subjectivity, and emotion. For both languages, the top-performing teams achieved F1 scores above 0.98.

Limitations

A major limitation of the dataset is its small size, particularly for Arabic, which restricts the development of more robust models. The challenging nature of academic essay collection is reflected in the limited dataset size. Future studies could focus on curating larger datasets to enable the creation of more challenging tasks and the development of more robust models.

Ethical Considerations

The datasets used in the shared task may reflect subjective biases or perspectives of the essay authors, even though they followed the provided instructions. Importantly, the datasets do not include any personal information, and no such information was collected during the data curation process. Therefore, we do not anticipate any ethical concerns related to privacy. Furthermore, the dataset was shared only with participants who signed an agreement, ensuring responsible use of the dataset.

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