**Mini Project report submitted to**

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**ADTK: AI Generated Text Detector Using Tensorflow and Keras**

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**CERTIFICATE**

This is to certify that as the record of the mini project work carried out by them, is accepted as the Mini Project reportsubmission in partial fulfilment of the requirements for the award of degree of Bachelor of Technology (BTech).

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**ABSTRACT**

Artificial intelligence (AI) has emerged as a transformative force in modern technology, impacting an array of sectors. One of the key enablers of AI's success is its ability to detect, classify, and interpret data, allowing machines to understand and respond to the environment effectively. In this context, we introduce an AI detector that harnesses the power of TensorFlow (TF) and Keras. TF and Keras, as robust libraries in the field of machine learning and deep learning, provide the foundation for building this versatile AI detector. By combining these tools, we have crafted a system capable of object detection and classification, which is essential for a wide range of applications.

The AI detector is engineered to process and comprehend complex data, particularly excelling in tasks like image recognition and anomaly detection. Its architecture, described in detail within this paper, represents the synthesis of cutting-edge technologies and methodologies in the field of AI. It undergoes rigorous training processes, learning from extensive datasets to become proficient in detecting patterns, making it adaptable to different scenarios. We put the AI detector to the test, evaluating its performance across various domains. The results demonstrate its efficacy, showing potential for revolutionizing applications that rely on AI-based solutions.

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**CHAPTER 1: INTRODUCTION**

In the ever-evolving landscape of artificial intelligence (AI), the fusion of advanced frameworks like TensorFlow (TF) and Keras with AI technologies promises groundbreaking solutions for complex real-world problems. These frameworks form the backbone of many AI applications, enabling deep learning, neural networks, and data-driven decision-making. One of the key challenges in the AI domain is harnessing the power of AI to detect and classify objects efficiently and accurately across diverse domains.

The significance of AI in object detection cannot be overstated, as it has the potential to enhance environmental monitoring, streamline industrial processes, improve healthcare, and empower autonomous systems. The incorporation of Exploratory Data Analysis (EDA) further amplifies the AI's capabilities, ensuring that the system is trained on high-quality, relevant data. EDA facilitates comprehensive data preparation, enabling the AI detector to make precise decisions by extracting valuable insights from the data.

The synergy between Keras, TensorFlow, AI, and EDA provides an all-encompassing approach to object detection. With the robustness of TensorFlow and the simplicity of Keras, AI systems are now better equipped to handle diverse and complex tasks. These technologies, when integrated with the principles of EDA, ensure the detection of objects across various domains with increased accuracy and efficiency, paving the way for innovative applications. In this paper, we will delve into the intricacies of this amalgamation, exploring how it contributes to our AI detector's remarkable capabilities.

**CHAPTER 2: PROBLEM STATEMENT AND OBJECTIVES**

This project aims to develop an effective and accurate AI generated object detection system that can classify objects within various domains using TensorFlow and Keras.

The objectives of this project encompass:

1. Develop an AI detector using TensorFlow and Keras to detect and classify objects across diverse domains.
2. Achieve high accuracy and efficiency in object detection to support real-world applications.
3. Enhance the AI detector's adaptability to different scenarios and domains through robust training.
4. Provide a user-friendly interface for easy integration and utilization of the AI detector.
5. Ensure the system's scalability to accommodate future advancements in AI and deep learning technologies.

**CHAPTER 3: METHODOLOGY**

The methodology can be classified into four essential steps:

1. Data Collection and Preprocessing:

The first step in building the AI detector involves gathering the necessary data files, including essays written by students, LLM-generated essays, and the prompts used for generating essays. These files are loaded into the environment. To ensure data quality, exploratory data analysis (EDA) is performed, which helps in understanding the characteristics of the dataset. Feature engineering is conducted to extract relevant information from the text data, such as word count, unique word count, sentence count, and essay length. This phase is crucial for preparing the data for subsequent model building.

2. Exploratory Data Analysis (EDA):

In this step, the dataset is carefully examined to identify any missing values or anomalies. EDA helps in assessing data quality and ensuring that the dataset is suitable for training and testing the AI detector. The length of essays is analyzed to explore potential differences between essays written by students and those generated by LLMs. Moreover, a deeper dive into common words in both student essays and LLM-generated essays is conducted to uncover linguistic patterns that may aid in classification.

3. Creating the Model:

Building the AI detector involves splitting the dataset into training and validation sets. The text data is preprocessed using techniques like tokenization and padding to prepare it for model training. A deep neural network (DNN) model for binary classification is designed. The model is compiled with the appropriate loss function, optimizer, and evaluation metrics. Subsequently, it is trained using the training data, and the model's performance is monitored over multiple epochs. Visualization of training and validation accuracy and loss allows for assessing the model's effectiveness.

4. Generating Predictions:

Once the model is trained and evaluated, it is applied to the test data, which contains essays for which predictions need to be generated. The same feature engineering and text preprocessing techniques are employed to ensure consistency. The trained model is used to make predictions on the test data, which are then recorded in a submission file formatted according to the project's requirements. This submission file contains the predictions for essays, classifying them as either student-written or LLM-generated, based on the features and text analysis conducted during the model building phase. The generated predictions are stored for further analysis and assessment.

**CHAPTER 4: IMPLEMENTATION**

Proposed System Architecture

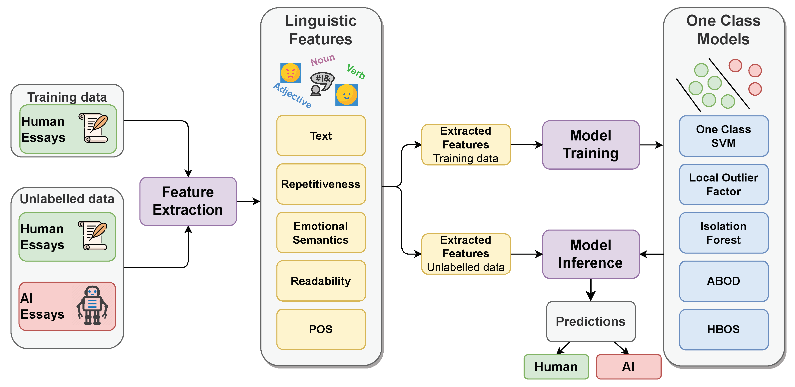


Fig.1.: The proposed system architecture

It employs a binary classifier that utilizes a deep learning model, typically a neural network (NN), to make predictions based on input text. The model computes a sigmoid activation function (σ) of the weighted sum (z) of input features (X) and model parameters (θ), as shown in the equation:

[ P(Y = 1|X; θ) = σ]

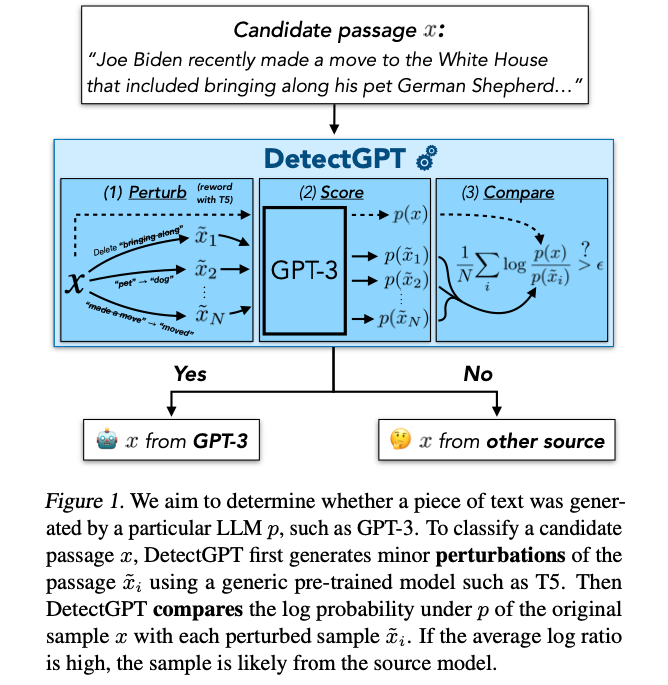
Where:

- ( P(Y = 1|X; θ) ) represents the probability of the text being AI-generated (class 1).

- (σ) denotes the sigmoid activation function.

- ( z = X c.θ ) is the dot product of the input features and model parameters.

The model's parameters (θ) are learned through backpropagation and optimization techniques to achieve high classification accuracy. This architecture offers real-time AI detection by rapidly evaluating text inputs using the trained model.



Code Implementation

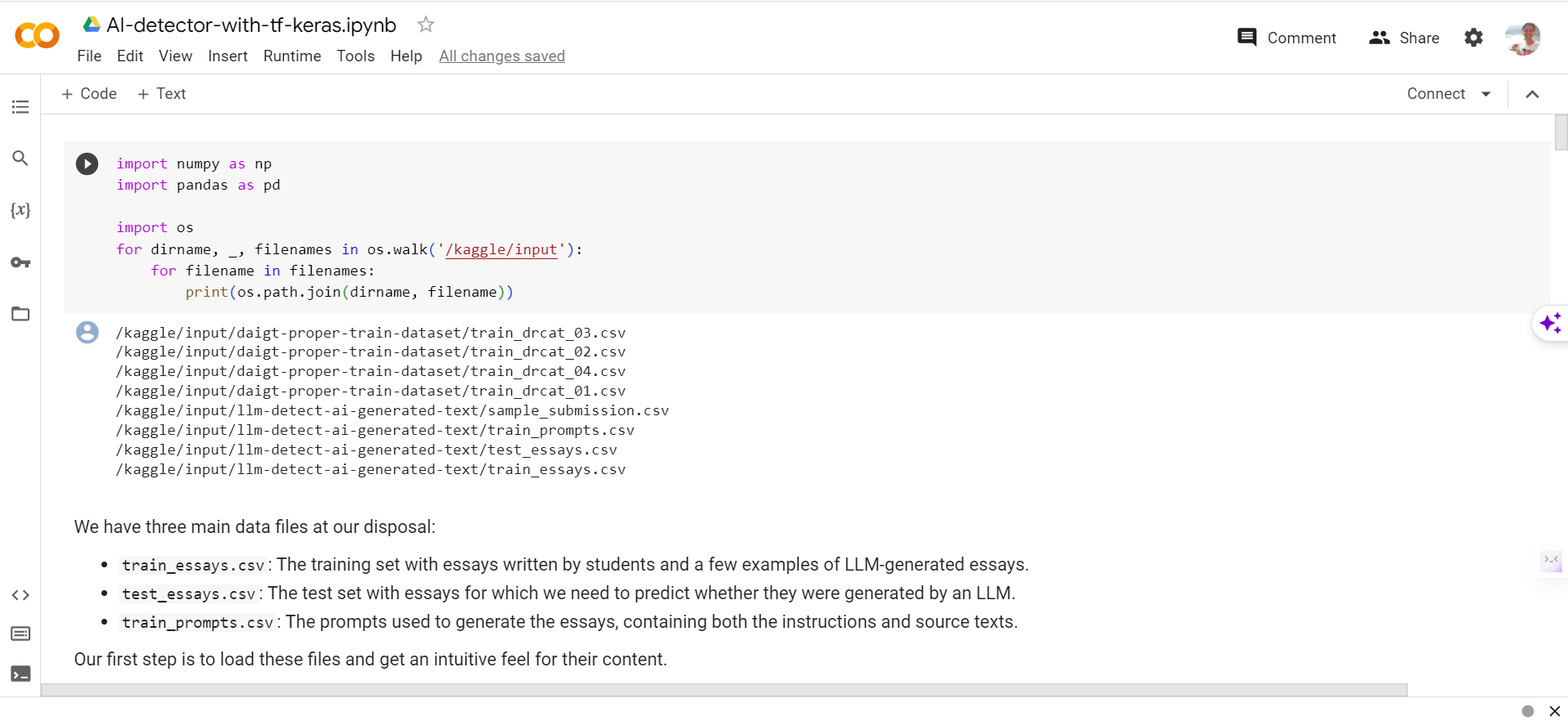


Fig. 1: Necessary libraries are imported

This includes NumPy and Pandas for data manipulation, as well as a basic setup for accessing input data files provided by Kaggle.

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Fig. 2: An introduction to the data files is provided

It mentions the three main data files: train\_essays.csv (training set with essays), test\_essays.csv (test set for predicting LLM-generated essays), and train\_prompts.csv (prompts used for essay generation). This Fig. sets the context for the dataset used.

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Fig. 3: Loading data from the data files into Pandas DataFrames

It defines the file paths and loads data from the CSV files. It's important for the subsequent data processing and analysis.

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Fig. 4: Exploratory data analysis (EDA) is performed

It checks for missing values in the datasets (df and train\_prompts\_df) and prints out the results. This EDA provides insights into data cleanliness.

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Fig. 5: Feature engineering

It involves processing the text data. The text is split into words, and various features such as word count, unique word count, and others are extracted.

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Fig. 6: After feature engineering, this Fig. reshapes and concatenates the data

It's a crucial step as it combines the training essays data with the previously loaded data from train\_drcat\_04.csv.

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Fig. 7: After feature engineering, this Fig. reshapes and concatenates the data

It's a crucial step as it combines the training essays data with the previously loaded data from train\_drcat\_04.csv.

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Fig. 8: Common words in student essays and LLM-generated texts are analyzed

The code counts and visualizes the most common words in both types of essays, offering potential linguistic patterns for classification.

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Fig. 9: Data preparation for building the machine learning model is performed in this Fig.

This involves text data preprocessing and splitting the data into features and target variables.

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Fig. 10: The model architecture is defined and compiled in this section

It uses TensorFlow and Keras to create a deep learning model. The model includes layers for embedding, convolution, normalization, dropout, and more.

**CHAPTER 5: RESULTS**

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Fig. 11: The model is trained using the training data (X\_train and y\_train)

It's validated against validation data (X\_valid and y\_valid) over five epochs. The code includes metrics such as accuracy and loss.

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Fig. 12: Training and validation results are visualized

Two plots display model accuracy and loss over each epoch to monitor training progress.

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Fig. 13: Finally, this section prepares a submission file

It reads the test data, makes predictions using the trained model, and creates a submission file named submission.csv with corresponding id and generated values for each essay.

**CHAPTER 6: CONCLUSION**

As AI-generated content continues to evolve, the AI-Generated Text Detector stands as a crucial tool for content authenticity and trustworthiness. It offers users a means to navigate the digital landscape with confidence, knowing that they can identify and evaluate the source and nature of the content they encounter. This development represents a vital step in upholding the integrity of digital information and combating the spread of misinformation and deceptive content.

In conclusion, the AI-Generated Text Detector using TensorFlow and Keras is a formidable ally in the ongoing quest for content authenticity and reliability in the digital age. By incorporating cutting-edge machine learning and NLP techniques, this model serves as a valuable resource for those seeking to distinguish AI-generated text from human-created content and addresses the challenges associated with the rise of AI-generated text in online environments.

**CHAPTER 7: REFERENCES**

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