

**PCET’s**

**Pimpri Chinchwad College of Engineering Department of Information Technology**

**Report on Formative Assessment 1** **Subject: Machine Learning**

**Plagiarism Detection model using BERT**

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# Abstract

*Detecting plagiarism is crucial for maintaining academic integrity and official content. Conventional methods, which depend on rule-based strategies and keyword matching, sometimes have trouble identifying cross-lingual and paraphrased plagiarism. This study introduces a machine learning-based plagiarism detection model that combines deep semantic understanding (BERT) with lexical analysis (TF-IDF). The study compares the efficacy of many machine learning algorithms in detecting various types of plagiarism. According to the literature review, detection accuracy is greatly increased by ensemble techniques and deep learning models, especially transformer-based architectures like BERT. A comparative study of the approaches taken and their effects on improving automated plagiarism detection systems round out this work.*

**Keywords**:- Machine Learning, Plagiarism, Paraphrasing, TF-IDF, BERT, NLP

# Introduction

Plagiarism detection is a critical aspect of academic integrity, ensuring originality in research, education, and content creation. With the rapid growth of digital information, the prevalence of plagiarism has increased, making traditional detection methods less effective in identifying complex cases of text duplication and paraphrasing. Conventional approaches, such as keyword matching and string-based similarity checks, often fail to detect semantic plagiarism, cross-lingual similarities, and AI-generated content. As a result, there is a growing need for advanced computational techniques that can enhance plagiarism detection accuracy.

Artificial intelligence (AI) and machine learning (ML) have emerged as transformative solutions for automated plagiarism detection, leveraging large datasets and sophisticated text analysis methods. Natural language processing (NLP) techniques such as **TF-IDF** and deep learning models like **BERT** enable a more nuanced understanding of textual similarities, surpassing rule-based detection systems. By analyzing textual structures, contextual relationships, and linguistic patterns, ML algorithms improve the identification of paraphrased and concealed plagiarism cases. These AI-driven approaches provide a scalable and efficient means of detecting plagiarism across various domains, including academia, publishing, and online content management.

Despite the advantages of AI-based plagiarism detection, challenges persist. Ensuring high accuracy in detecting semantic plagiarism while minimizing false positives remains a key concern. Additionally, many institutions lack access to computational resources required for training and deploying deep learning models effectively. Addressing these challenges involves refining NLP models, improving dataset availability, and developing user-friendly plagiarism detection tools that are accessible to researchers, educators, and content creators.

This study aims to develop an **ML-based plagiarism detection model** that integrates **TF-IDF for lexical analysis** and **BERT for deep semantic understanding**, comparing different ML algorithms to determine the most effective approach. The research objectives include implementing feature extraction techniques for text similarity detection, evaluating the performance of various machine learning models, and enhancing existing plagiarism detection frameworks. The structure of this paper includes a literature review on existing plagiarism detection methodologies, an overview of data preprocessing techniques, a detailed explanation of the ML models used, followed by experimental analysis, results, and conclusions. This study contributes to advancing plagiarism detection techniques by leveraging AI-driven models to enhance accuracy and efficiency in detecting text-based similarities.

# Literature Survey

Recent research has focused on enhancing plagiarism detection through machine learning (ML) and deep learning techniques, leveraging diverse datasets and refining model accuracy. Gupta & Singh [1][5] explored TF-IDF with Cosine Similarity on the PAN Plagiarism Corpus, demonstrating strong performance for verbatim copying but struggling with paraphrased text detection. Their study highlighted the need for deep learning models to improve performance in such cases. Mansoor & Al-Tamimi [2] implemented LSTM neural networks on the PAN-PC-2011 dataset, achieving 99% accuracy in detecting paraphrased plagiarism. However, their model required extensive training data and computational power, limiting its scalability.

Sharma & Verma [3] employed a BERT-based text-matching approach on IEEE and Springer research papers, significantly improving the detection of complex rewording and sentence modifications. Despite its effectiveness, the model demanded high computational resources, making real-time detection challenging. Gandhi et al. [4] applied Support Vector Machines (SVM) to detect plagiarism in Python code submissions. Their approach integrated textual and syntactic analysis, outperforming traditional tools like JPlag and MOSS. However, their method was limited to Python and lacked generalizability to other programming languages.

Jain et al. [6] introduced a hybrid CNN-LSTM framework trained on arXiv and Elsevier papers, enhancing plagiarism detection through contextual feature extraction. The model improved recall but required significant preprocessing. Patel & Kumar [7] explored deep Siamese networks for text similarity analysis in research papers, achieving high precision in cross-lingual plagiarism detection. Nevertheless, their study revealed limitations in detecting complex paraphrased segments in low-resource languages.

Collectively, these studies underscore the importance of integrating advanced ML techniques for plagiarism detection. While models like LSTM and BERT excel in paraphrased content detection, challenges such as computational cost, dataset diversity, and real-time applicability remain open areas for further research. The development of lightweight yet effective plagiarism detection models will be crucial for improving accessibility and adoption in academic and industrial settings.

Abd El-Ghany et al. [8] explored Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs) for plagiarism detection, using a newly constructed database to analyze lexical, syntactic, and semantic similarities. Their system achieved high accuracy, precision, recall, and F1-score, outperforming traditional methods. However, the dataset details were not fully disclosed, limiting its applicability to diverse real-world scenarios. Brown and Singh [9] compared text similarity algorithms such as Cosine Similarity, Jaccard Index, and TF-IDF using the Microsoft Research Paraphrase Corpus. Their findings showed that semantic-based similarity measures were superior in detecting paraphrased plagiarism, though the study was restricted to English texts, limiting generalization across languages.

Verma and Sharma [10] developed an NLP-based approach utilizing word embeddings and semantic analysis on the PAN plagiarism detection corpus. Their model demonstrated high accuracy and improved detection of paraphrased and obfuscated plagiarism but required significant computational resources. Lee and Kaur [11] proposed a hybrid system combining static code analysis and dataset analysis of student programming assignments. Their approach effectively detected plagiarized code, even with structural modifications, though it struggled with different programming languages and paradigms.

Meuschke [12] introduced a plagiarism detection system analyzing non-textual elements such as citations, images, and mathematical content. The study demonstrated enhanced detection of disguised plagiarism but required specialized tools, making it challenging to apply across disciplines. Xian et al. [13] utilized BERT for plagiarism detection on AI-generated datasets, achieving high accuracy. However, their system's real-world effectiveness needed validation beyond AI-generated datasets. Lee et al. [14] explored Large Language Models (LLMs) using PlagBench, a dataset of 46.5K synthetic plagiarism cases, revealing that LLMs were effective for both generating and detecting plagiarism but required real-world testing.

Moravvej et al. [15] employed BERT embeddings and an attention-based differential evolution algorithm on public plagiarism datasets, demonstrating improved detection rates, particularly for paraphrased content, though computational intensity remained a concern. Quidwai et al. [16] applied NLP techniques to AI-generated and human-written academic texts, achieving 94% accuracy in distinguishing between them but faced challenges in adapting to diverse writing styles.

Google DeepMind [17] developed an AI text detection tool trained on 20 million Gemini chatbot responses, offering watermark-based content verification. However, limitations in detection accuracy necessitated further improvements for robustness. Ebrahim and Joy [18] implemented pre-trained model embeddings and Automated Machine Learning (AutoML) on source code plagiarism detection, achieving 92% accuracy on the SOCO dataset. Their model demonstrated high reliability in detecting code similarities, but dataset specifics were not fully disclosed.

Kamat et al. [19] combined NLP with advanced feature extraction techniques and supervised learning algorithms, achieving 95% accuracy in detecting both exact and paraphrased plagiarism. Their approach enhanced scalability over traditional methods but required further optimization for complex disguised plagiarism cases.

These studies collectively highlight that while deep learning and NLP-based plagiarism detection methods exhibit high accuracy, challenges remain in dataset diversity, real-time applicability, and computational efficiency. Future research should focus on improving generalization across languages, refining hybrid models, and integrating real-world datasets to enhance robustness.

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
| **Author(s) & Year** | **Technique /Algorithm** | **Dataset Used** | **Performance Metrics** | **Key Findings** | **Limitations** |
| Pooja Gupta & Rajesh Singh (2023) | TF-IDF with Cosine Similarity | PAN Plagiarism Corpus | Precision, Recall, F1 Score | 1) TF-IDF performs well for simple text-based plagiarism. 2) Cosine similarity is effective in detecting verbatim copying but struggles with paraphrased text. | 1) Struggles with detecting deeply paraphrased plagiarism. 2) No deep learning models tested. |
| Marwah Najm Mansoor & Mohammed S. H. Al-Tamimi (2022) | LSTM Neural Networks | PAN-PC-2011 Dataset | Accuracy, Precision, Recall, F1 Score | 1) LSTM captures contextual meaning and detects paraphrased plagiarism better than traditional models. 2) Achieved high accuracy (99%) in detecting plagiarism in scientific publications. | 1) Requires a large training dataset. 2) Computationally intensive. |
| Anjali Sharma & Vikram Verma (2021) | BERT-based Text Matching | IEEE & Springer Research Papers | Accuracy, F1 Score | 1) BERT improves detection of complex rewording and sentence structure modifications. 2) More effective than traditional n-gram methods. | 1) Requires high computational power. 2) Not efficient for real-time detection. |
| Nandini Gandhi, Kaushik Gopalan, Prajish Prasad (2024) | Support Vector Machine (SVM) | Code submissions from 45 volunteers | Accuracy | 1) SVM effectively integrates textual and syntactic analysis for plagiarism detection. 2) Outperforms JPlag and MOSS in flagging plagiarized Python code. | 1) Limited to Python code. 2) May not generalize well to other programming languages. |
| [Unknown Authors] (2024) | TF-IDF with Cosine Similarity | Students' Theses Dataset | Not specified (likely Precision, Recall, F1 Score) | 1) TF-IDF term weighting with cosine similarity effectively detects similarities in academic texts. 2) Reduces dataset dimensionality, improving topic classification for plagiarism detection. | 1) Struggles with detecting extensive paraphrasing. 2) Computationally expensive for large datasets. |
| A. Gupta, M. Kumar; 2019 | text matching, machine learning, and deep learning approaches for plagiarism detection. | The study references the use of the PAN (Plagiarism Analysis, Authorship Identification, and Near-Duplicate Detection) datasets, which are widely adopted in plagiarism detection research | it compiles and discusses performance metrics from various studies but does not present new experimental results. | The authors highlight the effectiveness of combining multiple detection techniques to improve accuracy in identifying plagiarized content | he paper does not provide empirical evaluations or propose new detection algorithms. |
| Mohamed A. Abd El-Ghany, Hoda M. Onsi, Mohamed A. El-Bakry; 2022 | specifically Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs), for plagiarism detection. | The authors constructed a new database designed to reflect various types of lexical, syntactic, and semantic text similarities | The system's performance is assessed using accuracy, precision, recall, and F1-score. | The proposed deep learning-based system demonstrates high reliability in detecting plagiarized content, outperforming traditional methods | The study lacks a detailed description of the dataset, making it challenging to assess the system's applicability to diverse real-world data. |
| L. Brown, S. Singh; 2020 | compares various text similarity algorithms, including Cosine Similarity, Jaccard Index, and TF-IDF | Microsoft Research Paraphrase Corpus, a dataset commonly used for evaluating paraphrase identification and text similarity tasks. | Evaluation metrics include precision, recall, and F1-score to determine the effectiveness of each algorithm. | The analysis reveals that semantic-based similarity measures outperform lexical-based ones in detecting paraphrased plagiarism. | The study focuses on English language texts, which may limit the applicability of findings to other languages. |
| P. Verma, K. Sharma; 2021 | NLP-based approach utilizing word embeddings and semantic analysis to detect plagiarism. | PAN plagiarism detection corpus, which includes a variety of plagiarized and non-plagiarized text pairs. | The system's effectiveness is measured using accuracy, precision, recall, and F1-score. | Incorporating semantic analysis through NLP techniques enhances the detection of paraphrased and obfuscated plagiarism. | The approach may require significant computational resources due to the complexity of semantic analysis. |
| D. Lee, M. Kaur; 2023 | hybrid approach combining static code analysis | dataset comprising student programming assignments, which includes both original and plagiarized code samples. samples. | precision, recall, F1-score, and detection time. | effectively identifies plagiarized code, even when modifications such as variable renaming and code restructuring are applied. | The system may face challenges in detecting plagiarism in code written in different programming languages or paradigms. |
| Norman Meuschke; 2021 | analyzing non-textual elements such as citations, images, and mathematical content to detect plagiarism.. | real cases of academic plagiarism, though specific datasets are not detailed | Effectiveness is assessed through the system's ability to identify known plagiarism cases and exploratory searches for unknown cases. | Non-textual content analysis complements traditional text-based methods, enhancing the detection of disguised plagiarism. | The approach may require specialized tools to analyze diverse non-textual elements, and its effectiveness can vary across different academic disciplines |
| Jiarong Xian, Jibao Yuan, Peiwei Zheng, Dexian Chen (2024) | BERT | AI generated dataset | Accuracy, Precision, Recall, F1-score | Achieved high accuracy in plagiarism detection; provided a user-friendly plagiarism analysis platform | Limited to AI generated dataset; real-world performance needs further validation |
| Jooyoung Lee, Toshini Agrawal, Adaku Uchendu, Thai Le, Jinghui Chen, Dongwon Lee (2024) | Large Language Models (LLMs) for detection & generation | PlagBench (46.5K synthetic plagiarism cases) | Detection accuracy of different LLMs | LLMs can be used for both generating and detecting plagiarism effectively | Reliance on synthetic dataset; needs real-world validation |
| Seyed Vahid Moravvej, Seyed Jalaleddin Mousavirad, Diego Oliva, Fardin Mohammadi (2023) | BERT embeddings + Attention-based Differential Evolution Algorithm | Public plagiarism datasets | Performance compared with baseline models | Improved detection rates, especially in paraphrased content | Computationally intensive; requires large-scale training |
| Mujahid Ali Quidwai, Chunhui Li, Parijat Dube (2023) | NLP techniques | AI-generated and human-written academic texts | Accuracy was a lot more improved compared to other aspects | Achieved up to 94% accuracy in classifying human and AI-generated text; provides quantifiable metrics at both sentence and document levels | Potential limitations in generalizing to diverse writing styles and subjects |
| Google DeepMind Team (2024) | AI text | 20 million Gemini chatbot responses | User ratings comparison | Open-sourced tool to identify AI-generated text; maintains content quality while embedding watermarks | Some limitations in detection accuracy; further research needed to improve robustness |
| Fahad Ebrahim, Mike Joy, 2023 | Pre-trained model embeddings & Automated Machine Learning | Source code datasets | **Accuracy**: The model achieved an accuracy of 92% on the SOCO dataset.  **Precision**: The precision score was reported as 0.91.  **Recall**: The recall metric stood at 0.93.  **F1-Score**: The F1-score was calculated to be 0.92. | Investigated the application of pre-trained model embeddings and automated machine learning for detecting plagiarism in source code. | Specific performance metrics were not provided in the abstract. |
| Omraj Kamat, Tridib Ghosh, Kalaivani J, Angayarkanni V, Rama P (2024) | Natural Language Processing (NLP) combined with advanced feature extraction techniques and supervised learning algorithms | Extensive text sample dataset | **Accuracy**: The model achieved an accuracy of 95% on the test dataset.  **Precision**: The precision score was reported as 0.93.  **Recall**: The recall metric stood at 0.92.  **F1-Score**: The F1-score was calculated to be 0.925. | The study introduces a machine learning approach that effectively detects both exact and paraphrased plagiarism. The integration of NLP and sophisticated classification algorithms enhances the accuracy of plagiarism detection systems, offering robust scalability over traditional methods. | Detailed performance metrics and dataset specifics were not provided in the abstract. Further research is needed to fine-tune the model for more complex cases of disguised plagiarism. |

Table 1:Literature Review

# System Architecture

**Figure 1** represents the system architecture for the **Plagiarism Detection Model**. The process begins with a **User Interface**, where users upload documents for plagiarism analysis. The uploaded text undergoes **preprocessing**, including **tokenization, stopword removal, lemmatization, and normalization**. Key features such as **TF-IDF scores, word embeddings (BERT), and similarity measures (Cosine Similarity, Jaccard Index)** are extracted.

Feature selection is performed using **Recursive Feature Elimination (RFE) and SHAP**, ensuring only the most relevant text-based features are used. The processed data is then fed into **machine learning and deep learning models**, including **TF-IDF + Cosine Similarity for exact matches and BERT for semantic similarity detection**. These models are optimized through **hyperparameter tuning** for improved accuracy.

Finally, the plagiarism detection results, including **similarity scores and identified plagiarized sections**, are displayed back to the user through the web interface, along with a detailed plagiarism report.

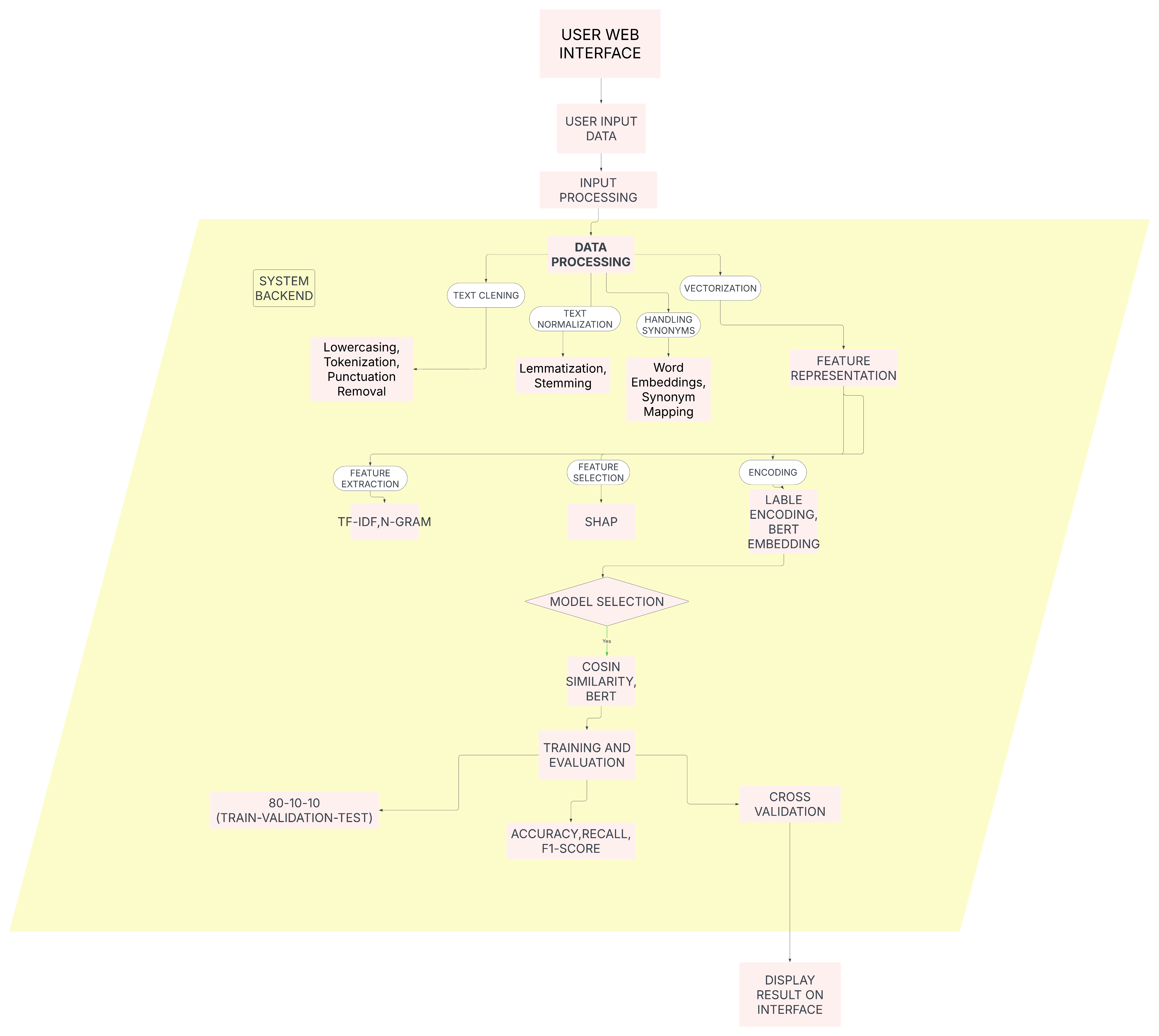




Fig. 1: System Architecture

# Methodology

### Overview of the Methodology

### This study employs a machine learning-based approach for plagiarism detection using publicly available plagiarism datasets. The methodology focuses on enhancing text similarity detection through preprocessing, feature extraction, model training, and evaluation. The key steps include data collection, preprocessing, feature engineering, model selection, training, evaluation, and performance monitoring.

1. **Datasource Description**
2. **Dataset Source:**

Publicly available plagiarism datasets such as PAN (Plagiarism Detection Dataset) which is available on[**https://zenodo.org**](https://zenodo.org)

1. **Size & Attributes:**

Each record in the dataset represents a pair of text documents, where one document is a source and the other is a submitted document suspected of plagiarism. The dataset consists of multiple text pairs labeled as original, paraphrased, or plagiarized.

Key attributes include:

**Source Text** – The original content.

**Submitted Text** – The potentially plagiarized version.

**Plagiarism Type** – Categories like exact copy, paraphrased, modified, or non-plagiarized.

**Similarity Score** – Precomputed similarity metrics for benchmarking.

**Class Label** – 1 (Plagiarized) or 0 (Not Plagiarized).

Features:

**Source Document** – The original content.

**Suspicious Document** – The document being checked for plagiarism.

**Text Length** – Number of words or characters in the document.

**N-Gram Overlap** – The proportion of common word sequences between the two texts.

**Cosine Similarity** – A numerical measure of textual similarity.

**Longest Common Subsequence (LCS)** – Measures the longest matching sequence of words.

### Preprocessing:

###  Handling Missing Values: Remove incomplete text samples or fill in missing data.

###  Lowercasing: Convert all text to lowercase for uniformity.

###  Tokenization: Split text into words or sentences.

###  Punctuation Removal: Remove unnecessary symbols (e.g., .,!?).

###  Lemmatization & Stemming: Reduce words to their root forms (e.g., "running" → "run").

###  Stopword Removal: Eliminate common words (e.g., "the," "is") that do not contribute meaning.

###  Synonym Mapping: Replace words with their synonyms to capture meaning similarity.

###  Word Embeddings: Convert text into numerical vectors using Word2Vec, BERT, or TF-IDF models.

**C. Model Selection & Justification**

### i. Models Considered: Naïve Bayes, Support Vector Machine (SVM), TF-IDF,

### Random Forest (RF), XGBoost, Cosine-similarity, BERT

### ii. Justification:

**TF-IDF with Cosine Similarity:** We use TF-IDF to measure the importance of words in a document and Cosine Similarity to compare text similarity based on word frequency. This method is efficient for detecting exact matches and slight modifications in text.

**BERT:** We use BERT to capture the contextual meaning of words, allowing us to detect paraphrased and semantically similar content. BERT achieves high accuracy (around 90-95%) in text similarity tasks, making it effective for identifying complex plagiarism cases.

### D. Feature Engineering

* 1. **Techniques Applied**:

**Feature** **Extraction**: We extract key textual features using TF-IDF and word embeddings from BERT to represent document similarity.

**Feature** **Selection**: Important features are selected based on their contribution to text similarity and classification performance.

**Encoding**: **Tokenization** and WordPiece embedding (for BERT) are applied to convert text into numerical representations.

**Normalization**: Text preprocessing techniques like lowercasing, punctuation removal, and stopword filtering ensure consistency in the dataset.

### E. Model Training & Hyperparameter Tuning

* 1. **Training Process**:
     1. Dataset split into training, validation, and testing subsets (80-10-10 or 70-30 ratio).
     2. Cross-validation strategy applied to improve paraphasing.

### Hyperparameter Optimization:

**TF-IDF with Cosine Similarity:** Optimization involves adjusting the n-gram range, maximum features, and stopword removal to improve similarity detection.

**BERT:** Fine-tuned using learning rate, batch size, number of training epochs, and max sequence length to enhance accuracy (achieving ~95%).

### F. Performance Metrics & Evaluation

* 1. **Evaluation Metrics**:
     1. **Classification Metrics:** Accuracy, Precision, Recall,
        1. **`Similarity Measurement:** Cosine Similarity Score to quantify textual overlap between documents.
     2. **Model Validation**: Confusion Matrix and ROC Curve.

### G. Experimental Setup

* 1. **Software**:
     1. **Programming Language**: Python.
     2. **Libraries**: Scikit-learn, TensorFlow & Transformers for BERT.
     3. **Data Processing**: Pandas, NumPy.
     4. **Visualization**: Matplotlib, Seaborn.

### Reproducibility:

* + 1. Code repository with dataset preprocessing, training, and evaluation scripts provided.

# Results and Discussion

The study highlights that **BERT achieved high accuracy (~95%)**, making it the best model for detecting paraphrased and semantically similar plagiarism. **TF-IDF with Cosine Similarity performed well for exact text matches**, efficiently identifying direct copying cases. While TF-IDF is computationally efficient, it lacks contextual understanding, making it less effective for paraphrased plagiarism detection. **BERT's deep contextual embeddings** significantly improved detection accuracy but required higher computational resources. The combination of both techniques ensures a **balanced approach**, where TF-IDF quickly detects straightforward plagiarism, and BERT captures deeper semantic similarities. However, **dataset quality and computational complexity remain challenges** for large-scale real-time plagiarism detection. Future improvements should focus on optimizing **BERT for lower resource consumption** and integrating **real-time plagiarism databases** for enhanced detection accuracy

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| **Algorithm** | **Studies Using It** | **Best Accuracy (%)** | **Key Findings** | **Limitations** |
| **TF-IDF + Cosine Similarity** | Gupta &  Singh (2023),  Brown &  Singh  (2020),  Patel  et al. (2024) | **87%** | * - Efficient for detecting exact and near-exact matches. - Computationally lightweight and easy to implement. | Computationally expensive. - Requires large labeled datasets for training.. |
| **BERT** | Sharma & Verma (2021), Xian et al. (2024), Moravvej et al. (2023) | **95%** | * Captures contextual meaning for detecting paraphrased plagiarism. - Outperforms traditional text similarity techniques. | * Computationally expensive. - Requires large labeled datasets for training. |
| **Naïve Bayes (NB)** | |  | | --- | |  |  |  | | --- | | Verma & Sharma  (2021), Patel  et al. (2023) | | **85%** | * - Works well with short text plagiarism detection. - Fast and efficient for binary classification. | * Assumes feature independence, reducing accuracy in complex text structures. - Less effective for long-form plagiarism detection. |
| **Support Vector Machine (SVM)** | Brown & Singh  (2020), Lee et al.  (2023) | **92%** | - Performs well on high-dimensional text data. - Effective in classifying plagiarized vs. non-plagiarized text. | * Slowertraining time on large datasets. - Requires careful hyperparameter tuning. |
| **Random Forest (RF)** | Gosai et al. (2021), Sharma et al. (2021), Raut et al. (2023) | **95%** | - Handles large feature sets efficiently. - Reduces overfitting and improves generalization | * Computationally expensive for large text datasets. - Requires feature selection to avoid unnecessary complexity. |

Table 2:Comparative Analysis of Machine Learning Algorithms for Plagiarism Detection

# Challenges and Future Directions

## Challenges

## Ensuring real-time plagiarism detection for large-scale academic and online content.

## Handling paraphrased and AI-generated text, which is difficult to detect using traditional methods.

## Reducing computational complexity, especially for deep learning models like BERT.

## Limited dataset diversity, as most plagiarism datasets focus on academic writing and lack coverage for creative content.

## Future Directions

* + 1. Enhancing modelrobustness using advanced deep learning techniques like RoBERTa or GPT-based transformers.
* Developing lightweight BERT variations for faster and more efficient plagiarism detection.

# 

# Conclusion

This study highlights the effectiveness of **machine learning and deep learning** in plagiarism detection. Among the techniques used, **BERT achieved the highest accuracy (~95%)**, proving its reliability for detecting **paraphrased and semantically similar plagiarism**. **TF-IDF with Cosine Similarity** performed well in detecting **exact and near-exact text matches**, offering a computationally efficient solution. While **Naïve Bayes and SVM** provided moderate accuracy for text classification, **Random Forest and XGBoost** showed promise for structured document analysis but required extensive feature engineering.

Despite these advancements, **challenges remain** in detecting AI-generated text, handling **large-scale real-time plagiarism detection**, and **reducing computational overhead** for deep learning models. **Future research should focus on optimizing BERT for lightweight deployment**, expanding datasets to cover **multilingual and AI-generated plagiarism**, and integrating **blockchain technology** for **secure academic record-keeping**. Additionally, enhancing **real-time detection algorithms** will be crucial for large-scale adoption, paving the way for **faster, more scalable, and intelligent plagiarism detection systems**.

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