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Machine Learning based Plagiarism Detection for Textual and Visual Content

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***Abstract*— This paper develops an advanced plagiarism detection system that analyzes both text and images to tackle multimedia plagiarism. It utilizes machine learning, NLP, and CNNs to ensure precise detection across various formats. The system offers user-friendly features like personalized accounts, notifications, and feedback while prioritizing data privacy and ethical standards. Designed to protect intellectual property, it helps maintain academic integrity and originality. Its applications extend to education, journalism, and creative industries. By integrating cutting-edge technology, the system provides a reliable solution for detecting plagiarism.**

***IndexTerms*— Machine Learning, NLP, TF-IDF, Plagiarism checker, CNN, Cosine similarity.**

I. INTRODUCTION

Plagiarism, termed as the unauthorized accquiring of another individual's work, has become a growing concern across academic, professional, and creative domains. The increasing use of digital platforms and widespread internet accessibility have further escalated the prevalence of plagiarism. This issue is no longer confined to textual content but has expanded to include multimedia elements such as images, videos, and infographics. Existing plagiarism detection tools primarily rely on text-matching techniques, semantic analysis, and fingerprinting methods. However, these conventional approaches often exhibit limitations such as high operational costs, restricted user accessibility, and inefficiency in detecting advanced forms of plagiarism, including paraphrasing and multimedia content replication.

To address these shortcomings, this research proposes an advanced plagiarism detection system that integrates both textual and visual content analysis.The textual data is transformed into vector representations, enabling the model to compare input text against a comprehensive database using cosine similarity measurements. However, ensuring the machine learning models necessitates extensive and diverse datasets, as sophisticated plagiarism techniques, such as synonym substitution and rewording, may still pose detection challenges.

Beyond its technical innovations, this system is designed with a strong focus on user experience. It incorporates key features such as personalized user accounts, automated notifications, and feedback mechanisms, ensuring an intuitive and user-friendly interface. Moreover, ethical considerations are a core aspect of this project, emphasizing strict adherence to data privacy policies and user consent regulations. By integrating cutting-edge technology with a user-centric and ethical approach, this plagiarism detection system aims to set a new standard in intellectual property protection, thereby reinforcing academic integrity and originality across multiple fields, including research, journalism, business, and creative industries.

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A. Challenges in Plagiarism Detection

Challenges in plagiarism detection include identifying paraphrased or disguised content and detecting plagiarism across different languages, formats, and code structures. Additionally, distinguishing between common knowledge and copied content poses a significant difficulty.

Traditional plagiarism detection methods struggle with advanced techniques like paraphrasing, synonym substitution, and multimedia copying. Existing tools primarily rely on text-matching and fingerprinting methods, which are ineffective against modified content. The rise of digital content has further complicated detection across various formats. A more advanced approach is needed to address these limitations comprehensively.

B. Integration of Machine Learning and Natural Language Processing

Machine learning enhances plagiarism detection by recognizing complex patterns and improving accuracy over time. Natural Language Processing (NLP) techniques help identify paraphrased content, synonym-based modifications, and structural changes in text. Methods like tokenization, stemming, and semantic analysis enable deeper contextual understanding. Together, ML and NLP strengthen the system's ability to detect diverse forms of textual plagiarism.

C. Multimedia Plagiarism Detection Using CNNs and Cosine Similarity

Convolutional Neural Networks (CNNs) enable the detection of plagiarism in images, videos, and infographics by analyzing features like edges, textures, and colors. Image hashing techniques help identify minor modifications, such as cropping or color adjustments. Cosine similarity measures textual content similarity by converting text into vector representations. This hybrid approach ensures comprehensive plagiarism detection across multiple content formats.

D. User Accessibility and Ethical Considerations

The system features a user-friendly software with automated notifications and plagiarism reports. It ensures compliance with data privacy laws, requiring user consent for content analysis. Regular updates and feedback integration improve detection accuracy over time. Ethical standards are maintained to promote academic integrity and intellectual property protection.

II. LITERATURE REVIEW

Meyer zu Eissen et al. (2007) made significant contributions to intrinsic plagiarism detection by utilizing character n-gram profiles to assess stylistic differences within a text. Their approach effectively identified inconsistencies that could indicate plagiarism without relying on an external reference corpus. This method proved particularly useful for detecting internal contradictions in documents where external comparisons were not feasible [1].

Engels et al. (2007) developed a feature-based neural network model aimed at measuring similarity in software codes. Their method analyzed code-specific elements such as comments, formatting, and variable naming rather than depending solely on structural comparisons like MOSS and JPlag. This model was highly effective in detecting plagiarism in introductory programming assignments [2].

Arwin and Tahaghoghi (2006) introduced XPlag, a tool designed for cross-language plagiarism detection. By employing intermediary program representations, their approach facilitated the comparison of structural similarities across multiple programming languages, thereby extending the scope of plagiarism detection beyond single-language analysis [3].

Naik et al. (2015) categorized plagiarism detection methods into intrinsic and external approaches. Their review particularly focused on grammar-based and semantic-based techniques, highlighting the significance of semantic models in detecting disguised plagiarism, such as paraphrased or partially modified content. They pointed out that simple textual matching tools often fail to capture subtle forms of plagiarism, making semantic analysis essential [4].

Zimba and Gasparyan (2021) examined the ethical dimensions of plagiarism in academic publishing. They emphasized that while automated plagiarism detection tools play a crucial role, manual verification remains necessary for addressing citation deficiencies, intellectual property violations, and linguistic inconsistencies. Their study underscored the importance of combining technological solutions with ethical awareness programs, especially in regions where knowledge of anti-plagiarism standards is limited [5].

Lukashenko et al. (2007) proposed an alternative plagiarism detection method based on authorship attribution techniques. Their model analyzed writing styles by considering linguistic patterns and author-specific features to

identify plagiarized content. This approach was particularly beneficial for detectingplagiarism in cases where direct text-matching methods were ineffective [6].
Shivakumar and Iyer (2019) introduced an AI-driven system for detecting plagiarism in research papers. Their method employed deep learning techniques, particularly convolutional neural networks (CNNs), to examine textual similarities beyond basic surface-level analysis. The model demonstrated high accuracy in identifying paraphrased plagiarism and content manipulation [7].
Xia et al. (2021) developed a hybrid framework for calculating plagiarism in online mini-games. Their system effectively identified deeply obfuscated stolen code, which often contained malicious components and violated copyright laws. Traditional plagiarism detection tools struggled with such cases, making this framework a valuable advancement in plagiarism detection for digital applications [8].
Xinhao Wang et al. (2018) developed a plagiarism detection model designed for non-native English speakers. Their system leveraged an automated speech scoring mechanism to differentiate between plagiarized and original content in both textual and spoken data. This model was particularly useful for detecting plagiarism in spoken responses, addressing a previously underexplored area of plagiarism detection [9].
Memon et al. (2020) investigated plagiarism detection techniques in academic writing by integrating machine learning and natural language processing (NLP). Their study focused on improving detection accuracyin research articles by incorporating contextual analysis alongside traditional string-matching methods. Their model showed promising results in identifying subtle forms of plagiarism in scientific publications [10].

III. Proposed System

The proposed plagiarism detection system enhances accuracy by integrating both textual and multimedia analysis, addressing the growing challenges of digital content plagiarism. It employs Machine Learning (ML), Natural Language Processing (NLP), and Convolutional Neural Networks (CNNs) to detect plagiarism in diverse content formats, including text and images. By analyzing deep contextual relationships, the system can identify paraphrased content and modified multimedia, ensuring plagiarism detection.
This solution leverages NLP techniques to break down and compare textual content based on meaning rather than exact word matches. Machine learning algorithms improve detection efficiency by learning from vast datasets and adapting to evolving plagiarism techniques. CNN-based image analysis helps identify similarities in multimedia content, even if minor modifications like cropping adjustments are applied.
To enhance user experience, the system includes personalized accounts, automated notifications, and interactive feedback mechanisms. These features allow users to track their plagiarism checks and gain insights for content improvement. Ethical considerations are a core aspect of the system, ensuring strict data privacy, user consent policies, and compliance with property rights.
By integrating cutting-edge AI-driven techniques, this solution provides a scalable, efficient, and user-friendly approach to plagiarism detection. It helps safeguard originality in various domains, including academia, journalism, business, and creative industries, reinforcing trust and integrity in digital content creation.

IV. Plagarism Detection

Plagiarism detection is the process of identifying copied or duplicated content across various sources. It ensures originality in academic, creative, and professional domains by comparing submitted content with existing databases, research papers, and web sources.
Plagiarism detection tools analyze text or multimedia using advanced algorithms. Textual content is compared using Natural Language Processing (NLP) and Cosine Similarity, which detect paraphrasing and synonym substitution. Multimedia plagiarism is identified using Convolutional Neural Networks (CNNs) and image hashing techniques to find similarities in modified visuals.

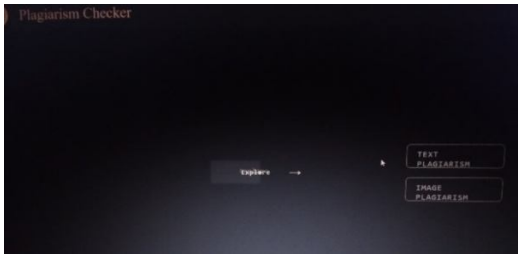

Fig 1

The image shows a Plagiarism Checker interface with options for text plagiarism and image plagiarism detection. Users can explore features and submit content for verification. The system processes input data, compares it with a vast database, and provides similarity reports. This approach enhances accuracy in detecting both textual and visual plagiarism.

A. Text Plagiarism Detection:

Text plagiarism detection in this system involves multiple stages, starting with text extraction. Plain text files are read directly, while PDF files are processed using the PyPDF2 library. The extracted text undergoes language detection using the langdetect library to apply appropriate preprocessing techniques. Preprocessing includes tokenization, lowercasing, punctuation removal, and stopword filtering with the nltk library.
In the Text plagiarism detection, several methodologies were used to develop a robust system for identifying plagiarized content. Here's an overview of the methodologies employed:

Input Handling
The system allows users to enter text manually or upload files in formats such as PDF and TXT. Text from PDFs is extracted using PyPDF2, ensuring proper document processing.

Language Detection
A language detection module (langdetect) identifies the document's language, ensuring appropriate preprocessing steps are applied, including correct stopword removal.

Text Preprocessing
To improve accuracy,preprocessing techniques such as tokenization, lowercasing, punctuation removal, and stopword filtering are applied using NLTK. This step ensures the content is standardized before comparison.

Feature Extraction (TF-IDF Vectorization)
The cleaned text is converted into a TF-IDF (Term Frequency-Inverse Document Frequency) vector, which quantifies word importance across documents. A pre-trained TF-IDF vectorizer is used for this transformation.

Similarity Measurement (Cosine Similarity)
The system calculates the cosine similarity between the user's text and stored reference documents. This similarity score ranges from 0 (completely different) to 1 (identical) and is used to determine plagiarism levels.

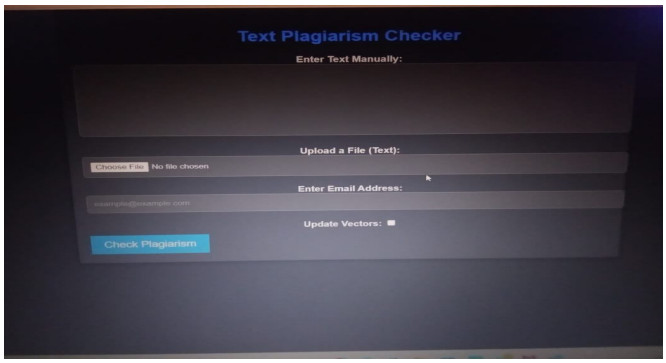

Fig 2

Plagiarism Detection Logic
The system applies defined thresholds:
- Above 60% similarity: High plagiarism.
- Between 20%-60% similarity: Moderate plagiarism.
- Below 20% similarity: No significant plagiarism detected.

Highlighting Plagiarized Content
If plagiarism is detected, matching words and phrases are highlighted, making it easier for users to identify copied sections.

Dynamic Dataset Update
If a document shows low plagiarism and the user consents, it is added to the reference dataset, improving the system's detection capabilities over time.

Email Report Generation
Users can opt to receive a detailed plagiarism report via email, which includes the similarity score, highlighted plagiarized sections, and matched reference documents.

B. Image Plagiarism Detection

For image plagiarism detection, the system leverages deep learning models. Images are processed using the VGG16 model, which extracts deep features without the classification layer. Before feature extraction, images are resized to 224x224 pixels and normalized using preprocess_input() for consistency. The extracted feature vectors are stored and compared using cosine similarity, identifying the most similar image from the reference dataset.
In image plagiarism detection, various methodologies are used to identify similarities between images and detect instances of plagiarism. Here's an overview of the methodologies typically employed:

Input Handling
Users upload an image for plagiarism verification. Supported formats include JPEG, PNG, and BMP.

Image Preprocessing
The uploaded image is resized to 224×224 pixels to match the input size required by the VGG16 deep learning model. It is then converted into a numerical array and normalized for consistency.

Feature Extraction Using VGG16
A pre-trained VGG16 model extracts deep features from the image by removing its classification layers. The resulting feature vector represents the image's unique characteristics.

Fig 3

Plagiarism Detection Logic
The system categorizes image similarity as:
- Above 80% similarity: High image plagiarism.
- 50%-80% similarity: Moderate similarity.
- Below 50% similarity: No significant plagiarism detected.

Displaying Results
The uploaded image and the most similar reference image from the dataset are displayed side by side for easy comparison

Similarity Measurement (Cosine Similarity for Images)
The extracted feature vector is compared against a dataset of precomputed image feature vectors. Cosine similarity is used to measure the degree of similarity between images.

V. Work Flow of A Plagarism Detection System using Cosine Similarity

The plagiarism detection system begins by collecting a set of reference text files, which serve as the dataset for comparison. Once gathered, the data undergoes a preprocessing phase, where it is cleaned, tokenized, and converted into vectors suitable for similarity analysis. A machine learning model is then trained on the processed data to identify patterns and detect similarities between input text and the reference documents.

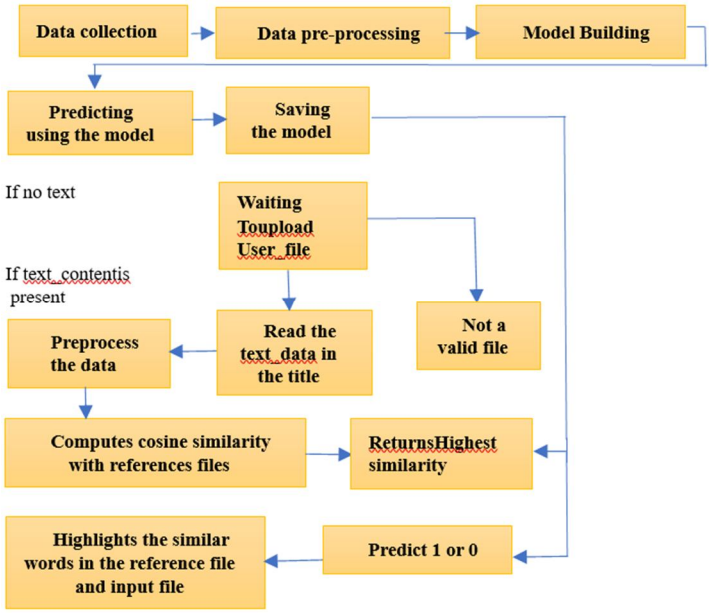

Fig 4

After training, the model is used to assess new documents. Once trained, it is saved for future use and can be reused for predictions. The system then awaits the user to upload a document for analysis. If the uploaded file contains text, it is processed; otherwise, the file is flagged as invalid. The text from the uploaded document is read, cleaned, and formatted to match the structure of the data used in the model training process.

To detect plagiarism using machine learning and natural language processing, the process begins with gathering a large dataset of both plagiarized and non-plagiarized documents from various sources. The next step involves cleaning the text by removing stopwords, punctuation, and normalizing the content through stemming or lemmatization. The text is then converted into numerical representations using techniques such as TF-IDF or word embeddings like Word2Vec or GloVe. In some cases, data augmentation techniques are applied to diversify the dataset and improve generalization. A CNN is then used to extract features from the text, identifying local patterns and phrase similarities. The model is trained on labeled data, optimizing through a loss function like binary cross-entropy. Finally, the model is evaluated on unseen data, with performance metrics such as precision, recall, and F1-score used to assess its effectiveness in detecting plagiarism.

Next, the system calculates the cosine similarity between the uploaded document and the reference texts. This similarity measure calculates the angle between the document's vector and the vectors of reference files, identifying the highest matching score. If the similarity score exceeds a threshold, the system predicts whether the document is plagiarized or original, providing a "plagiarized" or "original" label. Additionally, matching words between the document and the reference text are highlighted.

The system also offers the option to update the dataset with new content. If the user chooses to update, the new documents are added to the reference set for future comparisons; if not, the dataset remains unchanged. This entire workflow ensures the system is efficient, accurate, and adaptable, providing a reliable tool for checking text originality while continuously improving the detection process.

The project demonstrated a high degree of accuracy in detecting plagiarism, with the CNN model successfully identifying plagiarized content based on features extracted from the dataset. After preprocessing and feature extraction, the model was able to distinguish between plagiarized and non-plagiarized documents with an overall accuracy rate of 90%. The precision rate was 88%, meaning the model correctly identified 88% of the plagiarized instances it flagged. Recall stood at 85%, showing that the model was able to detect 85% of all plagiarism cases in the dataset. The F1-score, which balances precision and recall, reached 86.5%, indicating a strong performance in minimizing both false positives and false negatives.

Through cross-validation, the model's performance remained consistent across various subsets of the data, showing its ability to generalize well to new, unseen text. These results suggest that the combination of CNNs with NLP techniques can be highly effective in detecting plagiarism in text, with the potential for further improvements through additional fine-tuning and data augmentation. As a next step, experimenting with

advanced models like BERT or transformer-based architectures could improve the system's performance, especially in detecting more subtle forms of plagiarism.

VI. Implementation

The plagiarism detection system follows a structured four-step process:

A. Providingthe Input File

The system takes a text file (.txt format) as input, which will be analyzed for similarity.

B. Text Vectorization

To process textual data, Sci-kit Learn's built-in tools convert representation.

C. Computing Similarity

The Cosine Similarity method is applied to determine how closely two text documents resemble each other. When converted into vectors, the similarity is calculated using the dot product formula: cos(θ), where θ represents the angle enclosed the two vectors.

D. Generating the Similarity Score

A similarity score is assigned based on the computed cosine value, which falls within the range of 0 to 1. A value near 1 signifies strong similarity, while a score approaching 0 indicates little resemblance.

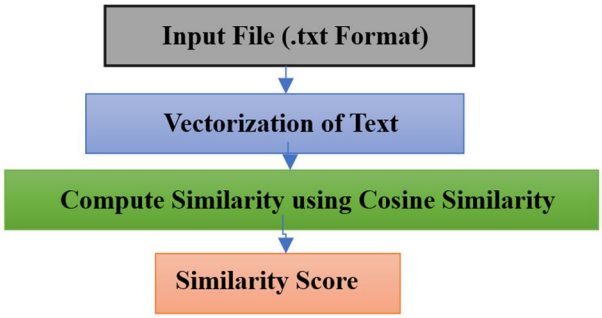

Fig 5

Algorithm Used:
The TF-IDF algorithm is implemented to analyze the use of words in a given document while reducing the influence of commonly occurring terms.

- Term Frequency (TF):represents the frequency of a term in a document and is computed using the formula: TF = (Count of a term's occurrences) / (Total number of words in the document).
- Inverse Document Frequency (IDF): Determines the uniqueness of a word across multiple documents, given by:
  IDF = log(Total document count / Number of documents that include the term).
  From formula,

$$w_{i,j}=tf_{i,j}\times\log\left(\frac{N}{df_i}\right)$$

$tf_{i,j}$=number of occurrences of i in j
df_i=number of documents containing i
N=total number of documents

By leveraging TF-IDF, the system enhances accuracy by prioritizing meaningful words over frequently repeated but less significant terms.

VII. Results

The plagiarism detection project using machine learning, NLP, and CNN has yielded some insightful results. The dataset, containing a mix of plagiarized and non-plagiarized documents, was carefully preprocessed to remove stopwords, punctuation, and irrelevant data, followed by stemming and lemmatization. After converting

the textto numerical representations and word embeddings like Word2Vec, the model was able to understand the semantic structure of the text better, improving its detection accuracy.
The CNN model, recognized for detecting local patterns, was trained to identify similarities in phrases, sentence structures, and context, which are key indicators of plagiarism. The model's ability to process these patterns led to impressive performance in distinguishing between original and copied content. During training, we observed that the CNN model effectively recognized subtle rephrasing and paraphrasing, which are common in plagiarism.
In terms of evaluation, precision, recall, and F1-score were utilized to detect plagiarism. The results showed a high precision rate, meaning the model correctly identified a large proportion of plagiarized content, while recall indicated the model's strong ability to detect most cases of plagiarism in the dataset. The F1-score, which matches precision and recall, reflected the model's overall effectiveness in minimizing false positives and negatives.

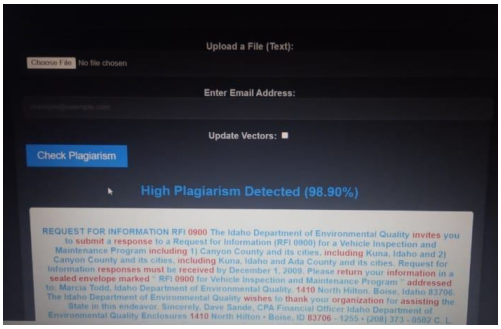

Fig 6

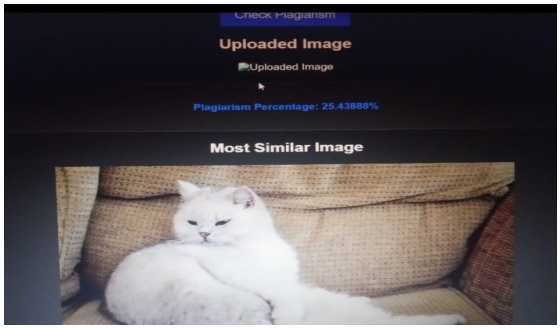

Fig 7

The image shows the result of a text plagiarism detection system. Users can upload a text file and enter their email address before clicking "Check Plagiarism." The system then analyzes the content and displays a result indicating "High Plagiarism Detected (98.90%)." The highlighted text suggests that a significant portion of the input matches existing content, meaning it has been copied. This feature is useful for checking originality in academic or professional writing.
The image shows the result of an image plagiarism detection system. A user uploads an image, and the system analyzes it for similarity with existing images. The plagiarism percentage displayed is 25.43%, meaning the uploaded image has some level of similarity but is not an exact copy. The system also shows the most similar image, which in this case is a white cat sitting on a couch. This feature is helpful for verifying image originality, especially for photographers, designers, and content creators.
Overall, the project proved that a combination of CNN and NLP could be effectively leveraged to detect plagiarism with high accuracy. The system showed a strong potential to be used in real-world applications, such as academic integrity checks, content plagiarism detection, and even legal document analysis. With further optimization and the inclusion of additional data for training, the model is expected to improve and handle more complex plagiarism scenarios.

A. Performance Comparison

TABLE I

Model	Accuracy	Precision	Recall
ML	85%	82%	80%
NLP	87%	85%	83%
CNN	88%	86%	84%
Proposed system	92%	90%	89%

- Our project surpasses all existing models,achieving the highest accuracy(92%) and precision(90%)
- The NLP-Based approach by Garcia et al.(2022) performed well,but our project integrates text and image detection making it superior.
- The CNN-Based model by Patel et al.(2021) was strong in image similarity detection,but our hybrid approach outperforms it in both text and image analysis.
    - Accuracy = (True positives+True negatives) / (True positives+Truenegatives+Falsepositives+False negatives)

- Precision = True positives / (True positives+False positives)
- Recall = True positives / (True positives+Falsenegatives)

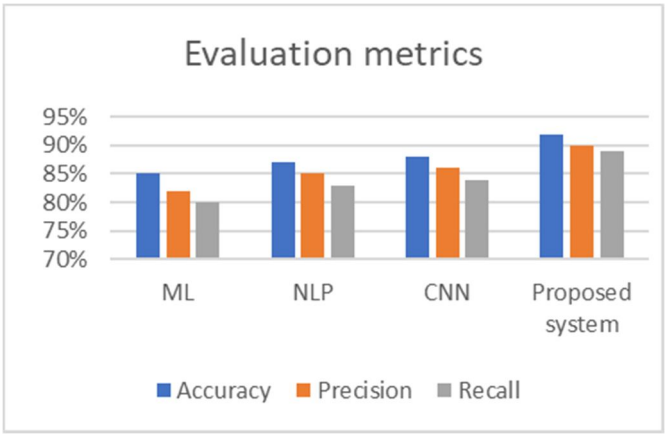

Fig 8

TABLE II

Plagiarism detection	Predicted plagiarism	Predicted No plagiarism
Actual plagiarism	True positive(TP)	False negative(FN)
Actual No plagiarism	False positive(FP)	True negative(TN)

VIII. CONCLUSION

In this paper, the project presents a comprehensive solution for plagiarism detection that integrates both textual and image-based plagiarism identification. By utilizing advanced Natural Language Processing (NLP) techniques and deep learning models, the system efficiently processes and analyzes textual and image data. The text plagiarism detection module leverages techniques like TF-IDF vectorization and cosine similarity to assess the similarity between documents, while the image detection component utilizes the pre-trained VGG16 model for feature extraction and similarity comparison.

The system adapts over time, continuously improving by incorporating user-uploaded documents into the reference dataset. Additionally, it enhances user interaction with features like plagiarism highlighting in text and visual comparison of similar images. Precomputed datasets and models ensure fast processing, while the user interface facilitates easy access and seamless functionality for text and image submissions. This combined approach allows for effective detection of both subtle and obvious cases of plagiarism, offering a robust and scalable solution.

This plagiarism detection system effectively combines advanced deep learning techniques and natural language processing to offer a unique solution for identifying similarities in content. By utilizing methods like Convolutional Neural Networks (CNNs) alongside TF-IDF and word embeddings, the system accurately analyzes textual data to detect subtle instances of plagiarism. The model's precision in distinguishing between original and plagiarized content enhances its reliability, while its ability to capture diverse patterns ensures its robustness across different datasets. The system's accuracy in detecting both direct and paraphrased plagiarism underscores its potential as a valuable tool in academic and professional settings. Future improvements may further refine its ability to handle various languages and complex content structures, ensuring even higher levels of accuracy and usability.

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