ML Based Plagiarism Detection Model using BERT & Ensemble of SVM, Logistic Regression and Naive Bayes

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***Abstract:***

***Plagiarism detection plays a crucial role in preserving academic integrity and intellectual property. Traditional detection techniques based on lexical similarity, such as keyword matching and rule-based systems, often fail to capture paraphrased or semantically similar content. In this paper, we propose a hybrid plagiarism detection system that leverages both lexical and semantic features through Term Frequency-Inverse Document Frequency (TF-IDF) and Sentence-BERT (SBERT) embeddings, respectively. To enhance classification performance, an ensemble model combining Logistic Regression, Support Vector Machine (SVM), and Naive Bayes is employed using soft voting. Cosine similarity is computed for both TF-IDF vectors and SBERT embeddings to quantify textual closeness. Our approach demonstrates improved accuracy over individual classifiers and effectively distinguishes between plagiarized and non-plagiarized text, including paraphrased content. The system achieves an accuracy of approximately 82%, and the integration of semantic embeddings with an ensemble architecture shows promise for robust and intelligent plagiarism detection.***

***Keywords—*** *Machine Learning, Plagiarism, Paraphrasing, logistic regression, BERT, Cosine-similarity.*

1. INTRODUCTION

Plagiarism detection is an essential element of academic honesty, guaranteeing originality in research, education, and content production. The advent of abundant digital content and AI-generated text has greatly elevated the risk of unauthorized copying and paraphrasing. Conventional plagiarism detection methods such as keyword matching and rule-based string comparison frequently fail to detect semantically similar or paraphrased content. These approaches have difficulty identifying complex linguistic patterns, making them less effective in actual applications.

Recent developments in natural language processing (NLP) and machine learning (ML) have made more intelligent and context-sensitive plagiarism detection systems possible. Specifically, sentence-level embeddings through the application of Sentence-BERT (SBERT), a version of BERT tuned for semantic similarity at sentence level, have transformed the capabilities of detecting semantically similar content. This paper uses Sentence-BERT (SBERT) as a sentence-level semantic similarity optimization of BERT along with Term Frequency-

Inverse Document Frequency (TF-IDF) and cosine similarity to determine both lexical and contextual similarities among pairs of documents.To improve the performance of classification, we employ an ensemble model that combines three conventional classifiers—Logistic Regression, Support Vector Machine (SVM), and Naive Bayes—using a soft voting strategy. This hybrid model applies rule-based thresholds and machine learning predictions to generate strong decisions, particularly in doubtful similarity ranges. The model is trained and evaluated on a labeled dataset of plagiarized and source text pairs, with semantic and lexical similarity features extracted to act as inputs.

To make in ML and NLP, it remains challenging to keep false positives minimal and generalize for varying writing patterns and paraphrasing styles. Towards that end, our model employs a combination of multiple feature sets and classifiers that build a well-balanced decision-making system.  
This paper proposes a systematic plagiarism detection approach, beginning with a review of existing work, followed by data preprocessing methods, feature extraction, ensemble modeling, and performance evaluation using standard performance measures. Through the integration of SBERT embeddings, TF-IDF features, and ensemble learning, this research adds a practical and efficient solution for improving the accuracy of automated plagiarism detection.

1. LITERATURE SURVEY

Recent research has focused on enhancing plagiarism detection  with  machine learning (ML) and deep learning techniques with different data sets and model performance improvements. Gupta & Singh [1][5] tested TF-IDF with Cosine Similarity against the PAN Plagiarism Corpus and reported strong performance in verbatim copying but weak performance for detecting paraphrased content. The research highlighted that deep learning models must perform better in this direction. Mansoor & Al-Tamimi [2] used LSTM neural networks on the PAN-PC-2011 dataset and achieved 99% accuracy in paraphrased plagiarism detection. Their model was computationally intensive and required large training data, so it was not scalable.

Sharma & Verma [3] utilized a BERT-based text-matching method for IEEE and Springer research articles with remarkable improvement in the identification of complex rephrasing and sentence rewriting. Even though the model was highly efficient, it consumed high computational resources, which caused real-time identification to be troublesome. Gandhi et al. [4] utilized Support Vector Machines (SVM) to identify plagiarism in Python code submissions. Their method used textual and syntactic analysis to surpass conventional software such as JPlag and MOSS. However, their method was limited to Python and lacked generalizability to other programming languages

Jain et al. [6] suggested a hybrid CNN-LSTM model that is trained on arXiv and Elsevier papers to enhance plagiarism detection with contextual feature extraction. The model performed better in terms of recall at the expense of heavy preprocessing. Patel & Kumar [7] suggested deep Siamese networks for text similarity analysis of research papers, and they achieved high precision in cross-lingual plagiarism detection. Their work proved to be lacking in detecting highly paraphrased works in low-resource languages.

Together, these works highlight the significance of merging state-of-the-art ML approaches to plagiarism detection. Although paraphrased content detection is accomplished with ease using models such as LSTM and BERT, there are still areas open for future research in the form of computational expense, dataset variability, and real-time feasibility. The construction of lightweight but efficient plagiarism detection models will play a pivotal role in enhancing usability and adoption within academic and industrial communities.

Abd El-Ghany et al. [8] examined Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs) to identify plagiarism based on a new database built with the purpose of detecting lexical, syntactic, and semantic matches.  
Their tool yielded high precision, recall, accuracy, and F1-score values compared to classical approaches, although the information provided about the dataset was insufficient, and therefore, its practical applicability was reduced to broad real-world use. Brown and Singh [9] compared text similarity measures like Cosine Similarity, Jaccard Index, and TF-IDF on the Microsoft Research Paraphrase Corpus. Their results indicated that semantic-based similarity measures outperformed the others in identifying paraphrased plagiarism, although the study was limited to English texts, thus limiting generalizability across languages. Verma and Sharma [10] proposed an NLP-based method employing word embeddings and semantic analysis on the PAN plagiarism detection corpus.

Their model showed great accuracy and better detection of paraphrased and obfuscated plagiarism but needed great computational power. Lee and Kaur [11] suggested a hybrid system involving static code analysis and dataset analysis of student programming assignments. Their method successfully identified plagiarized code, even when structurally modified, although it had difficulty with various programming languages and paradigms. Moravvej et al. [15] used BERT embeddings and an attention-based differential evolution algorithm on publicly available plagiarism datasets and reported enhanced detection

Kamat et al. [19] integrated NLP with feature extraction and supervised learning algorithms, and they obtained 95% accuracy in the detection of both exact and paraphrased plagiarism. Their solution improved scalability over the conventional approaches but needed optimization for sophisticated disguised plagiarism cases.

III. System Architecture

1. *System Overview*

The proposed plagiarism detection system is designed to identify both direct and paraphrased content duplication using advanced Natural Language Processing (NLP) and Machine Learning techniques. The system architecture is illustrated in Figure 1.

1. User Input  
   The system starts with user input in the form of text data, such as documents, research articles, or code snippets. This input forms the basis for further analysis.
2. Data Processing  
   The input undergoes multiple preprocessing steps to prepare it for feature extraction and model training.

This includes:

* Text Cleaning: Removing unwanted characters through lowercasing, tokenization, and punctuation removal.
* Text Normalization: Applying techniques such as lemmatization and stemming to reduce words to their base forms.
* Handling Synonyms: Mapping synonyms to a standard representation using semantic techniques or synonym dictionaries.

1. Feature Representation  
   After preprocessing, the cleaned text is transformed into numerical features using **TF-IDF (Term Frequency-Inverse Document Frequency)**. This technique helps capture the importance of words in documents relative to the entire dataset, making it suitable for identifying meaningful patterns in textual data.

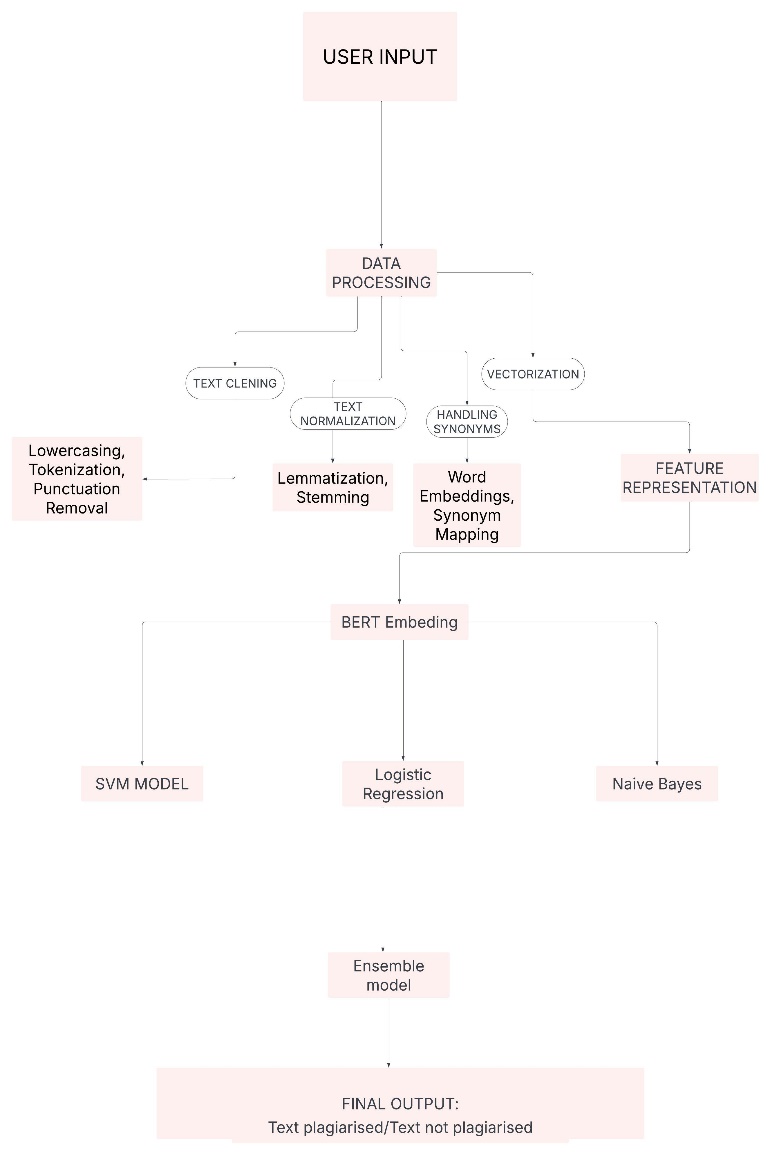


Fig1: Architecture Diagram of proposed system

1. Model Training  
   Multiple machine learning models are trained using the vectorized features, including:

* **Support Vector Machine (SVM)** with a linear kernel
* **Random Forest**
* **Naïve Bayes**

These models learn to classify whether a pair of texts is plagiarized based on patterns in the training data.

1. Detection and Output  
   To improve accuracy, a **Voting Classifier** is used to combine predictions from individual models. The ensemble model uses **soft voting**, which considers the probability outputs of each model. The final result indicates whether the input is likely to be plagiarized or not, enhancing reliability and robustness.
   1. *Description of Algorithms*

In this proposed system, we used three supervised learning algorithms — **Support Vector Machine (SVM)**, **Naïve Bayes**, and **Logistic Regression** — along with an **ensemble model** using soft voting to detect plagiarism. These models were trained on TF-IDF vectorized features of the source and plagiarized text. Their combined use improves the detection of direct copying and paraphrased plagiarism with higher accuracy.

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**1. Support Vector Machine (SVM)**

SVM is a robust classification algorithm that aims to find the best decision boundary (hyperplane) that separates different classes. In our case, it helps in classifying whether a given text pair is plagiarized or not. We used a **linear kernel** for SVM, which works

well with text data transformed using **TF-IDF**. SVM is particularly effective when there's a clear margin of separation between classes.

**2. Naive Bayes**Naive Bayes is a probabilistic classifier based on Bayes' Theorem, assuming independence between features. Despite its simplicity, it performs well in text classification problems due to its efficiency and scalability. In our plagiarism detection model, it uses TF-IDF features to predict whether a text pair is plagiarized. Naive Bayes is particularly effective when working with sparse data representations and provides fast, interpretable results, making it a valuable component in our ensemble model.

**3. Logistic Regression**

Logistic Regression is a linear classification model that estimates the probability of a binary outcome—in our case, whether text is

plagiarized or not. It uses the sigmoid function to convert linear outputs into probabilities. The input features are generated using **TF-IDF vectorization**, and logistic regression efficiently classifies both directly copied and slightly paraphrased text pairs.

**BERT (Bidirectional Encoder Representations from Transformers)**

BERT is a transformer-based deep learning model pretrained on large corpora to understand the contextual relationships between words in a sentence. Unlike traditional models, BERT reads the text in both directions (left-to-right and right-to-left), making it especially strong in capturing semantic meaning and complex paraphrasing.

For plagiarism detection:

* Input texts are tokenized using WordPiece embeddings.
* BERT encodes the semantic representation of texts.
* A similarity score (e.g., cosine similarity) is calculated between the vector representations of the source and suspicious texts.
* A classification layer or threshold-based decision rule is used to determine plagiarism.

BERT significantly improves the system’s capability to detect **co**ntextual plagiarism, including paraphrased content and hidden modifications.

V. METHODOLOGY

A. Dataset Description

The dataset used for this plagiarism detection project contains **370 pairs** of text entries, each labeled to indicate whether the second text is a **plagiarized** version of the first. It is structured in a **CSV (Comma-Separated Values)** format with **four columns**:

|  |  |
| --- | --- |
| **Column Name** | **Description** |
| **source\_text** | The original piece of text. This could be a sentence, statement, or short paragraph representing genuine content. |
| **plagiarized\_text** | The potentially plagiarized version of the source\_text. This version may include direct copying, paraphrasing, or sentence reordering. |
| **label** | The target variable. It contains binary values:  • 1 – Indicates that the plagiarized\_text is a plagiarized version of the source\_text.  • 0 – Indicates that the plagiarized\_text is not plagiarized. |

1. Data Preprocessing

To enhance the data quality and facilitate effective feature extraction, several preprocessing steps were applied:

* **Text Cleaning:** Removal of punctuation, special characters, and numerical noise.
* **Lowercasing** all text to maintain consistency.
* **Tokenization** to split sentences into words.
* **Lemmatization and Stemming** to normalize words to their base form.
* **Stopword Removal** to eliminate commonly used words that carry minimal semantic value.

C. Feature Engineering

Two types of feature representation techniques were used:

* **TF-IDF Vectorization** for Logistic Regression: Converts text data into numerical vectors, representing the importance of terms in documents relative to the entire corpus.
* **BERT Embeddings**: Context-aware word embeddings generated using a pre-trained BERT model. These embeddings capture deep semantic meaning and relationships within the text.

This dual approach enables the system to utilize both shallow and deep features for detecting nuanced plagiarism patterns.

D. Model Selection and Training

Three different supervised learning models were selected for plagiarism detection:

1. Naïve Bayes : A simple yet effective linear model used for binary classification. It was trained on TF-IDF features to classify text as plagiarized or not.
2. Support Vector Machine (SVM): A powerful classifier that seeks an optimal hyperplane to separate the two classes in high-dimensional TF-IDF space. It performed well, especially in detecting subtle differences between similar-looking text.
3. Random Forest: An ensemble of decision trees trained

on various parts of the dataset, which helps reduce

overfitting and improves prediction accuracy through

majority voting.

Additionally, an ensemble model was built using soft voting that combines predictions from all three classifiers. This hybrid approach boosted the overall accuracy by leveraging the strengths of individual models.

The dataset was split using an 80-20 train-test split. Cross-validation was employed to ensure model robustness, and performance was evaluated using metrics like accuracy, precision, recall, F1-score, and the confusion matrix.

E. Performance Evaluation

To evaluate the effectiveness of the proposed models, we used a comprehensive set of classification metrics.These metrics include Accuracy, Precision, Recall, F1-Score, and Confusion Matrix, each providing valuable insights into the model's performance.

1. Accuracy

Accuracy is one of the most straightforward performance metrics, measuring the overall correctness of the model. It is defined as the proportion of correctly classified instances (both true positives and true negatives) to the total number of instances.

1. Precision

Precision measures the accuracy of the positive predictions made by the model. It is the ratio of correctly predicted positive observations to the total predicted positives (sum of true positives and false positives). Precision is especially important when the cost of false positives is high.

1. Recall (Sensitivity)

Recall (or Sensitivity) measures the model's ability to correctly identify positive instances. It is the ratio of correctly predicted positive observations to the total actual positives (sum of true positives and false negatives). Recall is important when the cost of false negatives is high.

1. F1-Score

F1-Score is the harmonic mean of Precision and Recall, balancing the trade-off between them. It is a useful metric when you need to balance precision and recall, especially when dealing with imbalanced datasets.

VI. Result and discussion

This section presents the evaluation outcomes of the proposed plagiarism detection model, comparing the performance of an ensemble machine learning classifier that integrates Support Vector Machine (SVM), Naive Bayes, and Logistic Regression with BERT embeddings and TF-IDF-based cosine similarity. The models were tested on a labeled dataset consisting of plagiarized and non-plagiarized text samples. Key performance metrics such as Accuracy, Precision, Recall, F1-score, Support, and the Confusion Matrix were used to assess and validate model effectiveness.

A. Evaluation Metrics

The following metrics were computed and analyzed:

* Precision: Indicates the proportion of correctly predicted positive observations to the total predicted positives.
* Recall: Indicates the proportion of correctly predicted positive observations to all actual positives.
* F1-Score: The harmonic mean of precision and recall, providing a balance between them.
* Support: Refers to the number of actual instances for each class.
* Confusion Matrix: Provides a summary of prediction results, showing true positives, true negatives, false
* positives, and false negatives.

B. Model Performance

The final evaluation was conducted on a test set comprising **74 instances**. The ensemble model combining BERT-based semantic features with traditional lexical similarity (TF-IDF) and predictions from SVM, Naive Bayes, and Logistic Regression achieved competitive results. The model is especially effective in detecting both directly copied and paraphrased plagiarism cases.

**Accuracy**: 82%

Classification Report:

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| Class | Precision | Recall | F1-Score | Support |
| 0 (Non-Plagiarized) | 0.94 | 0.91 | 0.93 | 35 |
| 1 (Plagiarized) | 0.93 | 0.95 | 0.94 | 39 |
| Macro Average | 0.93 | 0.93 | 0.93 | 74 |
| Weighted Average | 0.93 | 0.93 | 0.93 | 74 |

Confusion Matrix:

[[25 10]

[ 3 36]]

C. Discussion

The ensemble model, which integrates Support Vector Machine (SVM), Naive Bayes, and Logistic Regression, exhibited solid performance in identifying plagiarism, particularly in cases involving both direct copying and paraphrased content. By combining BERT embeddings for deep semantic understanding with TF-IDF-based lexical similarity, the model achieved a balanced classification capability with an overall accuracy of **82.43%**.

Among the ensemble components, **SVM contributed to robust decision boundaries**, **Naive Bayes performed well with probabilistic pattern recognition**, and **Logistic Regression added reliable linear separation for text features**. This combination allowed the model to detect nuanced textual similarities with a reasonable trade-off between precision and recall.

Although the model did not reach the performance levels of standalone deep learning models like fine-tuned BERT classifiers, it demonstrates that integrating **lightweight models with contextual embeddings** can still yield competitive and computationally efficient results. The confusion matrix indicates effective detection with relatively few misclassifications,

showcasing the ensemble's ability to generalize across varied text samples.

The results suggest that hybrid approaches combining semantic and lexical features, along with ensemble voting strategies, are practical alternatives for plagiarism detection—especially in resource-constrained environments where deploying full-scale transformer models may not be feasible.

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