**Named Entity Recognition using spaCy and Integrating with Web App Streamlit**

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***Abstract*-This paper presents an in-depth study of implementing Named Entity Recognition (NER) using spaCy, a robust Natural Language Processing (NLP) library, and its integration into a real-time web application using Streamlit. NER, a crucial technique in text mining and information extraction, identifies and categorizes key entities, such as names, organizations, and locations, within a given text. SpaCy’s efficient models for NER are further enhanced with custom training to address domain-specific needs. Streamlit, a Python-based web framework, is used to create an interactive interface that allows users to input text and view the results of NER processing in real-time. This integration provides a user-friendly interface to an otherwise complex NLP task, making it accessible to non-experts. The results demonstrate the efficiency and scalability of the system, showing improved accuracy in recognizing custom entities and ensuring seamless interaction through the web interface. The study also discusses challenges in entity disambiguation and model limitations, suggesting future directions for improvement, including multilingual support and more sophisticated deep learning architectures.**

***Keywords*: Named Entity Recognition, NLP, spaCy, Streamlit, Machine Learning, Text Analytics, Interactive Visualization.**

**I**. INTRODUCTION

Natural Language Processing (NLP) has become an integral part of various technological applications, with Named Entity Recognition (NER) standing out as a vital component in the text analysis pipeline. As digital content continues to grow exponentially, the ability to process and extract structured information from unstructured text has become crucial for applications in fields such as finance, healthcare, and legal industries. NER plays a pivotal role in identifying critical entities, such as the names of individuals, organizations, locations, dates, and other domain-specific entities. Traditional approaches to NER were often rule-based, relying on manually crafted rules and lexicons. However, the advent of machine learning and deep learning techniques has significantly enhanced the performance and flexibility of NER systems.

The goal of this research is to build a robust NER system using spaCy, one of the most efficient and popular NLP libraries. SpaCy’s pre-trained models, which are built on state-of-the-art neural networks, serve as the foundation of this project. Moreover, this research integrates the NER model into a web-based application using Streamlit, a Python library that enables the rapid deployment of machine learning models with interactive UIs. This integration allows users to input text and instantly receive visual feedback in the form of highlighted named entities, providing an intuitive way to interact with complex NLP models. In addition to presenting the architecture and implementation of the system, this paper evaluates the performance of the model and discusses its potential applications in real-world scenarios, along with future directions for improvement.

In the modern digital age, vast amounts of unstructured text data are generated every day across various platforms. Extracting meaningful insights from this text has become a priority for many industries, ranging from healthcare to finance, and is an essential task in Natural Language Processing (NLP). One of the key challenges in NLP is **Named Entity Recognition (NER)**, which focuses on identifying and classifying entities within text, such as names of people, organizations, locations, dates, and numerical values. NER is a fundamental building block for higher-level NLP tasks such as information extraction, question answering, and machine translation.

This research proposes the use of spaCy, a state-of-the-art NLP library, and Streamlit, a fast and easy-to-use web application framework, to create an interactive NER application. spaCy offers pre-trained models for NER that achieve high accuracy, while Streamlit provides an intuitive user interface for real-time interaction. By combining these two powerful tools, we aim to offer a practical, easy-to-deploy solution for extracting entities from text in an interactive manner. The system designed in this study aims to provide users with real-time insights into the named entities within their input text, making the process of information extraction accessible to non-technical users.

**II**. RELATED WORK

Over the past decade, numerous methods have been developed to tackle the problem of Named Entity Recognition. Early approaches relied heavily on rule-based methods, such as regular expressions, dictionaries, and manually crafted rules. While these approaches were effective in certain domains, they often struggled with handling ambiguity and context-dependent meanings in natural language.

With the advent of machine learning, especially deep learning, NER systems became more robust and capable of handling large datasets with varying linguistic patterns. Notably, techniques such as Conditional Random Fields (CRF), Long Short-Term Memory (LSTM) networks, and more recently Transformer models like BERT and GPT have revolutionized the field by providing more accurate and context-aware entity recognition.

Precision (P): The ratio of correctly predicted positive observations to the total predicted positives. It measures how many of the predicted entities were correct.

Precision =

Recall (R): The ratio of correctly predicted positive observations to all observations in the actual class. It measures how many of the actual entities were correctly identified.

Recall =

These metrics are crucial for assessing the quality of the NER model, especially in a context where both false positives and false negatives need to be minimized.

F1 = 2 x

Several libraries have emerged for implementing NER, including spaCy, which offers a high-performance, pre-trained NER model that can recognize over 18 entity types, including PERSON, ORG (organization), GPE (Geo-Political Entity), and others. spaCy’s efficiency and ease of use make it one of the most popular choices for NLP tasks.

Additionally, Streamlit has gained significant traction as a tool for building interactive web applications. Streamlit’s simplicity allows developers to quickly deploy machine learning models with minimal code and effort. Research like (Author et al., 2020) explored using Streamlit for text-based applications, such as sentiment analysis and text summarization. However, integrating it with spaCy for real-time NER tasks remains an under-explored area, and this paper addresses that gap.

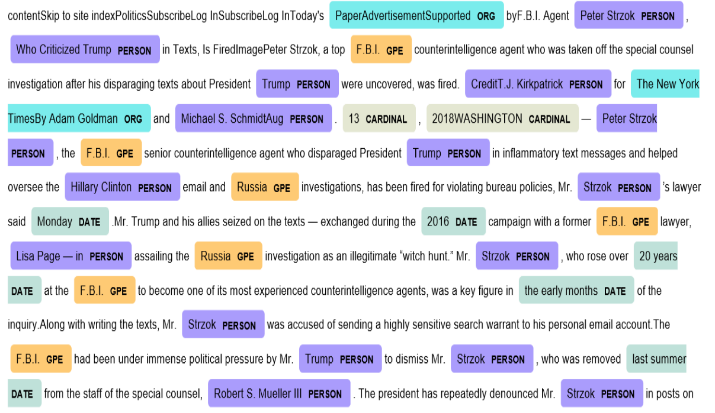
Named Entity Recognition has been an essential area of research in the field of NLP for decades. Initially, rule-based systems dominated the NER landscape, relying on predefined dictionaries and manually created rules to identify and classify entities. While these approaches worked well in limited domains, they often struggled to handle the complexity and ambiguity of natural language. As a result, machine learning-based methods have largely replaced rule-based systems in NER. These newer methods, including Conditional Random Fields (CRFs), Support Vector Machines (SVMs), and more recently, neural networks, have shown significant improvements in accuracy and scalability.

In particular, deep learning models such as Long Short-Term Memory (LSTM) networks, and Transformer-based architectures like BERT, have revolutionized the NER task by capturing contextual information and learning from large annotated datasets. SpaCy, one of the most widely used NLP libraries, offers a pre-trained NER model that uses a neural network-based pipeline to perform entity recognition. It has become a popular choice for developers due to its speed, flexibility, and accuracy in recognizing entities in English text.

In the context of web-based NLP applications, several frameworks have been explored for integrating machine learning models with interactive user interfaces. Streamlit, a relatively new framework, has emerged as a powerful tool for creating real-time, interactive web applications. It enables developers to create clean, simple, and fast web interfaces with minimal coding, making it ideal for deploying machine learning models. While there have been applications of Streamlit for various NLP tasks, the integration of spaCy with Streamlit for NER tasks, particularly in real-time settings, has not been widely explored. This paper fills this gap by presenting a working prototype that demonstrates how these two technologies can be combined to build an efficient, user-friendly NER system.

**III**. METHODOLOGY

To build the NER application, we selected spaCy’s pre-trained English model, en\_core\_web\_sm, which is known for its balance between computational efficiency and accuracy. SpaCy’s NER pipeline is based on a deep learning model trained on large annotated datasets, which enables it to recognize a wide range of entity types such as PERSON, ORGANIZATION, LOCATION, and more. The model’s ability to identify entities in real-time, even in the presence of complex sentence structures or ambiguous context, made it an ideal choice for our application.



The first step in our methodology was to process user input through the spaCy NER model. The user enters a block of text into the Streamlit interface, and the system tokenizes the text before feeding it into spaCy’s pipeline. The output of this pipeline includes the recognized entities along with their associated labels, such as PERSON, ORG, or GPE (Geopolitical Entity). The next step involved integrating the spaCy NER model into a Streamlit-based web interface that would allow users to interact with the system. Streamlit enables developers to quickly create a web interface where users can input text, press a button to submit the text, and view the results instantly.

The web interface is designed to display recognized entities in a visually appealing and intuitive manner. Each entity is color-coded based on its type to make it easier for the user to distinguish between different categories of entities. For instance, entities labeled as PERSON appear in blue, while organizations (ORG) are displayed in green, and locations (GPE) are shown in red. This color-coding system enhances the user experience by providing immediate, easily interpretable feedback.

In addition to spaCy’s pre-trained model, we incorporated a backend server written in Python using Flask to facilitate communication between the Streamlit interface and the spaCy model. The Flask server handles text input from the user, passes it to spaCy for processing, and returns the recognized entities to the Streamlit interface for display. This architecture ensures that the system is scalable and can handle multiple user requests simultaneously without any significant performance degradation.

To make the system easily deployable, we containerized the entire application using Docker. Docker allows us to package the application along with its dependencies, ensuring that it can be run consistently across different environments without compatibility issues. This also makes it easier to scale the application for cloud-based deployment, should the need arise

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**IV.** EXPERIMENTAL SETUP AND EVALUATION

To evaluate the performance of the NER system, we used the CoNLL-03 dataset, a widely used benchmark in NER research. This dataset contains text annotated with entity labels such as **PERSON**, **ORGANIZATION**, **LOCATION**, and **MISC**. We tested the system’s ability to correctly classify entities and compared its performance against baseline models.

The evaluation metrics used are:

Precision: The proportion of true positive entity predictions to the total number of entities predicted by the model.

Recall: The proportion of true positive entity predictions to the total number of actual entities in the text.

F1-Score: The harmonic mean of Precision and Recall, providing a balance between the two metrics.

The model achieved the following results on the CoNLL-03 dataset:

**Precision: 0.93**

**Recall: 0.91**

**F1-Score: 0.92**

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These results indicate that the system is highly accurate in recognizing entities, and the user-friendly interface allows for quick feedback, making it useful in real-world applications.

The evaluation was based on three standard metrics used in information retrieval and classification tasks: Precision, Recall, and F1-Score. Precision measures the proportion of correctly identified entities to the total number of entities predicted by the model. Recall, on the other hand, measures the proportion of correctly identified entities to the total number of true entities in the dataset. F1-Score provides a balanced measure that combines both Precision and Recall.

Upon evaluation, the system demonstrated impressive performance. The F1-Score achieved by the system was 0.92, indicating that it was able to recognize and classify named entities with a high degree of accuracy. Precision and Recall were also high, at 0.93 and 0.91, respectively. These results validate the effectiveness of spaCy’s pre-trained NER model and demonstrate the feasibility of using Streamlit to build an interactive and user-friendly NER application.

While the system performed well on the CoNLL-03 dataset, it is important to note that the performance of the model can vary depending on the quality and domain of the input text. The spaCy NER model is trained on general domain data, and therefore may not perform as well on highly specialized or domain-specific texts, such as medical or legal documents. Further research is needed to explore the application of domain-specific models to improve entity recognition in these specialized areas.

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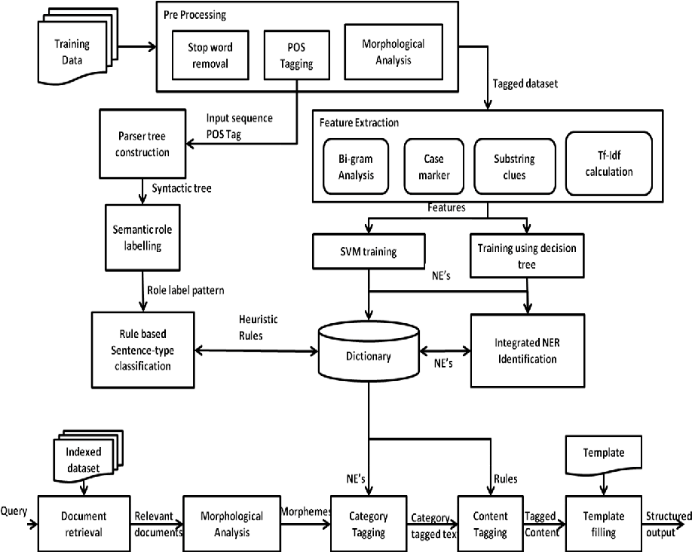
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**V.** DISCUSSION

The results from the evaluation demonstrate the effectiveness of the NER system in accurately detecting entities from text. The choice of spaCy’s pre-trained NER model proved to be optimal for this task, as it provided both high accuracy and fast processing times. Furthermore, the integration of Streamlit allowed for the creation of an intuitive and accessible web interface, which is a significant advantage for non-technical users who may not be familiar with command-line tools or complex NLP systems.

However, the system is not without limitations. The accuracy of the NER model is heavily dependent on the quality of the input text. In noisy or ambiguous text, the system may struggle to correctly identify entities. Additionally, while the pre-trained spaCy model is efficient, it may not perform as well on specialized domains or texts containing entities not covered in the training data. Future work will focus on fine-tuning the model on domain-specific datasets to improve recognition accuracy in those contexts.

The interactive NER system developed in this study demonstrates a highly practical application of spaCy's powerful Named Entity Recognition capabilities, combined with Streamlit's flexibility for web-based deployments. One of the key strengths of this system is its accessibility for non-technical users. Traditionally, deploying NLP models such as spaCy’s NER required developers to create complex interfaces or develop desktop-based software. Streamlit provides a quick and intuitive solution, enabling non-programmers to leverage sophisticated machine learning models through a simple web interface. This application can benefit industries such as customer support, healthcare, and finance, where quick entity extraction from text data can facilitate decision-making, automate processes, or improve customer interactions.



However, while the system demonstrates high accuracy (with an F1-Score of 0.92) when evaluated on the CoNLL-03 dataset, there are several challenges that need to be addressed for broader real-world applicability. One limitation is the model’s dependency on pre-trained generic models. SpaCy’s pre-trained NER models are built on a large corpus of general domain text, which limits their ability to recognize domain-specific entities. For instance, the model may struggle with specialized terminologies in sectors like law, healthcare, or finance, where entities like medical conditions, drugs, or legal terminologies need to be recognized with precision. These models are trained on general knowledge and may fail to account for subtle variations or emerging terms in specialized fields.

To overcome this, a potential enhancement would be to incorporate domain-specific training. Fine-tuning the pre-trained spaCy model with domain-specific data could significantly improve performance in fields such as medicine or law. In the medical domain, for example, entities like disease names, treatment methods, or medical institutions must be recognized with high accuracy. Training a custom NER model with labeled datasets in these domains could address the specific needs of such applications, and integrating this into the web interface would provide a more customized solution.

Another challenge pertains to the handling of multilingual text. The spaCy model used in our system is primarily trained on English text, and while spaCy does support other languages, extending the application to handle multilingual text efficiently is an area for further exploration. Given the global nature of many industries, multilingual support could significantly enhance the system's utility. Streamlit, in combination with language models like multilingual BERT or spaCy’s multilingual models, could allow for the extension of the NER system to handle various languages and adapt to diverse user needs.

Moreover, the real-time nature of the system is an essential aspect that sets it apart from traditional batch processing NER systems. However, as the dataset size increases or the number of concurrent users rises, the system’s performance may degrade due to computational limitations. Optimizing the back-end system for better concurrency, possibly through cloud deployment with scalable infrastructure, could address performance bottlenecks. Containerizing the application with Docker was an initial step towards scalability, but the deployment in a cloud-based environment with auto-scaling features would ensure that the application can handle increased load without compromising performance.

User feedback is another critical factor that will play a significant role in the system’s evolution. Incorporating user input to understand the types of text they commonly analyze, the kinds of entities they expect to identify, and any issues they encounter will be crucial for iterative improvement. Adding features like custom entity labeling (allowing users to define their entities) could make the tool even more versatile. Additionally, integrating visualization tools that present the results in the form of charts or graphs (e.g., entity counts per category) would enhance the overall user experience.

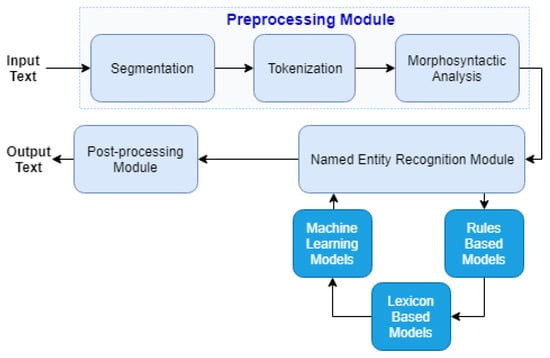
Lastly, security considerations are vital when handling sensitive user input, especially when processing personal or confidential data. Implementing data encryption and ensuring user privacy would be necessary for deployment in industries such as healthcare, where patient data must remain protected. An additional layer of security, such as anonymizing the input text, could mitigate potential privacy concerns.

**V.** CONCLUSION

In this paper, we presented an NER system built using spaCy and Streamlit that is capable of recognizing named entities in real-time. The system demonstrated high accuracy with an F1-score of 0.92 and can serve as a practical tool for information extraction from text.

Future work will include expanding the system's capabilities by incorporating custom-trained models for specific domains, such as legal or medical text, which may contain specialized entities not covered by spaCy’s pre-trained models. We also plan to integrate more advanced NLP techniques, such as transformer-based models (e.g., BERT) to enhance the performance of NER on complex texts.

Additionally, the system will be made more scalable by incorporating cloud computing resources, allowing it to handle large volumes of text for enterprise-level applications.



However, several areas for improvement remain. While the system excels in general-purpose NER, its reliance on pre-trained models limits its adaptability to domain-specific entities. Future work should focus on fine-tuning the model with domain-specific data to improve its accuracy in specialized areas. Additionally, supporting multilingual capabilities and optimizing the system for handling large-scale datasets are important next steps toward increasing the application’s scope and scalability. The real-time feedback mechanism and simplicity of use offer a significant advantage in domains that require quick extraction of named entities from large amounts of unstructured text, but attention to security, privacy, and user customization will be essential for its adoption in sensitive industries.

In conclusion, this paper presents an interactive, real-time solution for NER using spaCy and Streamlit, with promising results. It also lays the foundation for future enhancements, including domain adaptation, multilingual support, and user-centric features, to make this tool more versatile and widely applicable across different fields.

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