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AI-Powered Multilingual Entity Extraction System for Clinical Text Using OCR And Large Language Model

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multilingual medical data, medical entity extraction, natural language processing (NLP), large language models (LLMS), optical character recognition (OCR), multilingual interoperability, automated information extraction

ABSTRACT

The rapid growth of digital content has made it increasingly difficult for users to find relevant books efficiently. This project presents a Semantic Topic Modelling and Book Recommendation System using Natural Language Processing (NLP) techniques to provide personalized book suggestions based on content similarity. The system follows a content-based filtering approach, analysing book descriptions to identify relevant recommendations. The dataset is preprocessed by removing null values and cleaning textual data, followed by text normalization techniques such as lowercasing and stop-word removal. The processed text is then converted into numerical form using TF-IDF vectorization, which helps in identifying the importance of words in each book description. Cosine similarity is used to measure the similarity between different books, and based on these similarity scores, the system recommends the most relevant books to users. The application is developed using Streamlit, providing an interactive user interface with features such as random book suggestions, similarity-based recommendations, and the ability to explore books by specific authors. Additionally, caching techniques are implemented to improve performance and reduce computation time, ensuring efficient and fast recommendation generation. This project demonstrates the practical application of NLP in real-world recommendation systems and enhances user experience by delivering accurate and meaningful suggestions. Future improvements may include the integration of hybrid models and user preference learning to further enhance recommendation quality.

1. INTRODUCTION

Brief Information

The field of healthcare data processing has undergone significant transformation over the years, driven by rapid advancements in artificial intelligence, natural language processing, and intelligent automation technologies. Traditionally, medical records and prescriptions were maintained in unstructured formats

such as handwritten notes, printed documents, and region-specific languages. While these methods were widely used, they followed a generalized approach that did not effectively address challenges related to multilingual diversity, varying file formats, and efficient extraction of critical medical information. Such limitations often resulted in reduced accessibility, increased manual effort, and potential errors in interpreting healthcare data. Multilingual medical data processing represents an important advancement in modern healthcare systems by enabling accurate interpretation of medical information across different languages and formats. This approach focuses on extracting essential entities such as patient details, doctor information, diseases, medications, dosages, and symptoms from unstructured data sources. In this project, the system is designed to support multiple file formats including text files, PDFs, Word documents, spreadsheets, and images. It utilizes automated text extraction techniques such as document parsing and optical character recognition to process diverse inputs efficiently. This ensures improved data accessibility, minimizes human intervention, and enhances the reliability of information retrieval.

2. LITERATURE SURVEY

Healthcare data processing has evolved from manual and rule-based systems to advanced AI-driven approaches. Traditional methods were time-consuming, error-prone, and inefficient in handling unstructured and multilingual clinical data.

Optical Character Recognition (OCR) enables extraction of text from scanned documents and images, but lacks contextual understanding. Natural Language Processing (NLP) techniques improved text analysis, yet traditional models require extensive training and struggle with multilingual data.

Machine Learning approaches enhanced automation but depend on large datasets and lack flexibility in handling diverse clinical formats. Recently, Large Language Models (LLMs) have shown significant improvements by enabling context-aware processing, translation, and entity extraction without task-specific training.

2.1. Optical Character Recognition (OCR) in Medical Data

The field of healthcare data processing has undergone significant transformation with the advancement of Artificial Intelligence and digital technologies. Clinical data is often available in unstructured formats such as handwritten prescriptions, scanned documents, PDFs, and multilingual text, making it difficult to process and interpret efficiently. Traditional systems rely on manual methods or rule-based approaches, which are time-consuming, error-prone, and inefficient in handling large volumes of complex medical data.

Optical Character Recognition (OCR) plays an important role in converting image-based documents into machine-readable text, enabling digitization of clinical records. However, OCR alone cannot understand the context of the extracted text. Natural Language Processing (NLP) techniques improve text analysis, but traditional NLP models require extensive training and struggle with multilingual and unstructured data. Recent advancements in Large Language Models provide context-aware understanding, allowing efficient translation and accurate extraction of medical entities such as diseases, medications, and patient details.

2.2. Natural Language Processing and Large Language Models

Natural Language Processing enables understanding and analysis of clinical text. Traditional NLP techniques rely on predefined rules and training datasets, limiting flexibility. Large Language Models provide context-aware understanding, enabling accurate translation and extraction of medical entities from multilingual data.

Therefore, there is a need for an integrated AI-based system that can process diverse input formats, support multilingual data, and generate structured outputs. The proposed approach addresses these challenges by combining OCR and Large Language Models into a unified framework for efficient and accurate clinical data processing.

2.3. Natural Language Processing and Large Language Models

Natural Language Processing (NLP) is a key technology used for analyzing and understanding unstructured clinical text. In healthcare, NLP helps in identifying important information such as diseases, medications, and patient details from medical records. Traditional

NLP approaches rely on rule-based methods and statistical models, which require predefined patterns and extensive training data.

However, these traditional methods have limitations when dealing with complex medical terminology and multilingual data. They often struggle to understand context and fail to adapt to variations in language and document formats. This reduces their effectiveness in real-world healthcare applications where data is highly diverse and unstructured.

2.4. Multilingual Clinical Data Processing

Multilingual clinical data processing is an important aspect of modern healthcare systems. Medical records and prescriptions are often written in different languages, depending on the region and healthcare provider. This creates challenges in understanding and analyzing the data effectively, especially in global or diverse environments.Traditional systems are not designed to handle multiple languages efficiently. They often rely on basic language detection or manual translation, which can lead to errors and inconsistencies. Mixed-language documents further increase the complexity, making it difficult to extract accurate and meaningful information.

3. PROPOSED SYSTEM

The proposed system introduces an AI-powered multilingual entity extraction framework designed to process unstructured clinical data efficiently. It integrates Optical Character Recognition (OCR), language detection, translation, and Large Language Models (LLMs) into a unified pipeline. This system is capable of handling multiple input formats such as images, PDFs, text files, and documents, converting them into machine-readable text for further processing.

The workflow begins with input acquisition, where clinical data is collected and preprocessed. OCR is applied to extract text from image-based inputs, while document parsing techniques handle PDFs and other formats. The system then performs hybrid language detection to identify the source language and translates the content into a common language (English) using a Large Language Model. This ensures consistent processing of multilingual data. After translation, the system uses a Large Language Model to perform context-aware entity extraction. It identifies key medical entities such as patient details, doctor name, disease, medication, dosage, symptoms, age, and date. The extracted information is structured into formats like JSON, making it easy to store, analyze, and integrate with other healthcare systems. Additionally, the system can translate outputs into user-defined target languages, improving accessibility.

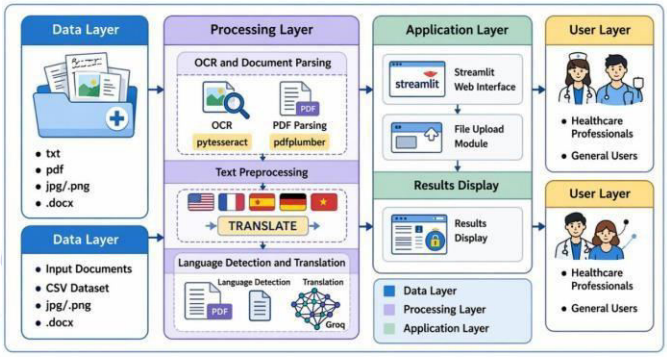


Fig 1: System Architecture Proposed Workflow

1. The system accepts clinical data from multiple formats such as PDFs, images, text files, Word documents, and spreadsheets.

2. Optical Character Recognition is applied to extract text from scanned documents and images, while document parsing is used for digital files.

3. The extracted text is cleaned and normalized by removing noise, special characters, and formatting inconsistencies.

4. The system detects the input language using a hybrid approach and translates it into English using a Large Language Model for uniform processing.

5. The Large Language Model analyzes the text and extracts key medical entities such as patient details, doctor name, disease, medication, dosage, symptoms, age, and date.

6. The extracted entities are structured into JSON format and can be translated into a user-defined language for better usability.

Advantages of Proposed System

• Automation: Eliminates manual data entry and reduces human effort

• Multilingual Support: Handles and translates multiple languages effectively

• High Accuracy: Uses LLMs for context-aware and precise entity extraction

• Multi-Format Support: Works with PDFs, images, text files, and documents

• Structured Output: Provides organized data in JSON format for easy analysis

• Scalability: Can be integrated with hospital systems and EHR platforms

• Time Efficient: Reduces processing time compared to traditional methods

• Improved Accessibility: Enables better understanding through language translationsis: Stores video and activity logs for post-event analysis.

4. RESULTS

The proposed system was successfully implemented and tested using clinical data in multiple formats such as images, PDFs, and text files. The OCR module effectively extracted text from scanned documents, while document parsing handled digital inputs efficiently.

The system accurately detected language, performed translation, and used a Large Language Model to extract key medical entities such as patient details, diseases, medications, and dosages. The extracted information was structured into JSON format for easy analysis.

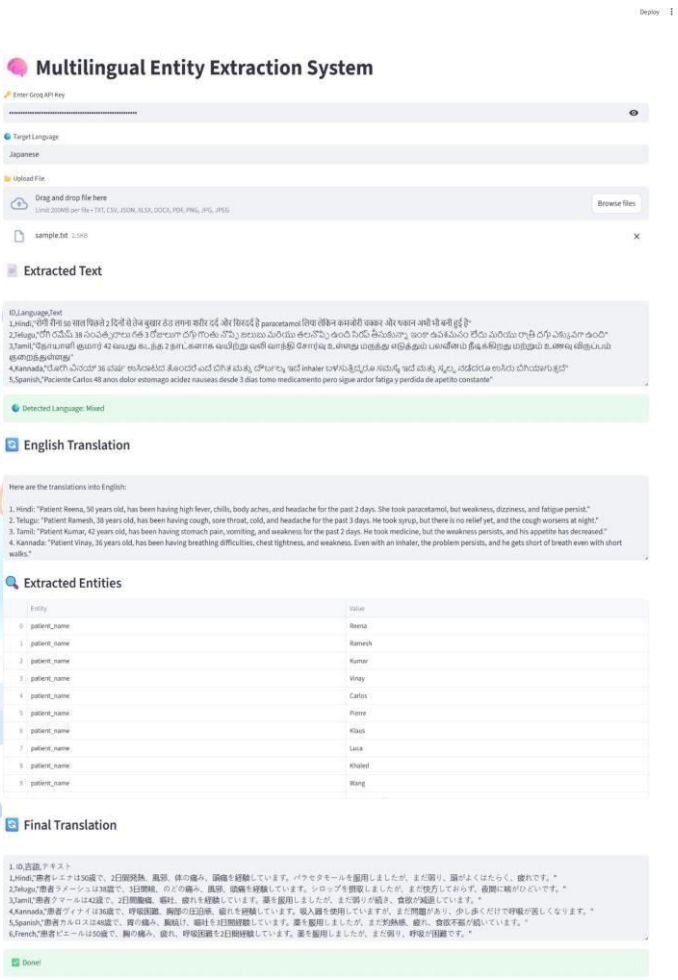
Overall, the system demonstrated good accuracy, reduced manual effort, and efficiently processed multilingual clinical data, making it a reliable and scalable solution for automated medical text extraction.

4.1. Experimental Setup

The system was tested in a controlled environment using an Intel i5 processor with 8GB RAM. The implementation was carried out using Python along with libraries such as OCR tools (Pytesseract), document parsers, and a Large Language Model via API. Various clinical inputs including images, PDFs, text files, and documents in different languages were used to evaluate system performance.

Results of Object Detection

The system successfully extracted text from multiple input formats using OCR and document parsing techniques. It accurately detected the input language, performed translation, and used a Large Language Model to identify key medical entities such as patient details, diseases, medications, dosages, and symptoms. The extracted entities were structured into JSON format, ensuring clarity and ease of analysis. The system demonstrated good accuracy and efficiency across multilingual and unstructured clinical data.Efficient detection of multiple individuals simultaneously.



A.Results of Motion Analysis

The system effectively processed clinical data from multiple formats such as images, PDFs, and text files. It successfully extracted text using OCR and document parsing techniques. The Large Language Model accurately identified key medical entities including patient details, diseases, medications, dosages, and symptoms.

• Accurateextraction ofmedical entities from unstructured text

• Ability tohandle multilingual clinical data

• Consistent generation of structured outputs in JSON format.

B. Results of Multilingual Processing

The The system efficiently detected the input language and performed translation into English for uniform processing. It also supported output translation into user-defined languages, improving accessibility and usability.

• Accurate language detection across different inputs

• Reliable translation with minimal information loss

• Effective handling of mixed-language clinical documents

Performance Results

The following table summarizes the performance evaluation metrics of the system:

Metric	Value
Entity Extraction Accuracy	88% – 93%
Language Detection Accuracy	85% – 90%
OCR Accuracy	<80%-88%
Processing Time	<2 secs
Structured Output Accuracy	High

Comparison with Existing System

The proposed system was compared with traditional surveillance approaches across key performance parameters:

Parameter	Existing System	Proposed System
Manual Effort	High	Minimal
Multilingual Support	Limited	Yes
Context Understanding	Low	High
Structured Output	No	Yes
Processing Speed	Limited	High
Accuracy	Moderate	High

The comparison confirms that the proposed system outperforms existing systems in terms of automation, realtime performance, behavior analysis, alert generation, scalability, and detection accuracy.

5. CONCLUSION

The proposed AI-powered multilingual entity extraction system for clinical text was successfully designed and implemented. By integrating OCR and Large Language Models, the system efficiently processes unstructured and multilingual clinical data. It accurately extracts key medical entities and converts them into structured formats, reducing manual effort and improving data accessibility.

The system demonstrates good performance in terms of accuracy, efficiency, and scalability. It is suitable for real-world healthcare applications such as hospitals, clinics, and electronic health record systems. Overall, the solution provides an effective approach for automated clinical data processing and medical information extraction.

The use of Optical Character Recognition enables accurate extraction of text from scanned documents, while the Large Language Model provides context-aware understanding of clinical content. The system successfully identifies and extracts key medical entities such as patient details, diseases, medications, dosages, and symptoms. Additionally, the multilingual capability ensures that clinical data from different languages can be processed efficiently and translated into a common format for consistency.

The results demonstrate that the system achieves good accuracy and significantly reduces manual effort and processing time compared to traditional methods. It provides structured outputs in JSON format, making the data easy to store, analyze, and integrate with healthcare systems such as Electronic Health Records (EHR). The system is scalable, flexible, and suitable for real-world deployment in hospitals, clinics, and healthcare organizations.

In conclusion, the proposed system offers a reliable and efficient solution for automated clinical text processing. It enhances data accessibility, improves decision-making, and supports the digital transformation of healthcare systems. With further improvements and integration, the system has strong potential to contribute to advanced healthcare analytics and intelligent medical data management.

FUTURE SCOPE

Although the proposed system demonstrates strong performance in multilingual clinical text processing, there are several opportunities for further enhancement and extension. One of the key improvements can be in

the accuracy of Optical Character Recognition, especially for handwritten prescriptions and low-quality scanned documents. Incorporating advanced deep learning-based OCR models and domain-specific preprocessing techniques can significantly improve text extraction quality in challenging conditions.

Another important area of enhancement is the use of domain-specific medical language models. Fine-tuning Large Language Models on specialized healthcare datasets can improve the accuracy of entity extraction and better handle complex medical terminology.

Additionally, expanding support for more regional and international languages will further improve the system's usability in diverse healthcare environments and enable better cross-lingual understanding.

The system can also be extended by integrating it with real-world healthcare infrastructures such as Electronic Health Record (EHR) systems, hospital management systems, and cloud platforms. This would enable large-scale deployment, real-time data processing, and centralized data management. Features such as mobile application support, real-time document scanning, and automated report generation can further enhance usability for healthcare professionals.

Furthermore, implementing strong data security and privacy mechanisms is essential to ensure compliance with healthcare regulations and protect sensitive patient information. Techniques such as data encryption, secure APIs, and access control can be incorporated. Future improvements may also include adding analytics and visualization dashboards, enabling predictive insights, and supporting advanced applications such as clinical decision support systems and medical research.

Conflict of interest statement

Authors declare that they do not have any conflict of interest.

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