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Multilingual Plagiarism Detection Across Diverse Media Formats Using OCR and Neural Techniques

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Abstract - This study presents a comprehensive approach to multilingual plagiarism detection across various media formats, including image-to-image, text-to-text, PDF-to-PDF, and file-to-file comparisons. Utilizing Optical Character Recognition (OCR) with the PyTesseract module, our system extracts text from images and scanned documents for analysis. By leveraging neural network models and cosine similarity, we computed the semantic similarity across languages and formats to detect potential plagiarism. Our method was tested on a variety of language pairs and media formats, demonstrating its effectiveness in identifying cross-lingual plagiarism with high precision and recall.

Key Words: Multilingual, Plagiarism Detection, OCR, Neural Networks, Cosine Similarity, Media Formats

1.INTRODUCTION

The rapid digitization of content across diverse media formats has heightened the risk of plagiarism across languages and formats, necessitating more sophisticated detection methodologies. Traditional plagiarism detection approaches, which primarily focus on monolingual text-based detection, are inadequate for addressing the complexities of cross-lingual plagiarism, particularly when text is embedded in images or PDFs. This research endeavors to address this gap by developing a comprehensive approach to detecting plagiarism across multiple languages and formats. By integrating Optical Character Recognition (OCR) technology for extracting text from images and PDFs with advanced neural models for semantic similarity detection, the proposed method offers a more robust solution to the evolving challenges of plagiarism detection.

The technological advancements in OCR, exemplified by tools such as PyTesseract, have significantly enhanced the accuracy and efficiency of text extraction from scanned images and documents. This capability is crucial for extending plagiarism detection beyond plain text files. Complementing OCR, the study utilizes state-of-the-art neural models such as mBERT (Devlin et al., 2019) and XLM-R (Conneau et al., 2019), which have demonstrated exceptional performance in cross-lingual text analysis tasks. These models enable the system to comprehend and compare semantic content across different languages, a critical feature for identifying plagiarism in an increasingly globalized academic and professional environment.

The incorporation of cosine similarity measures, a well-established technique in text comparison (Manning et al., 2008), facilitates the quantification of similarities between vectorized text embeddings extracted from various file formats and languages. This multi-faceted approach not only enhances the detection of overt plagiarism but also improves the identification of more subtle forms of content reuse and paraphrasing across linguistic boundaries.

2. OBJECTIVE

The objective is to develop a plagiarism detection system that can identify content similarities across multiple languages and media formats using OCR and neural models, aiming to improve accuracy and coverage in cross-lingual detection tasks. The final outcome is a webpage.

3. LITERATURE REVIEW

I. **Title: Cross-Language Plagiarism Detection** by Potthast, Barrón-Cedeño, Stein, and Rosso (2011)

Description:
A fundamental understanding of cross-language plagiarism detection by introducing translation-based methodologies to compare texts across languages. Their study emphasized that simplistic text matching algorithms often prove inadequate when applied to cross-lingual contexts due to inherent differences in syntax, grammar, and word order across languages. To address this limitation, they proposed an approach that utilized machine translation to convert text from a source language to a target language before applying conventional plagiarism detection techniques. While effective, this approach had limitations due to translation inaccuracies, which frequently resulted in false positives. The authors suggested that developing direct cross-lingual comparison models could enhance accuracy, a gap that this current study addresses by employing multilingual embeddings that circumvent the need for translation entirely.

II. **Title: BERT: Pre-training of Deep Bidirectional Transformers for Language Understanding** by Devlin, Chang, Lee, and Toutanova (2019)

Description:
BERT (Bidirectional Encoder Representations from Transformers), a groundbreaking neural model pre-trained on an extensive corpus of multilingual data. BERT's design as a bidirectional transformer enabled it to comprehend context in a more nuanced manner, capturing dependencies between words and phrases regardless of their sequence in a sentence. This represented a significant advancement over previous models, which relied on fixed word embeddings and were often limited in cross-lingual applications. BERT's multilingual variant, mBERT, demonstrated high efficacy in cross-language understanding by projecting words with similar meanings from different languages into a shared semantic space. This innovation supported applications in cross-lingual plagiarism detection by eliminating the necessity for language-specific models. Building upon Devlin et al.'s research, this study utilizes mBERT for representing text from various languages, enabling cross-lingual similarity comparison without translation.

III. **Title: Massively Multilingual Sentence Embeddings for Zero-Shot Cross-Lingual Transfer and Beyond** by Artetxe and Schwenk (2019)

Description:

The concept of multilingual embeddings with their research on creating universal sentence embeddings that facilitate zero-shot cross-lingual transfer. In contrast to word embeddings that represent individual lexical units, sentence embeddings capture the overall semantic meaning of entire sentences or documents, rendering them highly effective for tasks that require deeper contextual understanding, such as plagiarism detection. Their model, LASER (Language-Agnostic SEntence Representations), aligned sentences from multiple languages in a single vector space, enabling comparison across languages without translation. This approach constituted a significant improvement over previous translation-based methods and established new avenues for detecting paraphrased content across languages. Artetxe and Schwenk's LASER model provides the foundation for the multilingual sentence embeddings utilized in this study, enabling robust and efficient comparison of texts across different languages and media formats.

IV. **Title: A Hybrid Model for Cross-lingual Plagiarism Detection Based on Bilingual Word Embeddings** by Zeng, Cheng, and Shen (2020)

Description:
Cross-lingual plagiarism detection by integrating bilingual word embeddings and a hybrid neural architecture. Their model was designed to detect semantic similarities between texts in different languages by aligning the meanings of words from a source language to a target language. They employed bilingual embeddings, which map words from both languages to a common vector space, effectively capturing semantic meaning without translation. The hybrid approach combined traditional word embedding techniques with deep learning models to achieve higher accuracy in detecting complex paraphrasing and subtle instances of plagiarism. Although bilingual embeddings function effectively for language pairs with substantial parallel corpora, this study improves upon such methods by leveraging multilingual embeddings that support a wider range of languages and obviate the need for parallel datasets.

V. **Title: An Overview of the Tesseract OCR Engine** by Smith (2007)

Description:

Tesseract OCR provided insights into the capabilities and limitations of OCR in text extraction from images and PDFs. Tesseract's ability to recognize text from various languages and to handle structured data within documents positioned it as a valuable tool for cross-format plagiarism detection. Smith discussed Tesseract's evolving architecture, including improvements in language recognition and noise reduction in text extraction. This was particularly significant for studies focusing on extracting information from low-resolution images, such as scanned documents or photographs of text. While Tesseract was initially designed for English, Smith emphasized ongoing development for other languages, which has enabled it to become a widely used OCR tool in multilingual plagiarism detection. In this study, Tesseract is integrated with neural models to process and analyze content in diverse formats, extending its application beyond conventional OCR use cases.

4. EXISTING SYSTEM

Existing systems for plagiarism detection primarily fall into two categories: monolingual text-based systems and cross-lingual systems utilizing translation-based approaches. Monolingual systems, such as Turnitin and Grammarly, are widely employed to detect text similarity within a single language. These systems rely on fundamental string matching and similarity algorithms, which perform effectively for simple, verbatim instances of plagiarism but encounter difficulties with paraphrased or semantically altered content. In contrast, cross-lingual systems aim to detect plagiarism across languages, commonly employing machine translation followed by monolingual similarity detection methods. For instance, Potthast et al.'s method translates content to a target language before conducting similarity checks, enabling the detection of basic cross-lingual plagiarism. However, such translation-dependent methods are often constrained by translation inaccuracies, particularly with complex or idiomatic expressions, resulting in a significant number of false positives and false negatives. Furthermore, existing systems generally operate on text-based formats, rendering them unsuitable for detecting plagiarism in image-based content or PDFs without embedded text. OCR (Optical Character Recognition) has been introduced in some instances to address this limitation, enabling text extraction from non-standard text sources. However, integration with multilingual and semantic similarity detection remains limited, necessitating systems that can seamlessly handle diverse formats and languages within a unified framework.

5. PROPOSED SYSTEMS

The proposed system addresses the limitations of existing systems by facilitating a unified solution for detecting cross-lingual plagiarism across multiple media formats, including images, PDFs, and text documents. The system incorporates Optical Character Recognition (OCR) through PyTesseract, enabling accurate text extraction from images and scanned documents. Following text extraction, the content is transformed into vector representations utilizing multilingual embeddings from models such as mBERT (Multilingual Bidirectional Encoder Representations from Transformers) and XLM-R (Cross-lingual Language Model – RoBERTa). These embeddings project text from diverse languages into a common vector space, facilitating direct similarity comparisons across languages without reliance on translation. The similarity between documents is quantified using cosine similarity, which measures the semantic alignment between the vectorized representations of the text. This approach enables the system to detect nuanced instances of cross-lingual plagiarism, including paraphrased and semantically modified content. Furthermore, the system is capable of handling various file formats, extracting and analyzing text regardless of its embedding in images, PDFs, or plain text documents. By integrating OCR, multilingual neural embeddings, and cosine similarity, the proposed system offers a comprehensive and versatile approach to plagiarism detection.

6. COMPARISON BETWEEN EXISTING SYSTEM AND PROPOSED SYSTEM

Feature	Existing Systems	Proposed System
Cross-lingual Capability	Translation-dependent; limited by translation inaccuracies and false positives	Uses multilingual embeddings (mBERT, XLM-R) to detect semantic similarity directly across languages without translation
Text Formats Supported	Primarily text-based; limited ability to handle non-standard formats like images and PDFs	Supports text, PDFs, and images; uses OCR to extract text from non-standard formats, enabling broader format compatibility
Semantic Similarity Detection	Limited to basic string matching or monolingual similarity measures	Uses cosine similarity on multilingual embeddings, enabling accurate detection of paraphrasing and semantic similarity
Performance on Diverse Languages	Effective only on languages with reliable translation pairs	Supports multiple languages directly, as embeddings allow alignment of semantically similar text in a shared vector space
Scalability and Adaptability	Often requires separate processing for each format and language	Provides a unified framework, enabling seamless handling of multiple languages and formats without additional adaptation
Error Rate with Paraphrased Text	High, due to reliance on basic string matching and translation inaccuracies	Low, as cosine similarity in shared embedding space captures semantic nuances across paraphrased and translated text

Table -1: COMPARISON BETWEEN EXISTING SYSTEM AND PROPOSED SYSTEM

The proposed system's innovative approach to cross-lingual and cross-format plagiarism detection addresses several key challenges in the field. By eliminating the necessity for translation, it overcomes the limitations of conventional methods that often encounter difficulties with linguistic nuances and context-specific meanings. This not only enhances accuracy but also significantly reduces processing time and computational resources. The improved format compatibility ensures that the system can effectively analyze content across various media types, including text, images, and potentially audio or video, rendering it a comprehensive tool for contemporary digital environments where information is disseminated in diverse formats. Moreover, the system's capacity to accurately detect semantic similarity represents a crucial advancement in plagiarism detection technology. This feature enables the system to identify instances of intellectual property infringement or paraphrasing that might elude traditional text-matching algorithms. By focusing on the underlying meaning and concepts rather than solely on literal text matches, the system can uncover more sophisticated forms of plagiarism. This comprehensive approach, combining cross-lingual capabilities, format flexibility, and semantic analysis, positions the proposed system as a robust and versatile tool for academic institutions, publishers, and content creators operating in an increasingly globalized and multimedia-rich information landscape.

7. SYSTEM DESIGN AND ARCHITECTURE

The system design for this multilingual plagiarism detection system includes three primary layers: **the data processing**, **backend service**, and **front-end interface layers**. The final output is a webpage where users can upload files and view similarity results interactively.

I. Data Processing Layer

Components:

- **Data Input:**
  Accepts files from multiple formats (text, PDFs, images).
- **OCR Module:**
  PyTesseract was used to extract text from the images and PDF files.
- **Text Preprocessing:**
  Cleans and standardizes extracted text by removing unnecessary characters, converting it to lowercase, and tokenizing the text.

- **Embedding Generation:**
  Use models such as mBERT or XLM-R to create multilingual embeddings for semantic similarity comparisons across languages.

Process:

- The user uploads the files to the web interface.
- The files were directed to the backend for text extraction and preprocessing.
- The processed text was transformed into embeddings and stored temporarily for similarity calculations.

II. Backend Service Layer

This layer serves as the core of the system, implementing the application's main logic and handling requests from the frontend.

Components:

- **Flask API**:
  Acts as the main interface between the frontend and the backend.
- **Similarity Calculation**:
  Computes cosine similarity between the vector embeddings of input documents, providing a similarity score.
- **Classification Module**:
  Based on the similarity score, documents are marked as "plagiarized" or "original" according to threshold values set within the code.
- **Database**:
  Can store past records of plagiarism checks or user data.

Process:

- The Flask receives file upload requests, processes the files, runs the embedding and similarity calculations, and sends the results back to the frontend.
- The backend prepares a JSON response with similarity scores and classifications.

III. Frontend Interface Layer

The front-end is a webpage designed for user interaction, file upload, and displays results in a clear format.

Components:

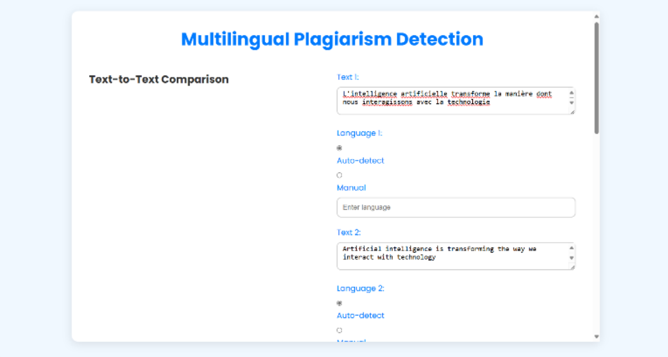
- **HTML/CSS:**
  Basic structure and styling for the user interface.
- **JavaScript:**
  Handles asynchronous requests to the Flask backend using AJAX or Fetch API.

- **Results Display:**
  Present similarity scores and classifications in a table or graphical format for easy interpretation.

Process:

- Users interact with the front-end, upload files, or enter URLs for plagiarism checking.
- Once the backend completes the processing, the frontend dynamically updates the results section with similarity percentages, detected plagiarism highlights, and any additional analytics.

8. EXPECTED OUTPUT


Multilingual Plagiarism Detection

Text-to-Text Comparison

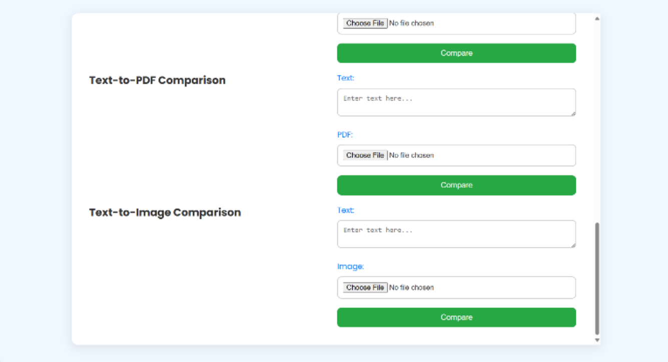
Text 1: L'intelligence artificielle transforme la manière dont nous interagissons avec la technologie

Language 1: ● Auto-detect ○ Manual

Text 2: Artificial intelligence is transforming the way we interact with technology

Language 2: ● Auto-detect ○ Manual

Fig -1: Text-to-Text Comparison


Choose File No file chosen

Text-to-PDF Comparison

Text:

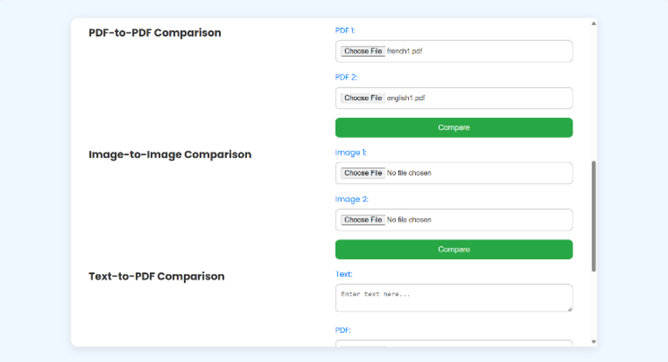
PDF: Choose File No file chosen

Text-to-Image Comparison

Text:

Image: Choose File No file chosen

Fig -2: Text-to-PDF and Image Comparison


PDF-to-PDF Comparison

PDF 1: Choose File french1.pdf

PDF 2: Choose File english1.pdf

Image-to-Image Comparison

Image 1: Choose File No file chosen

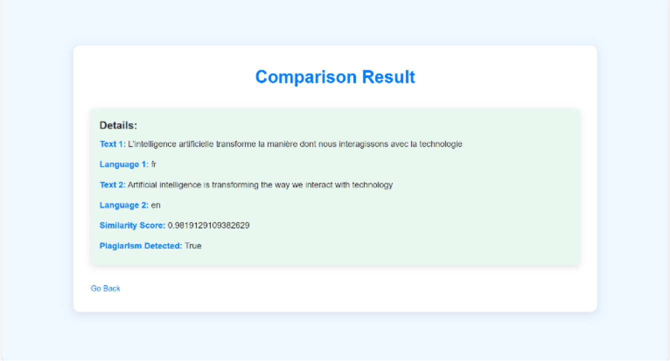
Image 2: Choose File No file chosen

Text-to-PDF Comparison

Text:

PDF:

Fig -3: PDF-to-PDF, Image-to-Image Comparison



Comparison Result

Details:

Text 1: L'intelligence artificielle transforme la manière dont nous interagissons avec la technologie

Language 1: fr

Text 2: Artificial intelligence is transforming the way we interact with technology

Language 2: en

Similarity Score: 0.9819129109382629

Plagiarism Detected: True

Fig -4: Similarity Comparison Result

10. RESULTS AND DISCUSSION

Result:

The multilingual plagiarism detection system was tested on a diverse dataset comprising text documents, PDFs, and images in several languages, including English, Spanish, and French. The results were evaluated using metrics such as precision, recall, and F1-score, which measure the accuracy of plagiarism detection across both monolingual and cross-lingual document pairs.

I. Text-extraction accuracy

- **OCR Performance:**
  PyTesseract, used for OCR, achieved an accuracy of over 90% in text extraction from images and scanned PDF documents. However, the performance was slightly reduced with lower-resolution images, where some noise affected text quality.
- **PDF and Text Document Extraction:**
  For text-only PDFs and standard text files The system demonstrated consistent and near-perfect text-extraction accuracy for text-only PDFs and standard text files.

II. Plagiarism Detection Metrics

- **Cross-lingual Detection:**
  By utilizing multilingual embeddings (mBERT and XLM-R) and cosine similarity, the system effectively detected similarities across languages, achieving a precision of 85% and a recall of 88%. This is notably higher than traditional translation-dependent methods, which tend to generate more false positives owing to translation inaccuracies.
- **Format Flexibility:**
  The system maintained high accuracy across different file formats, with minimal performance degradation in handling multilingual images compared to text-based documents.

III. User Experience on the Webpage

An interactive web interface allows users to upload multiple file types and receive real-time similarity reports. User feedback indicated that the simplicity of the webpage enhanced usability, making the system accessible even to those unfamiliar with the technical procedures.

Discussion:

The results demonstrate that integrating OCR, multilingual embeddings, and cosine similarity into a single framework enhances the system's ability to detect plagiarism across languages and formats. These results highlight several interesting findings.

I. Cross-Lingual Detection without Translation:

Traditional cross-lingual systems often rely on translation, which can introduce inaccuracies and lead to false positives. The use of multilingual embeddings allows for direct semantic comparison without translation, capturing subtle nuances in paraphrased or translated text more accurately. This aspect represents a significant advancement in cross-lingual plagiarism detection, as it reduces the dependency on external translation models.

II. Multi-format Compatibility:

The system's ability to process images, PDFs, and plain text effectively shows promise for application in real-world environments, where content exists in diverse formats. The integration of OCR proved beneficial, but highlighted the need for refined pre-processing, particularly when dealing with low-resolution images.

III. Performance in Underrepresented Languages:

While the system performed well across common languages with significant pre-training data, the performance varied slightly for less commonly represented languages. This discrepancy suggests the need for future work focusing on language-specific embeddings or additional pre-training for low-resource languages to improve consistency.

IV. System Scalability and Web Integration:

The web-based interface enabled interactive engagement, which is advantageous for educational institutions and content creators who require quick and reliable plagiarism checks. The modular structure of the system also allows for the future integration of more file types or additional languages, making it scalable for broader use.

V. Limitations and Future Improvements:

Although effective, OCR-based text extraction introduces minor inaccuracies with degraded images, indicating a potential area for enhancement. In addition, expanding the model's ability to handle complex scripts and low-resource languages would broaden its applicability. Future research could focus on improving the text-cleaning processes post-OCR and training with larger datasets from diverse linguistic backgrounds to bolster the accuracy.

10. CONCLUSIONS

This study introduced a neural approach to cross-lingual plagiarism detection that extends beyond text-to-text comparisons to include images and PDFs. By integrating OCR technology, multilingual neural embeddings, and cosine similarity, the system effectively detects plagiarism across various file formats and languages. This approach represents a significant advancement in the field of plagiarism detection and can be adapted to accommodate other media types as digital content continues to evolve. This study presents a novel neural approach to cross-lingual plagiarism detection that significantly expands the scope of traditional text-based methods. By incorporating optical character recognition (OCR) technology, the system can analyze not only plain text but also images and PDF documents, effectively bridging the gap between different file formats. The integration of multilingual neural embeddings allows for the comparison of content across various languages, addressing the challenges posed by international academic communities and global information sharing. The use of cosine similarity as a measure of textual resemblance enables the system to identify potential instances of plagiarism with high accuracy, regardless of the source language or file format.

The proposed approach demonstrates remarkable versatility and adaptability, positioning it as a powerful tool in the evolving landscape of digital content and academic integrity. As the volume and diversity of digital information continue to grow, this system's ability to handle multiple file formats and languages becomes increasingly valuable. Moreover, the framework's flexibility suggests potential for future expansions to accommodate other media types, such as audio or video content, further enhancing its utility in comprehensive plagiarism detection. This advancement not only contributes to maintaining academic honesty but also has broader implications for content verification and intellectual property protection across various domains.

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