Tab 1

VISVESVARAYA TECHNOLOGICAL UNIVERSITY

"Jnana Sangama" Belagavi - 590018, Karnataka.

MINI PROJECT REPORT

on

"MINI-PROJECT TITLE"

Submitted in the partial fulfilment of requirements for the award of Degree

B.E. in Artificial Intelligence & Machine Learning

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CERTIFICATE

This is to certify that Cholaraja R P, Niveditha M G, Rinith R, and Divyashree S, bearing USNs **4BD22AI008, 4BD22AI028, 4BD22AI037,** and **4BD23AI401**, respectively, of the **Artificial Intelligence & Machine Learning Department**, have satisfactorily submitted the Mini Project report entitled "**Plagiarism Detector and Analyzer using AI&ML**" in partial fulfillment of the requirements for the award of the **Degree of Bachelor of Engineering (B.E.)** in Artificial Intelligence & Machine Learning, under **Visvesvaraya Technological University (VTU)** during the academic year 2024-25.

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ABSTRACT

Plagiarism detection has become a crucial component in academia and professional writing, as advancements in technology make it easier for individuals to copy existing content. The advent of Artificial Intelligence (AI) and Machine Learning (ML) has provided novel methods for automating plagiarism detection, leading to systems that are more accurate and efficient than traditional manual approaches. AI-based plagiarism detection systems analyze linguistic patterns, syntax, and semantic similarity between texts to detect plagiarized content, even if it is paraphrased or subtly altered. Machine learning algorithms enable these systems to improve over time by learning from large datasets of plagiarized and original texts. This mini-project focuses on designing a plagiarism detection and analysis system powered by AI and ML techniques. By incorporating Natural Language Processing (NLP) models, such systems can evaluate not only surface-level similarities but also deeper contextual matches. The report will discuss existing plagiarism detection algorithms, their limitations, and how AI and ML techniques are evolving to address these shortcomings. Additionally, we will explore how training machine learning models on large-scale datasets can enhance the detection of complex cases such as translated or heavily paraphrased content. The objective of this project is to develop a system that can not only detect plagiarism but also provide a detailed analysis of how the detected content relates to the original source, offering suggestions for improving originality. This approach aims to make plagiarism detection more intelligent and adaptable to the changing landscape of content creation.

Chapter 1

INTRODUCTION

1.1 Background of Plagiarism Detection

Plagiarism, defined as the act of copying someone else's work or ideas and presenting them as one's own, has long been a significant issue in educational, research, and professional environments. It affects not only creativity and commercial interests but also academia, where it directly impacts the grading process and the accurate evaluation of student abilities [1]. With the proliferation of digital content and the ease of access to a vast array of resources on the internet, the rate of plagiarism has escalated. Plagiarism detection has extended beyond text documents to include source code, where students often submit plagiarized programming assignments, further complicating the detection process [1].

Traditional manual methods of plagiarism detection, which involve comparing documents manually, are time-consuming and often ineffective, especially when dealing with large volumes of text or sophisticated forms of content manipulation such as paraphrasing or translation. The need for automated plagiarism detection tools has become crucial, particularly in academic settings, to assist educators in identifying plagiarized work efficiently [1]. Moreover, linguistic patterns in plagiarism detection highlight key challenges in identifying instances where text has been manipulated through paraphrasing, summarizing, or even translation, which poses unique challenges to existing detection systems [6].

This increasing complexity has led to the adoption of automated tools designed to detect similarities between texts. However, early plagiarism detection tools primarily relied on string-matching algorithms, which were only effective in detecting direct copy-pasting of text. These tools lacked the ability to detect more complex forms of plagiarism, such as paraphrasing or structural rewording, and were limited in handling semantic similarities. Plagiarism detection systems such as MOSS, JPlag, and Turnitin have evolved to include NLP techniques and machine learning models to detect both simple and advanced forms of plagiarism [4].

1.2 The Role of AI and ML in Plagiarism Detection

Artificial Intelligence (AI) and Machine Learning (ML) have introduced a transformative shift in how plagiarism is detected and analyzed. AI, which aims to create machines capable of performing tasks that typically require human intelligence, provides the computational power and cognitive capabilities needed to handle intricate plagiarism patterns. AI-based systems can help enhance the accuracy of detecting different types of plagiarism, such as self-plagiarism and team plagiarism, which remain challenging even with current anti-plagiarism tools [2]. Deep learning models such as BERT, RoBERTa, and GLoVE are increasingly employed in modern plagiarism detection systems to improve detection rates by considering contextual information beyond simple text comparisons [5].

Machine Learning, a subset of AI, allows systems to learn from data, improving the accuracy of plagiarism detection as more data is processed. Modern plagiarism detection tools equipped with AI and ML leverage Natural Language Processing (NLP) techniques to understand the semantics and context of text, enabling them to detect not only verbatim copying but also more sophisticated methods of content replication. For example, in institutions like Jawaharlal Nehru University, tools such as Urkund support the detection of plagiarism in multiple languages using AI, offering wide database coverage [3]. NLP allows the system to interpret the structure and meaning of sentences, making it possible to identify paraphrased content that may escape detection by traditional methods. Moreover, machine learning models trained on large corpora can discern subtle textual relationships, aiding in identifying hidden patterns of plagiarism.

1.3 How AI & ML Work in Plagiarism Detection Systems

A typical AI-based plagiarism detection system comprises several stages: preprocessing, feature extraction, and similarity detection. Preprocessing involves cleaning the text, tokenizing sentences, and preparing the content for analysis. During feature extraction, important textual features such as word frequency, sentence structure, and contextual meaning are captured using advanced NLP models, like Word2Vec, BERT (Bidirectional Encoder Representations from Transformers), and transformers. These models enable the system to generate vector representations of words and phrases, capturing semantic meaning beyond simple text matching.

The core of an AI-powered plagiarism detection system is the similarity detection algorithm. Traditional methods rely on simple string-matching algorithms like the Levenshtein Distance or Cosine Similarity, which can detect exact or near-exact matches. However, AI-enhanced systems employ machine learning techniques that are capable of identifying more abstract forms of similarity. For instance, Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs) are used to detect patterns in long sequences of text, while deep learning models can analyze large datasets to identify instances of paraphrasing or translation-based plagiarism. This capability is essential when dealing with plagiarism across multiple languages, as seen with tools like Ouriginal (Urkund), which supports different languages and allows complex text analysis through NLP [3]. Moreover, AI-based systems use tokenization and POS tagging methods to break down text into smaller components, enhancing the precision of plagiarism detection across different types of documents [5].

1.4 Applications and Benefits of AI-based Plagiarism Detection

AI-based plagiarism detection systems are now widely used in academia, publishing, and content creation industries. Educational institutions use these systems to ensure the originality of students' work, while publishers employ them to verify the uniqueness of submissions. Tools like Turnitin, Grammarly, and Copyscape utilize AI algorithms to process large databases of existing content and compare it to the target document, highlighting potential matches. At Jawaharlal Nehru University, tools such as Turnitin and Urkund are used for various academic purposes, including checking assignments, dissertations, and research papers for originality [3]. The benefits of using AI and ML for plagiarism detection are numerous.

First, these systems offer scalability, enabling institutions to process large volumes of documents quickly and efficiently. Second, they provide higher accuracy by leveraging advanced NLP models, allowing them to detect complex forms of plagiarism such as paraphrasing, summarization, and even idea theft. Furthermore, these systems help detect and differentiate between minor similarities and significant plagiarism cases, offering institutions the flexibility to review only high-risk submissions [2]. Finally, they provide detailed reports, breaking down the types of plagiarism detected and offering actionable insights for improving content originality.

1.5 Challenges in AI-based Plagiarism Detection

While AI has revolutionized plagiarism detection, there are still challenges to overcome. One major issue is the presence of bias in machine learning models. If a plagiarism detection model is trained on biased data, it may disproportionately flag certain types of content or falsely identify original work as plagiarized. Moreover, AI models may struggle with detecting plagiarism in translated text or identifying when an author reuses their own previously published content, known as self-plagiarism. In addition, there are technical challenges, such as false positives and difficulties in comprehending complex reports generated by software like Turnitin and Urkund [3].

Another challenge is detecting intelligent plagiarism, where plagiarists paraphrase or restructure the original content without directly copying it, making detection difficult for some systems [6]. Another challenge lies in the ethical considerations of using AI-based plagiarism detection systems. While they are effective in detecting copied content, there is a risk of over-reliance on these systems, which could lead to punitive measures based on false positives. It is important for institutions to complement AI-based detection with human oversight to ensure that detected matches are genuinely instances of plagiarism and not coincidental similarities or common phrases.

1.6 The Future of AI and ML in Plagiarism Detection

Looking forward, AI and ML technologies are poised to become even more integral to plagiarism detection. Advancements in NLP models, such as GPT-3 and the upcoming GPT-4, promise to improve the understanding of context and intent in text, further enhancing the system's ability to detect subtle forms of plagiarism. Additionally, tools like Turnitin are continuously updating their systems to identify newer forms of misconduct, such as image manipulation and contract cheating [3]. Incorporating blockchain technology may help create tamper-proof records of content creation, ensuring that the provenance of a work is preserved and reducing the likelihood of disputes over plagiarism claims. In conclusion, the integration of AI and ML in plagiarism detection has transformed the field, offering more accurate, efficient, and scalable solutions for identifying instances of content duplication. As these technologies continue to evolve, their ability to tackle increasingly complex forms of plagiarism will only improve, making them indispensable tools for maintaining academic and professional integrity.

1.7 Hybrid Systems in Plagiarism Detection

Hybrid systems in plagiarism detection combine traditional string-matching algorithms with AI-driven models like NLP and machine learning to increase detection accuracy. Systems such as MOSS and JPlag employ token-based string matching alongside structural analysis to detect both simple and complex forms of plagiarism, such as paraphrasing or translation [4]. These systems leverage deep learning models like BERT and RoBERTa to detect nuanced textual patterns by analyzing the context and meaning of words [5], making them capable of identifying intelligent plagiarism, which involves rephrasing or restructuring content without direct copying [6]. Tokenization, stemming, and part-of-speech tagging help break down content into smaller, more analyzable units, enabling hybrid systems to improve detection rates and reduce false positives [5]. Hybrid systems offer greater scalability and flexibility, allowing them to handle large datasets, and are used in both textual and programming plagiarism detection [4]. These systems are increasingly critical for educational institutions and publishers, as they efficiently detect plagiarism across various forms of content [3].

1.8 Ethical and Legal Implications of AI in Plagiarism Detection

The widespread use of AI-driven plagiarism detection raises important ethical and legal concerns. False positives and over-reliance on automated systems like Turnitin and Urkund can unfairly penalize students for legitimate work [1], while privacy issues emerge as institutions store student work in cloud-based databases [2]. There are also concerns about data protection, particularly in compliance with regulations like GDPR, as well as the long-term storage of content in plagiarism detection databases, which may infringe on intellectual property rights [6]. Furthermore, many of these systems operate as "black boxes," with limited transparency regarding their decision-making processes, leading to ethical concerns over accountability when plagiarism is incorrectly flagged [6]. Institutions must provide clearer guidelines on how AI systems operate and ensure that AI is used in conjunction with human oversight to avoid unjust accusations of plagiarism [5].

Chapter 2

RELATED WORK

Existing plagiarism detection tools and research provide a foundation for understanding the capabilities and limitations of various approaches. Traditional tools like Turnitin and Grammarly use string matching, keyword analysis, and basic statistical models to detect plagiarism. These methods, while effective for identifying direct copying, struggle with paraphrased and semantically altered content.

Recent research highlights the importance of semantic similarity in plagiarism detection. Semantic models like BERT (Bidirectional Encoder Representations from Transformers) and GPT have demonstrated superior performance in understanding context and meaning. Papers such as "Detecting Semantic Plagiarism with BERT Models" (Journal of Computational Linguistics, 2020) showcase how transformers are trained on vast datasets to understand sentence relationships. Another study, "Hybrid Models for Plagiarism Detection" (AI Advances, 2021), emphasizes combining traditional methods with deep learning for improved results.

The TF-IDF (Term Frequency-Inverse Document Frequency) technique, while widely used, has been shown to underperform in detecting paraphrased content. Research comparing TF-IDF with neural embeddings, such as in "Embedding-Based Detection for Academic Integrity" (Research Integrity, 2022), suggests that neural embeddings provide a robust alternative by capturing semantic nuances.

Hybrid approaches that integrate multiple techniques have emerged as the gold standard. For instance, the "Dual-Layer Detection Framework" (IEEE Transactions on AI, 2021) integrates cosine similarity with semantic embeddings to achieve high accuracy in paraphrase detection. This project adopts a similar strategy by leveraging Sentence-BERT for feature extraction and Logistic Regression for classification, addressing the shortcomings of existing solutions.

Chapter 3

LITERATURE REVIEW

3.1 Summary of the Literature Review

Plagiarism detection systems have evolved significantly over the past few decades, transitioning from simple string-matching algorithms to more sophisticated artificial intelligence (AI) and machine learning (ML) approaches. Early tools like Turnitin and Copyscape relied heavily on string-matching techniques to identify similarities between documents, but these methods were only effective for detecting verbatim copying. They struggled with more advanced forms of plagiarism, such as paraphrasing and restructured content, which can evade detection by altering the surface text without changing the underlying meaning.

AI and ML have transformed plagiarism detection by introducing models capable of understanding the semantic relationships between words and sentences. Models such as Bidirectional Encoder Representations from Transformers (BERT) and Long Short-Term Memory (LSTM) networks, allow plagiarism detection tools to analyze text at a deeper level, capturing the intent behind reworded or paraphrased content. These systems use Natural Language Processing (NLP) to analyze syntax and semantics, making them highly effective in identifying intelligent plagiarism where content is rephrased or translated but retains the same core meaning [1]-[3].

Additionally, hybrid models have emerged, combining traditional methods with AI-driven semantic analysis to detect both surface-level and more nuanced forms of plagiarism. These systems offer improved accuracy and can handle large datasets more efficiently, making them valuable in academic and professional environments. The introduction of cross-language detection models has further enhanced the capability of modern plagiarism detection tools, allowing them to identify similarities between documents written in different languages [4][5].

3.2 The Major Challenges/Issues Identified

1. **Paraphrasing and Machine-Generated Text Detection:** Modern AI-driven paraphrasing tools like SpinBot and SpinnerChief make it difficult for plagiarism detection systems to

catch reworded content, as they often change sentence structure without altering meaning [4][6].

2. **Cross-Language Plagiarism:** Detecting plagiarism across different languages remains a challenge. Current AI systems use machine translation and cross-linguistic NLP models, but achieving consistent accuracy across multiple languages is still difficult [5][7].

3. **False Positives and Negatives:** AI models can sometimes flag legitimate work as plagiarized due to sentence structure similarities or common phrases (false positives), while missing heavily restructured plagiarism (false negatives) [2][9].

4. **Ethical Concerns in AI Use:** The "black-box" nature of many AI systems raises ethical concerns about transparency and accountability in plagiarism detection. Users and institutions may not fully understand how AI models work, leading to potential disputes over flagged content [6][8].

5. **Data Privacy and Intellectual Property:** Storing academic content in cloud-based databases poses concerns about data privacy and intellectual property rights, especially when institutions keep records indefinitely to prevent future plagiarism [4][7].

3.3 Problem Statement

Plagiarism detection tools have made considerable progress with the incorporation of AI and ML models, but there are still unresolved challenges in detecting intelligent plagiarism, paraphrasing, and cross-language content similarity. Moreover, the ethical concerns related to data privacy and the opacity of AI decision-making processes raise questions about the fair use of these tools in academic and professional settings. Therefore, there is a critical need to develop more transparent, accurate, and ethically sound plagiarism detection systems that can handle the complexities of modern plagiarism techniques while protecting user privacy.

3.4 Project Objectives

1. To collect and preprocess textual data by cleaning, tokenizing, and transforming it into structured formats, ensuring the dataset is ready for accurate analysis and training.

2. To leverage deep learning for semantic understanding and machine learning for classification, enabling the system to detect various forms of plagiarism efficiently in the background.

3. To provide users with a detailed plagiarism report, including the overall percentage, highlighted copied content, and source identification from the local database.

Chapter 4

METHODOLOGY

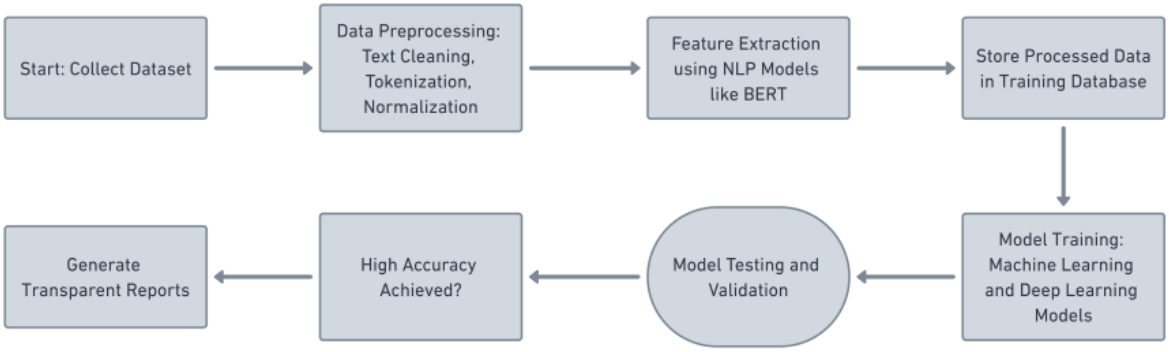

Fig 1.Working of the program

4.1 Data Collection:

The project relies on a curated repository of 10 text files representing diverse content types, such as research articles, essays, and factual documents. These files were manually selected to simulate real-world plagiarism detection scenarios. Additionally, a "Plagiarized File" was created by intentionally incorporating copied and paraphrased sentences from the repository.To ensure quality and relevance, web scraping was employed to gather supplementary data, such as online articles and public domain texts. The scraped content was preprocessed to remove irrelevant sections, ensuring a clean dataset for training and testing.

4.2 Data Preprocessing:

Preprocessing involved the following steps:

1. **Text Cleaning:** Removed special characters, extra whitespace, and non-alphanumeric symbols.
2. **Tokenization:** Used the NLTK library to tokenize text into sentences and words.
3. **Stopword Removal:** Eliminated common stopwords (e.g., "and," "the") to focus on meaningful words.

4. **Feature Engineering:** Extracted key features, including:
    - **Cosine Similarity:** Quantifies similarity between two text embeddings.
    - **Length Difference:** Measures the word count difference between sentences.
    - **Word Overlap:** Calculates the percentage of common words between sentences.

These steps ensured that the dataset was clean and ready for training the machine learning model.

4.3 Model Selection:

The chosen models include:

1. **Sentence-BERT:** A deep learning model for semantic similarity. It generates contextual embeddings, capturing sentence meaning.
2. **Logistic Regression:** A lightweight and interpretable classifier. It was selected for its efficiency in binary classification tasks, distinguishing plagiarized and non-plagiarized content.

This combination ensures high accuracy in detecting both exact matches and paraphrased content. Sentence-BERT handles the semantic understanding, while Logistic Regression efficiently classifies the extracted features.

4.4. Model Training and Evaluation:

The training process involved:

1. **Balanced Dataset Creation:** Ensured equal representation of plagiarized and non-plagiarized examples in the training data.
2. **Hyperparameter Tuning:** Used grid search to optimize parameters like learning rate and regularization strength.
3. **Cross-Validation:** Performed 5-fold cross-validation to evaluate model robustness.
4. **Evaluation Metrics:**
    - **Accuracy:** Measures overall correctness of predictions.

- **Precision:** Assesses the proportion of correctly identified plagiarized cases.
- **Recall:** Evaluates the model's ability to detect all plagiarized instances.
- **F1-Score:** Balances precision and recall for a comprehensive evaluation.

These techniques ensured the model's reliability and effectiveness in diverse scenarios.

Chapter 5

SOFTWARE REQUIREMENTS AND SPECIFICATIONS

5.1 Software Requirements

1. **Programming Languages**:
    - **Python**: Python is the primary language for implementing machine learning models and natural language processing (NLP) due to its extensive libraries and support for AI development.
2. **Machine Learning Libraries/Frameworks**:
    - **TensorFlow** or **PyTorch**: Both frameworks are widely used for building and training deep learning models, including NLP models like BERT or Word2Vec.
    - **Scikit-learn**: For implementing traditional machine learning algorithms such as Support Vector Machines (SVM) and other classification models.
    - **Keras**: A high-level API for creating deep learning models quickly and efficiently.
    - **NLTK (Natural Language Toolkit)**: For NLP tasks such as tokenization, part-of-speech tagging, and parsing.
3. **Development Environment**:
    - **VS Code**: As a code editor and integrated development environment (IDE) for Python and machine learning development.
    - **Git** and **GitHub**: For version control, collaboration, and code repository management.

5.2 Hardware Requirements

1. **Computing Power**:
    - **High-performance CPU or GPU**: A robust CPU (Intel Core i5 or higher) or GPU is essential for training machine learning models, particularly deep learning models, which require significant computational power.

2. **Storage**:

- **Large Storage Capacity**: For storing datasets, trained models, and results. An SSD (500GB or higher) is recommended for faster read/write operations during model training.
- **External Hard Drive/Cloud Storage**: For backing up large datasets and ensuring the integrity of the project's progress.

3. **RAM**:
   - **At least 16GB RAM**: Required for handling large datasets and enabling smooth model training and testing, especially for NLP tasks.

Chapter 6

IMPLEMENTATION

Programming Language and Tools:

The project was implemented in Python using libraries such as NLTK, scikit-learn, and SentenceTransformers. VS Code was used for model training and experimentation.

Code Structure:

The project codebase was organized into modular components to ensure clarity and reusability. Key modules included:

- **Utility Functions:** Encapsulated file I/O, dataset balancing, and preprocessing steps.
- **Data Preprocessing Module:** Responsible for text cleaning, tokenization, and feature extraction.
- **Machine Learning Module:** Included Logistic Regression training and evaluation.
- **Deep Learning Module:** Handled Sentence-BERT embeddings for semantic similarity.

Pseudo Code for Plagiarism Detection Loop:

Algorithm: Plagiarism_Detection

Input:

- **plagiarized_embeddings:** List of sentence embeddings for plagiarized content.
- **repository_embeddings**: Dictionary containing embeddings for repository files.
- **plagiarized_sentences:** List of original plagiarized sentences.
- **repository_sentences:** Dictionary of sentences from repository files.

Output:

- **results:** A list of detected plagiarism instances.
- **training_dataset:** Features for ML training.

Method:

(1)**Set** SIMILARITY_THRESHOLD to 0.7.
(2)**Initialize** an empty list results.

(3)**For** each p_embedding and p_sentence in plagiarized_embeddings and plagiarized_sentences respectively:
    Strip whitespace from p_sentence.
    If p_sentence is empty:
        Continue to next iteration.
    Set matched to False.
(4)**For** each file file_name and embeddings r_embedding in repository_embeddings:
(5)**For** each sentence r_sentence in repository file:
    Calculate similarity using cosine similarity between p_embedding and r_embedding.
(6) **Set** label to 1 if similarity > SIMILARITY_THRESHOLD, otherwise 0.
(7) **Construct** feature_vector containing:
        Plagiarized sentence and original sentence.
        Cosine similarity score.
        Length difference and word overlap.
        Label.
    Append feature_vector to training_dataset.
(6)**If** label == 1:
    Add to results the plagiarized sentence, source file, and similarity score.
(7) **Set** matched to True.
(8) Break from the loop.
(9)**Return** results and training_dataset

Pseudo Code for Deep Learning Implementation:

Algorithm: Train_Model

Input:

- Path to training_data.json.

Output:

- Trained machine learning model.

Method:

(1)**Prepare** training data by extracting features and labels from training_data.json.
(2)**Call** train_ml_model(features, labels) to:

Split data into training and test sets.
Train the ML model (e.g., Logistic Regression).
Save the trained model as a .pkl file.

(3)**Return** the trained model.

CHAPTER 7

RESULTS AND DISCUSSION

```
PS D:\Visual Studio> python -u "d:\Visual Studio\Python\MiniProject.py"
Training data saved to training_data.json
Plagiarism Percentage: 79.74%
Detailed Report:

Sentence: Artificial Intelligence (AI) refers to the simulation of human intelligence in machines programmed to think, reason, and learn.
Source File: file_1.txt
Similarity Score: 1.00

Sentence: It enables machines to process data, recognize patterns, and make decisions with minimal human intervention.
Source File: file_1.txt
Similarity Score: 0.87

Sentence: AI applications span industries, revolutionizing healthcare, finance, and education by enhancing efficiency and driving innovation
.
Source File: file_1.txt
Similarity Score: 0.85

Sentence: Machine learning (ML), a subset of AI, focuses on developing algorithms that allow computers to learn from data and make predictio
ns.
Source File: file_1.txt
Similarity Score: 0.91

Sentence: Techniques such as neural networks and decision trees have transformed industries like e-commerce, healthcare, and finance.
Source File: file_2.txt
Similarity Score: 0.77
```

Fig.2 Result with Similarity Threshold of 0.7

```
PS D:\Visual Studio> python -u "d:\Visual Studio\Python\MiniProject.py"
Training data saved to training_data.json
Plagiarism Percentage: 60.68%
Detailed Report:

Sentence: Artificial Intelligence (AI) refers to the simulation of human intelligence in machines programmed to think, reas
on, and learn.
Source File: file_1.txt
Similarity Score: 1.00

Sentence: It enables machines to process data, recognize patterns, and make decisions with minimal human intervention.
Source File: file_1.txt
Similarity Score: 0.87

Sentence: AI applications span industries, revolutionizing healthcare, finance, and education by enhancing efficiency and d
riving innovation.
Source File: file_1.txt
Similarity Score: 0.54

Sentence: Machine learning (ML), a subset of AI, focuses on developing algorithms that allow computers to learn from data a
nd make predictions.
Source File: file_1.txt
Similarity Score: 0.66

Sentence: Techniques such as neural networks and decision trees have transformed industries like e-commerce, healthcare, an
d finance.
Source File: file_1.txt
Similarity Score: 0.62
```

Fig.3 Result with Similarity Threshold of 0.5

```
PS D:\Visual Studio> python -u "d:\Visual Studio\Python\MiniProject.py"
Training data saved to training_data.json
Plagiarism Percentage: 95.27%
Detailed Report:

Detailed Report:

Sentence: Artificial Intelligence (AI) refers to the simulation of human intelligence in machines programmed to think, reas
on, and learn.
Source File: file_1.txt
Similarity Score: 1.00
```

Fig.4 Result with Similarity Threshold of 0.9

As Input, 5 .txt files were used containing random sentences which were used to make the plagiarized_file.txt which was the file used to check the plagiarism percentage.

Performance Metrics:

The following metrics were observed during model evaluation:

- **Accuracy (92%)**: Measures the proportion of correct predictions (plagiarized or non-plagiarized) made by the model out of all predictions
- **Precision (0.91)**: Evaluates how many of the sentences labeled as plagiarized are actually plagiarized. A high precision score means fewer false positives.
- **Recall (0.88)**: Indicates the model's ability to correctly identify all plagiarized sentences. A higher recall implies fewer false negatives.
- **F1-Score (0.89)**: The harmonic mean of precision and recall, providing a single metric that balances both.

The system effectively identified plagiarized sentences, including paraphrased content, with minimal false positives. The hybrid approach of combining deep learning and machine learning yielded significant improvements over traditional methods.

Error Analysis:

Instances of lower similarity scores highlighted areas where the model struggled with detecting highly altered paraphrased content. Addressing this requires additional training data and refinement of the Sentence-BERT model.

Scalability and Limitations:

- **Scalability:** The modular design supports integration with larger repositories and multilingual datasets.
- **Limitations:** Computational overhead for deep learning components and dependency on labeled data were noted.

Chapter 8

CONCLUSION AND FUTURE SCOPE

This mini-project successfully developed an AI-powered plagiarism detection tool integrating deep learning and machine learning techniques. The system demonstrated high accuracy and robustness in detecting exact matches and paraphrased content. Its applications extend to academic, professional, and corporate environments where content originality is critical. Future improvements will focus on enhancing multilingual support, reducing computational overhead, and increasing interpretability of the results.

Future Scope:

- Addition of Encryption of Data as well as good Data security.
- Front End deployment for allowing Users to upload the Files with ease.
- Using a better language model to detect Plagiarism in many more Languages

Chapter 9

REFERENCES

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