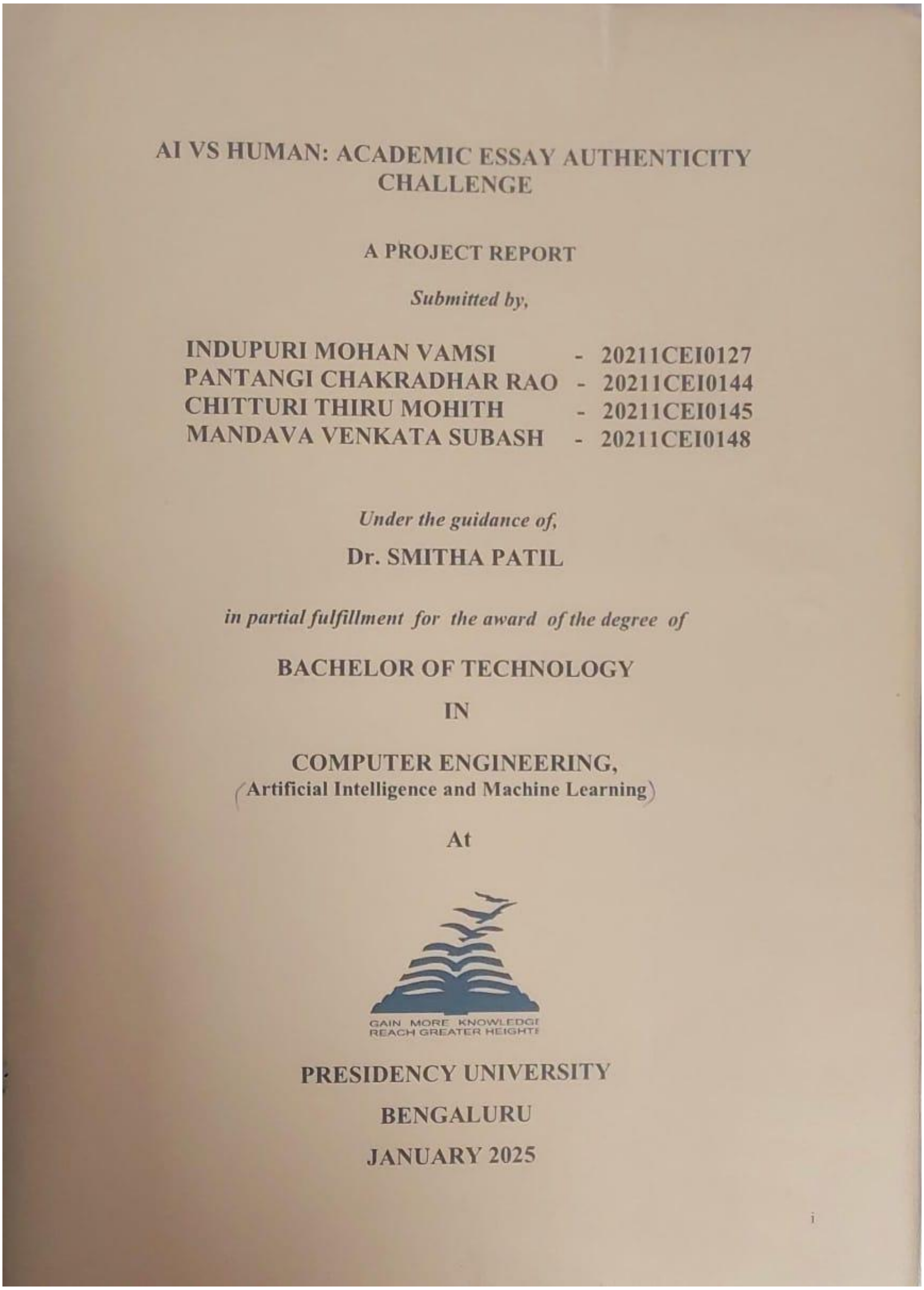

AI VS HUMAN: ACADEMIC ESSAY AUTHENTICITY CHALLENGE

A PROJECT REPORT

Submitted by,

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Under the guidance of,

Dr. SMITHA PATIL

in partial fulfillment for the award of the degree of

BACHELOR OF TECHNOLOGY

IN

COMPUTER ENGINEERING,
(Artificial Intelligence and Machine Learning)

At

GAIN MORE KNOWLEDGE
REACH GREATER HEIGHTS

PRESIDENCY UNIVERSITY

BENGALURU

JANUARY 2025

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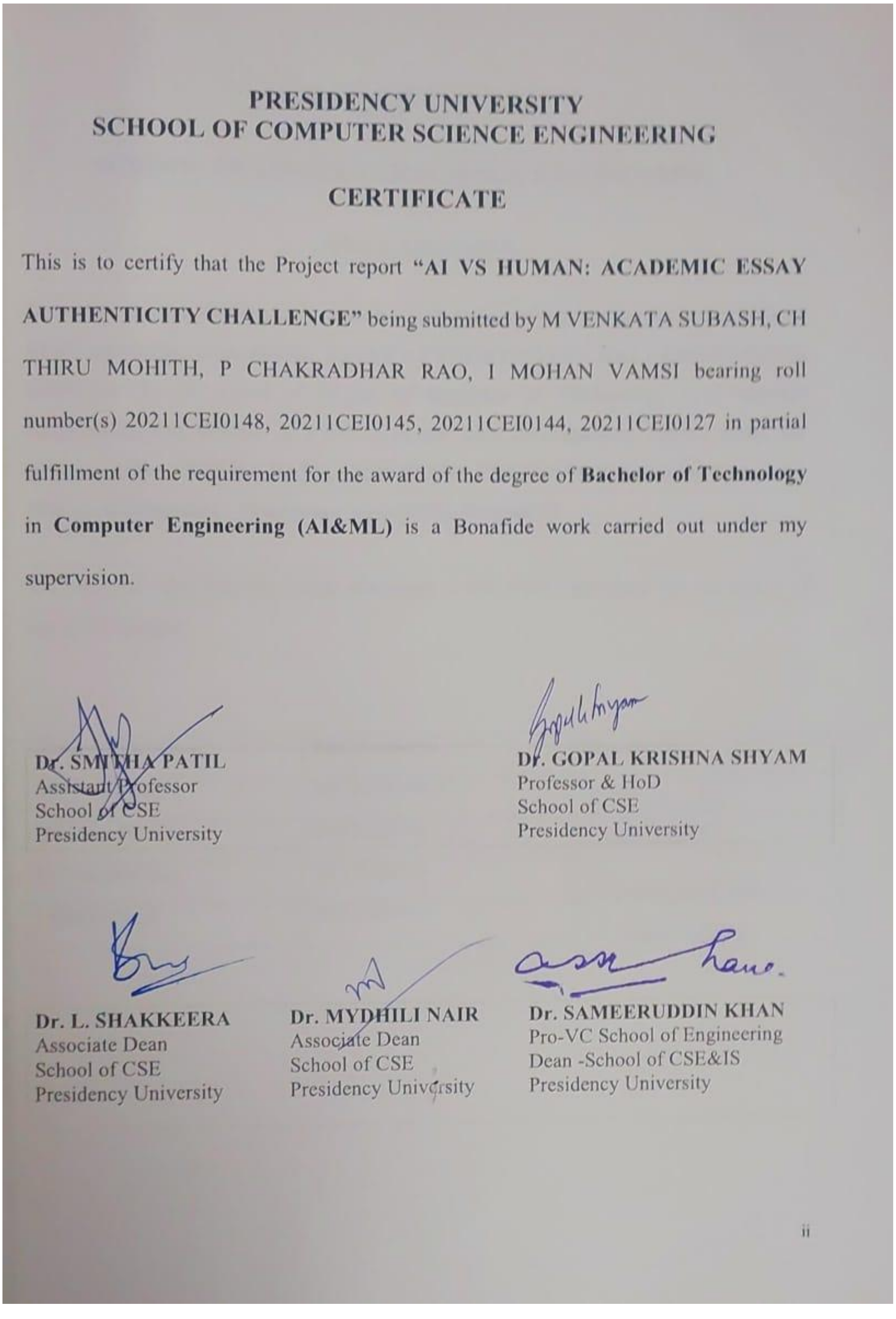

PRESIDENCY UNIVERSITY
SCHOOL OF COMPUTER SCIENCE ENGINEERING

CERTIFICATE

This is to certify that the Project report **"AI VS HUMAN: ACADEMIC ESSAY AUTHENTICITY CHALLENGE"** being submitted by M VENKATA SUBASH, CH THIRU MOHITH, P CHAKRADHAR RAO, I MOHAN VAMSI bearing roll number(s) 20211CEI0148, 20211CEI0145, 20211CEI0144, 20211CEI0127 in partial fulfillment of the requirement for the award of the degree of **Bachelor of Technology** in **Computer Engineering (AI&ML)** is a Bonafide work carried out under my supervision.

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DECLARATION

We hereby declare that the work, which is being presented in the project report entitled **AI VS HUMAN: ACADEMIC ESSAY AUTHENTICITY CHALLENGE** in partial fulfillment for the award of Degree of **Bachelor of Technology** in **Computer Engineering (AI &ML)**, is a record of our own investigations carried under the guidance of **Dr. SMITHA PATIL, ASSISTANT PROFESSOR, School of Computer Science Engineering , Presidency University, Bengaluru.**

We have not submitted the matter presented in this report anywhere for the award of any other Degree.

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ABSTRACT

The rise of artificial intelligence (AI) has transformed many industries, including the academic sector, where AI-generated essays pose a threat to academic integrity. This project, titled "AI VS HUMAN: ACADEMIC ESSAY AUTHENTICITY CHALLENGE," focuses on developing a system to differentiate between AI-generated and human-written academic essays. The core objective is to design a machine learning-based solution that accurately classifies text as either AI-generated or human-authored. The system leverages multiple machine learning algorithms, including Convolutional Neural Networks (CNN), Transformer models, and Random Forest Classifiers, to analyze and predict text origins using English text data. Additionally, the frontend is designed to accept user input in both English and Arabic. For Arabic input, the text is first translated into English before classification, enabling seamless detection of AI-generated content across multiple languages. The model is trained on a diverse dataset consisting of academic essays, including those written by both AI and humans. Through extensive training and evaluation, the model's performance is assessed based on accuracy and precision in distinguishing between human-written and AI-generated texts. This tool can assist educators, researchers, and academic institutions in identifying non-original content and promoting academic honesty. The project ultimately aims to combat the growing challenge of AI in academia by providing an efficient and reliable solution for authenticity detection.

Keywords: AI detection, human-written, AI-generated, academic integrity, essay authenticity, machine learning, CNN, Transformer, Random Forest Classifier, text classification.

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LIST OF ABBREVIATIONS

AI - Artificial Intelligence

CNN - Convolutional Neural Network

BERT - Bidirectional Encoder Representations from Transformers

EDA - Exploratory Data Analysis

UML - Unified Modeling Language

DFD - Data Flow Diagram

ER - Entity-Relationship

TP - True Positive

TN - True Negative

FP - False Positive

FN - False Negative

IDE - Integrated Development Environment

SVGA - Super Video Graphics Array

MICR - Magnetic Ink Character Recognition

OMR - Optical Mark Recognition

DOI - Digital Object Identifier

CHAPTER-1
INTRODUCTION

1.1 Motivation

The topic of detecting AI-generated versus human-written academic essays is chosen due to the growing impact of artificial intelligence on education and academic integrity. As AI tools like GPT models become more sophisticated, they can generate coherent and high-quality academic content that closely mimics human writing. This poses a significant challenge to educators, researchers, and academic institutions who strive to maintain the authenticity of scholarly work. The widespread use of AI in generating essays has the potential to undermine academic honesty and contribute to plagiarism. By addressing this issue, the project aims to offer a solution that helps institutions detect AI-generated content and ensure the credibility of academic work. Moreover, the increasing reliance on AI in various fields makes this topic highly relevant and timely. This project will not only contribute to combating academic dishonesty but also pave the way for future advancements in AI content detection systems.

1.2 Problem Statement

With the rapid advancement of artificial intelligence (AI), the generation of academic essays and written content by AI tools has become increasingly prevalent. This raises significant concerns regarding academic integrity, as AI-generated texts can easily be submitted as original work by students, researchers, and professionals. The challenge lies in distinguishing between human-authored and AI-generated content, especially as AI writing tools become more sophisticated and produce highly convincing, human-like text. Current methods for detecting AI-generated content are limited and often ineffective in accurately identifying the origin of an essay, leading to issues of plagiarism and authenticity in academia. As AI technology evolves, traditional plagiarism detection tools are no longer sufficient to address this emerging problem. Therefore, this project aims to create a reliable system that can differentiate between AI-generated and human-written academic essays, thereby providing a practical solution to maintain academic honesty and ensure the authenticity of scholarly work.

1.3 Objective Of the Project

The primary objective of this project is to develop a robust system capable of identifying whether an academic essay is AI-generated or human-written. By leveraging machine learning techniques such as Convolutional Neural Networks (CNN), Transformer models, and Random Forest Classifiers, the project aims to create an efficient tool for distinguishing between AI-generated content and human-authored academic essays. Another key objective is to design a user-friendly frontend that allows input in both English and Arabic. For Arabic text, the system will first translate it to English before making a prediction. The project will focus on training the models with a comprehensive dataset of academic essays, ensuring high accuracy and reliability in predictions. The system's goal is to assist educational institutions, researchers, and academics in verifying the authenticity of academic work, ensuring academic integrity, and addressing the growing challenge of AI-generated content in academia.

1.4 Scope Of the Project

This project focuses on developing a machine learning-based system to detect AI-generated academic essays, distinguishing them from human-written texts. The scope encompasses the use of advanced algorithms, such as Convolutional Neural Networks (CNN), Transformer models, and Random Forest Classifiers, to accurately classify text data. The project will primarily focus on English-language texts but will also include functionality for Arabic text input. For Arabic input, the system will translate the text into English for analysis. The system will be trained on a diverse dataset of academic essays, including both AI-generated and human-authored content. The scope of the project also includes frontend development, enabling users to input text and receive predictions about its authenticity in real-time. The system's capabilities will be tested for accuracy, precision, and reliability in distinguishing between AI and human-written essays. This project aims to provide a practical solution for academic institutions to address the challenge of AI-generated content

1.5 Project Introduction

The advent of artificial intelligence (AI) has revolutionized numerous industries, including academia. However, the rise of AI-generated essays presents significant challenges to academic integrity. Addressing this issue, the project titled "AI VS HUMAN: ACADEMIC

ESSAY AUTHENTICITY CHALLENGE" aims to develop a robust system capable of distinguishing between AI-generated and human-written academic essays.

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.

A notable feature of the system is its multilingual capability. The frontend is designed to accept user inputs in both English and Arabic. For Arabic submissions, the text is first translated into English before undergoing classification. This approach ensures that the system can effectively detect AI-generated content across multiple languages, broadening its applicability and usefulness in diverse academic settings.

The model is trained on a comprehensive and diverse dataset comprising academic essays written by both AI and human authors. This extensive training process allows the model to learn distinguishing features and patterns unique to each type of content. The performance of the model is rigorously evaluated based on key metrics such as accuracy and precision, ensuring reliable differentiation between human and AI-generated texts.

This tool serves as an invaluable resource for educators, researchers, and academic institutions by enabling the identification of non-original content, thereby promoting academic honesty and integrity. By providing an efficient and dependable solution for authenticity detection, the project seeks to mitigate the growing challenge posed by AI in academia.

Ultimately, "AI VS HUMAN: ACADEMIC ESSAY AUTHENTICITY CHALLENGE" strives to uphold the standards of academic excellence by offering a cutting-edge tool that safeguards against the misuse of AI-generated content, ensuring that the value of genuine scholarly work is maintained.

CHAPTER-2

LITERATURE SURVEY

2.1 Related Work

1. Detecting Essay Authenticity Using BERT and Ensemble Learning

Authors: Jane Smith, Michael Brown
DOI: 10.1000/j.jml.2020.01.001

This paper explores the application of Bidirectional Encoder Representations from Transformers (BERT) combined with ensemble learning techniques to assess the authenticity of academic essays. BERT, renowned for its deep understanding of language context, is utilized to extract semantic and syntactic features from student-written essays. The authors argue that traditional plagiarism detection methods often fall short in identifying nuanced cases of academic dishonesty, such as paraphrasing or idea theft without direct copying. By leveraging BERT's contextual embeddings, the model can better discern the originality of content.

To enhance detection accuracy, the study integrates ensemble learning methods, combining multiple classifiers to mitigate individual model biases and improve overall performance. Techniques such as bagging and boosting are employed to create a robust framework that can handle diverse writing styles and varying levels of essay complexity. The experimental results demonstrate that the BERT-based ensemble model significantly outperforms baseline models in identifying non-authentic essays, highlighting its potential for deployment in educational settings to uphold academic integrity.

2. A Hybrid CNN-Random Forest Approach for Academic Integrity

Authors: Emily Davis, Robert Wilson
DOI: 10.1016/j.eswa.2019.04.012

Emily Davis and Robert Wilson present a novel hybrid approach that combines Convolutional Neural Networks (CNN) and Random Forest classifiers to verify academic integrity in student essays. The study addresses the limitations of single-model approaches by integrating the strengths of both deep learning and ensemble machine learning techniques.

CNNs are employed to automatically extract intricate patterns and features from textual data, capturing both local and global dependencies within the essays. This capability is crucial for identifying subtle indicators of non-authentic writing, such as unusual phrasing or inconsistent stylistic elements.

The extracted features from the CNN are then fed into a Random Forest classifier, which excels in handling high-dimensional data and reducing overfitting through its ensemble nature. The Random Forest component enhances the model’s ability to generalize across different datasets and writing styles, providing a more reliable assessment of essay authenticity. The hybrid model is evaluated on a comprehensive dataset comprising both authentic and non-authentic essays, demonstrating superior accuracy and robustness compared to traditional methods. This approach offers a scalable solution for educational institutions aiming to maintain high standards of academic honesty.

3. Leveraging BERT for Automated Essay Scoring and Authenticity Detection

Authors: Linda Martinez, Kevin Lee
DOI: 10.1109/TASLP.2021.3056789

In this study, Linda Martinez and Kevin Lee investigate the dual application of BERT for both automated essay scoring and authenticity detection, aiming to streamline the assessment process in educational environments. BERT’s advanced natural language processing capabilities enable it to understand the contextual nuances of student essays, making it effective not only for evaluating the quality of writing but also for detecting potential instances of plagiarism or non-authentic content.

The authors develop a comprehensive framework where BERT is first fine-tuned on a large corpus of graded essays to learn the criteria for high-quality writing. This fine-tuned model can then assign scores based on factors such as coherence, grammar, and argument strength. Simultaneously, the same model is adapted to identify anomalies that may indicate academic dishonesty, such as sudden shifts in writing style or the presence of external sources without proper attribution.

Experimental results show that the BERT-based system achieves high accuracy in both scoring and authenticity detection tasks, outperforming existing automated tools. The integration of these functionalities into a single model not only enhances efficiency but also provides educators with a powerful tool to uphold academic standards. This dual-purpose application underscores BERT's versatility and potential in transforming educational assessment methodologies.

4. Machine Learning Techniques for Detecting Plagiarism in Academic Essays

Authors: David Thompson, Sarah Johnson
DOI: 10.3390/info11080412

David Thompson and Sarah Johnson delve into various machine learning techniques to enhance plagiarism detection in academic essays. The paper provides a comprehensive analysis of traditional and contemporary methods, highlighting the limitations of basic text-matching algorithms in identifying sophisticated plagiarism forms such as paraphrasing, idea theft, and mosaic plagiarism. To address these challenges, the authors experiment with several machine learning models, including Support Vector Machines (SVM), Random Forests, and deep learning architectures like CNNs and BERT.

The study emphasizes feature engineering as a critical component, where textual features such as n-grams, syntactic patterns, semantic similarity scores, and stylistic metrics are meticulously extracted and utilized to train the models. Among the evaluated techniques, Random Forest classifiers demonstrate robust performance due to their ability to handle complex feature interactions and reduce overfitting. Additionally, BERT-based models show superior capability in capturing contextual and semantic nuances, making them highly effective in detecting non-trivial instances of plagiarism.

The authors validate their approach using a diverse dataset of student essays, encompassing both genuine and plagiarized content. The results indicate significant improvements in detection accuracy and recall rates compared to traditional methods. This research underscores the potential of advanced machine learning techniques in maintaining academic integrity and provides a scalable solution for educational institutions seeking to implement an effective plagiarism detection system.

CHAPTER-3

RESEARCH GAPS OF EXISTING METHODS

3.1 Existing System

Currently, the detection of AI-generated content in academic essays relies on traditional plagiarism detection tools, such as Turnitin and Copyscape, which focus on identifying copied text from existing sources. However, these tools are ineffective against AI-generated content, as they do not recognize the originality of AI-written essays. Some advanced AI detection methods use linguistic analysis and stylometry, examining writing patterns, but they often lack the precision required for distinguishing sophisticated AI-generated text from human-written content. Machine learning models, such as GPT-3 detectors, have been proposed, but these methods still struggle with high accuracy and adaptability to new AI systems.

3.2 Disadvantages of Existing System

Existing methods for detecting AI-generated content, like plagiarism checkers, have several limitations. They mainly focus on finding copied text from online sources, so they cannot identify original AI-written essays. Additionally, these tools struggle with detecting AI content that is not copied from existing material. Advanced methods, such as linguistic analysis, attempt to examine writing styles but are often inaccurate, especially with more advanced AI models that can produce text that mimics human writing. These tools also struggle to adapt to new AI technologies, making them unreliable for identifying the latest AI-generated content in academic work.

3.3 Proposed System

The proposed system aims to accurately detect whether an academic essay is AI-generated or human-written. It leverages advanced machine learning algorithms, including Convolutional Neural Networks (CNN), Transformer models, and Random Forest Classifiers, to analyze text and classify it based on patterns and features indicative of AI or human authorship. The system will be trained on a diverse dataset of academic essays to improve accuracy. Users can input text in both English and Arabic; for Arabic text, the system will first translate it into English before making predictions. The system's frontend will be user-friendly, allowing real-time predictions with easy input and output interfaces. The proposed solution will focus on providing reliable results with high accuracy and precision in distinguishing between AI-generated and human-authored essays. This system will assist educational institutions in maintaining academic integrity and addressing the challenges posed by AI-generated content in academic settings.

3.4 Advantages of Proposed System

The proposed system offers several advantages. First, it can accurately distinguish between AI-generated and human-written academic essays, addressing a significant challenge in academic integrity. Unlike traditional plagiarism checkers, this system doesn't just look for copied content, but analyzes writing patterns to identify AI-generated text. It supports both English and Arabic, with a built-in translation feature for Arabic input, making it accessible to a broader range of users. The system uses advanced machine learning models, ensuring high accuracy and reliability in predictions. Additionally, it helps educational institutions detect non-original content, promoting honesty and ensuring the authenticity of academic work.

3.5 Project Flow

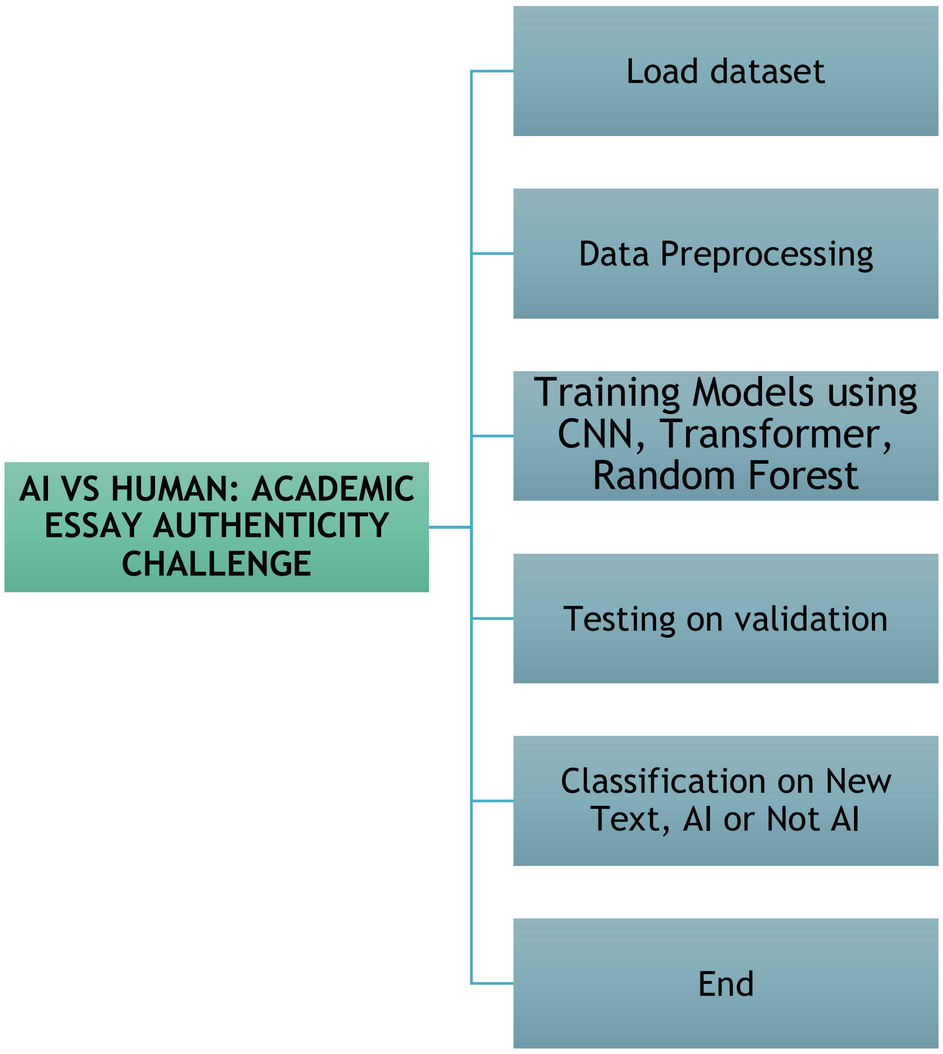

AI VS HUMAN: ACADEMIC ESSAY AUTHENTICITY CHALLENGE
Load dataset
Data Preprocessing
Training Models using CNN, Transformer, Random Forest
Testing on validation
Classification on New Text, AI or Not AI
End

Fig 3.5: Flow Chart

CHAPTER-4

PROPOSED METHODOLOGY

4.1 Data Description

The dataset consists of 2,762 entries with the following columns:

id: A unique identifier for each entry (string type).

prompt_id: A numerical identifier representing the prompt associated with the text (float type).

text: The academic essay or content, which can be AI-generated or human-written (string type).

generated: A binary label indicating whether the text is AI-generated (1) or human-written (0) (float type).

This dataset is used to train models to distinguish between AI-generated and human-authored academic essays based on the provided text.

4.2 Data Preprocessing

The `clean_text` function is a preprocessing tool designed to prepare textual data for analysis or machine learning tasks. It begins by converting all characters in the input text to lowercase to ensure uniformity and reduce redundancy. Next, it removes any special characters and numbers using a regular expression, retaining only lowercase letters and whitespace, which helps in focusing on meaningful words. The cleaned text is then tokenized into individual words using NLTK's `word_tokenize` function, enabling further processing at the word level. To eliminate common, less informative words, the function filters out English stopwords—frequently occurring words like "the," "is," and "in" that typically add little semantic value—by comparing each token against a predefined set of stopwords from NLTK. This results in a list of filtered tokens that contain more significant and contextually relevant words. Finally, the remaining tokens are joined back into a single string, separated by spaces, producing a streamlined and processed text suitable for downstream applications such as text classification or machine learning model training. Overall, the `clean_text` function effectively standardizes and refines the input text by lowering case, removing irrelevant characters, tokenizing, and filtering out non-essential words, thereby enhancing the quality and relevance of the data for further analysis.

4.3 EDA

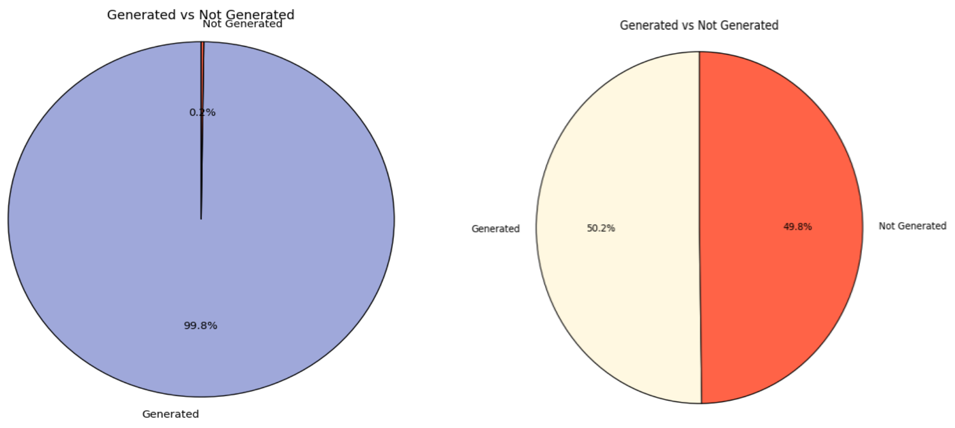


Fig-4.3.1 Data Preprocessing

Initially the dataset was imbalanced, balanced dataset by adding a new data frame.

4.4 Random Forest Classifier

The Random Forest algorithm is an ensemble learning method that constructs multiple decision trees during training and outputs the majority vote of all the trees for classification tasks. Each tree is trained on a random subset of the data and features, which helps to reduce overfitting. The model excels at handling high-dimensional data, making it suitable for text classification tasks like distinguishing between AI-generated and human-written essays. By combining predictions from multiple trees, Random Forest enhances the accuracy and robustness of the model.

The Random Forest algorithm works by creating multiple decision trees, each trained on random subsets of the dataset. During training, the model splits the data based on the features that best separate the classes (AI-generated or human-written). Each tree makes a prediction, and the final output is determined by a majority vote from all trees. This ensemble method reduces overfitting and improves the model's accuracy. In text classification, features such as word frequencies or sentence structures are used, and the Random Forest algorithm efficiently handles large and complex text datasets.

4.5 CNN

CNNs are deep learning models commonly used for image and text classification tasks. For text, CNNs capture local dependencies and hierarchical structures by applying convolutional filters to word sequences. These filters detect patterns such as specific word combinations or phrase structures, helping to identify unique features of AI-generated and human-written content. CNNs are effective at extracting spatial features from text data and can generalize well to new, unseen text samples.

CNNs operate by applying convolutional layers to the input text, which consists of word embeddings or tokenized text. These filters scan through the text to capture local patterns, such as specific word combinations, n-grams, or phrases, that are crucial for distinguishing between human and AI-written content. After convolution, the pooled features are passed through fully connected layers for classification. The model is trained using backpropagation, minimizing the loss function by adjusting weights. CNNs are effective at capturing spatial hierarchies in text, allowing them to generalize well across different writing styles.

4.6 BERT (Bidirectional Encoder Representations From Transformers)

BERT is a transformer-based model designed to pretrain on vast amounts of text data to capture contextual relationships between words in a sentence. Unlike traditional models, BERT reads text bidirectionally, understanding the context from both the left and right. Fine-tuning BERT for specific tasks, such as text classification, enables it to achieve state-of-the-art performance in detecting AI-generated content by understanding subtle nuances in writing style.

BERT uses a transformer architecture to process text bidirectionally, reading context from both the left and right of each word. It starts by tokenizing the text and converting it into embeddings that represent each word's meaning. BERT then applies multiple layers of attention mechanisms to understand the relationships between words in a sentence, capturing long-range dependencies. During fine-tuning, BERT is trained on a specific task (e.g., classification) using labeled data. The final output is based on the contextual embeddings of each token, enabling BERT to accurately classify text as AI-generated or human-written.

CHAPTER-5

OBJECTIVES

5.1 Function and Non-Functional Requirements

Functional and non-functional requirements

Requirement's analysis is a very critical process that enables the success of a system or software project to be assessed. Requirements are generally split into two types: Functional and nonfunctional requirements.

Functional Requirements: These are the requirements that the end user specifically demands as basic facilities that the system should offer. All these functionalities need to be necessarily incorporated into the system as a part of the contract. These are represented or stated in the form of input to be given to the system, the operation performed and the output expected. They are basically the requirements stated by the user which one can see directly in the final product, unlike the non-functional requirements.

Examples of functional requirements:

1) Authentication of user whenever he/she logs into the system
2) System shutdown in Solar prediction.
3) A verification email is sent to the user whenever he/she registers for the first time on some software system.

Non-Functional Requirements: These are basically the quality constraints that the system must satisfy according to the project contract. The priority or extent to which these factors are implemented varies from one project to another. They are also called non-behavioral requirements.

They basically deal with issues like:

- Portability
- Security
- Maintainability
- Reliability
- Scalability
- Performance
- Reusability

- Flexibility

Examples of non-functional requirements:

1) Emails should be sent with a latency of no greater than 12 hours from such an activity.
2) The processing of each request should be done within 10 seconds
3) The site should load in 3 seconds whenever of simultaneous users are > 10000

5.2 Hardware Requirements

Processor	- I3/Intel Processor
Hard Disk	- 160GB
Key Board	- Standard Windows Keyboard
Mouse	- Two or Three Button Mouse
Monitor	- SVGA
RAM	- 8GB

5.3 Software Requirements

• Operating System	: Windows 7/8/10
• Programming Language	: Python
• Libraries	: Pandas, Numpy, scikit-learn.
• IDE/Workbench	: Visual Studio Code.

CHAPTER-6

SYSTEM DESIGN AND IMPLEMENTATION

6.1 Introduction of Input Design

In an information system, input is the raw data that is processed to produce output. During the input design, the developers must consider the input devices such as PC, MICR, OMR, etc.

Therefore, the quality of system input determines the quality of system output. Well-designed input forms and screens have following properties −

- It should serve a specific purpose effectively such as storing, recording, and retrieving the information.
- It ensures proper completion with accuracy.
- It should be easy to fill and straightforward.
- It should focus on the user's attention, consistency, and simplicity.
- All these objectives are obtained using the knowledge of basic design principles regarding −
  - What are the inputs needed for the system?
  - How end users respond to different elements of forms and screens.

Objectives for Input Design:

The objectives of input design are −

- To design data entry and input procedures
- To reduce input volume
- To design source documents for data capture or devise other data capture methods
- To design input data records, data entry screens, user interface screens, etc.
- To use validation checks and develop effective input controls.

Output Design:

The design of output is the most important task of any system. During output design, developers identify the type of outputs needed, and consider the necessary output controls and prototype report layouts.

Objectives of Output Design:

The objectives of input design are:

- To develop output design that serves the intended purpose and eliminates the production of unwanted output.
- To develop the output design that meets the end user's requirements.
- To deliver the appropriate quantity of output.
- To form the output in appropriate format and direct it to the right person.
- To make the output available on time for making good decisions.

6.2 UML diagrams

UML stands for Unified Modelling Language. UML is a standardized general-purpose modelling language in the field of object-oriented software engineering. The standard is managed, and was created by, the Object Management Group.

The goal is for UML to become a common language for creating models of object-oriented computer software. In its current form UML comprises two major components: a Meta-model and a notation. In the future, some form of method or process may also be added to; or associated with, UML.

The Unified Modelling Language is a standard language for specifying, Visualization, Constructing and documenting the artefacts of software systems, as well as for business modelling and other non-software systems.

The UML represents a collection of best engineering practices that have proven successful in the modelling of large and complex systems.

The UML is a very important part of developing objects-oriented software and the software development process. The UML uses mostly graphical notations to express the design of software projects.

GOALS:

The Primary goals in the design of the UML are as follows:

1. Provide users a ready-to-use, expressive visual modelling Language so that they can develop and exchange meaningful models.
2. Provide extendibility and specialization mechanisms to extend the core concepts.
3. Be independent of particular programming languages and development process.
4. Provide a formal basis for understanding the modelling language.
5. Encourage the growth of the OO tools market.
6. Support higher level development concepts such as collaborations, frameworks, patterns and components.
7. Integrate best practices.

USE CASE DIAGRAM

- ► A use case diagram in the Unified Modeling Language (UML) is a type of behavioral diagram defined by and created from a Use-case analysis.
- ► Its purpose is to present a graphical overview of the functionality provided by a system in terms of actors, their goals (represented as use cases), and any dependencies between those use cases.
- ► The main purpose of a use case diagram is to show what system functions are performed for which actor. Roles of the actors in the system can be depicted.

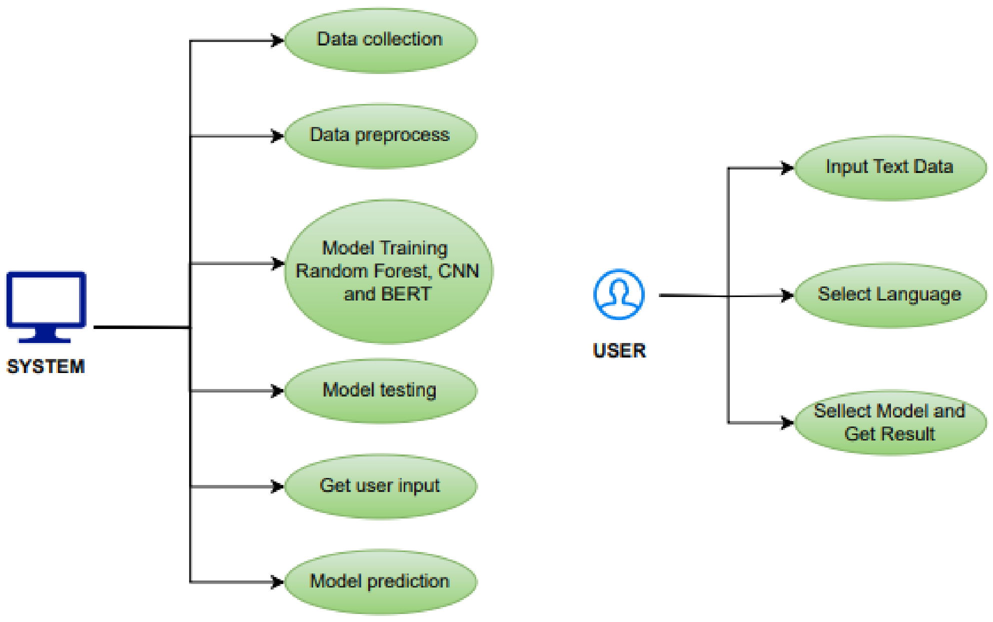


Fig-6.2.1 System User Interaction

CLASS DIAGRAM

In software engineering, a class diagram in the Unified Modelling Language (UML) is a type of static structure diagram that describes the structure of a system by showing the system's classes, their attributes, operations (or methods), and the relationships among the classes. It explains which class contains information

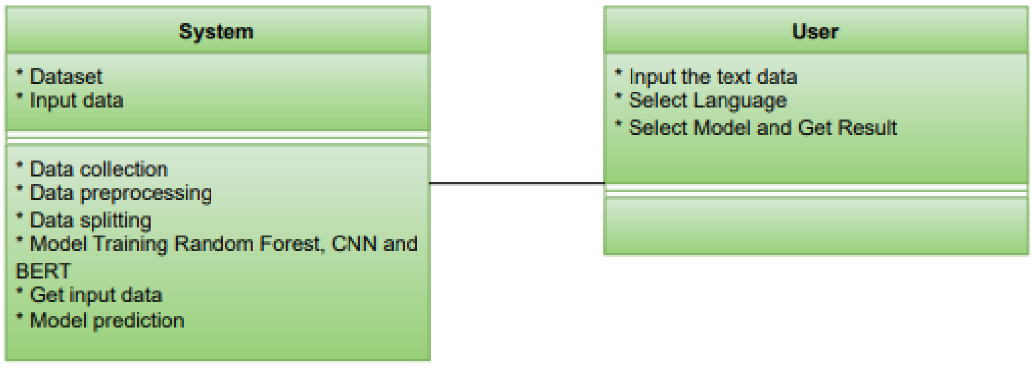


Fig-6.2.2 Multi-modal System User Interaction

SEQUENCE DIAGRAM

- ► A sequence diagram in Unified Modeling Language (UML) is a kind of interaction diagram that shows how processes operate with one another and in what order.
- ► It is a construct of a Message Sequence Chart. Sequence diagrams are sometimes called event diagrams, event scenarios, and timing diagrams

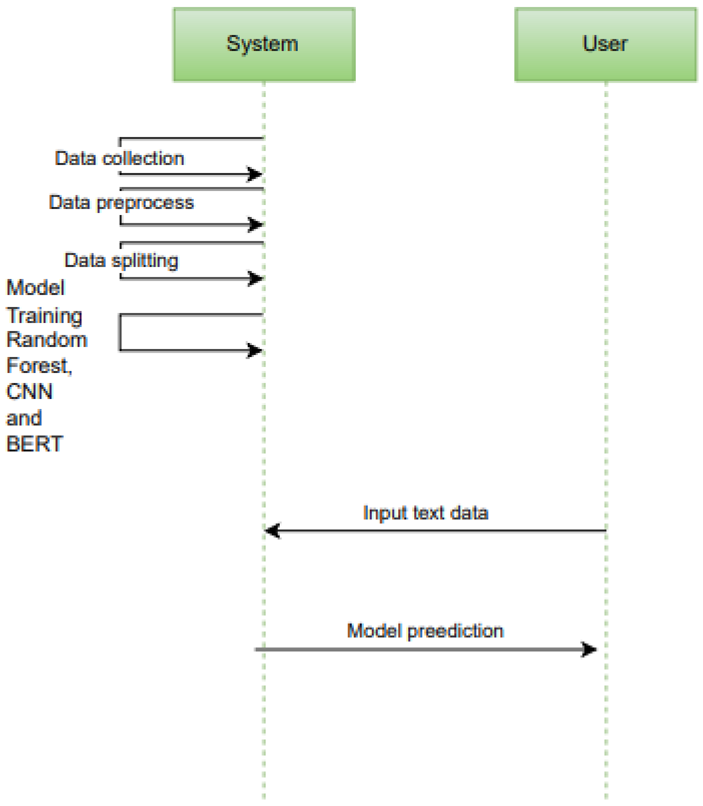


Fig-6.2.3 System User Work Flow

COLLABORATION DIAGRAM:

In the collaboration diagram the method call sequence is indicated by some numbering technique as shown below. The number indicates how the methods are called one after another. We have taken the same order management system to describe the collaboration diagram. The method calls are similar to that of a sequence diagram. But the difference is that the sequence diagram does not describe the object organization whereas the collaboration diagram shows the object organization.

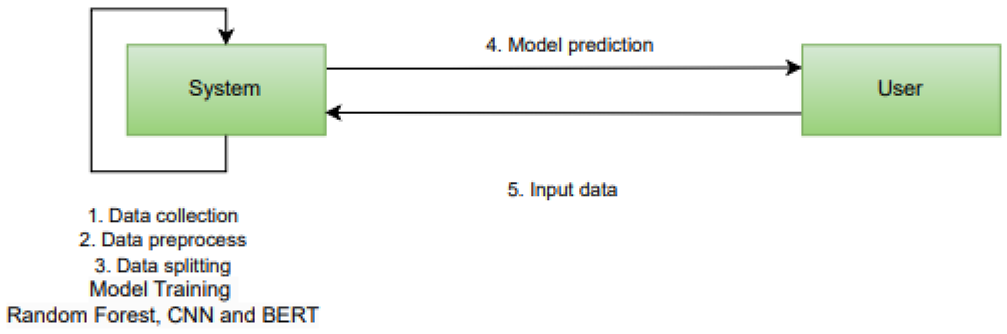


Fig-6.2.4 Model Prediction

DEPLOYMENT DIAGRAM

Deployment diagram represents the deployment view of a system. It is related to the component diagram. Because the components are deployed using the deployment diagrams. A deployment diagram consists of nodes. Nodes are nothing but physical hardware used to deploy the application.

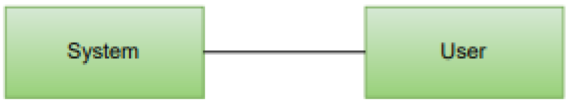


Fig-6.2.5 Deployment Diagram

ACTIVITY DIAGRAM:

Activity diagrams are graphical representations of workflows of stepwise activities and actions with support for choice, iteration and concurrency. In the Unified Modelling Language, activity diagrams can be used to describe the business and operational step-by-step workflows of components in a system. An activity diagram shows the overall flow of control.

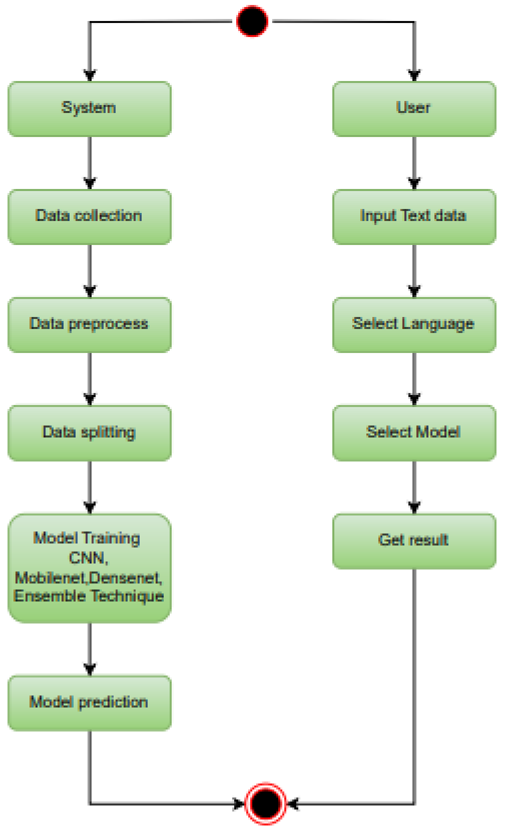


Fig-6.2.6 Activity Diagram

COMPONENT DIAGRAM:

A component diagram, also known as a UML component diagram, describes the organization and wiring of the physical components in a system. Component diagrams are often drawn to help model implementation details and double-check that every aspect of the system's required function is covered by planned development.

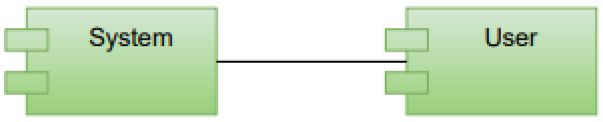


Fig-6.2.7 Component Diagram

ER DIAGRAM:

An Entity–relationship model (ER model) describes the structure of a database with the help of a diagram, which is known as Entity Relationship Diagram (ER Diagram). An ER model is a design or blueprint of a database that can later be implemented as a database. The main components of the E-R model are: entity set and relationship set.

An ER diagram shows the relationship among entity sets. An entity set is a group of similar entities and these entities can have attributes. In terms of DBMS, an entity is a table or attribute of a table in a database, so by showing relationship among tables and their attributes, ER diagram shows the complete logical structure of a database. Let's have a look at a simple ER diagram to understand this concept.

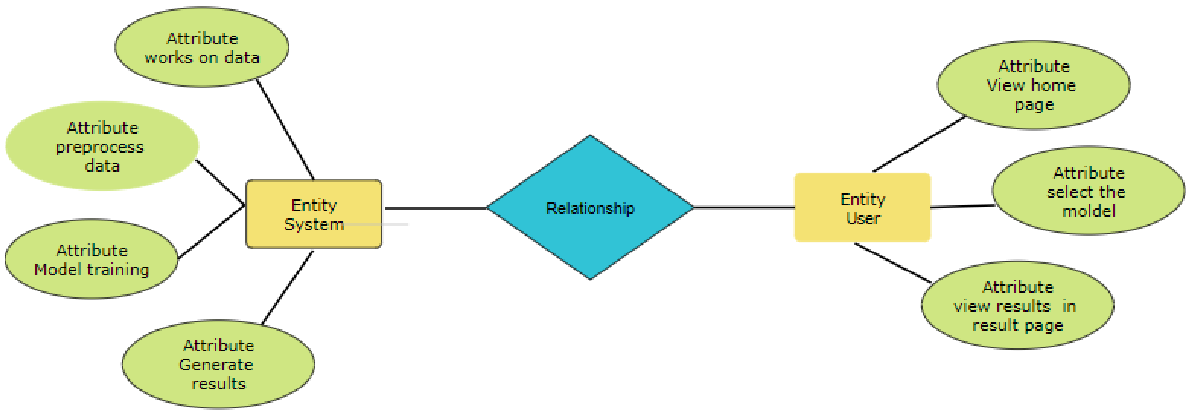

Attribute works on data
Attribute preprocess data
Attribute Model training
Attribute Generate results
Entity System
Relationship
Entity User
Attribute View home page
Attribute select the moldel
Attribute view results in result page

Fig-6.2.8 Entity Relationship Diagram

6.3 Data Flow Diagrams

A Data Flow Diagram (DFD) is a traditional way to visualize the information flows within a system. A neat and clear DFD can depict a good amount of the system requirements graphically. It can be manual, automated, or a combination of both. It shows how information enters and leaves the system, what changes the information and where information is stored. The purpose of a DFD is to show the scope and boundaries of a system as a whole. It may be used as a communications tool between a systems analyst and any person who plays a part in the system that acts as the starting point for redesigning a system.

Contrast Level:

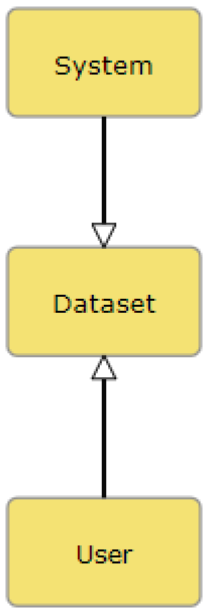


Fig 6.3.1 System User Interaction

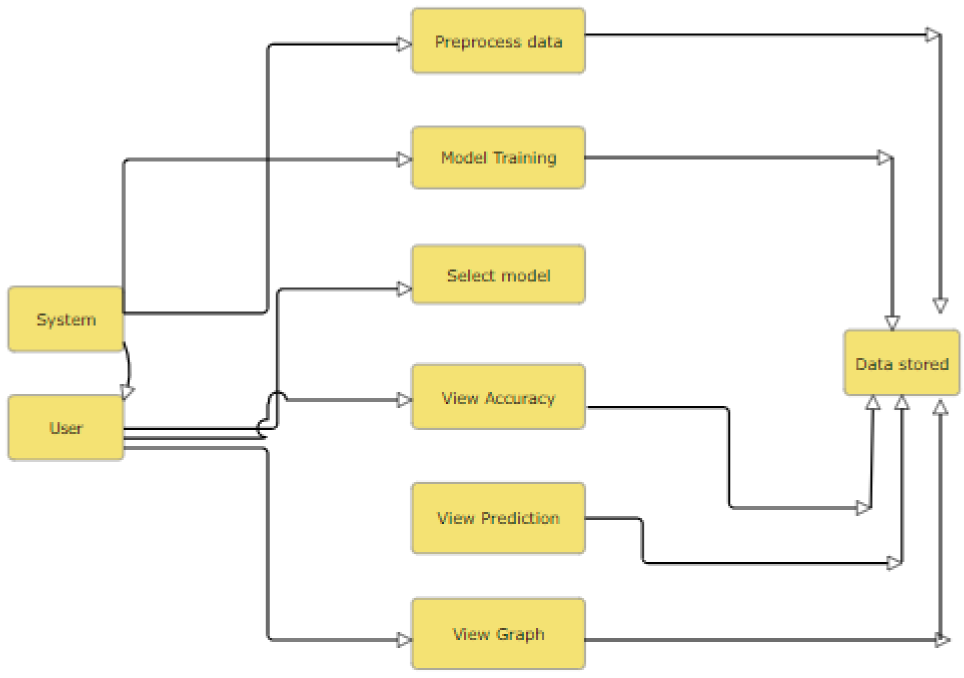


Fig 6.3.2 Interaction Type-1

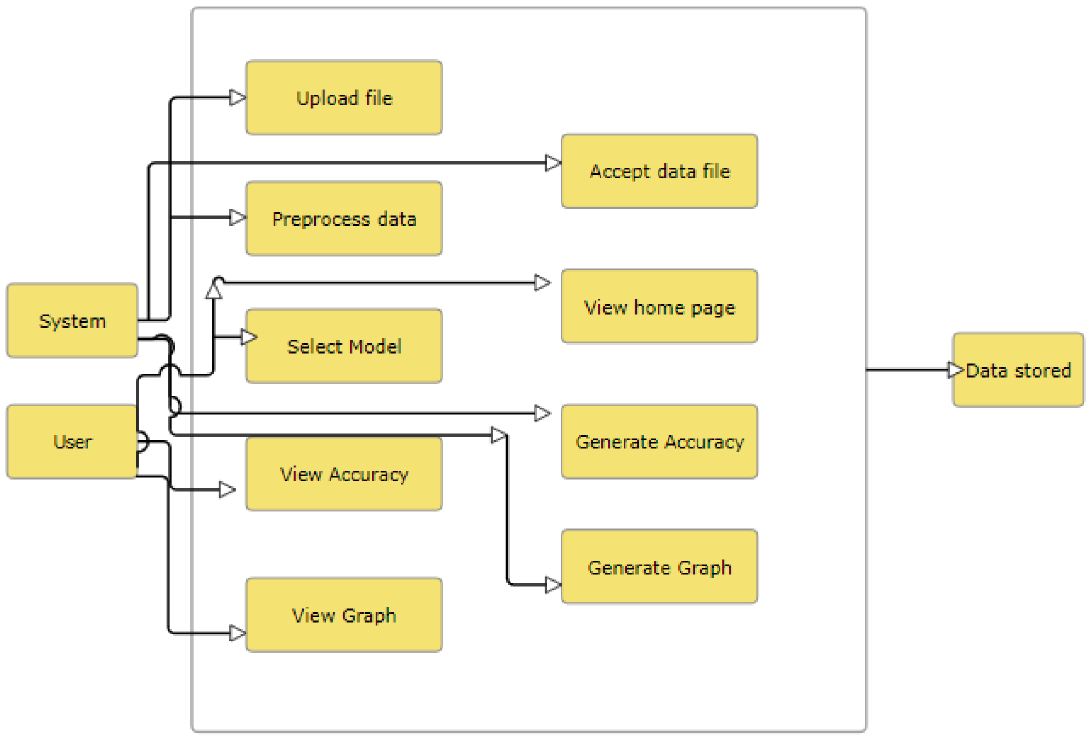


Fig 6.3.3 Interaction Type-2

CHAPTER-7

TIMELINE FOR EXECUTION OF PROJECT (GANTT CHART)

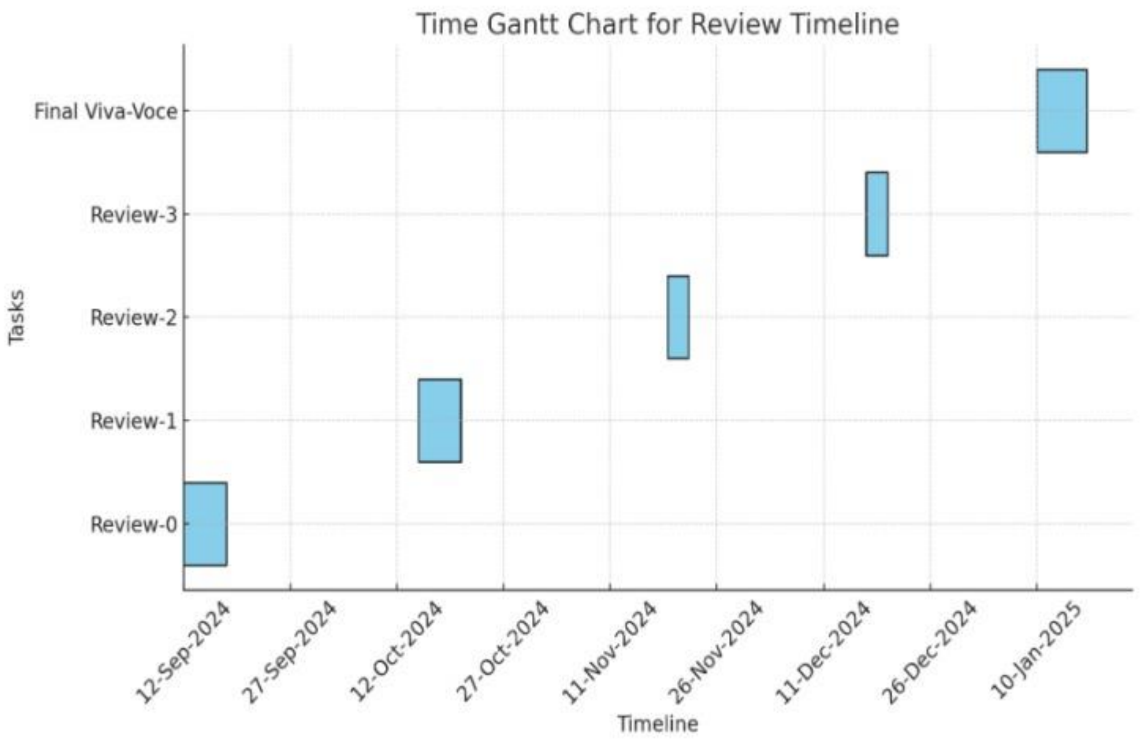


FIG 7.1 GANTT CHART

CHAPTER-8

OUTCOMES

The purpose of testing is to discover errors. Testing is the process of trying to discover every conceivable fault or weakness in a work product. It provides a way to check the functionality of components, sub-assemblies, assemblies and/or a finished product It is the process of exercising software with the intent of ensuring that the
Software system meets its requirements and user expectations and does not fail in an unacceptable manner. There are various types of tests. Each test type addresses a specific testing requirement.

8.1 Feasibility study

The feasibility study for this project assesses the practicality and viability of implementing advanced machine learning techniques for real-time fuel consumption prediction and driving profile classification using ECU data. Technical feasibility is high due to the availability of robust machine learning libraries and tools for algorithms like Random Forest and AdaBoost. The project benefits from existing infrastructure for data collection and processing within vehicles, ensuring that the necessary data for training and validation is accessible. Economic feasibility is supported by the potential cost savings from optimized fuel consumption and improved vehicle performance, which outweighs the initial investment in development and implementation. Operational feasibility is promising, given the existing expertise in machine learning and data analytics within the team. Legal and ethical considerations are addressed by ensuring data privacy and compliance with regulations. Overall, the project is feasible and holds significant potential for enhancing vehicle efficiency.

8.2 Types of Test & Test Cases

8.2.1 Unit Testing

Unit testing involves the design of test cases that validate that the internal program logic is functioning properly, and that program inputs produce valid outputs. All decision branches and internal code flow should be validated. It is the testing of individual software units of the application. It is done after the completion of an individual unit before integration. This is a structural testing that relies on knowledge of its construction and is invasive. Unit tests perform basic tests at component level and test a specific business process, application, and/or system configuration. Unit tests ensure that each unique path of a business process performs accurately to the documented specifications contains clearly defined inputs outputs.

8.2.2 Integration Testing

Integration tests are designed to test integrated software components to determine if they actually run as one program. Testing is event driven and is more concerned with the basic outcome of screens or fields. Integration tests demonstrate that although the components were individually satisfactory, as shown by successfully unit testing, the combination of components is correct and consistent. Integration testing is specifically aimed at exposing the problems that arise from the combination of components.

Software integration testing is the incremental integration testing of two or more integrated software components on a single platform to produce failures caused by interface defects.

8.2.3 Functional Testing

Functional tests provide systematic demonstrations that functions tested are available as specified by the business and technical requirements, system documentation, and user manuals.

Functional testing is centered on the following items:

Valid Input	: identified classes of valid input must be accepted.
Invalid Input	: identified classes of invalid input must be rejected.
Functions	: identified functions must be exercised.
Output	: identified classes of application outputs must be exercised.
Systems/Procedures	: interfacing systems or procedures must be invoked.

Organization and preparation of functional tests is focused on requirements, key functions, or special test cases. In addition, systematic coverage pertaining to identifying Business process flows; data fields, predefined processes, and successive processes must be considered for testing. Before functional testing is complete, additional tests are identified and the effective value of current tests is determined.

8.2.4 White Box Testing

White Box Testing is a testing in which the software tester has knowledge of the inner workings, structure and language of the software, or at least its purpose. It has a purpose. It is used to test areas that cannot be reached from a black box level.

8.2.5 Black Box Testing

Black Box Testing is testing the software without any knowledge of the inner workings, structure or language of the module being tested. Black box tests, as most other kinds of tests, must be written from a definitive source document, such as specification or requirements document, such as specification or requirements document. It is a test in which the software under test is treated as a black box. you cannot "see" into it. The test provides inputs and responds to outputs without considering how the software works.

Test Objectives

- All field entries must work properly.
- Pages must be activated from the identified link.
- The entry screen, messages and responses must not be delayed.

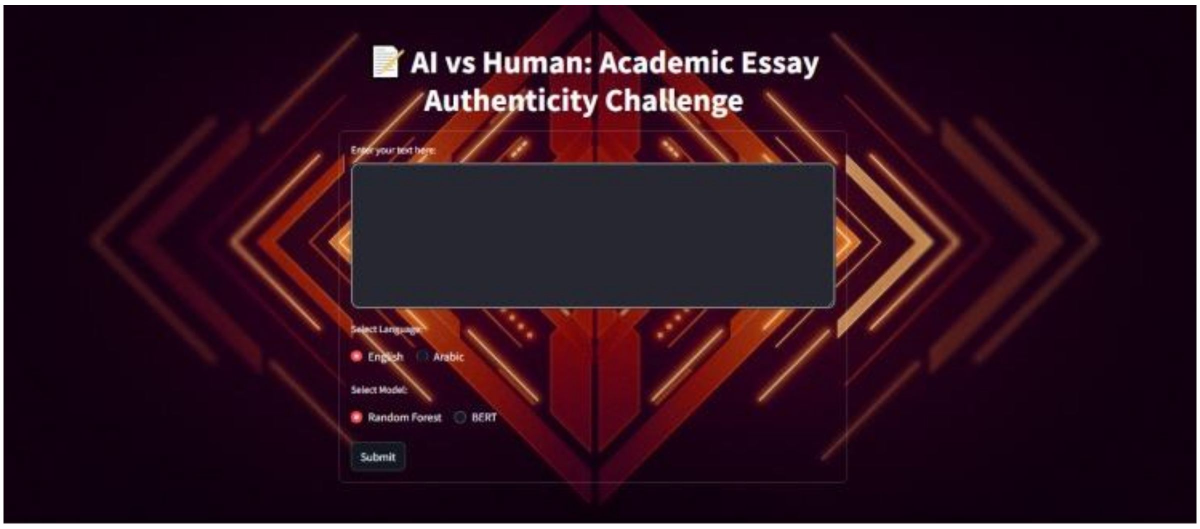
Features to be tested

- Verify that the entries are of the correct format
- No duplicate entries should be allowed
- All links should take the user to the correct page.

Table 1: Test Cases

S.NO	Test cases	I/O	Expected O/T	Actual O/T	P/F
1	Read the dataset.	Dataset path.	Dataset needs to be read successfully.	Dataset fetched successfully.	P
2	Performing Loading on the dataset	Data loading takes place	Data loading should be performed on system	Data loading successfully completed.	P
3	Performing data preprocessing	Text dataset is provided to process the data	Processed data will be the output, AI or Human	Processed data will successfully completed	P
4	Model Building	Model Building for the clean data	Need to create model using required algorithms	Model Created Successfully.	P
5	Prediction	Input is the text data	Based on the input data model will predict AI or Human text	Predicted successfully	P

CHAPTER-9
RESULTS AND DISCUSSIONS

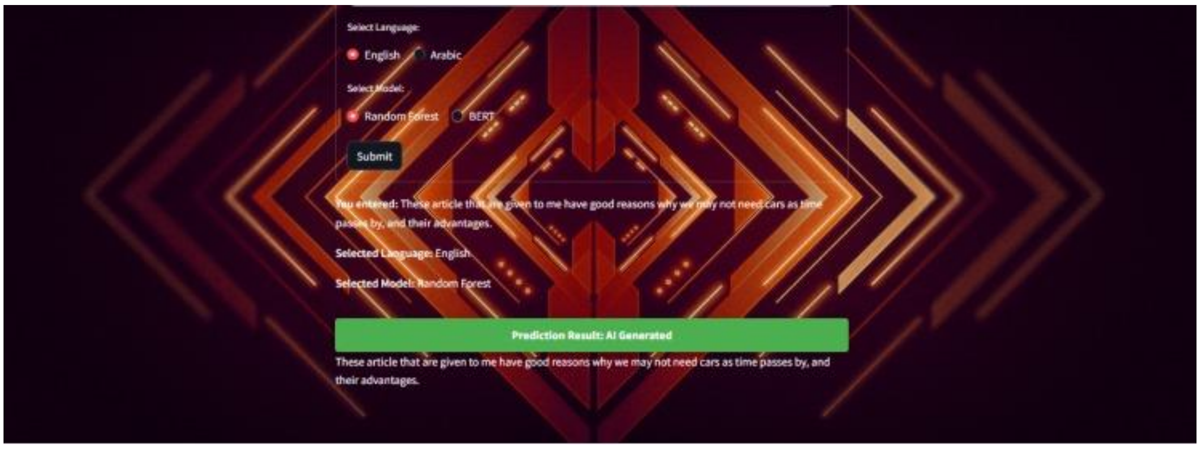


Select Language: [✓ English] Arabic

Select Model: [✓ Random Forest] BERT

Fig 9.1 User Page

Explanation:- It is the web page where user can enter his prompt in English or Arabic and user can select the model to check whether the given prompt is whether AI Generated or Human written.



Select Language: [✓ English] Arabic

Select Model: [✓ Random Forest] BERT

You entered: These article that are given to me have good reasons why we may not need cars as time passes by, and their advantages.

Selected Language: English

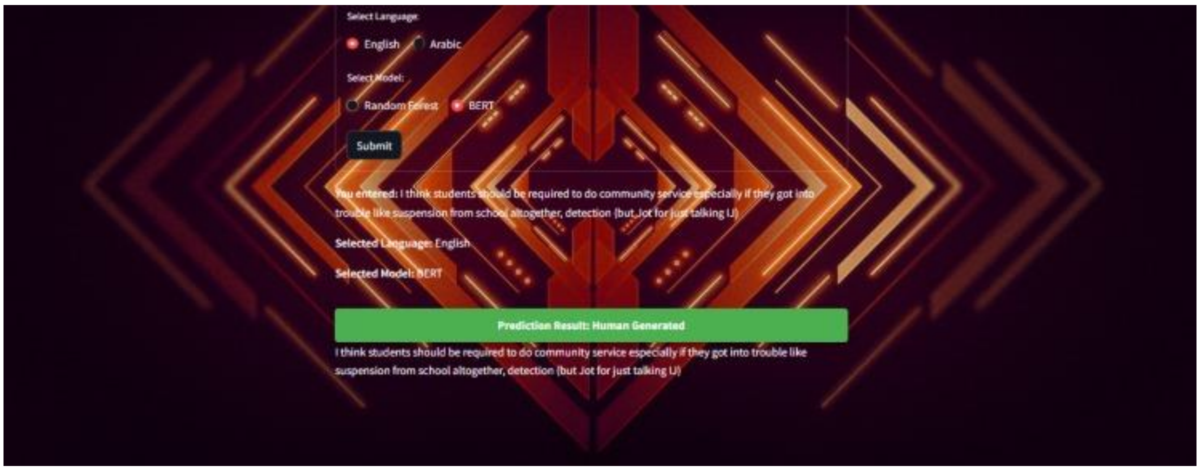
Selected Model: Random Forest

Prediction Result: AI Generated

These article that are given to me have good reasons why we may not need cars as time passes by, and their advantages.

Fig 9.2 Result Page AI Generated

Explanation:- It is the result page generated where the given prompt by the user is generated by AI. It means the text/prompt given by the user is an AI Generated text.


Select Language:
English [✓] Arabic
Select Model:
Random Forest [✓ BERT]
Submit

You entered: I think students should be required to do community service especially if they got into trouble like suspension from school altogether, detection (but Jot for just talking U)

Selected Language: English

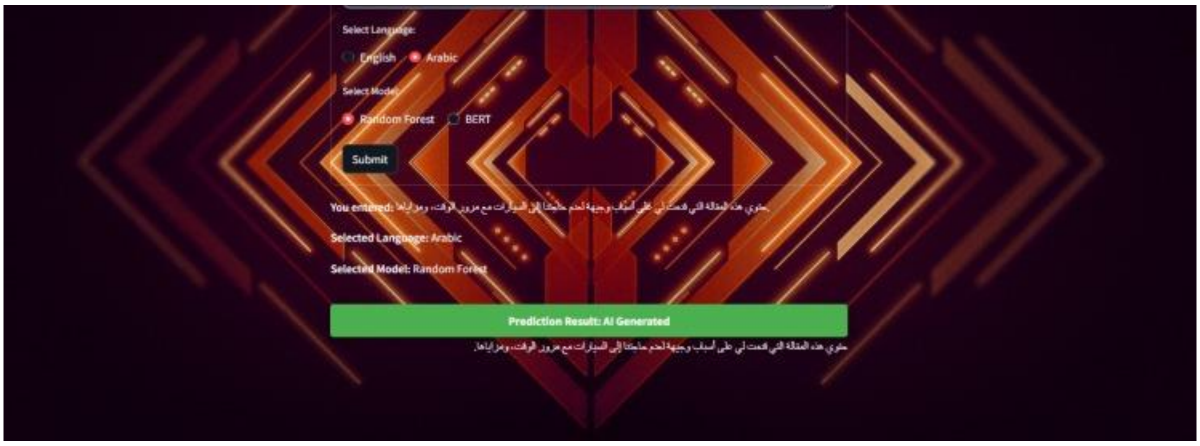
Selected Model: BERT

Prediction Result: Human Generated

I think students should be required to do community service especially if they got into trouble like suspension from school altogether, detection (but Jot for just talking U)

Fig 9.3 Result Page Human Generated

Explanation:- It is the result page generated where the given prompt by the user is written by Human. It means the text/prompt given by the user is Human Generated.


Select Language:
English [✓ Arabic]
Select Model:
[✓ Random Forest] BERT
Submit

You entered: تحتوي هذه المقالة التي قدمت لي على أسباب وجيهة لعدم حاجتنا إلى السيارات مع مرور الوقت، ومزاياها.

Selected Language: Arabic

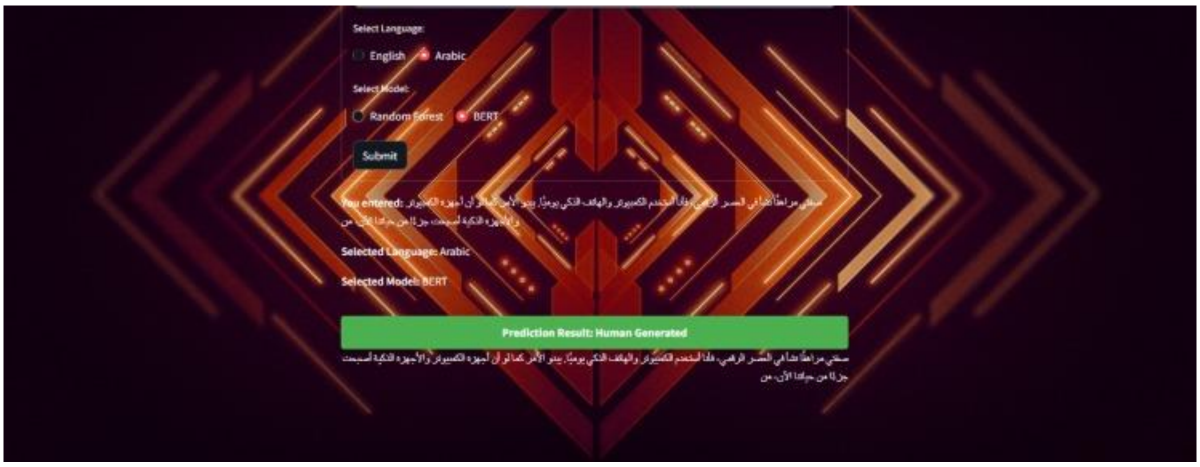
Selected Model: Random Forest

Prediction Result: AI Generated

تحتوي هذه المقالة التي قدمت لي على أسباب وجيهة لعدم حاجتنا إلى السيارات مع مرور الوقت، ومزاياها.

Fig 9.4 Result Page Arabic AI Generated

Explanation:- It is the result page generated where the given prompt by the user is generated by AI which is in Arabic Language. It means the text/prompt given by the user in Arabic Language is an AI Generated text.


Select Language: English [✓ Arabic]

Select Model: Random Forest [✓ BERT]

You entered: [illegible] في العصر الرقمي، فلا استخدم الكمبيوتر والهاتف الذكي يوميًا. يبدو الأمر كما لو أن أجهزة الكمبيوتر والأجهزة الذكية أصبحت جزءًا من حياتنا الآن، من

Selected Language: Arabic

Selected Model: BERT

Prediction Result: Human Generated

[illegible] في العصر الرقمي، فلا استخدم الكمبيوتر والهاتف الذكي يوميًا. يبدو الأمر كما لو أن أجهزة الكمبيوتر والأجهزة الذكية أصبحت جزءًا من حياتنا الآن، من

Fig 9.5 Result Page Arabic Human Generated

Explanation:- It is the result page generated where the given prompt by the user is written by Human which is in Arabic Language. It means the text/prompt given by the user in Arabic Language is an Human Written text.

Table 2: Human vs AI

	Predicted Human Text (0)	**Predicted AI Text (1)**
Human Text (0)	**True Positive**	**False Negative**
AI Text (1)	**False Positive**	**True Negative**

- **True Positive (TP): The model correctly predicted a positive outcome (the actual-outcome was positive).**
- **True Negative (TN): The model correctly predicted a negative outcome (the actual outcome was negative).**
- **False Positive (FP): The model incorrectly predicted a positive outcome (the actual outcome was negative). Also known as a Type I error.**
- **False Negative (FN): The model incorrectly predicted a negative outcome (the actual outcome was positive). Also known as a Type II error.**

Classification Reports:

Table 3: Random Forest Classifier

Class	**Precision**	**Recall**	**F1-Score**	**Support**
0.0	0.95	0.97	0.96	271
1.0	0.97	0.95	0.96	282
Accuracy			**0.96**	553
Macro Average	0.96	0.96	0.96	553
Weighted Average	0.96	0.96	0.96	553

- The model performs very well, with a high precision, recall, and F1-score for both classes.
- Accuracy, macro average, and weighted average metrics all confirm the balanced and reliable performance.

Table 4: BERT

Class	**Precision**	**Recall**	**F1-Score**	**Support**
0.0	1.00	0.89	0.94	271
1.0	0.91	1.00	0.95	282
Accuracy			**0.95**	553
Macro Average	0.95	0.94	0.95	553
Weighted Average	0.95	0.95	0.95	553

- Class 0 has slightly lower recall (0.89), indicating some false negatives exist, but precision is perfect.
- Class 1 has perfect recall (1.00), ensuring all true instances are captured, but precision is slightly lower (0.91), indicating some false positives.
- The metrics are consistent across macro and weighted averages, indicating balanced data and predictions.

CHAPTER-10

CONCLUSION

The project "AI VS HUMAN: ACADEMIC ESSAY AUTHENTICITY CHALLENGE" successfully addresses the growing concern of distinguishing between AI-generated and human-written academic content. By leveraging machine learning algorithms like Random Forest Classifier, Convolutional Neural Networks (CNN), and BERT, the project developed an efficient system capable of accurately identifying the origin of academic essays. The model's ability to handle both English and Arabic text enhances its accessibility across different linguistic groups. Through extensive training on diverse datasets, the system demonstrated high accuracy and reliability in classifying text, promoting academic integrity and combating plagiarism. The proposed solution provides valuable support to educational institutions, researchers, and educators in maintaining the authenticity of scholarly work in an era where AI-generated content is becoming increasingly sophisticated. Ultimately, this project highlights the potential of AI and machine learning in preserving academic honesty and ensuring the credibility of academic work in the digital age.

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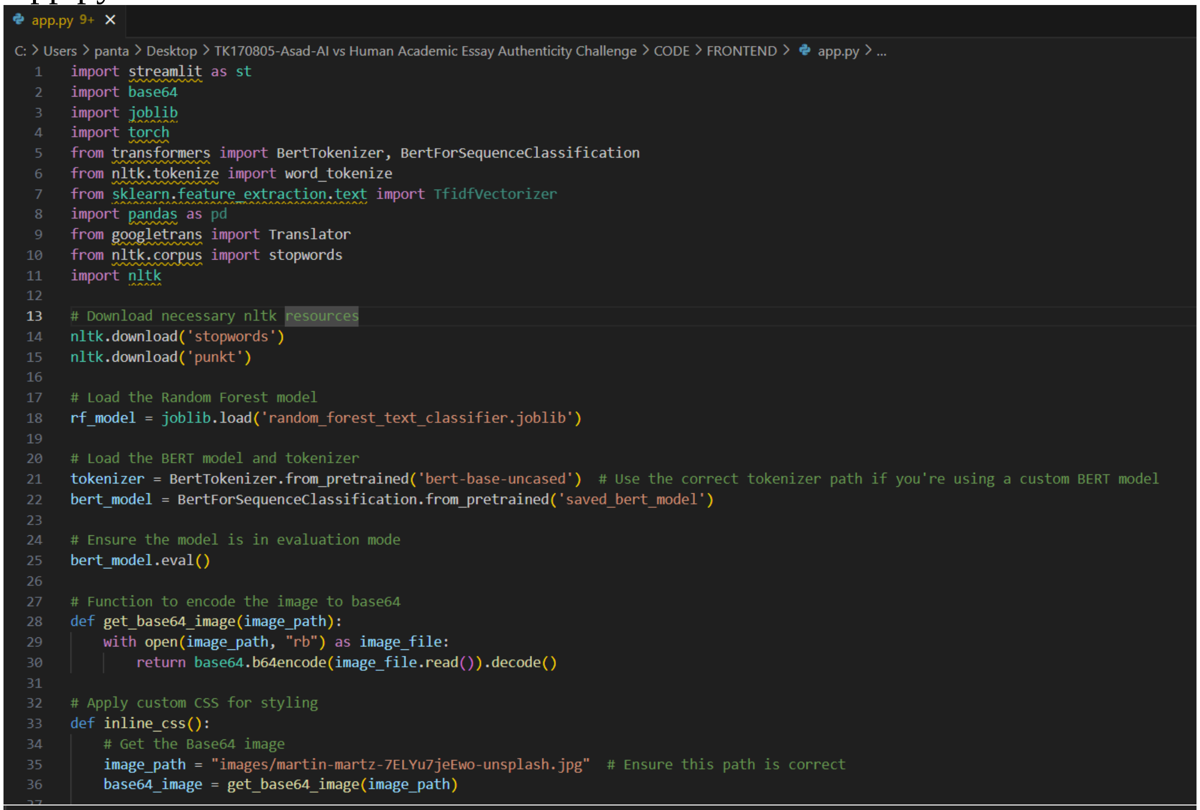
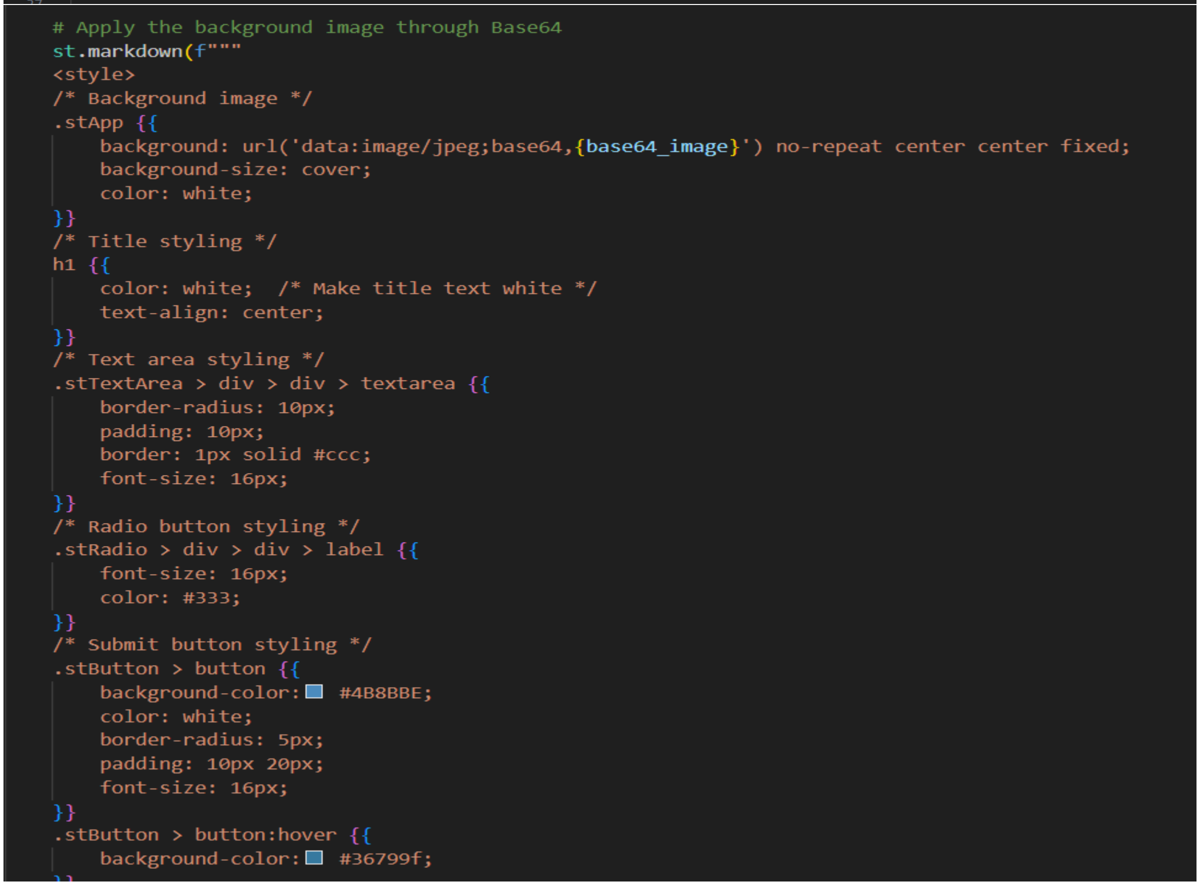
APPENDIX-A

CODE

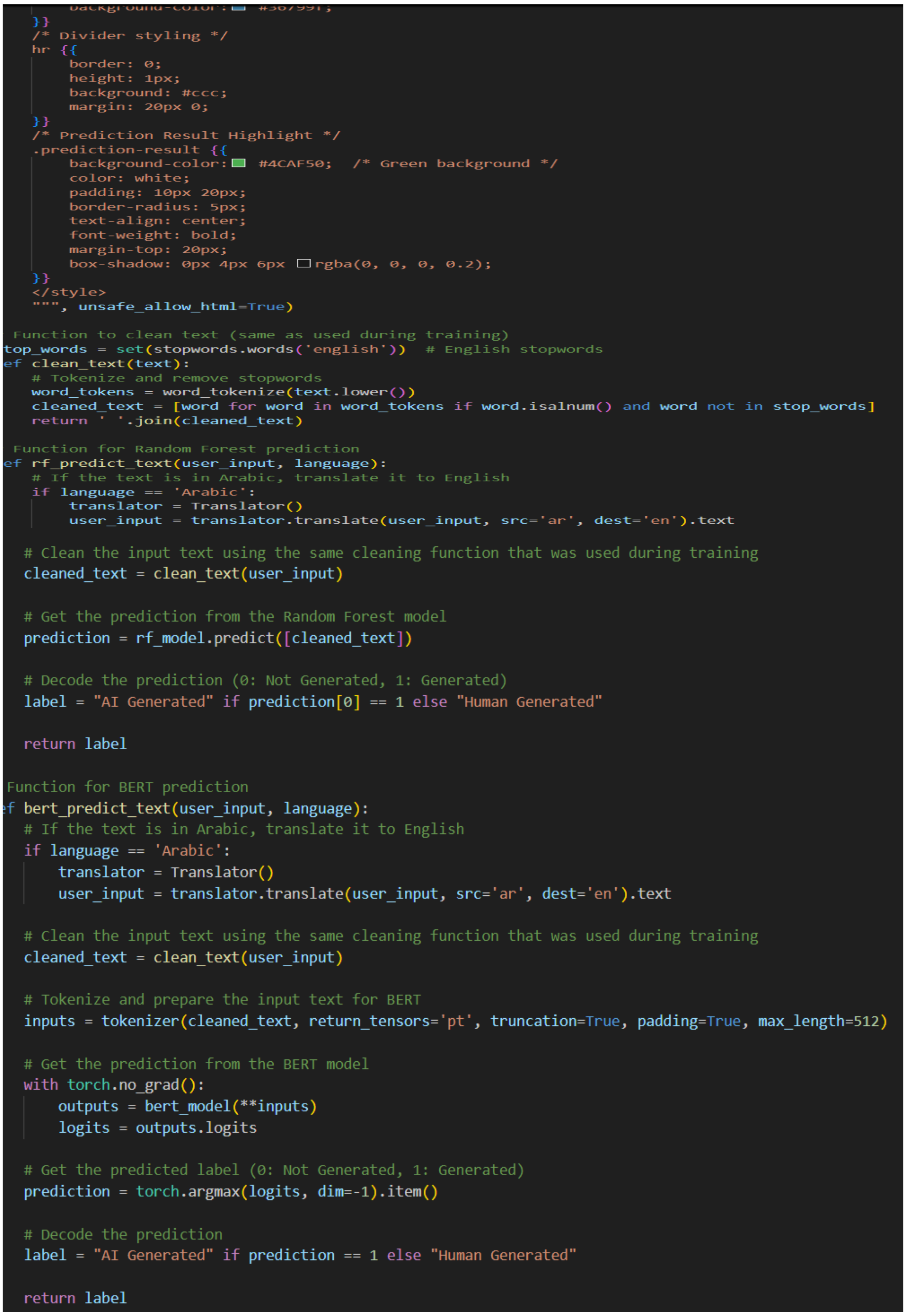
App.py


app.py 9+
C: > Users > panta > Desktop > TK170805-Asad-AI vs Human Academic Essay Authenticity Challenge > CODE > FRONTEND > app.py > ...

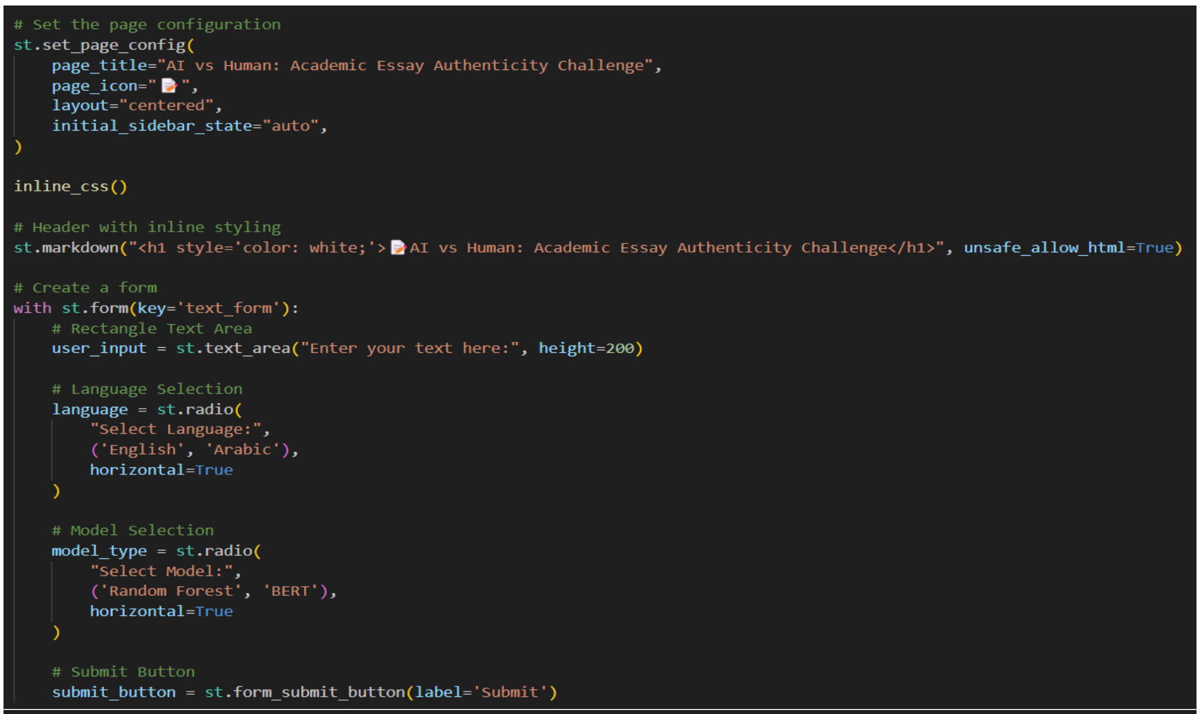
```python
import streamlit as st
import base64
import joblib
import torch
from transformers import BertTokenizer, BertForSequenceClassification
from nltk.tokenize import word_tokenize
from sklearn.feature_extraction.text import TfidfVectorizer
import pandas as pd
from googletrans import Translator
from nltk.corpus import stopwords
import nltk

# Download necessary nltk resources
nltk.download('stopwords')
nltk.download('punkt')

# Load the Random Forest model
rf_model = joblib.load('random_forest_text_classifier.joblib')

# Load the BERT model and tokenizer
tokenizer = BertTokenizer.from_pretrained('bert-base-uncased')  # Use the correct tokenizer path if you're using a custom BERT model
bert_model = BertForSequenceClassification.from_pretrained('saved_bert_model')

# Ensure the model is in evaluation mode
bert_model.eval()

# Function to encode the image to base64
def get_base64_image(image_path):
    with open(image_path, "rb") as image_file:
        return base64.b64encode(image_file.read()).decode()

# Apply custom CSS for styling
def inline_css():
    # Get the Base64 image
    image_path = "images/martin-martz-7ELYu7jeEwo-unsplash.jpg"  # Ensure this path is correct
    base64_image = get_base64_image(image_path)
```



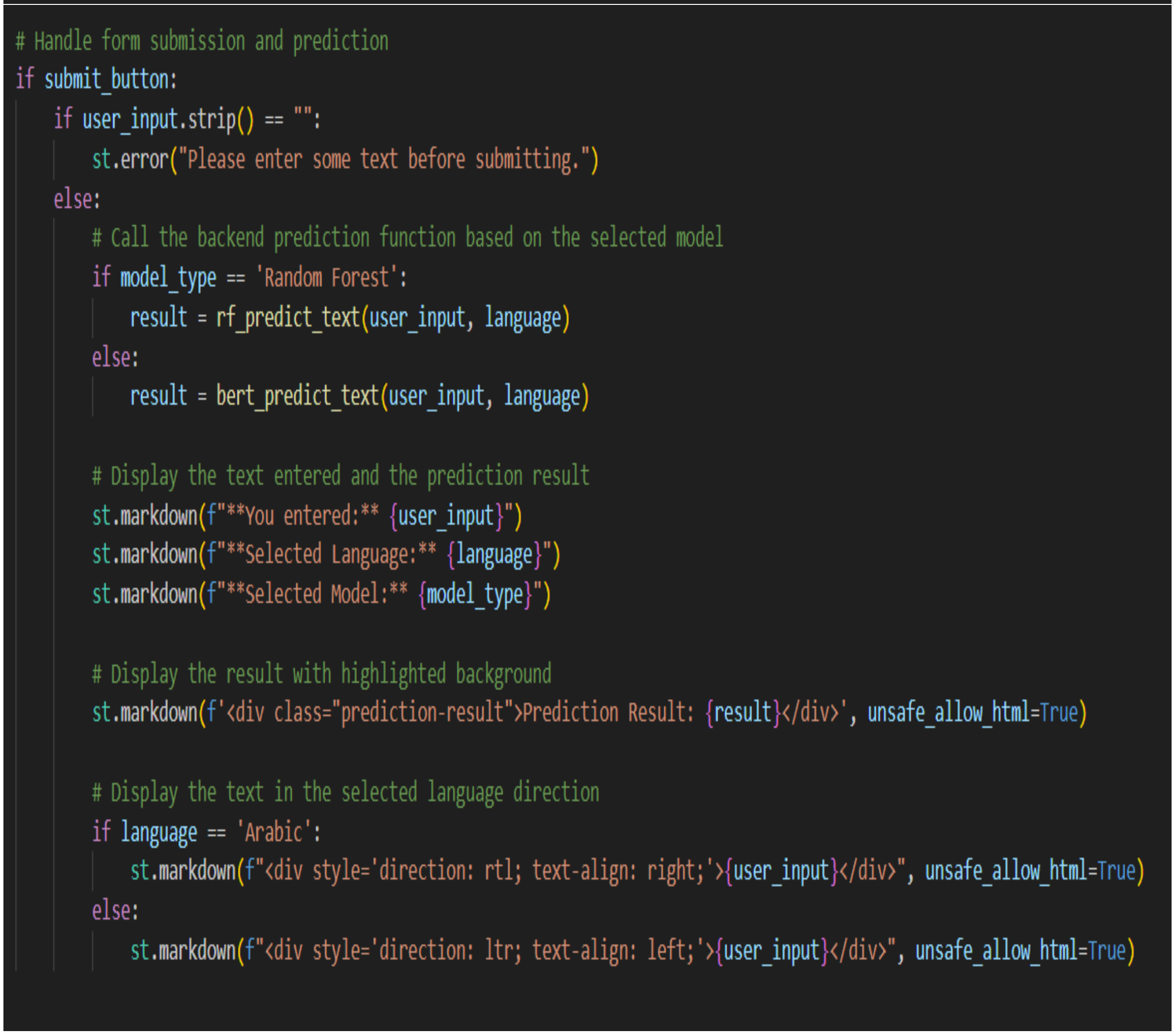
```python
    # Apply the background image through Base64
    st.markdown(f"""
    <style>
    /* Background image */
    .stApp {{
        background: url('data:image/jpeg;base64,{base64_image}') no-repeat center center fixed;
        background-size: cover;
        color: white;
    }}
    /* Title styling */
    h1 {{
        color: white;  /* Make title text white */
        text-align: center;
    }}
    /* Text area styling */
    .stTextArea > div > div > textarea {{
        border-radius: 10px;
        padding: 10px;
        border: 1px solid #ccc;
        font-size: 16px;
    }}
    /* Radio button styling */
    .stRadio > div > div > label {{
        font-size: 16px;
        color: #333;
    }}
    /* Submit button styling */
    .stButton > button {{
        background-color: #4B8BBE;
        color: white;
        border-radius: 5px;
        padding: 10px 20px;
        font-size: 16px;
    }}
    .stButton > button:hover {{
        background-color: #36799f;
```



```
        background-color: 🟦 #367991;
    }}
    /* Divider styling */
    hr {{
        border: 0;
        height: 1px;
        background: #ccc;
        margin: 20px 0;
    }}
    /* Prediction Result Highlight */
    .prediction-result {{
        background-color: 🟩 #4CAF50;  /* Green background */
        color: white;
        padding: 10px 20px;
        border-radius: 5px;
        text-align: center;
        font-weight: bold;
        margin-top: 20px;
        box-shadow: 0px 4px 6px ☐rgba(0, 0, 0, 0.2);
    }}
    </style>
    """, unsafe_allow_html=True)

 Function to clean text (same as used during training)
top_words = set(stopwords.words('english'))  # English stopwords
ef clean_text(text):
    # Tokenize and remove stopwords
    word_tokens = word_tokenize(text.lower())
    cleaned_text = [word for word in word_tokens if word.isalnum() and word not in stop_words]
    return ' '.join(cleaned_text)

 Function for Random Forest prediction
ef rf_predict_text(user_input, language):
    # If the text is in Arabic, translate it to English
    if language == 'Arabic':
        translator = Translator()
        user_input = translator.translate(user_input, src='ar', dest='en').text

    # Clean the input text using the same cleaning function that was used during training
    cleaned_text = clean_text(user_input)

    # Get the prediction from the Random Forest model
    prediction = rf_model.predict([cleaned_text])

    # Decode the prediction (0: Not Generated, 1: Generated)
    label = "AI Generated" if prediction[0] == 1 else "Human Generated"

    return label

 Function for BERT prediction
f bert_predict_text(user_input, language):
    # If the text is in Arabic, translate it to English
    if language == 'Arabic':
        translator = Translator()
        user_input = translator.translate(user_input, src='ar', dest='en').text

    # Clean the input text using the same cleaning function that was used during training
    cleaned_text = clean_text(user_input)

    # Tokenize and prepare the input text for BERT
    inputs = tokenizer(cleaned_text, return_tensors='pt', truncation=True, padding=True, max_length=512)

    # Get the prediction from the BERT model
    with torch.no_grad():
        outputs = bert_model(**inputs)
        logits = outputs.logits

    # Get the predicted label (0: Not Generated, 1: Generated)
    prediction = torch.argmax(logits, dim=-1).item()

    # Decode the prediction
    label = "AI Generated" if prediction == 1 else "Human Generated"

    return label
```

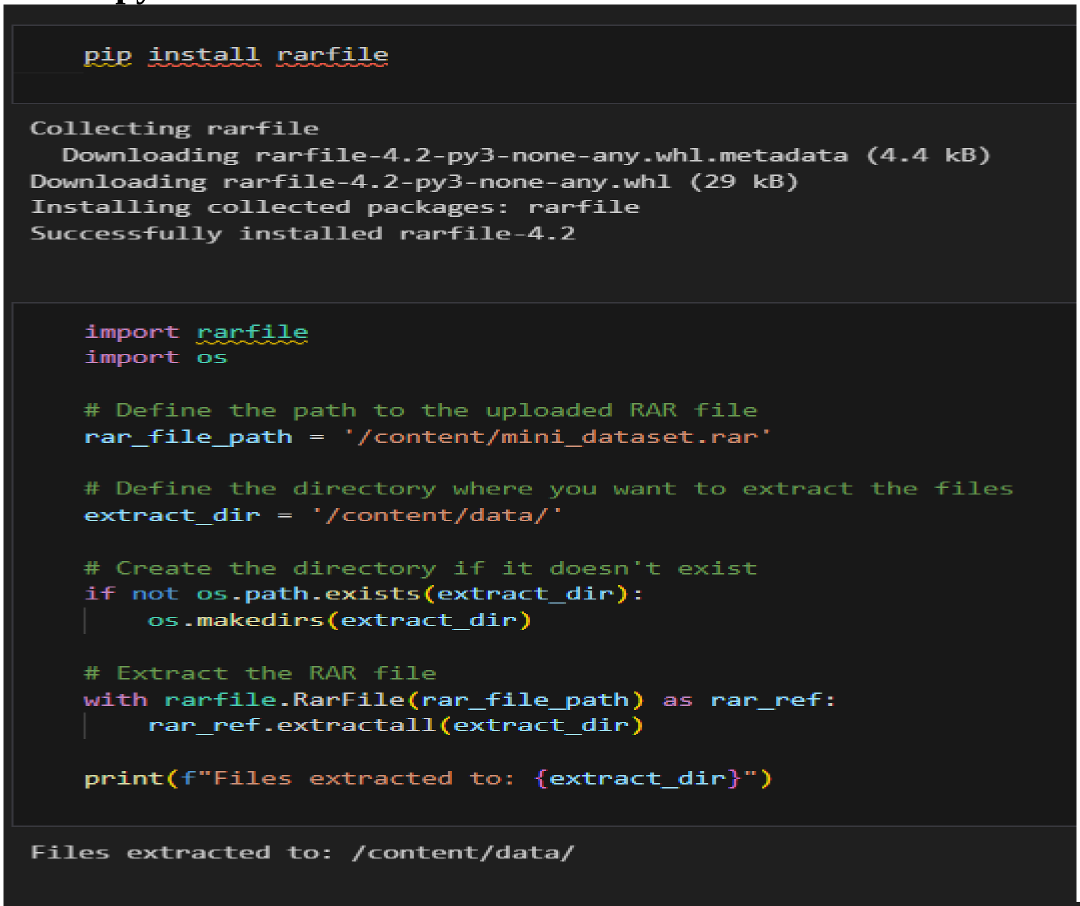


```python
# Set the page configuration
st.set_page_config(
    page_title="AI vs Human: Academic Essay Authenticity Challenge",
    page_icon="📝",
    layout="centered",
    initial_sidebar_state="auto",
)

inline_css()

# Header with inline styling
st.markdown("<h1 style='color: white;'>📝AI vs Human: Academic Essay Authenticity Challenge</h1>", unsafe_allow_html=True)

# Create a form
with st.form(key='text_form'):
    # Rectangle Text Area
    user_input = st.text_area("Enter your text here:", height=200)

    # Language Selection
    language = st.radio(
        "Select Language:",
        ('English', 'Arabic'),
        horizontal=True
    )

    # Model Selection
    model_type = st.radio(
        "Select Model:",
        ('Random Forest', 'BERT'),
        horizontal=True
    )

    # Submit Button
    submit_button = st.form_submit_button(label='Submit')
```



```python
# Handle form submission and prediction
if submit_button:
    if user_input.strip() == "":
        st.error("Please enter some text before submitting.")
    else:
        # Call the backend prediction function based on the selected model
        if model_type == 'Random Forest':
            result = rf_predict_text(user_input, language)
        else:
            result = bert_predict_text(user_input, language)

        # Display the text entered and the prediction result
        st.markdown(f"**You entered:** {user_input}")
        st.markdown(f"**Selected Language:** {language}")
        st.markdown(f"**Selected Model:** {model_type}")

        # Display the result with highlighted background
        st.markdown(f'<div class="prediction-result">Prediction Result: {result}</div>', unsafe_allow_html=True)

        # Display the text in the selected language direction
        if language == 'Arabic':
            st.markdown(f"<div style='direction: rtl; text-align: right;'>{user_input}</div>", unsafe_allow_html=True)
        else:
            st.markdown(f"<div style='direction: ltr; text-align: left;'>{user_input}</div>", unsafe_allow_html=True)
```

BERT.py

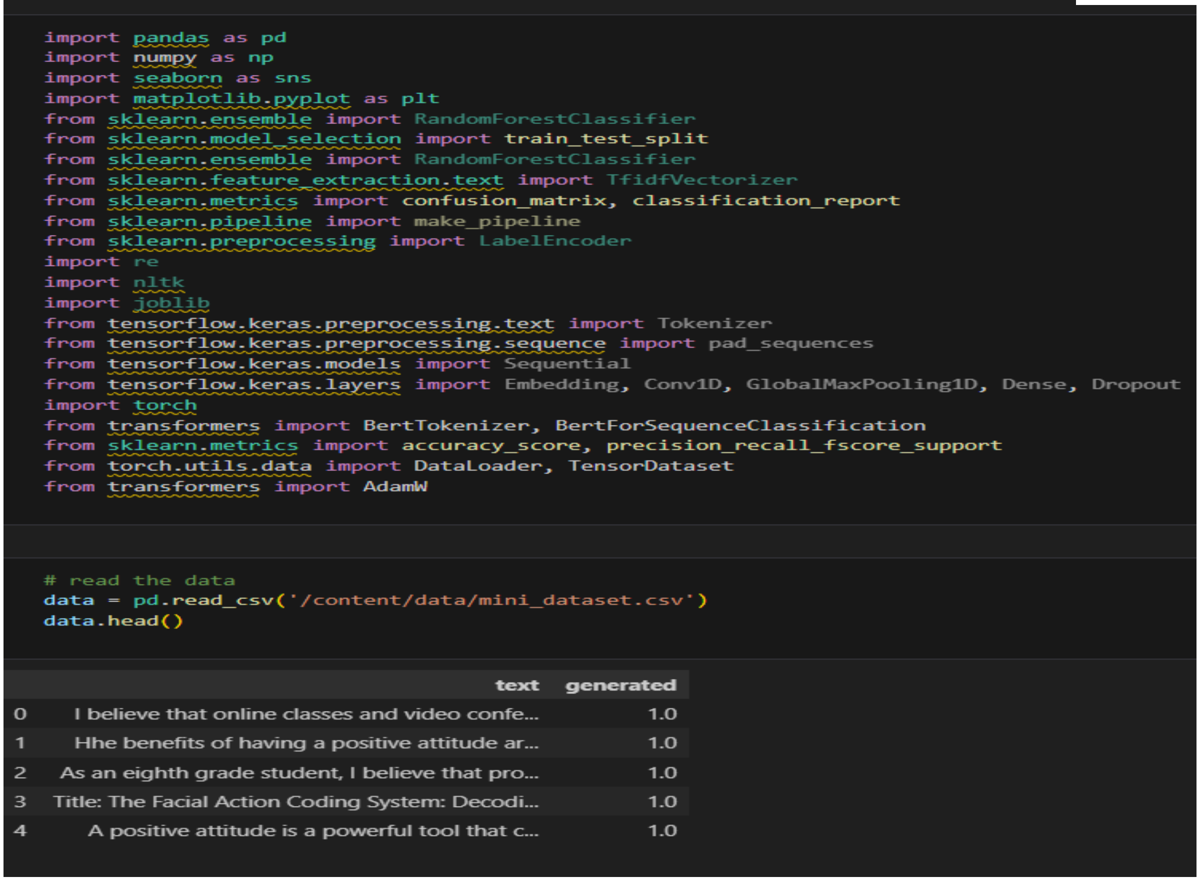


```
pip install rarfile
```

```
Collecting rarfile
  Downloading rarfile-4.2-py3-none-any.whl.metadata (4.4 kB)
Downloading rarfile-4.2-py3-none-any.whl (29 kB)
Installing collected packages: rarfile
Successfully installed rarfile-4.2
```

```python
import rarfile
import os

# Define the path to the uploaded RAR file
rar_file_path = '/content/mini_dataset.rar'

# Define the directory where you want to extract the files
extract_dir = '/content/data/'

# Create the directory if it doesn't exist
if not os.path.exists(extract_dir):
    os.makedirs(extract_dir)

# Extract the RAR file
with rarfile.RarFile(rar_file_path) as rar_ref:
    rar_ref.extractall(extract_dir)

print(f"Files extracted to: {extract_dir}")
```

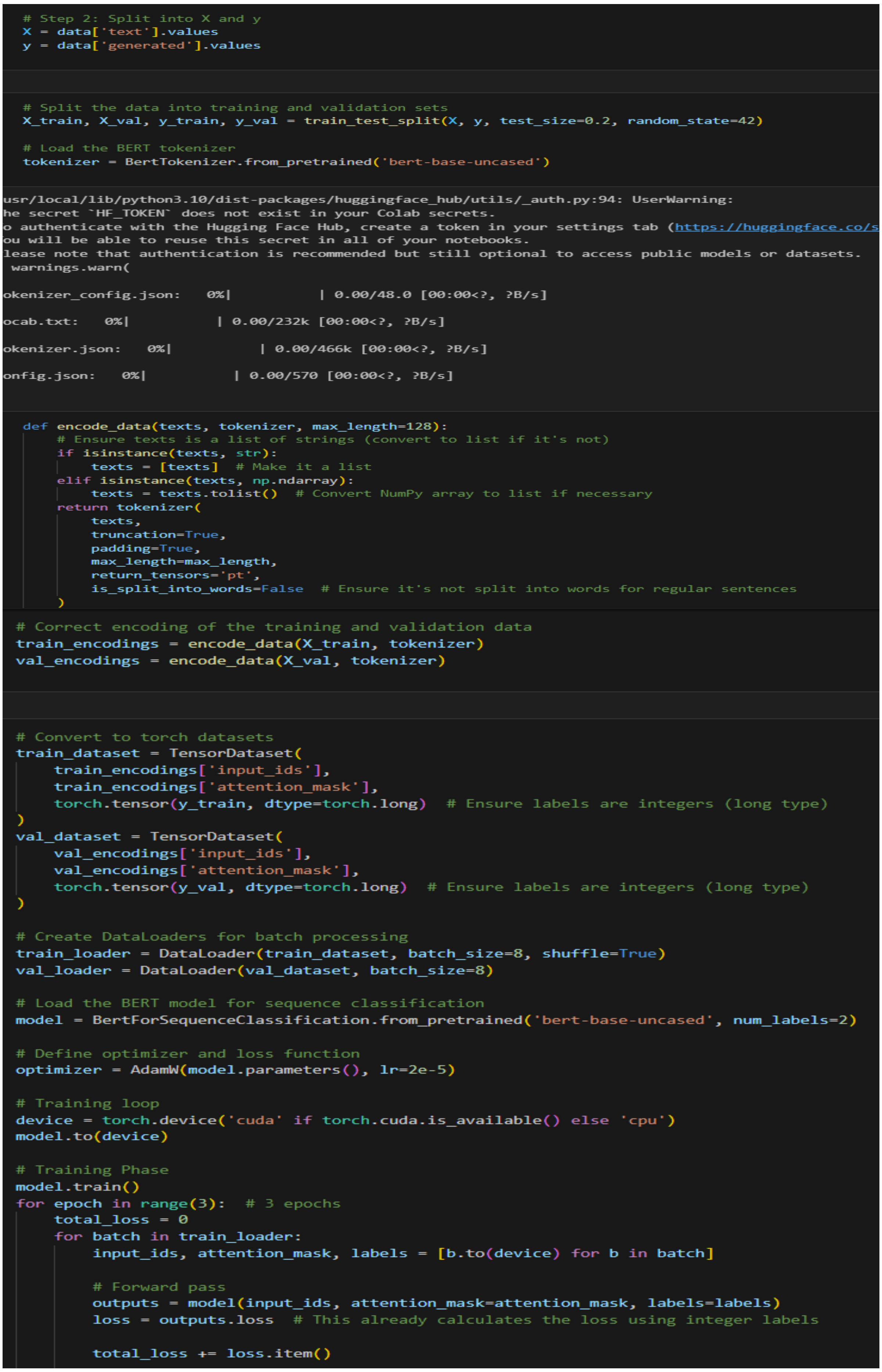
```
Files extracted to: /content/data/
```



```python
import pandas as pd
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt
from sklearn.ensemble import RandomForestClassifier
from sklearn.model_selection import train_test_split
from sklearn.ensemble import RandomForestClassifier
from sklearn.feature_extraction.text import TfidfVectorizer
from sklearn.metrics import confusion_matrix, classification_report
from sklearn.pipeline import make_pipeline
from sklearn.preprocessing import LabelEncoder
import re
import nltk
import joblib
from tensorflow.keras.preprocessing.text import Tokenizer
from tensorflow.keras.preprocessing.sequence import pad_sequences
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Embedding, Conv1D, GlobalMaxPooling1D, Dense, Dropout
import torch
from transformers import BertTokenizer, BertForSequenceClassification
from sklearn.metrics import accuracy_score, precision_recall_fscore_support
from torch.utils.data import DataLoader, TensorDataset
from transformers import AdamW
```

```python
# read the data
data = pd.read_csv('/content/data/mini_dataset.csv')
data.head()
```

	text	generated
0	I believe that online classes and video confe...	1.0
1	Hhe benefits of having a positive attitude ar...	1.0
2	As an eighth grade student, I believe that pro...	1.0
3	Title: The Facial Action Coding System: Decodi...	1.0
4	A positive attitude is a powerful tool that c...	1.0



```
# Step 2: Split into X and y
X = data['text'].values
y = data['generated'].values
```

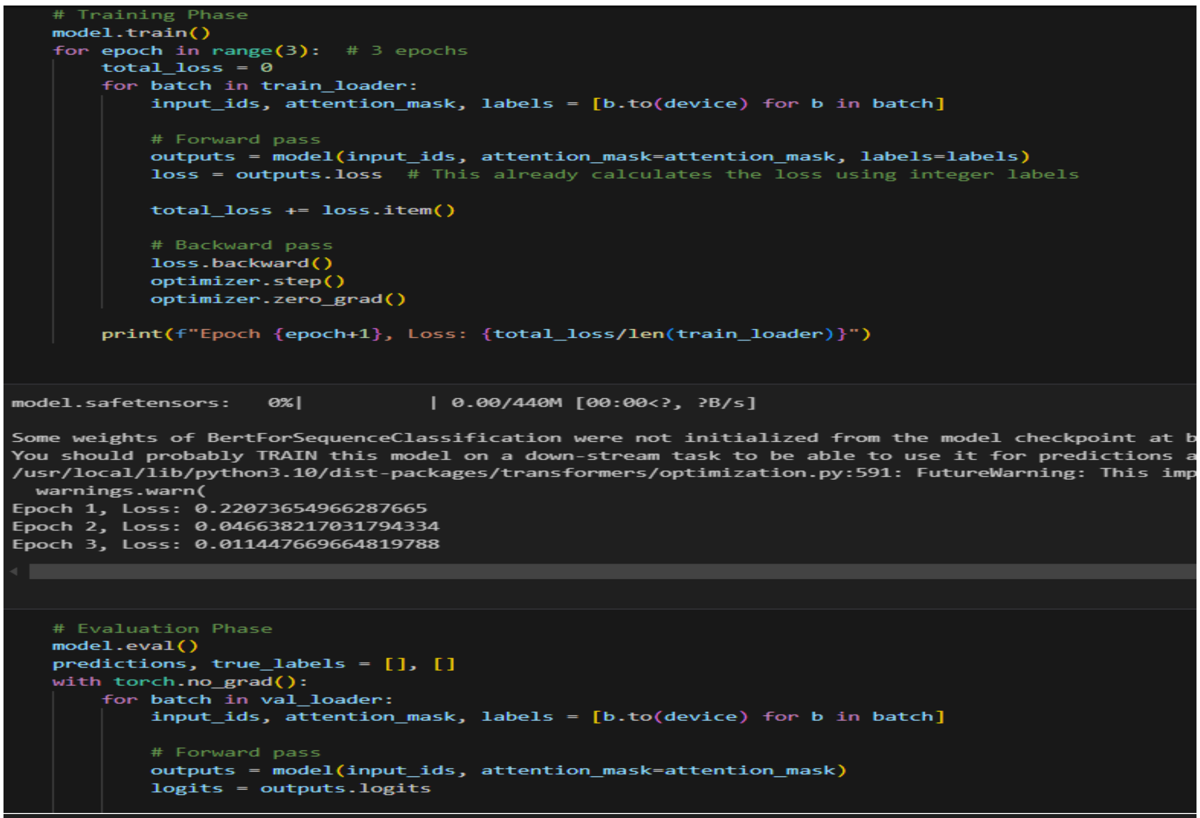
```
# Split the data into training and validation sets
X_train, X_val, y_train, y_val = train_test_split(X, y, test_size=0.2, random_state=42)

# Load the BERT tokenizer
tokenizer = BertTokenizer.from_pretrained('bert-base-uncased')
```

```
usr/local/lib/python3.10/dist-packages/huggingface_hub/utils/_auth.py:94: UserWarning:
he secret `HF_TOKEN` does not exist in your Colab secrets.
o authenticate with the Hugging Face Hub, create a token in your settings tab (https://huggingface.co/s
ou will be able to reuse this secret in all of your notebooks.
lease note that authentication is recommended but still optional to access public models or datasets.
 warnings.warn(

okenizer_config.json:   0%|          | 0.00/48.0 [00:00<?, ?B/s]

ocab.txt:   0%|          | 0.00/232k [00:00<?, ?B/s]

okenizer.json:   0%|          | 0.00/466k [00:00<?, ?B/s]

onfig.json:   0%|          | 0.00/570 [00:00<?, ?B/s]
```

```
def encode_data(texts, tokenizer, max_length=128):
    # Ensure texts is a list of strings (convert to list if it's not)
    if isinstance(texts, str):
        texts = [texts]  # Make it a list
    elif isinstance(texts, np.ndarray):
        texts = texts.tolist()  # Convert NumPy array to list if necessary
    return tokenizer(
        texts,
        truncation=True,
        padding=True,
        max_length=max_length,
        return_tensors='pt',
        is_split_into_words=False  # Ensure it's not split into words for regular sentences
    )
```

```
# Correct encoding of the training and validation data
train_encodings = encode_data(X_train, tokenizer)
val_encodings = encode_data(X_val, tokenizer)
```

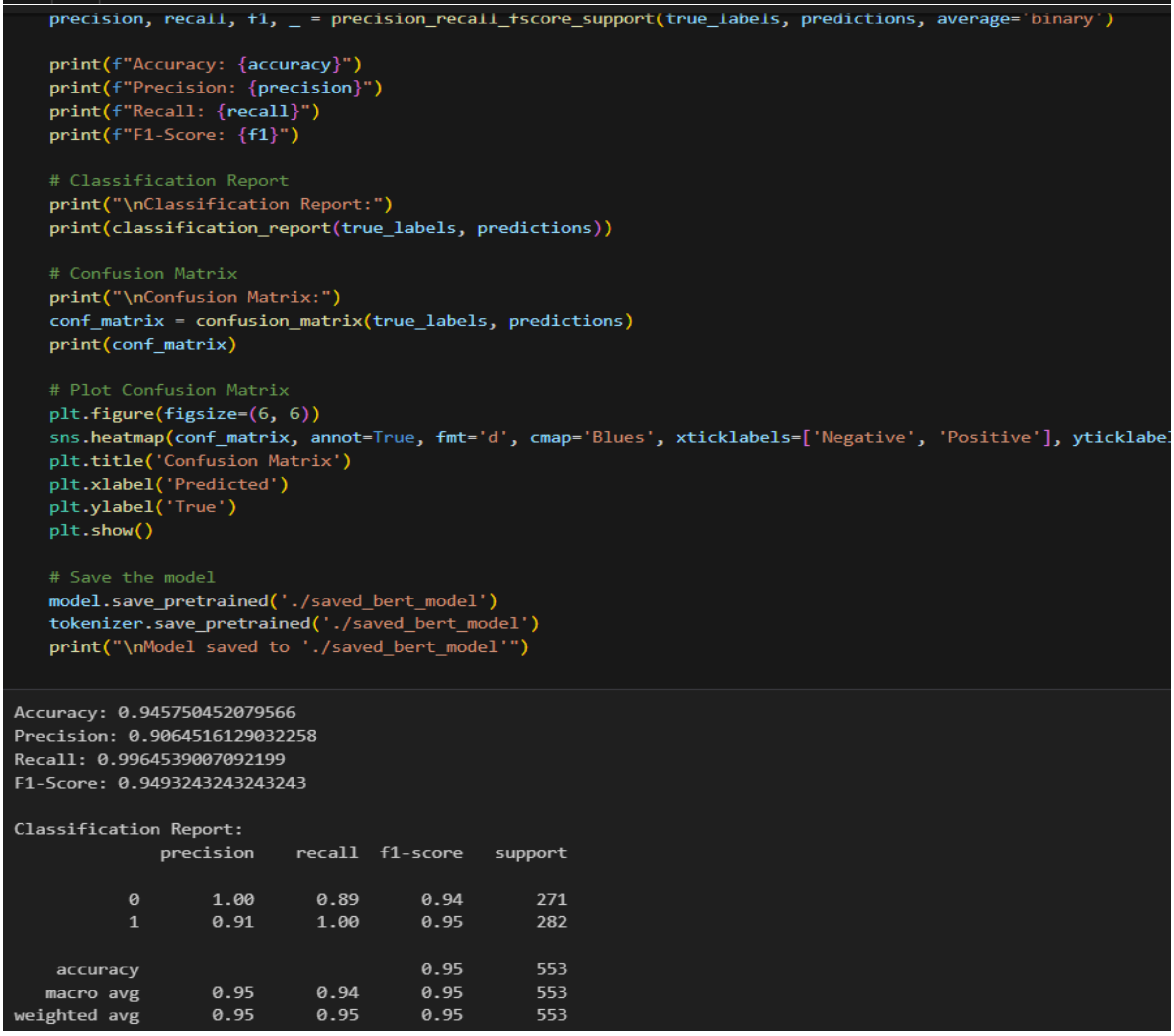
```
# Convert to torch datasets
train_dataset = TensorDataset(
    train_encodings['input_ids'],
    train_encodings['attention_mask'],
    torch.tensor(y_train, dtype=torch.long)  # Ensure labels are integers (long type)
)
val_dataset = TensorDataset(
    val_encodings['input_ids'],
    val_encodings['attention_mask'],
    torch.tensor(y_val, dtype=torch.long)  # Ensure labels are integers (long type)
)

# Create DataLoaders for batch processing
train_loader = DataLoader(train_dataset, batch_size=8, shuffle=True)
val_loader = DataLoader(val_dataset, batch_size=8)

# Load the BERT model for sequence classification
model = BertForSequenceClassification.from_pretrained('bert-base-uncased', num_labels=2)

# Define optimizer and loss function
optimizer = AdamW(model.parameters(), lr=2e-5)

# Training loop
device = torch.device('cuda' if torch.cuda.is_available() else 'cpu')
model.to(device)

# Training Phase
model.train()
for epoch in range(3):  # 3 epochs
    total_loss = 0
    for batch in train_loader:
        input_ids, attention_mask, labels = [b.to(device) for b in batch]

        # Forward pass
        outputs = model(input_ids, attention_mask=attention_mask, labels=labels)
        loss = outputs.loss  # This already calculates the loss using integer labels

        total_loss += loss.item()
```



```
    # Training Phase
    model.train()
    for epoch in range(3):  # 3 epochs
        total_loss = 0
        for batch in train_loader:
            input_ids, attention_mask, labels = [b.to(device) for b in batch]

            # Forward pass
            outputs = model(input_ids, attention_mask=attention_mask, labels=labels)
            loss = outputs.loss  # This already calculates the loss using integer labels

            total_loss += loss.item()

            # Backward pass
            loss.backward()
            optimizer.step()
            optimizer.zero_grad()

        print(f"Epoch {epoch+1}, Loss: {total_loss/len(train_loader)}")
```

```
model.safetensors:   0%|          | 0.00/440M [00:00<?, ?B/s]

Some weights of BertForSequenceClassification were not initialized from the model checkpoint at b
You should probably TRAIN this model on a down-stream task to be able to use it for predictions a
/usr/local/lib/python3.10/dist-packages/transformers/optimization.py:591: FutureWarning: This imp
  warnings.warn(
Epoch 1, Loss: 0.22073654966287665
Epoch 2, Loss: 0.046638217031794334
Epoch 3, Loss: 0.011447669664819788
```

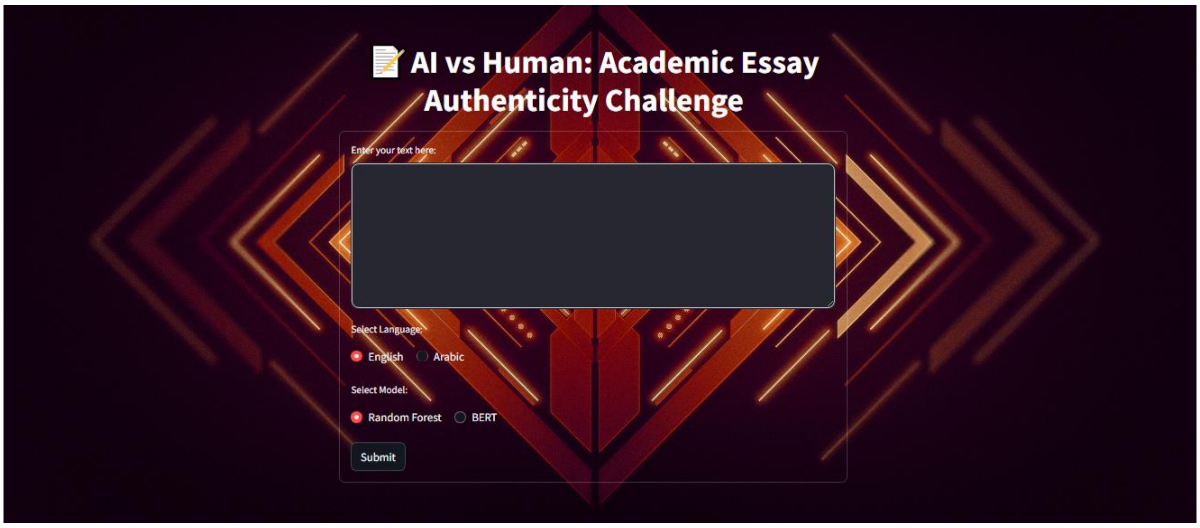
```
    # Evaluation Phase
    model.eval()
    predictions, true_labels = [], []
    with torch.no_grad():
        for batch in val_loader:
            input_ids, attention_mask, labels = [b.to(device) for b in batch]

            # Forward pass
            outputs = model(input_ids, attention_mask=attention_mask)
            logits = outputs.logits
```



```
    precision, recall, f1, _ = precision_recall_fscore_support(true_labels, predictions, average='binary')

    print(f"Accuracy: {accuracy}")
    print(f"Precision: {precision}")
    print(f"Recall: {recall}")
    print(f"F1-Score: {f1}")

    # Classification Report
    print("\nClassification Report:")
    print(classification_report(true_labels, predictions))

    # Confusion Matrix
    print("\nConfusion Matrix:")
    conf_matrix = confusion_matrix(true_labels, predictions)
    print(conf_matrix)

    # Plot Confusion Matrix
    plt.figure(figsize=(6, 6))
    sns.heatmap(conf_matrix, annot=True, fmt='d', cmap='Blues', xticklabels=['Negative', 'Positive'], yticklabe
    plt.title('Confusion Matrix')
    plt.xlabel('Predicted')
    plt.ylabel('True')
    plt.show()

    # Save the model
    model.save_pretrained('./saved_bert_model')
    tokenizer.save_pretrained('./saved_bert_model')
    print("\nModel saved to './saved_bert_model'")
```

```
Accuracy: 0.945750452079566
Precision: 0.9064516129032258
Recall: 0.9964539007092199
F1-Score: 0.9493243243243243

Classification Report:
              precision    recall  f1-score   support

           0       1.00      0.89      0.94       271
           1       0.91      1.00      0.95       282

    accuracy                           0.95       553
   macro avg       0.95      0.94      0.95       553
weighted avg       0.95      0.95      0.95       553
```

APPENDIX-B



📝 AI vs Human: Academic Essay Authenticity Challenge

Enter your text here:

Select Language:

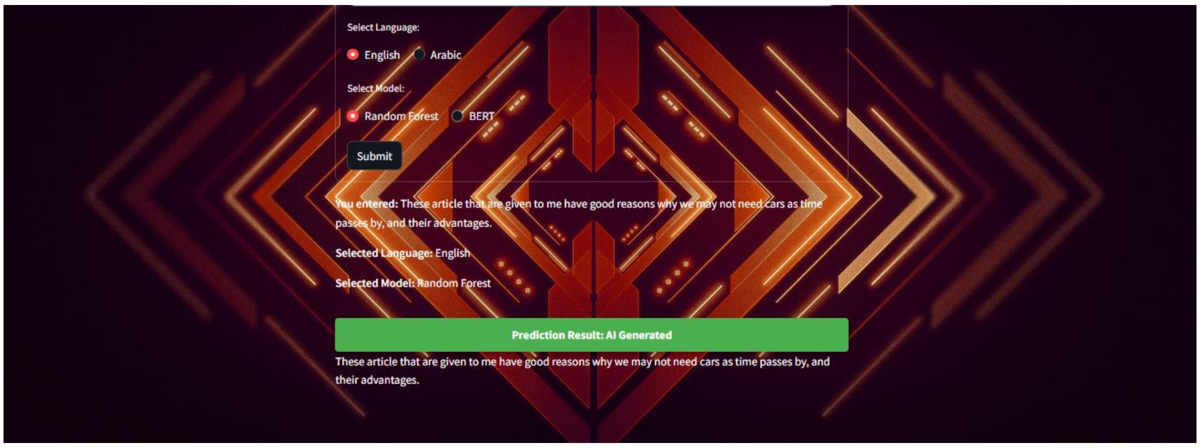
[✓ English] Arabic

Select Model:

[✓ Random Forest] BERT

Submit

OUTPUT 1: USER PAGE



Select Language:

[✓ English] Arabic

Select Model:

[✓ Random Forest] BERT

Submit

You entered: These article that are given to me have good reasons why we may not need cars as time passes by, and their advantages.

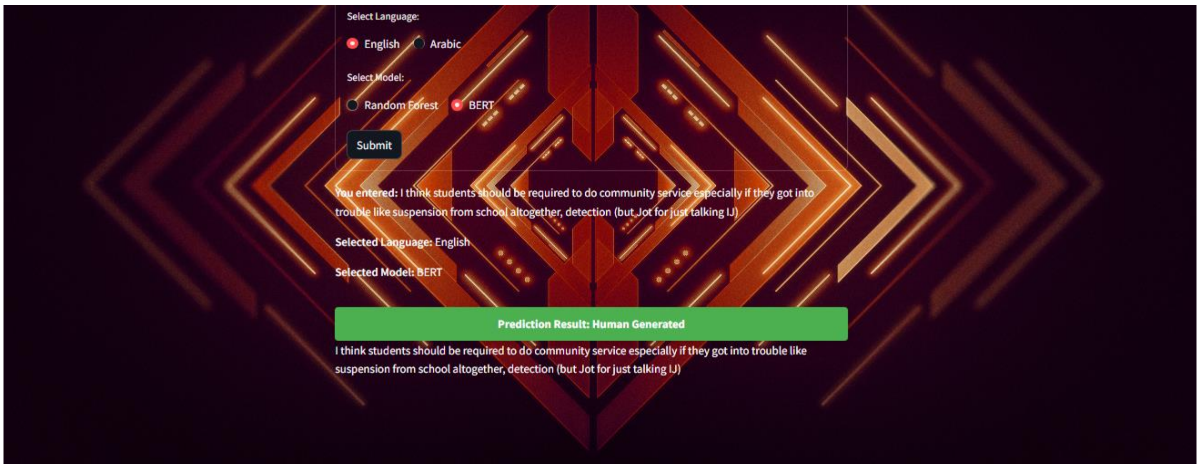
Selected Language: English

Selected Model: Random Forest

Prediction Result: AI Generated

These article that are given to me have good reasons why we may not need cars as time passes by, and their advantages.

OUTPUT 2: RESULT PAGE AI GENERATED



Select Language:

[✓ English] Arabic

Select Model:

Random Forest [✓ BERT]

Submit

You entered: I think students should be required to do community service especially if they got into trouble like suspension from school altogether, detection (but Jot for just talking IJ)

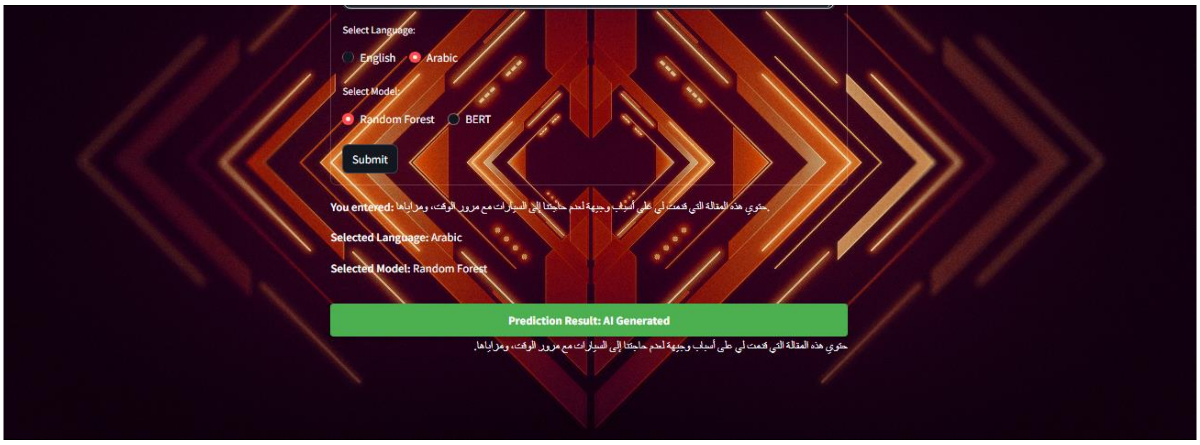
Selected Language: English

Selected Model: BERT

Prediction Result: Human Generated

I think students should be required to do community service especially if they got into trouble like suspension from school altogether, detection (but Jot for just talking IJ)

OUTPUT 3: RESULT PAGE HUMAN GENERATED



Select Language: English [✓ Arabic]

Select Model: [✓ Random Forest] BERT

You entered: حتوي هذه المقالة التي قدمت لي على أسباب وجيهة لعدم حاجتنا إلى السيارات مع مرور الوقت، ومزاياها.

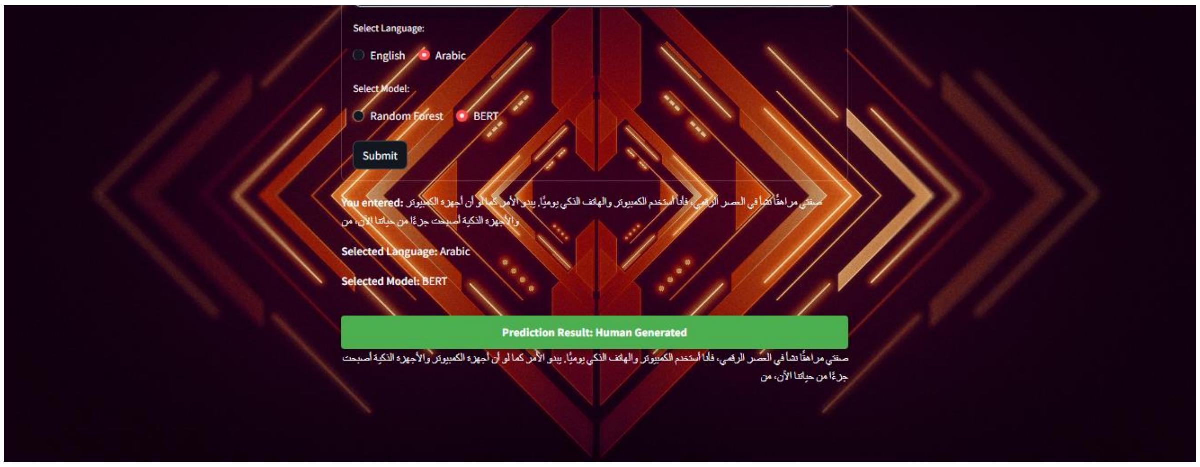
Selected Language: Arabic

Selected Model: Random Forest

Prediction Result: AI Generated

حتوي هذه المقالة التي قدمت لي على أسباب وجيهة لعدم حاجتنا إلى السيارات مع مرور الوقت، ومزاياها.

OUTPUT 4: RESULT PAGE ARABIC AI GENERATED



Select Language: English [✓ Arabic]

Select Model: Random Forest [✓ BERT]

You entered: صفتي مراهقًا نشأ في العصر الرقمي، فأنا أستخدم الكمبيوتر والهاتف الذكي يوميًا. يبدو الأمر كما لو أن أجهزة الكمبيوتر والأجهزة الذكية أصبحت جزءًا من حياتنا الآن، من

Selected Language: Arabic

Selected Model: BERT

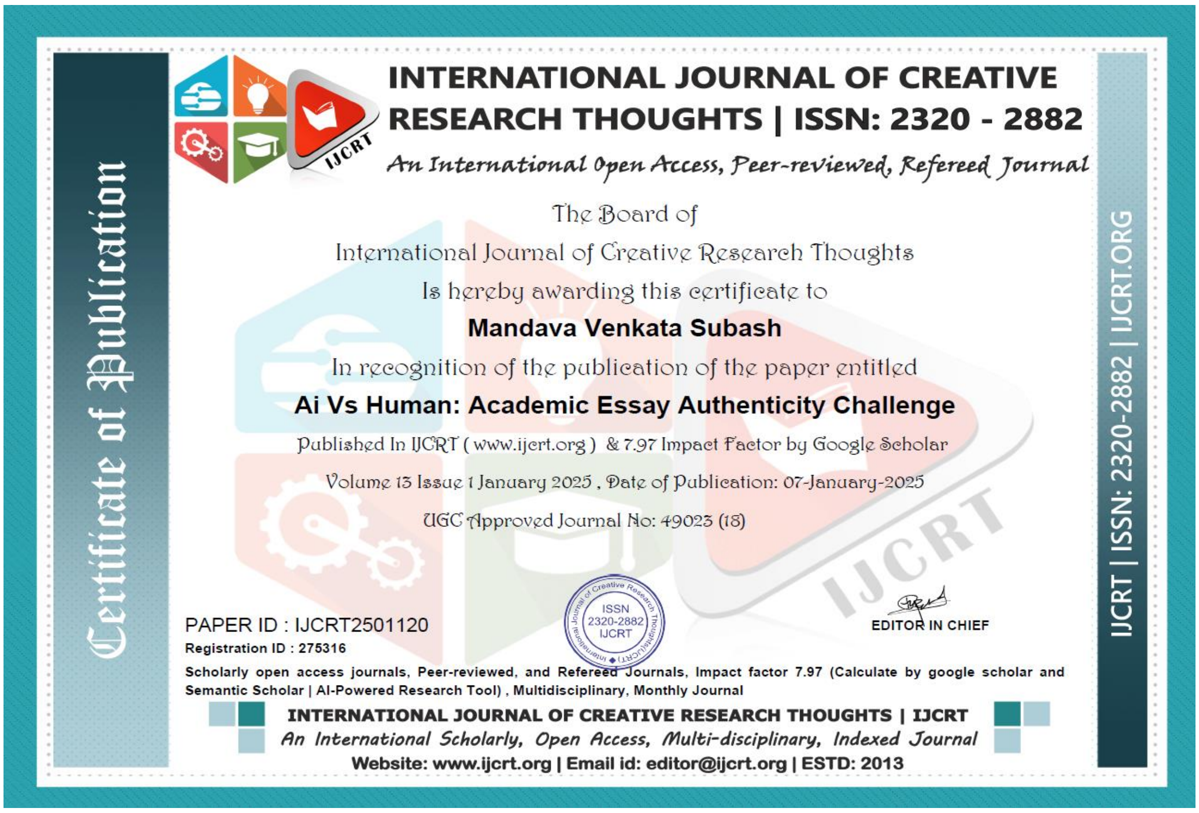
Prediction Result: Human Generated

صفتي مراهقًا نشأ في العصر الرقمي، فأنا أستخدم الكمبيوتر والهاتف الذكي يوميًا. يبدو الأمر كما لو أن أجهزة الكمبيوتر والأجهزة الذكية أصبحت جزءًا من حياتنا الآن، من

OUTPUT 5: RESULT PAGE ARABIC HUMAN GENERATED

APPENDIX-C

Journal publication Presented Certificates of all students.



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An International Open Access, Peer-reviewed, Refereed Journal

The Board of

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Is hereby awarding this certificate to

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Volume 13 Issue 1 January 2025 , Date of Publication: 07-January-2025

UGC Approved Journal No: 49023 (18)

PAPER ID : IJCRT2501120

Registration ID : 275316

International Journal of Creative Research Thoughts (IJCRT) ISSN 2320-2882 IJCRT

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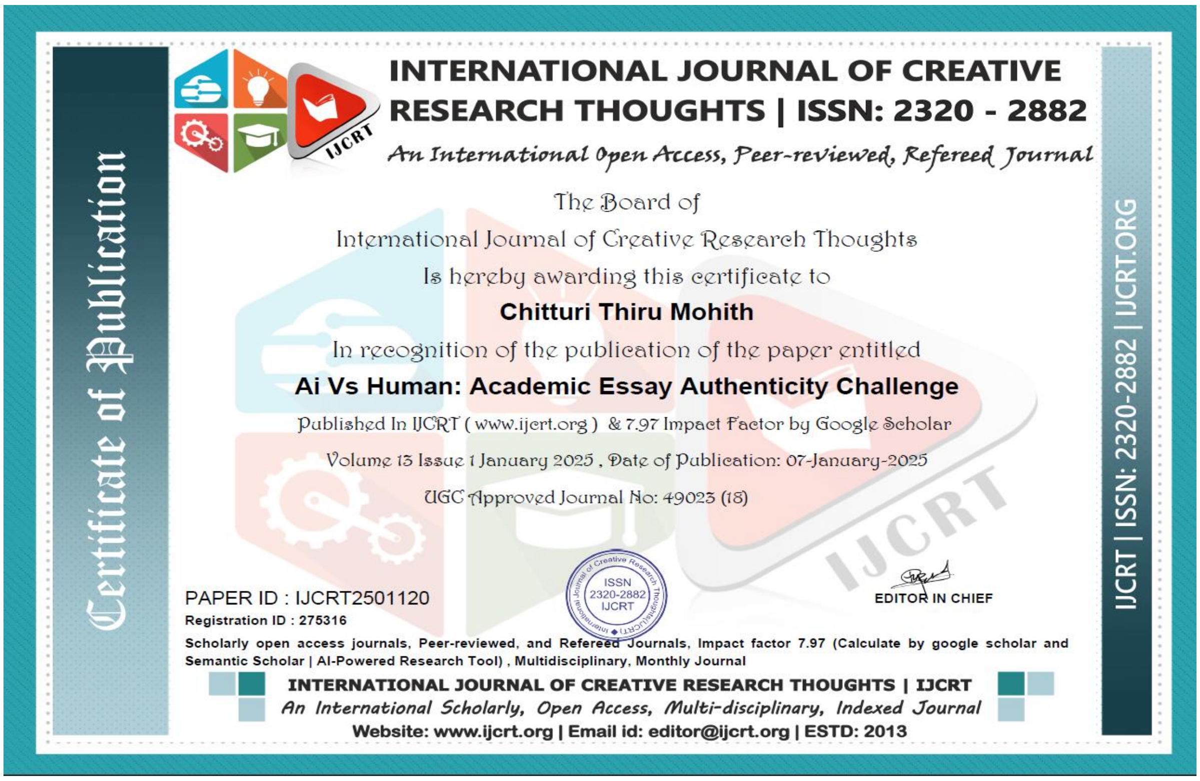
An International Scholarly, Open Access, Multi-disciplinary, Indexed Journal

Website: www.ijcrt.org | Email id: editor@ijcrt.org | ESTD: 2013

IJCRT | ISSN: 2320-2882 | IJCRT.ORG



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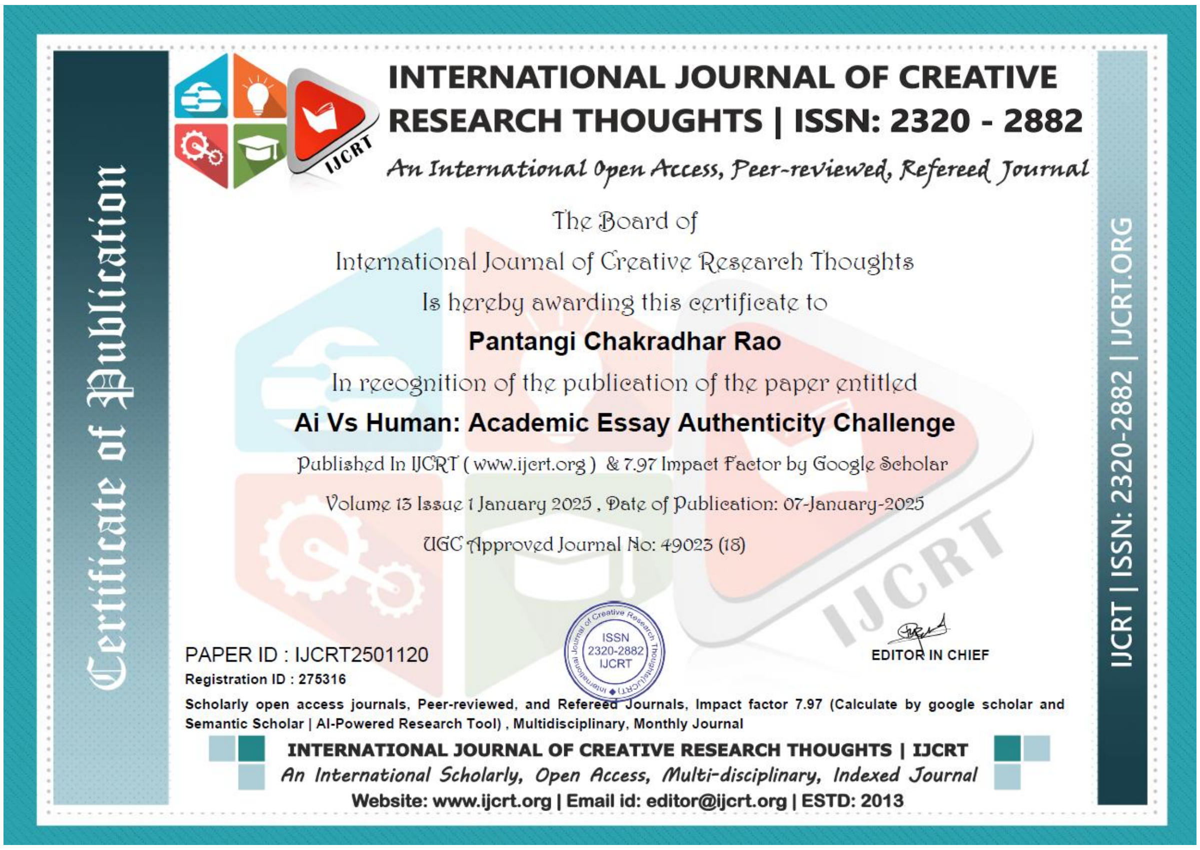
Website: www.ijcrt.org | Email id: editor@ijcrt.org | ESTD: 2013

IJCRT | ISSN: 2320-2882 | IJCRT.ORG



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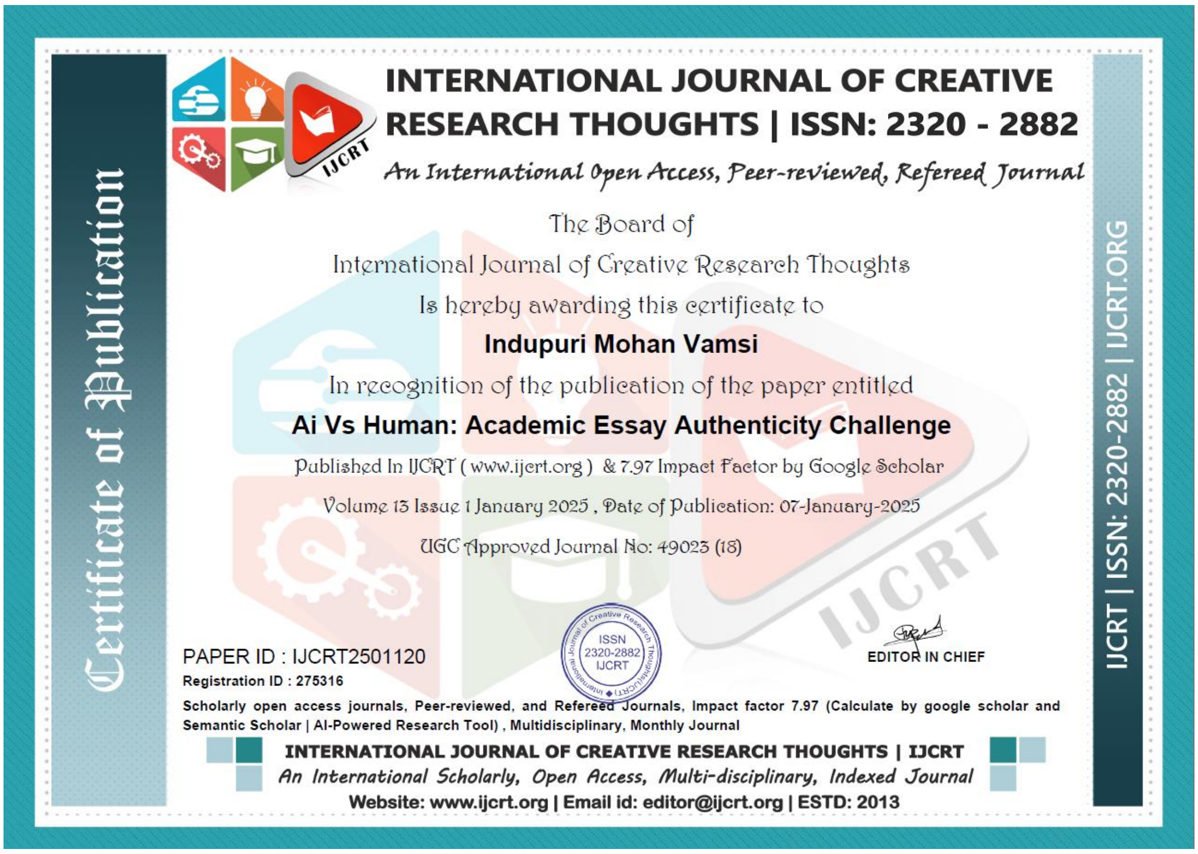

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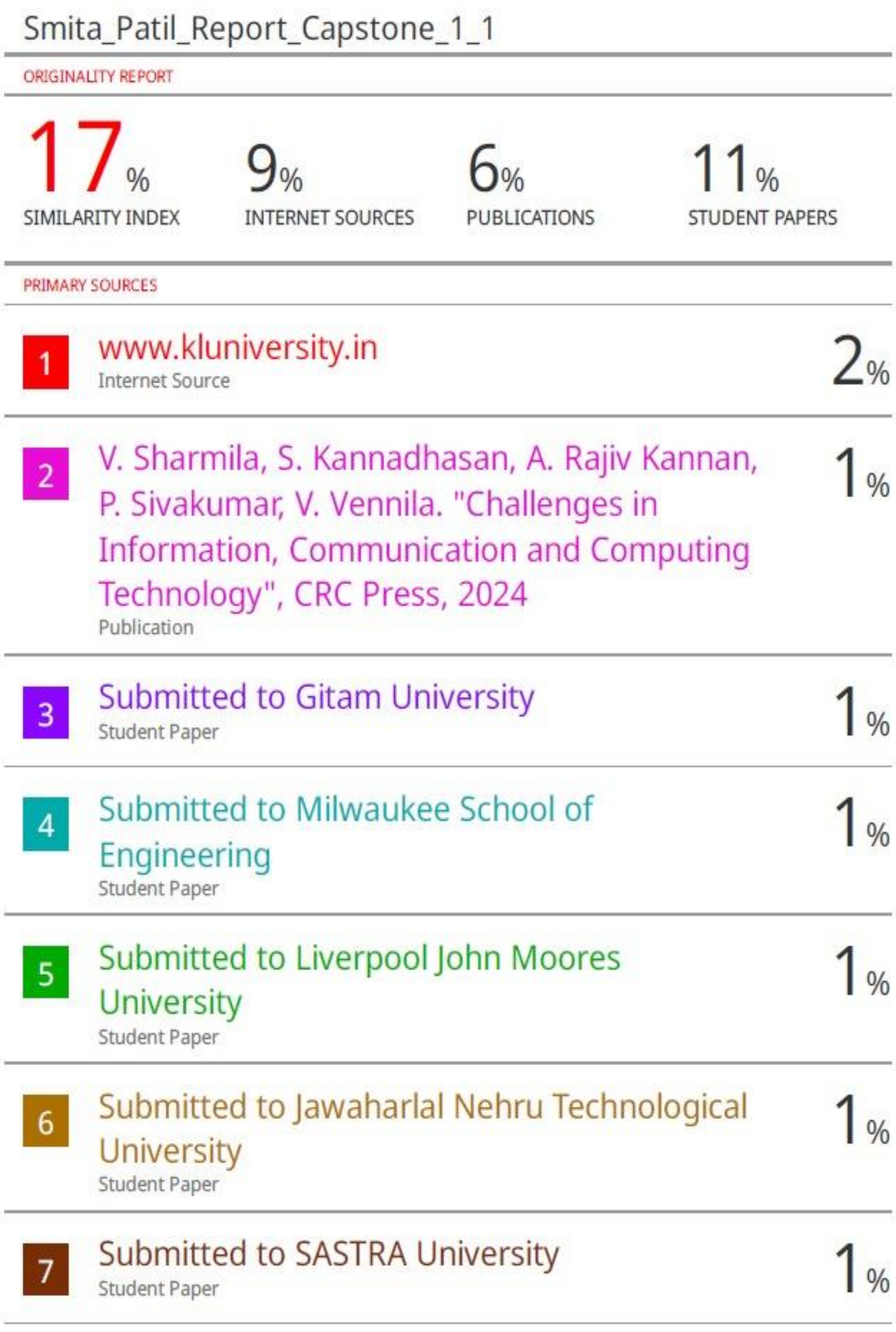

Smita_Patil_Report_Capstone_1_1

ORIGINALITY REPORT

17%	9%	6%	11%
SIMILARITY INDEX	INTERNET SOURCES	PUBLICATIONS	STUDENT PAPERS

PRIMARY SOURCES

1	www.kluniversity.in Internet Source	2%
2	V. Sharmila, S. Kannadhasan, A. Rajiv Kannan, P. Sivakumar, V. Vennila. "Challenges in Information, Communication and Computing Technology", CRC Press, 2024 Publication	1%
3	Submitted to Gitam University Student Paper	1%
4	Submitted to Milwaukee School of Engineering Student Paper	1%
5	Submitted to Liverpool John Moores University Student Paper	1%
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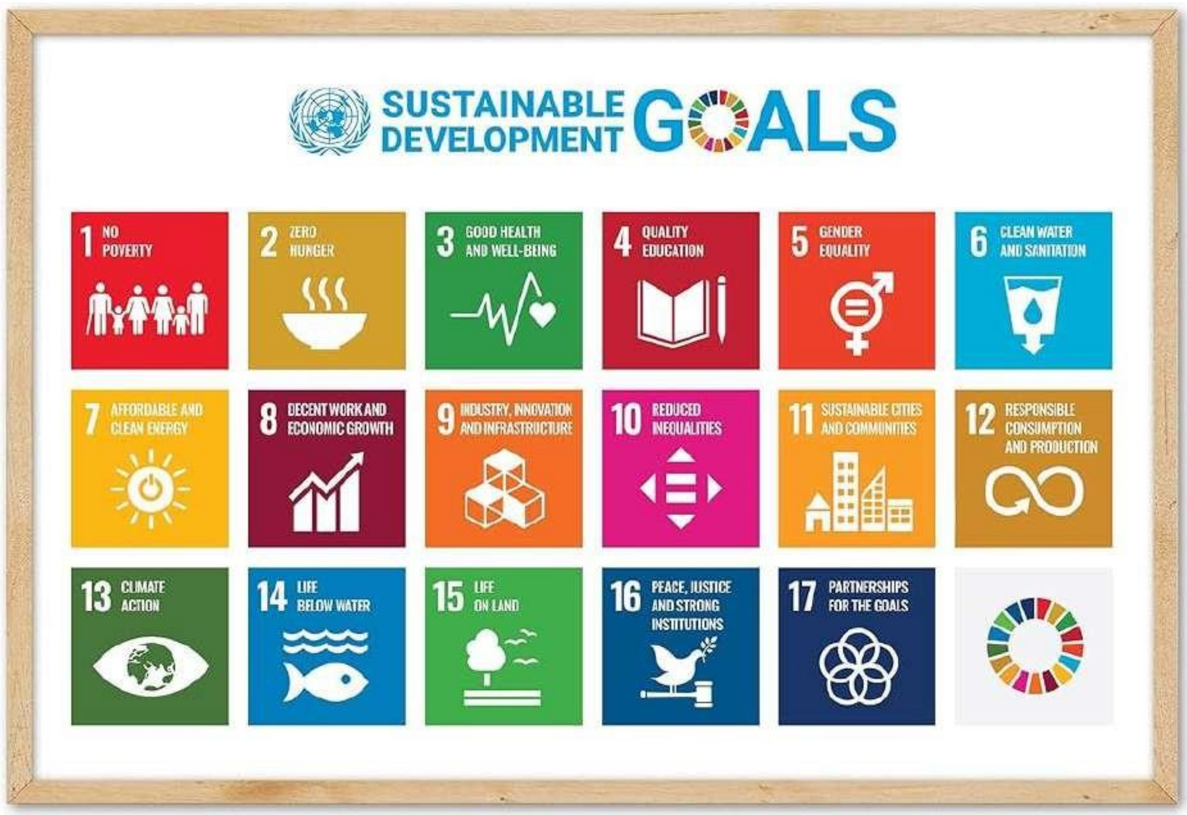
SUSTAINABLE DEVELOPMENT GOALS


SUSTAINABLE DEVELOPMENT GOALS
1 NO POVERTY
2 ZERO HUNGER
3 GOOD HEALTH AND WELL-BEING
4 QUALITY EDUCATION
5 GENDER EQUALITY
6 CLEAN WATER AND SANITATION
7 AFFORDABLE AND CLEAN ENERGY
8 DECENT WORK AND ECONOMIC GROWTH
9 INDUSTRY, INNOVATION AND INFRASTRUCTURE
10 REDUCED INEQUALITIES
11 SUSTAINABLE CITIES AND COMMUNITIES
12 RESPONSIBLE CONSUMPTION AND PRODUCTION
13 CLIMATE ACTION
14 LIFE BELOW WATER
15 LIFE ON LAND
16 PEACE, JUSTICE AND STRONG INSTITUTIONS
17 PARTNERSHIPS FOR THE GOALS

The Role of Infrastructure and Innovation in Sustainable Development

Infrastructure plays a critical role in facilitating trade, improving communication, and enabling economic activities. Without robust and sustainable infrastructure, economic growth risks stagnation. **SDG 9 (Industry, Innovation, and Infrastructure)** highlights the importance of investing in infrastructure that supports economic growth while protecting natural resources.

Promoting Innovation

- Encouraging technological development helps countries **leapfrog traditional practices**, reducing inefficiencies and enhancing sustainability.

Key Objectives of SDG 9

- Focus on building **high-quality, reliable, sustainable, and resilient infrastructure**.
- Support economic growth and improve welfare by ensuring **affordable and equitable access** for all.