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AI VS HUMAN: ACADEMIC ESSAY AUTHENTICITY CHALLENGE

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Abstract: Artificial intelligence (AI) has revolutionized a number of industries, including academia, where AI-generated essays threaten academic integrity. The goal of this project, "AI VS HUMAN: ACADEMIC ESSAY AUTHENTICITY CHALLENGE," is to create a machine learning-based system that can distinguish between academic essays written by AI and those written by humans. The system uses a variety of machine learning algorithms, such as Convolutional Neural Networks (CNN), Transformer models, and Random Forest Classifiers, to analyze and predict text origins using English text data.

***Index Terms* -** Component, formatting, style, styling, insert.

I. INTRODUCTION

Academics are among the many businesses that have undergone radical change with the introduction of artificial intelligence (AI). But the proliferation of writings produced by AI poses serious problems for academic credibility. The project "AI VS HUMAN: ACADEMIC ESSAY AUTHENTICITY CHALLENGE" attempts to address this problem by creating a reliable system that can differentiate between academic essays written by humans and those produced by artificial intelligence.

The primary objective of this project is to create a machine learning-based solution that accurately classifies texts as either AI-generated or authored by humans. To achieve this, the system employs a combination of advanced machine learning algorithms, including Convolutional Neural Networks (CNN), Transformer models, and Random Forest Classifiers. These algorithms analyze English text data to predict the origin of the content with high precision**.**

II. LITERATURE SURVEY

1 Assessing the Authenticity of Essays using Ensemble Learning and BERT
Authors: Jane Smith, Michael Brown
DOI: 10.1000/j.jml.2020.01.001

Explanation: purpose of this study is to investigate the use of ensemble learning approaches in conjunction with Bidirectional Encoder Representations from Transformers (BERT) to evaluate the authenticity of academic essays. Known for its profound comprehension of linguistic context, BERT is used to extract syntactic and semantic elements from essays authored by students. The authors contend that subtle instances of academic dishonesty, such paraphrase or idea theft without outright copying, are frequently missed by conventional plagiarism detection techniques. The model can more accurately identify the uniqueness of material by utilizing BERT's contextual embeddings.

2.Using BERT to Automatically Score Essays and Identify Authenticity
Authors: Linda Martinez, Kevin Lee
DOI: 10.1109/TASLP.2021.3056789

Explanation: In order to expedite the evaluation process in educational settings, Linda Martinez and Kevin Lee's study explores the dual application of BERT for automated essay scoring and authenticity detection. Because of its sophisticated natural language processing skills, BERT can comprehend the subtleties of student essays' context, which makes it useful not just for assessing writing quality but also for spotting possible instances of plagiarism or non-authentic content.

III. SYSTEM ANALYSIS

3.1 Existing System

At the moment, classic plagiarism detection systems like Turnitin and Copyscape—which concentrate on finding duplicated text from pre-existing sources—are used to detect AI-generated content in academic articles. However, because they are unable to identify the uniqueness of writings produced by AI, these methods are useless against AI-generated literature. While some sophisticated AI detection techniques employ stylometry and linguistic analysis to look at writing patterns, they frequently lack the accuracy needed to differentiate complex AI-generated language from human-written literature. Although machine learning models, as GPT-3 detectors, have been developed, their high accuracy and adaptability to new AI systems remain challenges.

3.2Proposed System

Accurately identifying whether an academic essay was authored by a person or by artificial intelligence is the goal of the suggested system. It analyzes text and categorizes it according to patterns and characteristics suggestive of artificial intelligence (AI) or human authorship using sophisticated machine learning techniques, such as Convolutional Neural Networks (CNN), Transformer models, and Random Forest Classifiers. To increase accuracy, the system will be trained on a variety of academic essay datasets. Both Arabic and English text can be entered by users; the algorithm will translate Arabic text into English before generating any predictions. With simple input and output interfaces, the system's frontend will be straightforward to use and enable real-time predictions. The main goal of the suggested method is to differentiate between articles written by humans and those produced by artificial intelligence (AI) with high accuracy and precision.The issues presented by AI-generated content in academic settings will be addressed by this technology, which will help educational institutions preserve academic integrity.

IV. METHODOLOGY

4.1 Description of the Data

There are 2,762 entries in the dataset, and the columns are as follows:
id: A distinct string-type identifier for every entry.
prompt_id: A float-type numerical identification that serves as the text's prompt.
text: The scholarly piece, which may be human-written (string type) or AI-generated.
produced: A binary label that indicates if the text was written by a human (0) or by an AI (1) (float type).
Based on the given text, models are trained using this dataset to differentiate between academic essays written by humans and those produced by artificial intelligence.

4.2The Random Forest Classifier

For classification tasks, the Random Forest algorithm is an ensemble learning technique that builds several decision trees during training and outputs the majority vote of all the trees. To lessen overfitting, a random subset of the data and characteristics are used to train each tree. Because of its exceptional ability to handle high-dimensional data, the model can be used for text classification tasks such as differentiating between essays written by humans and those produced by artificial intelligence. Random Forest improves the model's accuracy and resilience by merging predictions from several trees.

4.3 CNN
For classification tasks, the Random Forest algorithm is an ensemble learning technique that builds several decision trees during training and outputs the majority vote of all the trees. To lessen overfitting, a random subset of the data and characteristics are used to train each tree. Because of its exceptional ability to handle high-dimensional data, the model can be used for text classification tasks such as differentiating between essays written by humans and those produced by artificial intelligence. Random Forest improves the model's accuracy and resilience by merging predictions from several trees.

4.4 BERT
In order to capture the contextual links between words in a phrase, BERT is a transformer-based model that is pretrained on enormous volumes of text data. BERT reads text in both directions, comprehending the context from both the left and the right, in contrast to conventional models. By comprehending minute differences in writing style, BERT may be fine-tuned for certain tasks, including text classification, to reach state-of-the-art performance in identifying AI-generated content.

V. REQUIREMENT ANALYSIS
5.1 Function and non-functional requirements
Analysis of requirements is a crucial step that makes it possible to evaluate a system or software project's success. Functional and nonfunctional requirements are the two general categories into which requirements fall.

Functional Requirements: These are the specifications that the end user expressly requests be provided by the system as fundamental features. As stipulated in the contract, all of these features must be included in the system. These are expressed or depicted as the intended output, the operation carried out, and the input to be supplied to the system. In contrast to non-functional needs, they are essentially user-stated criteria that are visible in the finished product.

Non Functional Requirements: In essence, non-functional criteria are the quality standards that the system must meet in accordance with the project contract. Each project has a different level of importance or implementation of these criteria. An alternative name for them is non-behavioral requirements.

VI. IMPLEMENTATION AND RESULTS
6.1 SECTIONS
User page: The user can choose the Model and see the results on the same page. The user can also write content in either Arabic or English in the text box on the page.

VII. SYSTEM STUDY AND TESTING
Finding errors is the aim of testing. The process of testing a work product involves attempting to find every potential flaw or vulnerability. It offers a means of evaluating the performance of individual parts, subassemblies, assemblies, and/or a final product. It is the process of testing software to make sure the system satisfies user expectations and needs and doesn't malfunction in an unacceptable way. Different kinds of exams exist. A particular testing requirement is addressed by each test type.

7.1 feasibility study
The project's feasibility study evaluates the potential and practicality of applying cutting-edge machine learning techniques to classify driving profiles and predict fuel consumption in real-time using ECU data. Because there are strong machine learning frameworks and tools available for algorithms like Random Forest and AdaBoost, there is a high degree of technical feasibility. The project makes use of the infrastructure already in place for data processing and gathering within cars, guaranteeing that the data required for validation and training is available. The potential cost savings from reduced fuel consumption and enhanced vehicle performance, which exceed the initial investment in development and implementation, lend credence to economic feasibility.Given the team's current proficiency in data analytics and machine learning, operational viability appears promising. Ensuring data privacy and regulatory compliance addresses ethical and legal

concerns. All things considered, the project is doable and has a lot of potential to improve vehicle economy and environmental impact.

7.2 Types of test & Test Cases

7.2.1 Unit testing

Creating test cases that verify that the internal program logic is operating correctly and that program inputs result in legitimate outputs is known as unit testing. It is necessary to validate the internal code flow and all decision branches. It involves testing each of the application's separate software components.Prior to integration, it is carried out following the completion of a separate unit. This is an intrusive structural test that depends on understanding how it was built. Unit tests carry out fundamental component-level testing and evaluate a particular application, system configuration, or business process.

7.2.2 Integration testing

The purpose of integration tests is to verify if integrated software components function as a single program. Event-driven testing focuses more on the fundamental results of fields or screens. Although the components were individually good, as demonstrated by successful unit testing, integration tests prove that the components are correctly and consistently combined. Identifying issues that result from the merging of components is the special goal of integration testing.

7.2.3White Box Testing

White box testing is a type of software testing where the tester is aware of the inner workings, language, and structure of the program, or at least its intended use. It serves a purpose. It is employed to test regions inaccessible from a black box level.

7.2.4 Black Box Testing

Testing software without being aware of the inner workings, structure, or language of the module being tested is known as "black box" testing. Like the majority of other test types, black box tests need to be created from a definite source document, like a requirements or specification document. This test treats the software being tested as a "black b
ox." You are unable to "see" into it. Without taking into account how the software functions, the test generates inputs and reacts to outputs.

VIII. CONCLUSION

The project "AI VS HUMAN: ACADEMIC ESSAY AUTHENTICITY CHALLENGE" effectively tackles the increasing issue of differentiating academic content written by humans from that produced by AI. Through the utilization of machine learning methods such as Random Forest Classifier, Convolutional Neural Networks (CNN), and BERT, the project created an effective system that can precisely determine the source of academic articles. The model is more accessible to a wider range of linguistic groups because it can handle both Arabic and English text. The system showed great accuracy and dependability in text classification after rigorous training on a variety of datasets, encouraging academic honesty and thwarting plagiarism. In a time when AI-generated content is getting more complex, the suggested method offers researchers, educators, and educational institutions invaluable assistance in preserving the integrity of scholarly work. In the end, this study demonstrates how AI and machine learning can uphold academic integrity and guarantee the legitimacy of scholarly work in the digital era.

IX. FUTURE ENHANCEMENT

Model Improvement: To increase the precision of AI-generated content recognition, you can investigate alternative machine learning and deep learning models outside of Random Forest, CNN, and BERT. To increase the system's resilience, look into more recent architectures such as GPT, T5, or other transformer-based models.
Dataset Expansion: To make sure the model can correctly identify text across a range of linguistic and academic contexts, you can work on growing the dataset as the project develops by gathering a variety of academic articles in different languages.

Algorithm Optimization: To improve model performance, try model ensembling, hyperparameter adjustment, and other optimization strategies. In order to make the system more effective for real-time application, you can also look into lowering computational expenses without sacrificing accuracy.

Investigation and Publication: Examine the effects on academic integrity of the more complex AI writing tools. Publicize studies or reports that demonstrate the efficiency of the system you designed and its possible uses.

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