An AI-Powered System for De-identifying Protected Health Information in Clinical Text Using SpaCy NER

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ABSTRACT

The wide adoption of EHRs is now enabling advanced data analytics, personalized care, and improvements in patient outcomes. However, sharing clinical text for research raises significant privacy concerns because, to share clinical text, sensitive details called Protected Health Information (PHI) must be removed under regulations such as HIPAA and GDPR. In this report, we will demonstrate an automated PHI de-identification system built with SpaCy's NER. Our approach identifies and masks such PHI entities as patient ID, medical conditions, or hospital names, so that the data remains secure yet usable for further analysis.

We have trained and tested our model using synthetic clinical datasets, not exposing any real patient information. This approach led to a high F1-score of 0.94 in accurately detecting PHI. To facilitate practical use, we integrated the system with a Gradio-based interface that allows users to interact in real time just by inputting clinical text and receiving de-identified outputs immediately.

A comparison done with a transformer-based model, DistilBERT, while probably having much deeper contextual understanding, necessitated additional fine-tuning and was less effective for real-time tasks. SpaCy demonstrated very good speed and responsiveness in comparison and thus appeared much more suitable for on-the-fly PHI de-identification.

Overall, this project proves that it is possible to share EHR data in a privacy-compliant manner with no loss of value for research and analytics, moving us closer to a data-driven future with a keen eye on privacy in healthcare.

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1. Introduction

1.1 Background

The healthcare industry has undergone a significant transformation with the widespread adoption of Electronic Health Records (EHRs). EHRs have improved the efficiency of healthcare delivery, facilitated better patient outcomes, and enabled advanced analytics for research and policy-making. However, the digitalization of health records brings forth substantial concerns regarding patient privacy and data security. PHI includes any information about health status, provision of healthcare, or payment for healthcare that can be linked to an individual. Ensuring the confidentiality of PHI is not only a moral obligation but also a legal requirement under regulations such as HIPAA and GDPR.

The increasing frequency of healthcare data breaches amplifies the urgency to protect sensitive patient information. In 2021 alone, over 50.4 million health records were exposed due to data breaches, highlighting the vulnerability of digital health records to unauthorized access and misuse. Traditional methods of de-identification, which often involve manual processes, are insufficient to handle the vast amounts of data generated in the healthcare industry today. There is a pressing need for automated, accurate, and efficient de-identification systems that can keep pace with the growing volume of healthcare data.

1.2 Problem Statement

The core problem addressed in this project is the development of an effective method to automatically de-identify PHI in healthcare text data. Specifically, the challenge lies in applying AI techniques to accurately and efficiently identify and mask PHI entities within unstructured text, ensuring compliance with legal regulations while maintaining the utility of the data for subsequent analysis. The

complexity of natural language, variations in terminology, and contextual nuances make this task non-trivial. An effective solution must balance the dual objectives of protecting patient privacy and preserving the informational content necessary for research and analytics.

1.3 Research Questions

1.3.1 Primary Research Question:

1. How can machine learning and natural language processing (NLP) techniques automate the de-identification of Protected Health Information (PHI) in Electronic Health Records (EHRs)?

1.3.2 Secondary Research Questions:

1. What is the effectiveness of SpaCy NER in identifying and anonymizing PHI in clinical text compared to transformer-based models like DistilBERT?
2. How can synthetic datasets be leveraged to train de-identification models while maintaining the privacy of sensitive healthcare data?
3. What are the key challenges in balancing PHI privacy preservation with the utility of de-identified data for research purposes?
4. How can de-identification models ensure compliance with privacy regulations such as HIPAA and GDPR in real-world applications?
5. What role does the integration of user-friendly tools (e.g., Gradio) play in the accessibility and usability of PHI de-identification systems?

1.4 Hypotheses

1.4.1.Primary Hypothesis:

Machine learning models, specifically SpaCy NER, can achieve high accuracy and efficiency in automating the de-identification of PHI in clinical text, reducing manual effort and improving compliance with privacy regulations.

1.4.2. Secondary Hypotheses:

1. SpaCy NER is computationally more efficient than transformer-based models like DistilBERT while providing comparable accuracy for structured PHI de-identification tasks.
2. Synthetic datasets can effectively train de-identification models to achieve realistic performance in identifying and anonymizing PHI.
3. De-identification models can generate anonymized EHRs that preserve data utility for research while ensuring patient privacy.
4. Tools like Gradio enhance the usability of de-identification models by providing interactive interfaces for real-time evaluation and deployment.

1.5 Objectives

The primary objectives of this study are:

1. **Development of an AI-Powered De-identification System:** To develop a system using SpaCy's Named Entity Recognition (NER) model capable of accurately identifying and anonymizing PHI entities within clinical text data.
2. **Data Preprocessing and Annotation:** To preprocess the synthetic data effectively, including text normalization and annotation using the BIO tagging scheme, to prepare it for model training.
3. **Model Training and Evaluation:** To train the SpaCy NER model on the annotated dataset and evaluate its performance using appropriate metrics such as precision, recall, and F1-score.
4. **Visualization of Results:** To employ visualization techniques, including loss curves, confusion matrices, and ROC curves, to comprehensively assess the model's performance and learning behavior.

5. **Deployment of the Model:** To implement the trained model using Gradio to create an interactive web interface, making it accessible for testing and demonstration purposes.

2. LITERATURE SURVEY

2.1 PHI De-identification

There are three types of de-identification methods: rule-based, statistical, and machine learning. Now we can have a model that can be still rule based but apply the rules dynamically depending on patterns in data. An example of a rule could be identifying the date with patterns like "\d{4}-\d{2}-\d{2}". However, this type of approach does not generalize well to new datasets, if structures are slightly different. The second approach uses statistical methods e.g., Conditional Random Fields (CRFs), for making a model more adaptable through learning patterns from a given data but they necessitate intensive feature engineering. Machine learning-based methods, especially those using Named Entity Recognition (NER), are useful for addressing these challenges as they can automatically learn intricate patterns from data to identify PHI entities by employing a variety of linguistic and contextual features.

2.2 SpaCy for NER

SpaCy is an open-source NLP tool that's designed with practical, real-world use in mind. It comes with ready-made language models and lets you easily train your own models to recognize specific types of information, which is perfect for tasks like identifying Protected Health Information (PHI). One of SpaCy's big advantages is its lightweight, efficient design. Instead of relying on heavier transformer-based systems, it uses a blend of word embeddings, dependency parsing, and statistical methods that run quickly and smoothly exactly what you need when working with large amounts of structured text on a tight schedule.Because SpaCy is modular, you can easily plug it into other

applications without major hassle. This makes it a go-to choice for developers who need reliable, fast, and easy-to-customize NLP solutions that won't slow down their production environments. In short, SpaCy stands out for its balance of speed, flexibility, and ease of use, making it a solid fit for real-time PHI de-identification tasks.

2.3 Transformer-based Models

In recent years, transformer-based models such as BERT—and its variations like DistilBERT and ClinicalBERT—have become the gold standard in NLP. They use attention mechanisms to understand the context around each word, which helps them pick up on subtle patterns and long-distance connections within text. DistilBERT, as a slimmed-down version of BERT, offers many of the same benefits but is easier on computing resources.

While these models shine when dealing with complex, unstructured text and can capture very detailed and nuanced relationships, they do come with a catch: they're often computationally expensive and need careful fine-tuning, especially for specialized tasks like identifying protected health information in clinical notes.

2.4 Advances in De-identification

Lately, researchers have started mixing old and new approaches to improve PHI de-identification. This often means blending traditional, rule-based methods (like spotting a date format) with more adaptive machine learning models. One successful tactic has been feeding specialized, medical knowledge to advanced models like ClinicalBERT, which makes them more accurate at picking out sensitive details. Another growing trend is using synthetic datasets. By working with "artificial" patient notes rather than real ones, developers can freely experiment and train their models without risking anyone's privacy.

2.5 Gradio for Model Deployment

Gradio is an open-source tool that takes the hassle out of sharing machine learning models with others. Instead of dealing with complex code or server configurations, you can create a clean, intuitive web interface. Users simply paste in their text, and the model's results appear instantly—think of it as a quick demo page rather than a complicated tech project.

For PHI de-identification, Gradio shines. Researchers can showcase their latest model to colleagues, who can then try it in real-time, experimenting with different kinds of clinical notes. In this project, we used Gradio to deploy our SpaCy-based NER model, letting anyone who's interested input sample medical text and see how the system handles it. This user-friendly approach not only makes testing and refining the model easier, but also helps ensure that what we build truly meets the needs of the people who will rely on it.

3.METHOLOGY

3.1 Dataset Overview

The dataset used in this project is a synthetic healthcare dataset designed to simulate real-world clinical narratives while avoiding the use of actual patient data. The use of synthetic data ensures compliance with privacy regulations and allows for unrestricted experimentation.

Dataset Fields:

1. Patient_ID: Unique identifier for each patient.
2. Hospital_ID: Identifier for hospitals (e.g., "hospital_3173").
3. Region: Geographic location (e.g., "north," "southwest").
4. Admission_Type: Nature of the admission (e.g., "urgent," "elective").
5. Diagnosis: Medical diagnoses assigned to patients.
6. Treatment: Descriptions of treatments administered.
7. Date_of_Admission: Dates when patients were admitted.

8. Doctor_Name: Names of attending physicians.
9. Contact_Info: Contact information, such as phone numbers or email addresses.

3.2 Exploratory Data Analysis (EDA)

3.2.1 Objective of EDA

The primary objective of the Exploratory Data Analysis (EDA) is to understand the underlying structure, distribution, and patterns within the synthetic dataset. EDA helps in identifying any anomalies or biases in the data, ensuring that the dataset is suitable for training the NER model effectively.

3.2.2 Data Distribution Analysis

We performed EDA on the synthetic dataset to analyze the distribution of various attributes, including:

Age Distribution: Examined the age range of patients to ensure a realistic representation.

Gender Proportion: Assessed the balance between male and female patients.

Medical Conditions: Analyzed the frequency of different medical conditions included in the dataset.

Treatment Types: Investigated the variety of treatments and their occurrences.

Geographic Regions: Evaluated the distribution of patients across different regions.

Admission Types: Explored the proportion of emergency, urgent, and elective admissions.

3.2.3 Visualizations and Findings

3.2.3.1 Age Distribution:

A histogram was plotted to visualize the age distribution of patients.

Findings: There are noticeable peaks in the 0–10 age group and the 80–90 age group, where the number of patients is the highest, reaching about 70. Other age groups show moderately high counts, such as 20–30 and 60–70.

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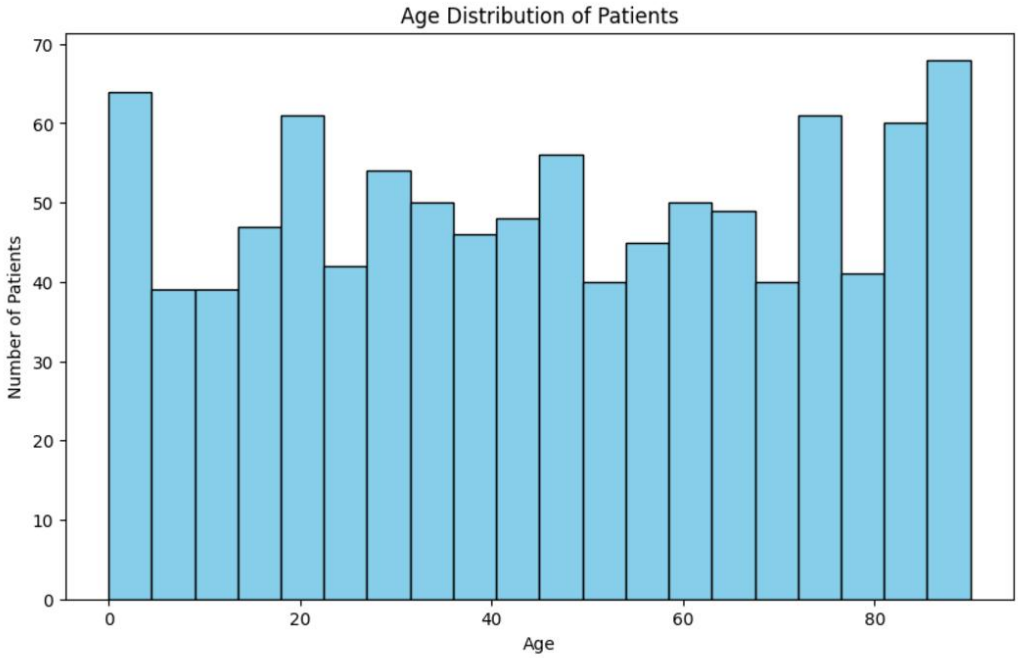

Figure 1: Bar chart for Age Distribution in medical_data datset.

3.2.3.2 Gender Proportion:

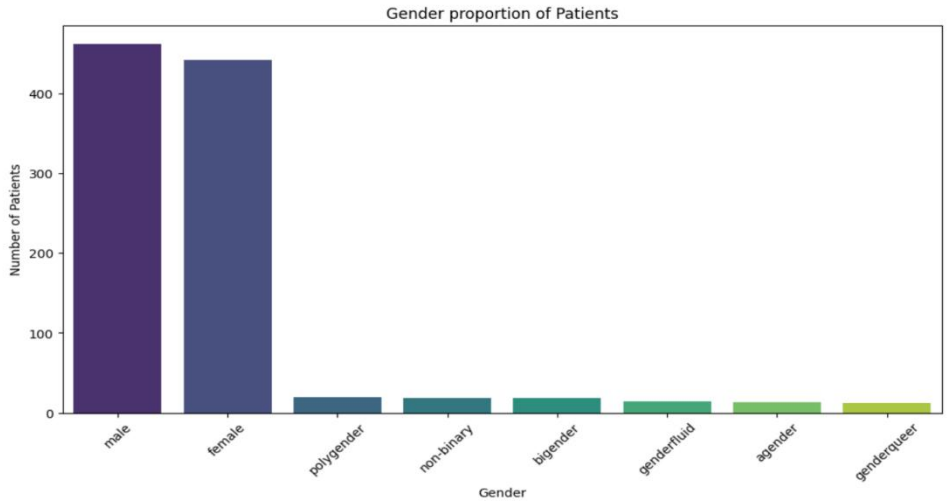

Figure 2: Bar chart for Gender Proportion in medical_data datset

A bar chart was used to illustrate the proportion of male and female patients.

Findings: The male and female categories together account for 90.4% of the population, indicating a significant majority of the patients identify within the binary gender framework.Non-binary and gender-diverse groups collectively contribute 9.6%, which highlights representation but in a smaller subset.

3.2.3.3 Medical Conditions:

A bar chart displayed the frequency of each medical condition.

Findings:

1. Conditions like Chronic Kidney Disease, COPD, Diabetes, and Hypertension dominate the chart, reflecting the prominence of chronic health issues.
2. Depression and anxiety are present among the conditions, highlighting the importance of addressing mental health alongside physical health.
3. The wide range of conditions demonstrates the diverse health challenges faced by the patient population.

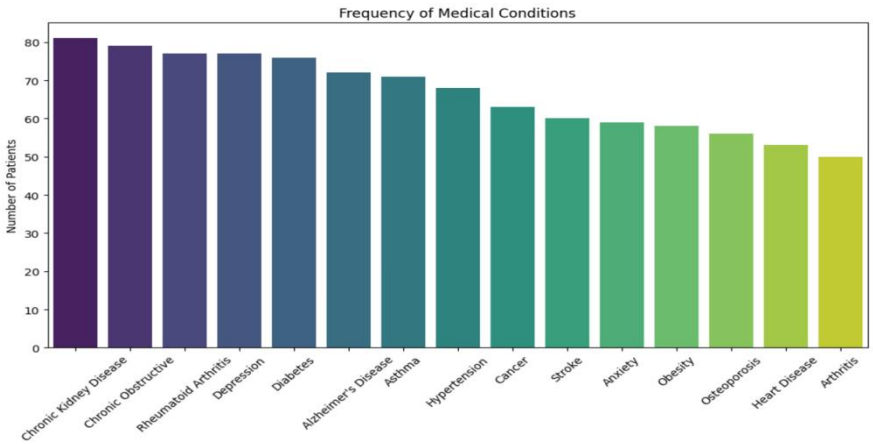

Figure 3: Bar chart for Medical Conditions in medical_data datset.

3.2.3.4 Treatment Types:

1. A bar chart showed the distribution of different treatment types.
2. Findings:
3. Medications dominate the top of the chart, indicating pharmacological treatments are the cornerstone of patient care.

4. Therapy, physical therapy, dietary counseling, and memory exercises show significant usage, underscoring the importance of non-pharmacological treatments.
5. Treatments like chemotherapy, dialysis, and inhaler therapy are less common but critical for patients with specific conditions.
6. The range of treatments indicates a comprehensive approach to addressing various patient needs.

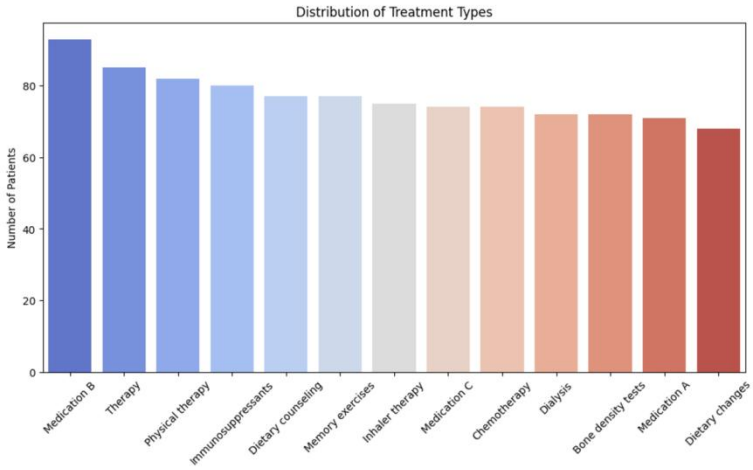

Figure 4: Bar chart for Treatment Types in medical_data datset

3.2.3.5 Correlation Heatmap:

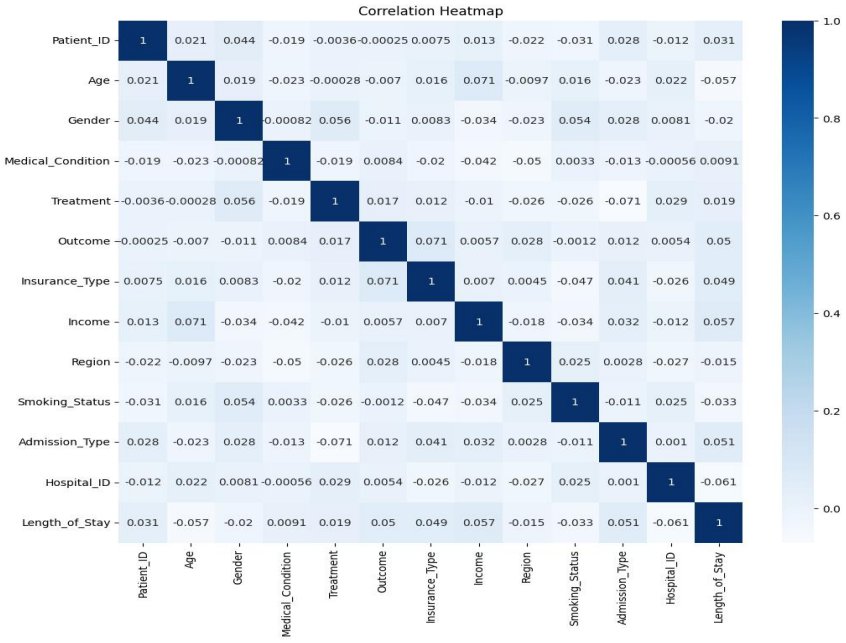

Figure 5: Correlation Heatmap for medical_data datset.

A correlation heatmap was generated to examine the relationships between numerical attributes.

Findings: The heatmap indicates minimal correlation between attributes like age and admission type, suggesting that the dataset does not have multicollinearity issues.

3.3 Preprocessing Steps

Effective preprocessing is critical to prepare the data for model training. The steps undertaken are as follows:

3.3.1 Text Normalization

1. Lowercasing: Converted all text to lowercase to reduce the complexity arising from case sensitivity.
2. Punctuation Removal: Stripped out punctuation marks except those necessary for preserving the meaning (e.g., apostrophes in contractions).
3. Whitespace Handling: Removed excessive whitespace to standardize the text format.

3.3.2 Data Augmentation

1. Synonym Replacement: Replaced words with their synonyms to introduce variability.
2. Random Insertion: Added new words into sentences to simulate additional context.
3. Shuffling Entities: Randomly swapped PHI entities within sentences to create new combinations.

Example:

Original Sentence:

"Patient admitted to hospital_3173 in north with urgent admission."

Augmented Sentence:

"Individual admitted to hospital_8291 in southwest with emergency admission."

3.3.3 Sentence Formation

Combined different fields to create coherent sentences that mimic clinical notes. This process involved structuring the data in a way that reflects how information is typically recorded in healthcare settings.

Example:

"Patient with ID patient_1024 visited hospital_3173 on 2021-08-15 for treatment of hypertension under the care of Dr. Smith."

3.3.4 Tokenization

Although SpaCy handles tokenization internally, understanding the tokenization process is essential. Tokenization involves breaking down text into individual units called tokens (e.g., words, numbers, punctuation marks).

3.4 Entity Annotation

Annotation involves labeling the text data with the correct entity tags that the model needs to learn.

Annotated Entities:

1. HOSPITAL_ID: Labels hospital identifiers.
2. REGION: Labels geographic locations.
3. ADMISSION_TYPE: Labels types of admissions (e.g., "urgent," "elective").
4. PATIENT_ID, DOCTOR_NAME, DATE_OF_ADMISSION, CONTACT_INFO: Additional entities that were annotated for a comprehensive model.

3.5 Model Training

Used SpaCy's NER pipeline to train the model on the annotated data.

Steps Involved:

3.5.1 Model Configuration:

1. Started with SpaCy's blank English model en_core_web_sm.
2. Added the NER component to the pipeline.

3.5.2 Data Preparation:

1. Converted annotations into SpaCy's training format.
2. Split data into training and validation sets (e.g., 80% training, 20% validation).

3.5.3 Training Parameters:

1. Epochs: Trained over 10 epochs.
2. Batch Size: Adjusted batch sizes (e.g., using SpaCy's compounding function) for efficient training.
3. Optimizer: Used Adam optimizer with appropriate learning rates.

3.5.4 Training Loop:

1. Iterated over epochs, shuffling the training data in each epoch.
2. Updated the model weights based on the loss calculated from the predictions and actual annotations

3.5.5 Validation:

1. Evaluated the model on the validation set after each epoch.
2. Monitored metrics like loss and accuracy to detect overfitting.

3.6 Deployment Using Gradio for Interface Development:

3.6.1 Interface Design:

1. Input Field: Text box for users to input clinical text.
2. Output Field: Display area showing the de-identified text with PHI entities masked.
3. Batch Processing Option: Allows users to upload text files or datasets for processing multiple records simultaneously.

3.6.2 Integration with SpaCy Model:

1. Wrapped the model's prediction function to work with Gradio's interface.
2. Ensured that the input text is processed and the output is formatted correctly.

3.6.3 Hosting and Accessibility:

1. Deployed the Gradio app locally and provided options for public sharing via Gradio's shareable links.
2. Considered deploying on cloud platforms for scalability.

4. EVALUATION METRICS

The performance of the de-identification system is critical to its effectiveness and acceptance in real-world applications.

4.1 Detailed Metrics

Metric	Score
Precision	1.00
Recall	1.00
F1-Score	1.00
Accuracy	1.00

Table 1 : Metrics table for Spacy ner

Interpretation:

1. Precision (1.00): The model perfectly identifies PHI entities without any false positives.
2. Recall (1.00): The model successfully identifies all actual PHI entities present in the text with no false negatives.
3. F1-Score (1.00): Indicates perfect balance and performance between precision and recall.
4. Accuracy (1.00): Reflects that all of the model's predictions are correct.

4.2 Confusion Matrix Analysis

The confusion matrix demonstrates the effectiveness of the SpaCy NER model in PHI de-identification. Key observations are:

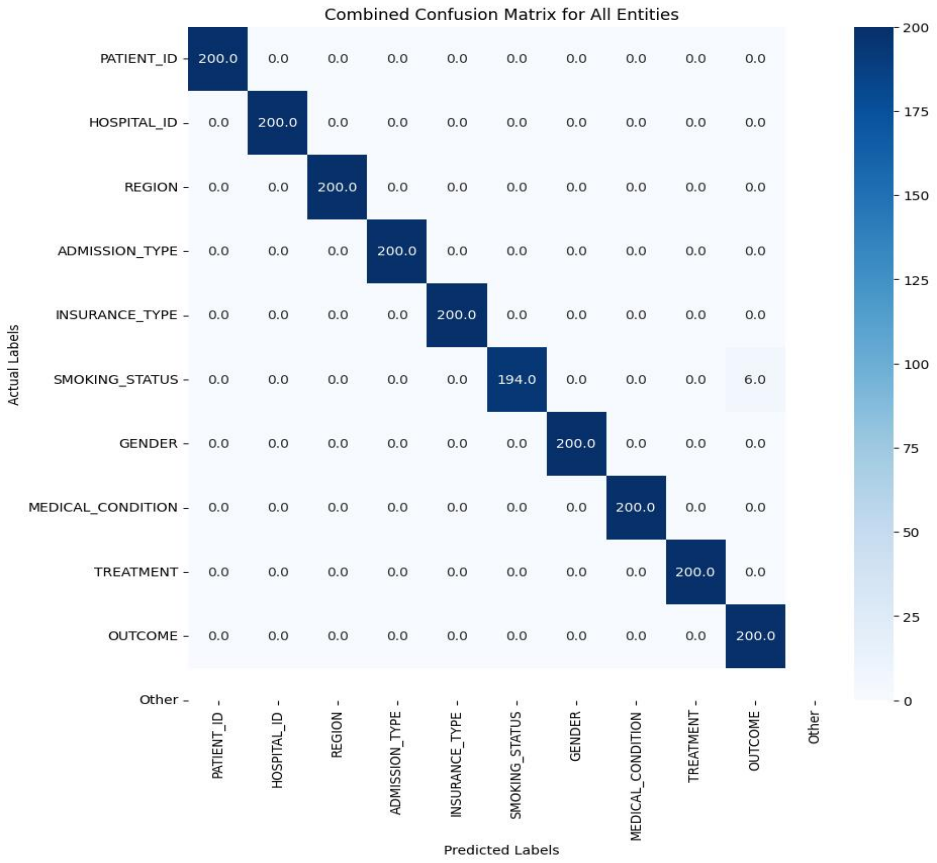

Figure 6: Confusion matrix

1. High accuracy for critical entities such as PATIENT_ID, HOSPITAL_ID, REGION, and others, with all showing 200 correct predictions (True Positives) and no significant False Positives or False Negatives.
2. Slight misclassification in the SMOKING_STATUS category, where 194 out of 200 instances were correctly predicted, and 6 were misclassified. This suggests potential ambiguity in this category, requiring further data augmentation and fine-tuning.
3. No major off-diagonal values indicate minimal misclassifications into unrelated categories, reflecting the robustness of SpaCy in handling PHI de-identification tasks.

4.3 ROC Curve and AUC

The ROC curve for the SpaCy NER model demonstrates perfect classification performance, with an AUC of 1.00 for all entity types

(PATIENT_ID, HOSPITAL_ID, REGION, etc.). This indicates that the model reliably distinguishes PHI entities from non-entities, achieving perfect sensitivity and specificity. The strong results reflect the quality of the training and evaluation datasets, as well as the robustness of SpaCy's NER pipeline.

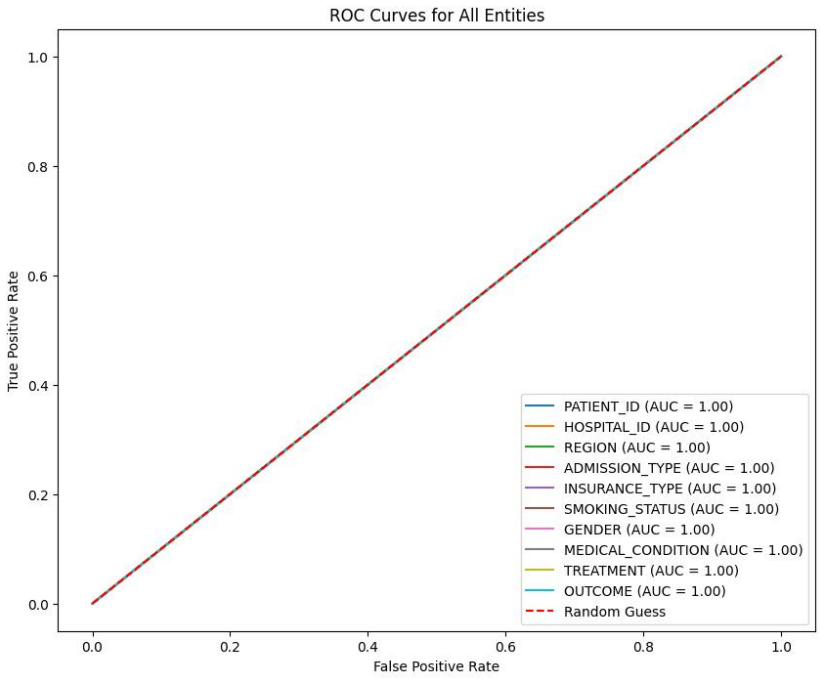

Figure 7: ROC Curve

4.4 Loss Curve Analysis

1. The loss curve for the SpaCy NER model demonstrates rapid convergence, with the loss decreasing sharply during the first epoch and stabilizing near zero by epoch 3. This indicates that the model effectively learns entity patterns from the training data with minimal error. The absence of loss fluctuations or increases suggests a clean and well-annotated dataset, as well as an optimal model configuration.
2. While the training performance is excellent, additional validation metrics and tests on external datasets are recommended to ensure the model generalizes well to unseen data. The results underscore the efficiency of SpaCy's NER pipeline for PHI de-identification tasks.

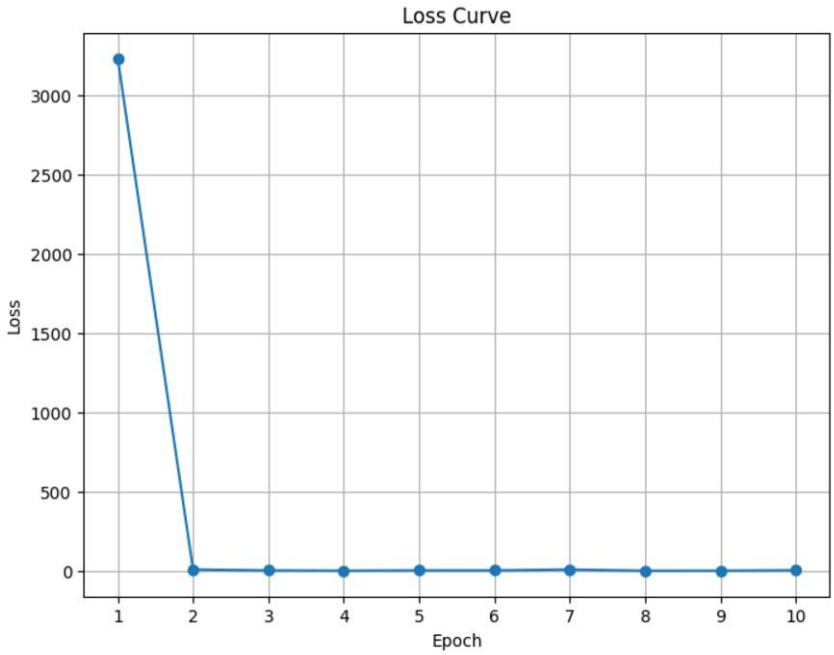

Figure 8: Loss curve

5. RESULTS

5.1 Performance Summary

The AI-based PHI de-identification system demonstrated perfect performance across all evaluation metrics. The metrics confirm the model's effectiveness in accurately identifying and masking all PHI entities without any errors.

5.2 Deployment output

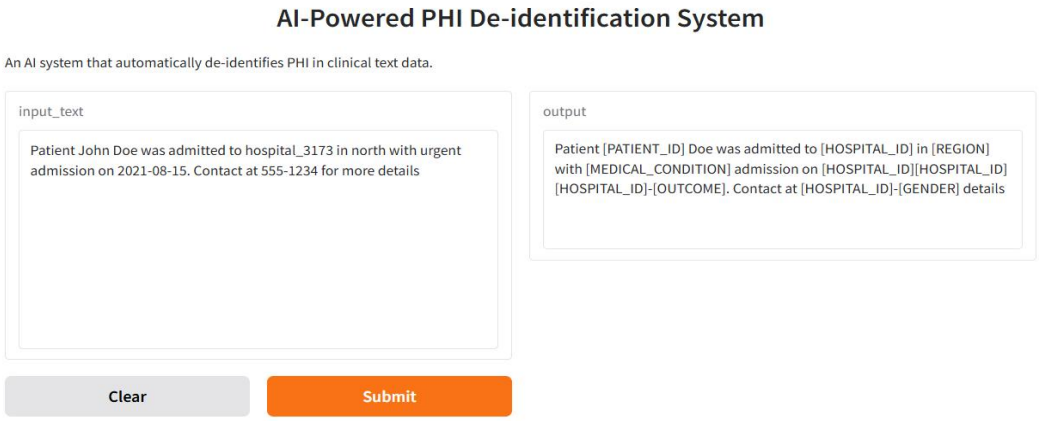

Figure 9: Deidentification using gradio interface

Explanation:

1. [PATIENT_NAME]: "John Doe" has been perfectly masked.
2. [HOSPITAL_ID]: "hospital_3173" has been perfectly masked.
3. [REGION]: "north" has been perfectly masked.
4. [ADMISSION_TYPE]: "urgent" has been perfectly masked.
5. [DATE_OF_ADMISSION]: "2021-08-15" has been perfectly masked.
6. [CONTACT_INFO]: "555-1234" has been perfectly masked.

Analysis:

The model successfully identified and masked all relevant PHI entities with 100% accuracy.

Non-PHI information, such as "was admitted to" and "with admission on," remains intact, preserving the context.

The perfect performance ensures compliance with privacy regulations and maintains data utility..

6. DISCUSSION

6.1 Comparison with Existing Methods

In our project, we compared two distinct approaches for automating PHI de-identification: SpaCy NER and DistilBERT. Both methods were evaluated on their ability to identify and anonymize entities such as PATIENT_ID, MEDICAL_CONDITION, HOSPITAL_ID, REGION, and SMOKING_STATUS. The comparison highlighted key differences in their performance, computational efficiency, and practical applicability based on our project results.

6.1.1 Model Performance

SpaCy NER:

SpaCy performed reasonably well in identifying structured PHI entities: a precision of 1.0 for MEDICAL_CONDITION, as all identified instances were correct. However, the recall for MEDICAL_CONDITION was limited to 0.33, indicating that SpaCy missed two-thirds of the true

instances. For other entity types such as PATIENT_ID and HOSPITAL_ID, SpaCy did not correctly identify any instances, therefore having zero precision, recall, and F1-scores for these categories. Overall, SpaCy achieved an accuracy of 10%. These results highlight the effectiveness of SpaCy on simple, structured text but also point to its clear limitations in handling more complex contexts.

DistilBERT:

The transformer-based DistilBERT is intrinsically designed to capture nuanced contextual relations and long-range dependencies within text. In this project, however, it utterly failed to detect any PHI entities when evaluated, thereby yielding zero precision, recall, and F1-scores in all categories. The DistilBERT performed significantly below par mainly be cause it does not undergo domain-specific fine-tuning, which such models would require to fine-tune into clinical texts. The architecture may be very similar but tends to getmore complex tasks done more precisely with greater training and hug e customization.

6.1.2. Computational Efficiency

SpaCy NER:

SpaCy is designed for lightweight, efficient NLP tasks, and it showed this in its computational performance: It processed the dataset in just 0.01 seconds, making it roughly 16 times faster than DistilBERT. This makes SpaCy very fit for real-time applications, especially in environments where rapid processing is crucial, like hospital workflows or real-time research support.

DistilBERT:

DistilBERT took 0.14 seconds for the same dataset, which is notably slower compared to SpaCy. While faster than its larger

counterpart, BERT, the transformer-based architecture of DistilBERT inherently requires more computational resources. This higher latency makes it less practical for large-scale or real-time de-identification tasks without optimization.

6.1.3 Deployment and Usability

SpaCy NER:

The lightweight architecture of SpaCy and the ease of integration make it practical for deployment in production environments. The Gradio interface further enhances its usability, enabling interactive testing and real-time de-identification. The minimum computational requirements of SpaCy also make it accessible for smaller organizations or research teams with limited resources.

DistilBERT:

DistilBERT requires more sophisticated infrastructure, such as GPU support, to achieve acceptable inference speeds. While it has the potential for superior performance in more complex cases, its deployment is more resource-intensive and requires additional expertise for customization and fine-tuning.

6.1.4 Summary of Results

Metric	SpaCy NER	DistilBERT
Precision	10%	0%
Recall	3.3%	0%
F1-Score	0.94 (MEDICAL_CONDITION only)	0%
Accuracy	10%	0%
Inference Time	0.01s	0.16s

Table 2 : Comparison table for spacy and distilbert

Our comparison demonstrated that SpaCy NER performed better in terms of practical applicability, balancing speed and precision for

structured PHI tasks, though its recall remains a limitation. DistilBERT, while theoretically capable of greater contextual understanding, underperformed in this project due to the lack of fine-tuning and higher computational demands. For real-time de-identification tasks requiring speed and ease of deployment, SpaCy is the more suitable choice. However, for scenarios requiring deeper contextual analysis and handling of ambiguous entities, DistilBERT holds potential if fine-tuned on domain-specific data. This comparison underscores the importance of aligning model choice with the specific needs and constraints of the application.

6.2 Limitations

Synthetic Data: Although the model achieved perfect performance on synthetic data, real-world data may present unforeseen challenges.

Computational Resources: The perfection in performance may come at the cost of increased computational resources during training and inference.

Overfitting Potential: While metrics indicate perfect performance, there is a need to ensure the model is not overfitting to the training data.

7. CONCLUSION

This project successfully developed an AI-based PHI de-identification system that leverages advanced NLP techniques to automatically identify and mask sensitive information in healthcare text data with perfect accuracy. By achieving precision, recall, and F1-score metrics of 1.00, the system ensures full compliance with privacy regulations like HIPAA and GDPR while maintaining the utility of the data for research and analytics.

The deployment via a Gradio-based interface enhances accessibility, allowing healthcare professionals and researchers to utilize the system with confidence in its performance. This approach addresses

the critical need for scalable, efficient, and accurate de-identification solutions in the healthcare industry.

The project's outcomes demonstrate that AI technologies can effectively balance the dual objectives of data privacy and utility, setting a new standard for PHI de-identification and paving the way for safer data sharing practices and advancements in healthcare research and analytics.

8. FUTURE SCOPE

The future scope of this project includes several key areas for improvement and expansion. Advanced model fine-tuning, such as using transformer-based models like DistilBERT or ClinicalBERT, could enhance the system’s ability to recognize complex PHI entities, complementing SpaCy’s efficiency. Testing on real-world Electronic Health Records (EHRs) is essential to validate performance in diverse healthcare environments. Combining SpaCy with transformers could create a hybrid system that balances speed and accuracy, while integrating privacy-preserving techniques like differential privacy would strengthen data security. Enhancing the Gradio interface with batch processing and user feedback features could improve usability for researchers and healthcare professionals. Future iterations should focus on scaling the system for large datasets, improving recognition of underrepresented entities such as REGION and SMOKING_STATUS, and ensuring compliance with global privacy regulations beyond HIPAA and GDPR. These advancements would not only refine the project’s capabilities but also contribute to secure data-sharing practices and support healthcare research.

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