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## *Table of Contents*

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<b>Original Manuscript</b> .....	5
<b>Supplementary Files</b> .....	36
Figures .....	37
Figure 1.....	38
Figure 2.....	39
Figure 3.....	40
Figure 4.....	41
Figure 5.....	42
Figure 6.....	43
Figure 7.....	44
Figure 8.....	45
Figure 9.....	46
Multimedia Appendixes .....	47
Multimedia Appendix 1.....	48
Multimedia Appendix 2.....	48
Multimedia Appendix 3.....	48
Multimedia Appendix 4.....	48

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## Abstract

**Background:** The digitization of healthcare, facilitated by the adoption of electronic health records (EHRs) systems, has revolutionized data-driven medical research and patient care. While this digital transformation offers substantial benefits in healthcare efficiency and accessibility, it concurrently raises significant concerns over privacy and data security. Initially, the journey towards protecting patient data de-identification saw the transition from rule-based systems to more mixed approaches including machine learning for de-identifying patient data. Subsequently, the emergence of Large Language Models (LLMs) has represented a further opportunity in this domain, offering unparalleled potential for enhancing the accuracy of context-sensitive de-identification. However, despite LLMs offering significant potential, the deployment of the most advanced models in hospital environments is frequently hindered by data security issues and the extensive hardware resources required.

**Objective:** The objective of our study is to design, implement, and evaluate de-identification algorithms using fine-tuned moderate-sized open-source language models, ensuring their suitability for production inference tasks on personal computers.

**Methods:** We aimed to replace personal identifying information (PII) with generic placeholders or labeling non-PII texts as 'ANONYMOUS', ensuring privacy while preserving textual integrity. Our dataset, derived from over 425,000 clinical notes from the adult emergency department of the Bordeaux University Hospital in France, underwent independent double annotation by two experts to create a reference for model validation with 3,000 clinical notes randomly selected. Three open-source language models of manageable size were selected for their feasibility in hospital settings: Llama 2 7B, Mistral 7B, and Mixtral 8x7B. Fine-tuning utilized the quantized Low-Rank Adaptation (qLoRA) technique. Evaluation focused on PII-level (Recall, Precision and F1-Score) and clinical note-level metrics (Recall and BLEU metric), assessing de-identification effectiveness and content preservation.

**Results:** The generative model Mistral 7B demonstrated the highest performance with an overall F1-score of 0.9673 (vs. 0.8750 for Llama 2 and 0.8686 for Mixtral 8x7B). At the clinical notes level, the same model achieved an overall recall of 0.9326 (vs. 0.6888 for Llama 2 and 0.6417 for Mixtral 8x7B). This rate increased to 0.9915 when only names were to be deleted with Mistral 7B. Four notes out of the total 3000 failed to be fully pseudonymized for names: in one case, the non-deleted name belonged to a patient, while in the other cases, it belonged to medical staff. Beyond the fifth epoch, the BLEU score consistently exceeded 0.9864, indicating no significant text alteration due to the process.

**Conclusions:** Our research underscores the significant capabilities of generative NLP models, with Mistral 7B standing out for its superior ability to de-identify clinical texts efficiently. Achieving notable performance metrics, Mistral 7B operates effectively without requiring high-end computational resources. These methods pave the way for a broader availability of pseudonymized clinical texts, enabling their use for research purposes and the optimization of the healthcare system.

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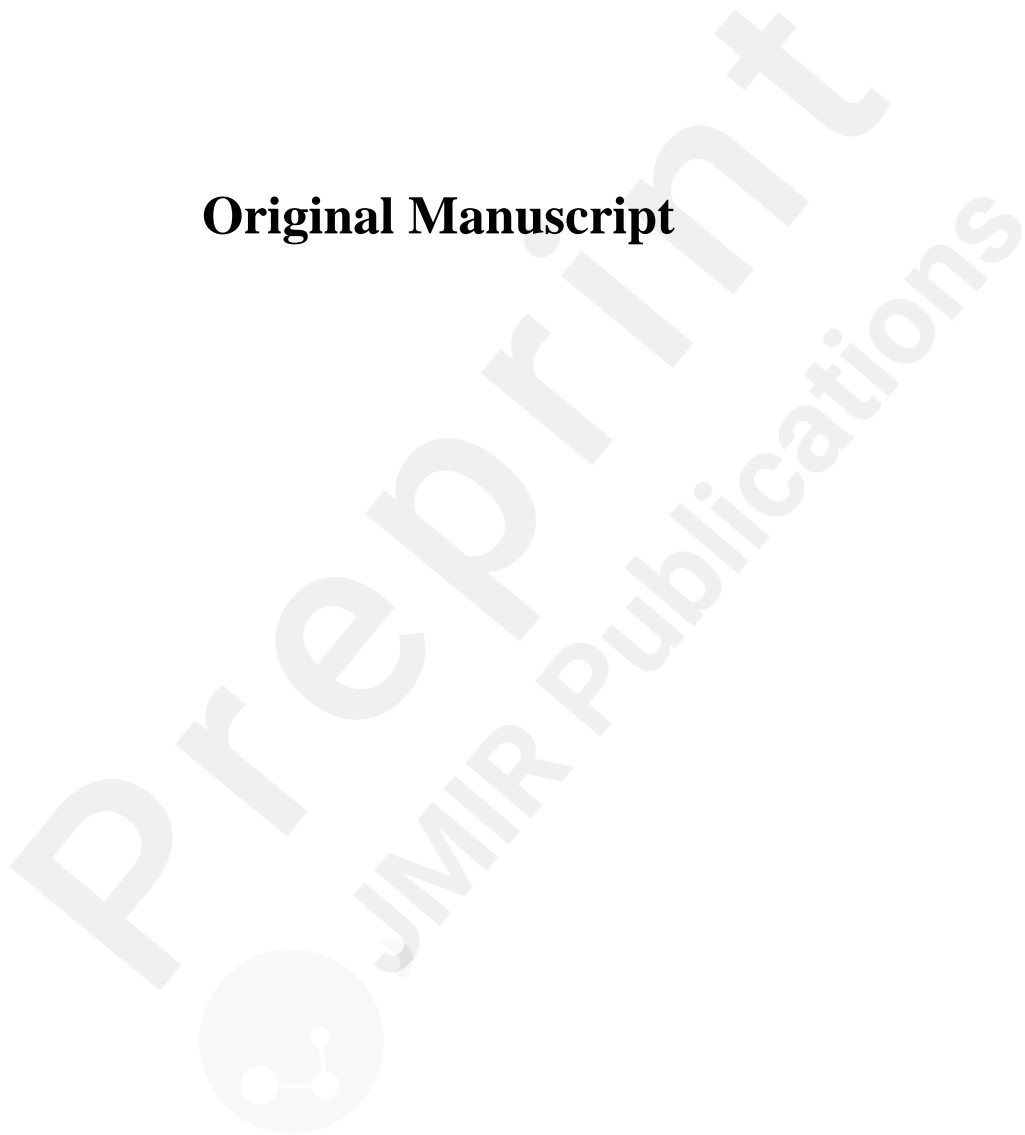
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## Harnessing Moderate-Sized Language Models for Reliable Patient Data De-identification in Emergency Department Records: An Evaluation of Strategies and Performance

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## Abstract

**Background:** The digitization of healthcare, facilitated by the adoption of electronic health records (EHRs) systems, has revolutionized data-driven medical research and patient care. While this digital transformation offers substantial benefits in healthcare efficiency and accessibility, it concurrently raises significant concerns over privacy and data security. Initially, the journey towards protecting patient data de-identification saw the transition from rule-based systems to more mixed approaches including machine learning for de-identifying patient data. Subsequently, the emergence of Large Language Models (LLMs) has represented a further opportunity in this domain, offering unparalleled potential for enhancing the accuracy of context-sensitive de-identification. However, despite LLMs offering significant potential, the deployment of the most advanced models in hospital environments is frequently hindered by data security issues and the extensive hardware resources required.

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**Conclusions:** Our research underscores the significant capabilities of generative NLP models, with Mistral 7B standing out for its superior ability to de-identify clinical texts efficiently. Achieving notable performance metrics, Mistral 7B operates effectively without requiring high-end computational resources. These methods pave the way for a broader availability of pseudonymized clinical texts, enabling their use for research purposes and the optimization of the healthcare system.

**Keywords:** de-identification ; Large Language Model ; electronic health records ; Transformers ; Natural Language Processing ; Nursing notes ; General Data Protection Regulation ; Fine-tuning ; French nursing notes



## Introduction

The digitization of medical data has profoundly transformed healthcare, facilitating the easy and efficient sharing of patient information [1]. This digital transition, embodied by electronic health records (EHRs) systems, offers promising opportunities for data-driven solutions, research, and surveillance on a pan-European scale [2]. Yet, alongside the many advantages of digitization come significant concerns about the privacy and security of sensitive patient data [3]. The European General Data Protection Regulation (GDPR) emphasizes the necessity of stringent data protection measures, particularly for health-related information [2]. Clinical notes, which often encompass identifiable patient details, must adhere to these standards to safeguard patient confidentiality [Loi informatique et liberté]. Before of any data sharing researchers face the critical task of developing and integrating methods that mask sensitive data, guaranteeing protection against any unauthorized access [4]. Our team was recently faced with this challenge in a project aimed at classifying clinical notes from emergency services to extract the necessary information for the establishment of a trauma observatory [5].

Manual de-identification of medical records is not feasible, as it is expensive in terms of personnel resources and the time required to accomplish the task. Alternatively, multiple strategies have been implemented for the automated de-identification of medical records [6,7]. These methods evolved from systems based on explicit rules, regular expressions or dictionaries [8–16], to techniques using machine learning [17–19].

In recent years, the evolution of language models, particularly those based on transformer architectures, has reshaped the landscape of natural language processing (NLP). Transformers, introduced by Vaswani et al. In 2017 [20], provided a novel approach to handling sequential data using self-attention mechanisms, thereby obviating the need for recurrent layers and significantly augmenting training efficiency. This pivotal innovation paved the way for the advent of progressively sophisticated and expansive models. Transformer-based language models of a moderate scale, particularly through customized and fine-tuned versions of the architecture BERT [21], have demonstrated high capabilities in various healthcare applications. These models excel in understanding and processing complex clinical texts, enabling tasks such as predicting patient outcomes and identifying medical events. For instance, a recent study highlighted the effectiveness of fine-tuned BERT models in analyzing clinical notes to predict occurrences of falls, showcasing the model's ability to comprehend subtle nuances in medical language [22]. Additionally, BERT models offer significant benefits for tasks like Named Entity Recognition (NER). Those models offer notable benefits for de-identification, thanks to their capacity to discern patterns among words and phrases. They have the ability to learn from diverse text types means they can effectively tackle various pseudonymization challenges, as they can be trained to erase a wide range of identifiable details across different document types.

The burgeoning of computational resources and datasets has since kindled a shift towards the construction of massive models, embedded with trillions of parameters [23–25]. As they grew in size, their generalization aptitude and versatility witnessed substantial enhancement, optimizing tasks such as de-identification. In

2023, Liu et al. underscored the potential of leveraging the GPT-4's inherent capacity for zero-shot in-context learning. A salient highlight of their methodology was its ability to maintain the original structure and meaning of the text after the removal of confidential details. While the capabilities of GPT-4 are undeniable, its application in the realm of healthcare presents serious ethical and legal dilemmas, primarily concerning data privacy and patient confidentiality. On the one hand, due to the vastness of the model, local hosting of GPT-4 is not feasible, therefore, data should be transmitted to external servers, in this case OpenAI's infrastructure. On the other hand, considering the confidentiality of the weights, only locally hosted servers are regulatory compliant. Furthermore, considering GPT-4 is a proprietary model, organizations cannot fully control or audit the underlying mechanics or data handling processes

From a regulatory perspective, sending personal health information (PHI) externally contravenes many data protection regulations, most notably the GDPR in Europe and the Health Insurance Portability and Accountability Act (HIPAA) [26,27] in the United States. This raises not just data sovereignty issues but also infringes on patient rights, as they might not have explicitly consented for their data to be processed in external environments. Hence, while the technological feats of models like GPT-4 are commendable, their real-world applications, especially in sensitive sectors like healthcare, require careful consideration and possibly, significant adjustments to ensure full regulatory compliance and ethical integrity.

Generative language models significantly smaller in size (several billion parameters compared to over a trillion for GPT-4) have been recently developed and made available to the public under licenses that allow for almost unrestricted use (Llama 2 by Meta [28]) or even under open-source terms (Mistral [29]).

The objective of our study is to design, implement and evaluate de-identification methods involving proper prompt engineering and fine-tuning of three, open-source language models (Llama 2 7B, Mistral 7B and Mixtral 8x7B [30]). These models were selected for their moderate size, making them suitable for deployment on personal computers for production inference tasks.

## Methods

We first attempted to perform the task using only prompt engineering and zero-shot inference. Because we failed to achieve any significant results we improved the selected models' capability to de-identify clinical texts using quantized Low-Rank Adaptation (qLoRA) [31] fine-tuning with a dataset of instruction/response pairs. In practice, the task consists in replacing personal identifying information (PII) (name, location, dates, telephone number, email, identification numbers) with generic placeholders, represented as '[XXXXX]', or, when no PII is detected, by generating the text as 'ANONYMOUS'. The ultimate goal of this procedure is to preserve text content, ensuring adherence to privacy and confidentiality requirements.

## Data source, datasets allocations and annotation

Within the emergency department, triage is conducted by triage nurses. This process involves the collection of information on each patient, including medical history, current symptoms, vital signs, and personal details. It is these data that we have at our disposal in our study. For this investigation, we curated our dataset from a repository containing 425,680 clinical free-text notes (see Multimedia Appendix 1), authored by a nurse

during the initial reception and triage of individuals at the Bordeaux University Hospital's adult emergency department over the period spanning from January 2013 to December 2022. A subset of 6,097 clinical notes was randomly selected and independently annotated by two experts. Any arising discrepancies were adjudicated by a third expert, thus establishing a reference database. From this curated sample of 6,097 clinical notes, 3,000 were delineated to constitute a test dataset, upon which accuracy metrics were evaluated (Figure 1). The residual 3,097 clinical notes, alongside an additional sample of 3,000 clinical notes designed using filters and keywords search to encompass a broad spectrum of identifying scenarios, comprised the validation dataset.

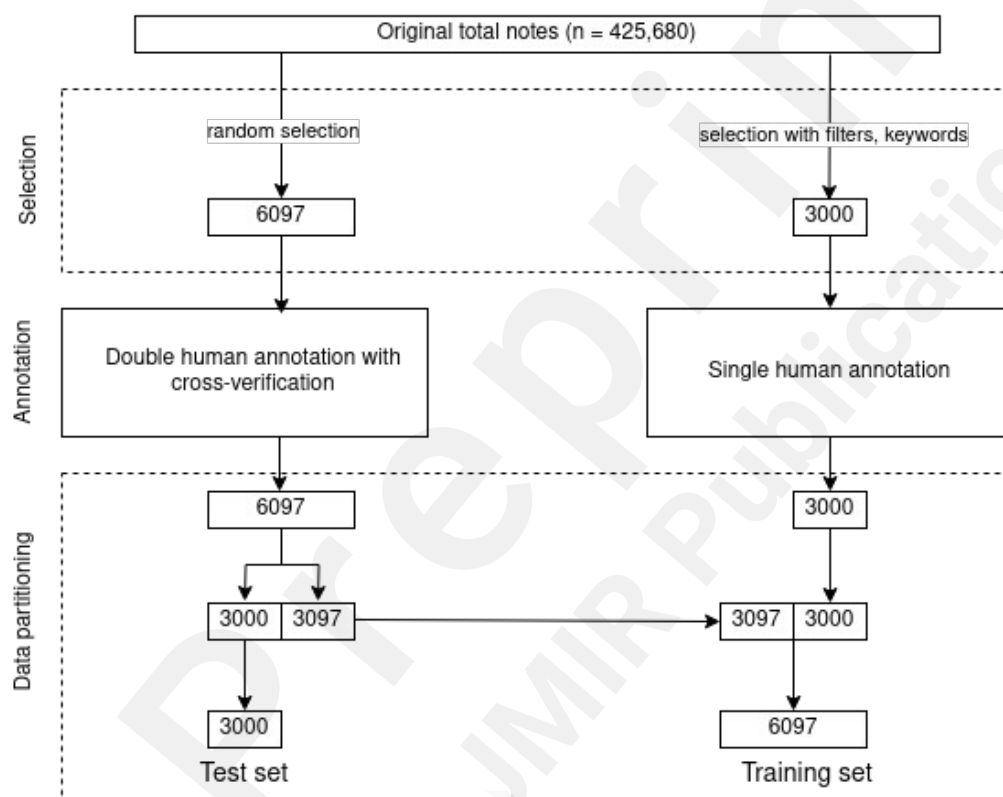


Figure 1: Data Preparation: Annotation and Splitting into Training and Test Sets

In order to further assess whether the de-identification performances of the models varies with the type of PII, we classified identifying information within clinical notes into six distinct categories (Table 1). These categories were utilized by annotators to label such information in the test dataset. While we have taken care to remove obvious PII like names, addresses, and identification numbers, it's important to note that de-identification cannot be considered as a strict anonymization process. For instance, in cases of rare diseases or very specific descriptions, re-identification could theoretically be possible. Because every clinical history is unique, ensuring complete anonymity is unattainable. Our goal is to pseudonymize data, striking a balance

between patient confidentiality and data utility for research, as removing all sensitive information will significantly diminish the data's usefulness.

*Table 1: PII categories description in medical records*

Type	Code	Description
Individual Names	<b>NAME</b>	Includes both first and last names of individuals (including patients and medical staff) or of relatives, employers, or household members of the individuals, ensuring personal identification.
Dates	<b>DATE</b>	Pertains to specific dates related to medical events, appointments, or personal milestones, formatted as day/month/year.
Geographic Identifiers	<b>LOC</b>	Covers names of geographic locations like cities, medical facilities, or addresses, facilitating location-based identification.
Phone Numbers	<b>TEL</b>	Comprises all forms of telephone numbers for direct contact, including mobile and landline numbers.
Email Addresses	<b>MAIL</b>	Encompasses electronic mail addresses, allowing for digital communication.
Miscellaneous Identifiers	<b>OTHER</b>	A catch-all category for unique identifiers not covered by other categories, including social security numbers, medical analysis codes, and URLs for patient images.

## Selected models

We have selected three language models that share the following two characteristics: being open-source and of sufficiently small size for the production phase to be implemented on affordable PC-type systems. These are Llama 2 7B, Mistral 7B and Mixtral. Llama 2 7B is developed by Meta. Launched in 2023, this is a 7-billion-parameter model, which is claimed to exhibit a good balance between performance and efficiency. We also selected the Mistral 7B model, introduced to the public in October 2023. It has demonstrated superior performance, either matching or surpassing that of Llama 2 13B in extensive benchmarks and showing comparable results to Llama 1 34B in specific domains like reasoning, mathematics, and code generation. In December 2023 the Mixtral 8x7B model was released. It is described as a Sparse Mixture of Experts (SMoE) language model. Its key innovation lies in the routing of inference tasks through one selected expert out of eight, enabled by an additional routing layer. Consequently, despite its 8x7B size with respect to fine-tuning, Mixtral achieves a significant efficiency by requiring an eightfold reduction in parameters for inference task.

## Fine-tuning and inference

Each model was subjected to the same prompt/response pairs of clinical notes. The fine-tuning process was uniformly standardized across all three models, albeit with variations in batch sizes and quantization rates to accommodate our hardware constraints. The fine-tuning configuration for Mistral 7B and LLaMa 2 7B involved a batch size of 24 records per GPU, while Mixtral utilized a batch size of 20. The models were fine-tuned over 15 epochs, utilizing the AdamW optimizer with a learning rate of 5e-5 and a weight decay of 0,01. We employed the qLoRA technique, allowing for specific adjustments in selected parts of the model, such as query, key, value, output, and gates projection modules while preserving the overall architecture integrity. The LoRA configuration included rank setting of 32, a learning rate multiplier (alpha) set to 64, with a dropout of 0.1, and without any bias setting. Additionally, to optimize computational efficiency and minimize memory consumption, the models were quantized to 8-bit precision for both 7B models, and 4-bit precision for Mixtral. At every fine-tuning epoch, the inference was induced for each model.

The computational undertakings of this research were performed on a server running Ubuntu 22.04, outfitted with four A100 GPUs, collectively boasting 320 GB of VRAM.

## Evaluation

In evaluating the de-identification performance of personal data within clinical notes, our analysis is

structured around two primary methodologies. The first methodology operates at the PII-level, enabling us to provide estimates of recall, precision, and F1 scores that are comparable with previous work in the literature. The second methodology focuses on clinical notes as the statistical unit, enabling us to assess the variation in recall performance according to the category of PII. This latter approach needs to be complemented by the measurement of a BLEU score to assess potential modifications in the text. The assessment of the number of successful de-identifications was conducted through a comparison with the manually annotated test dataset.

### *PII-Based Metrics*

This approach centers on treating each PII as an independent statistical unit. This perspective allows us to gauge the precision and recall of our de-identification efforts at the most granular level. Recall in this context is conceptualized as the proportion of PIIs accurately identified and removed from the clinical notes.

$$\text{Recall}_{PII} = \frac{\text{number of correctly de-identified PII per clinical notes}}{\text{total number of PII per clinical notes}}$$

Precision, meanwhile, reflects the accuracy of our model to identifying and eliminating actual PIIs, distinguishing between correct identifications and false positives.

$$\text{Precision}_{PII} = \frac{\text{number of correctly de-identified PII per clinical notes}}{\text{total number of PII tagged}}$$

The summary F1 measure is:

$$F1 = \frac{2}{\frac{1}{\text{precision}} + \frac{1}{\text{recall}}}$$

### *Clinical Note-Based Metrics*

The second approach adopts the entire clinical note as the statistical unit of analysis. Here we evaluate the success of de-identification on a document-wide scale, marking a 'success' when every PII within a note has been successfully de-identified. Such a measure offers insight into the overall effectiveness of our de-identification protocols. Recall, in this instance, measures the ratio of fully de-identified notes to those containing any PII.

$$\text{Recall} = \frac{\text{number of correctly de-identified clinical notes among identifying clinical notes}}{\text{total number of identifying clinical notes}}$$

Because the clinical notes in the validation set are annotated by indicating the nature of the PII (according to the categories in Table 1), it is possible to detail the variations in recall by category. The relevance of precision is altered in this context, as it necessitates a different consideration of what constitutes an pseudonymization attempt, denoted by the presence of a pseudonymization tag. Instead, the potential alteration of content possibly induced by the de-identification process was measured using the BiLingual

Evaluation Understudy (BLEU) score [32].

$$BLEU = BP \cdot \exp\left(\sum w_n \log p_n\right)$$

where BP is the brevity penalty,  $w_n$  the weight for each n-gram, and  $p_n$  the precision of n-grams. We set  $n=4$  for the BLEU score calculation, aligning with common practice in NLP to capture up to four-gram coherence, thereby ensuring a comprehensive evaluation of content preservation.

## Results

### Data overview

Very few notes contained PII's categorized as email addresses and 'other.' These categories are included in the training sample due to an ad-hoc selection process, which utilized filters to ensure representation, as half of the set was selected this way. Our examination of the test sample, which consists entirely of randomly selected clinical notes, reveals that names, places, and dates are the most prevalent types of PII. The categories of identifying data in the training and test sets are summarized in Table 2.

Table 2: Enhanced distribution of PII in train and tests sets

	Train set	Test set
<b>Clinical notes</b>		
Non-anonymous medical notes	3442 (56.5%)	935 (31.2%)
Randomly selected medical notes	3097	3000
Ad-hoc selected medical notes	3000	-
Total count	6097	3000
<b>PII Categories</b>		
NAME	3016	555
LOCATION	1801	715
TELEPHONE	650	41
EMAIL	13	0
DATE	2404	607
OTHER	33	1
Total number of PII	7917	1919

Regarding the length of clinical notes, they range from 8 to 3916 characters (with an average of 443 characters) in the training set and from 3 to 2138 characters (averaging 439 characters) in the test set. A total of 935 clinical notes in

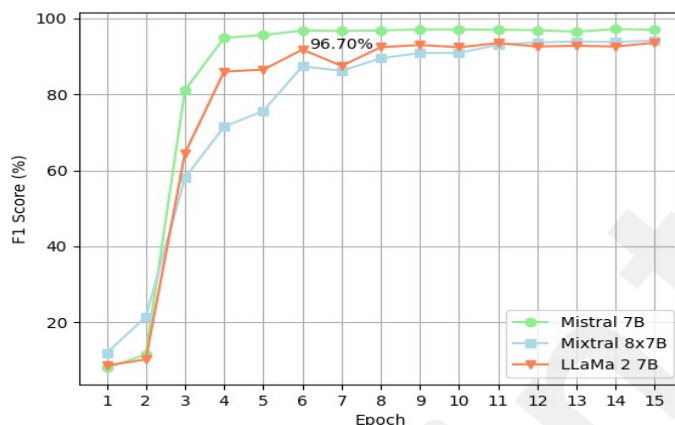


Figure 2: Plot of F1-score by epoch: PII as statistical unit.

### Performance using PII-based metrics

Figure 2 plots the change in the F1 score over the 15 epochs of fine-tuning for the three respective models. The Mistral 7B model quickly reaches a performance plateau, where its F1 score stabilizes, whereas the Mixtral 8x7B and Llama2 7B models exhibit a slower rate of improvement, with both reaching a plateau in their F1 scores around the 12th epoch.

### Recall analysis

The recall estimates of the three models are shown in Figure 3 and 4.

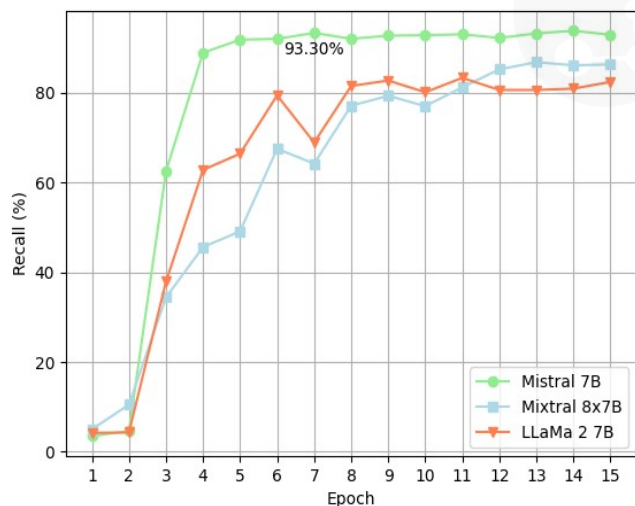


Figure 3: Plot of Recall by epoch: clinical notes as statistical unit.

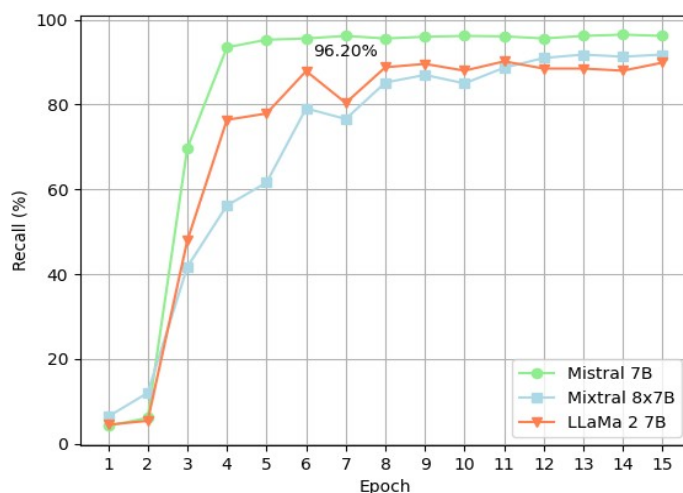


Figure 4: Plot of Recall by epoch: PII as statistical unit. [unpublished, peer-reviewed preprint]

Mistral 7B and Mixtral 8x7B achieved better overall recall. The Mistral 7B and Mixtral 8x7B models demonstrated marked enhancements in their de-identification efficacy across epochs, starting from the third epoch onward. Notably, the Mistral 7B model has shown a rapid improvement in performance, achieving a performance plateau by the sixth epoch. Conversely, the Mixtral 8x7B model's improvement trajectory was more gradual, reaching a performance stable performance level by the thirteenth epoch. The overall success rate appears not to improve beyond epoch 7 for the Mistral 7B model. Consequently, in the subsequent analysis, this epoch was selected for comparing success rates across categories.

As shown in Figure 5-8, Mistral 7B consistently outperformed Mixtral 8x7B and Llama 2 across all data identification categories. Despite Mixtral's performance improving over time, it still did not surpass Mistral 7B. Using Mistral 7B, a 100% recall was observed for phone numbers (Figure 5) and recall was lower for locations (Figure 6) than for names (Figure 7).

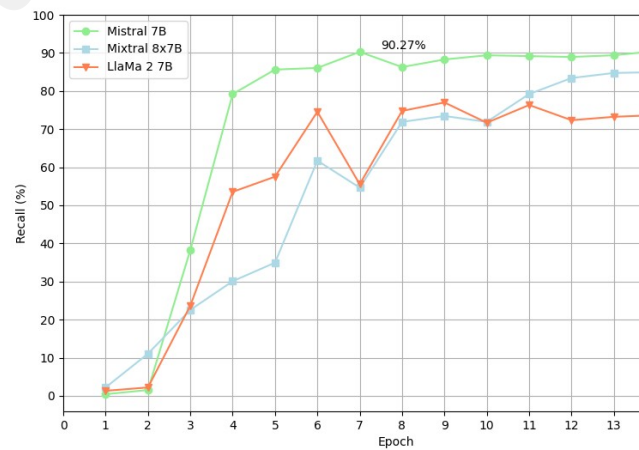


Figure 5: Plot of Recall by epoch for DII: LOC

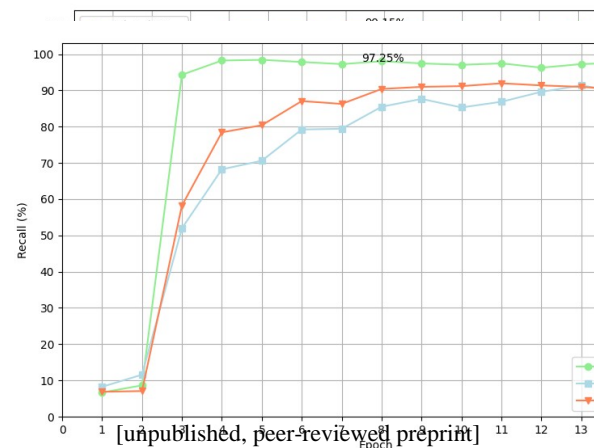


Figure 8: Plot of Recall by epoch for PII: D



## BLEU score

BLEU-4 scores were calculated to assess whether the models modified the texts at the note level. During the de-identification process, medical texts remained almost unchanged as demonstrated by a consistent high BLEU-4 score (Figure 9) beyond epoch 5.

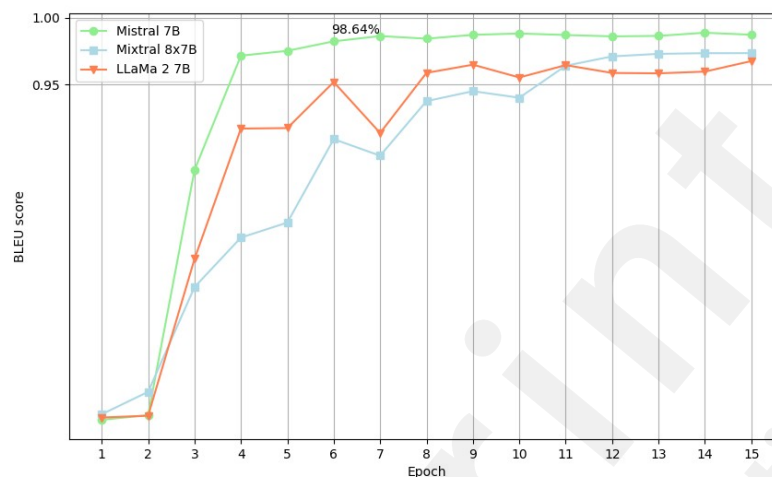


Figure 9: Plot of BLEU score by epoch: clinical note as statistical unit.

## Results summary at Epoch 7

The Table 3 below presents a summary of performance metrics achieved by our models at epoch 7.

Table 3: Fine-tuned models performance at Epoch 7

Model	Clinical notes		PII	
	Recall	Precision	Recall	F1
Mistral 7B	0.9326	0.9721	0.9625	0.9673
Llama 2 7B	0.6888	0.9596	0.8041	0.8750
Mixtral 8x7B	0.6417	0.9852	0.7655	0.8616

The results demonstrate that the Mistral 7B model outperforms both the Mixtral 8x7B and Llama 2 7B with a F1 score of 0.9673. When using clinical note as the statistical unit, the recall is also much higher (0.9326) for Mistral 7B than Llama 2 and Mixtral 8x7B models.

## Error analysis

In epoch 7 of the Mistral 7B model, a total of 63 clinical notes were not properly pseudonymized, as detailed in Table 4. Among these, location (LOC) errors were the most frequent, with 44 instances. Deleting geographical and institutional identifiers then remains a significant challenge (with a recall of 86.1%).

Specifically, 31 notes still included names of health or social service facilities, while 12 notes still included names of cities. Conversely, errors involving names (NAME) were significantly fewer, with only 4 instances, including one patient name and three doctors' names, resulting in a high recall of 99.8% for this category. Date-related errors (DATE) were observed in 14 notes (with a recall of 97.8%).

*Table 4: Summary of de-identification errors at Epoch 7*

Errors	Count
Total	63
Returned ANONYMOUS	29
Annotation Error	34
<b>Errors in PII categories</b>	
NAME	4
LOC	44
DATE	14
OTHER	1

The test dataset, comprising 3,000 clinical notes, underwent a post-hoc examination to identify any inaccuracies resulting from manual annotations that would have been detected by all 15 versions of our three finely-tuned models, spanning epochs 1 to 15. Through this process, we were able to pinpoint 65 notes in which the model detected personally identifiable information through the medical histories that were categorized as anonymous (i.e., without identifying data, 2,066 clinical notes), in which the model detected personally identifying information that had been overlooked by human annotators.

We observed that the models outperformed human annotation in 9 clinical records from the test set. Specifically, in these 9 records, 5 locations (LOC), 3 names (NAMES), and 1 date (DATE) were omitted during manual annotation. The remaining 53 records present annotation errors from the models. Therefore, the total number of actual personally identifiable information (PII) amounts to 1928, contrary to the 1919 initially identified by our experts.

Subsequently, corrections were made to the test dataset based on these findings, and main outcomes were recomputed in an additional sensitive analysis. The metric measurements after accounting for these modifications are only slightly altered from the original results (see Multimedia Appendix 2 for the details).

## Discussion

### Principal Findings

In this study, we assessed the performance of three generative NLP models in the de-identification of clinical text documents. The generative model Mistral 7B demonstrated the highest performance with an overall F1-

score of 0.9673. At the clinical notes level, the same model achieved an overall recall of 0.9326, with this rate increasing to 0.9915 for the deletion of names. The evaluation was based on a test dataset of 3000 clinical notes, among which only four notes failed to be fully de-identified for names; in one case, the identifying name was that of a patient. Because the method relies on the use of generative models, we also measured potential text alterations generated by the process. Beyond the fifth epoch, the BLEU score consistently exceeded 0.9864.

## Strengths

Our work distinguishes itself from the existing scientific literature by employing a method that does not rely on NER and uses moderate-sized models. Instead, the use of generative LLMs allows for the production of text that is pseudonymized by removing PII components. This is the reason why we added metrics that use clinical notes as the statistical unit. This led us to use the BLEU metric to assess potential text alterations. Another consequence of this method is that no hyperparameters are set which made it possible to avoid the use of separate test and validation dataset partitions. The size of our training and test samples, independently annotated by two experts, constitutes a significant strength in our study. To our knowledge, no other study has used a test sample of such size (3,000 notes). Yet, it is crucial to have the means to detect rare errors if the ultimate goal is to develop a system that guarantees the pseudonymization of clinical texts. We deliberately limited our model selection to those whose implementation does not require powerful servers and can be executed on personal computers equipped with a consumer-grade graphics card. The largest model is Mixtral 8x7B, which has approximately eight times more parameters than the other two models. Mixtral 8x7B shares the same architecture as Mistral 7B, with the distinction that each layer consists of 8 feed-forward blocks. Although training it requires significant memory capacity, this is not the case during the inference phase, during which only two of the feed-forward blocks are utilized, selected by a network acting as a router.

## Limitations

**Annotation Process Inaccuracies:** During the annotation process, we observed some inaccuracies. To assess the impact of these inaccuracies on our metrics, we conducted a post-hoc analysis, taking into account corrections made by the model. Although this analysis revealed few variations, it is important to note that some errors may still remain in the text set, undetected by the model. These undetected errors could potentially affect the overall performance of the model.

**Model Choice:** We opted for a fine-tuned LLM-based approach over a dedicated NER model due to pragmatic considerations. Our hypothesis was that a targeted human annotation process, with expert annotators pinpointing PII within texts, would be more effective than a broad NER annotation effort, given the same time investment. Focusing on essential PII elements helps us minimize the ambiguities that broader NER annotations often entail. This focus leads to improved precision and recall rates during the training phase. Furthermore, this approach is in line with the TARPON project's objectives, which prioritize the accurate removal of PII from unstructured medical texts.

The default choice for identification tasks is usually a bidirectional transformer, starting from the hypothesis that the relationship of a word with its context before and after that word allows for better comprehension of the role of those words and therefore should be more suited for NER tasks. However, this hypothesis no longer holds when dealing with generative models. Since the goal here is to generate redacted text, the provided prompt has access to the entire corrected phrase. Consequently, relative to a given word, implications cannot be considered unidirectional.

**Model Sharing Constraints:** Another significant limitation is that our model was fine-tuned using non-anonymous clinical texts, which prevents us from sharing the model's weights with the community. Sharing the model's weights could potentially allow for the extraction of the original training data. This limitation restricts the model's reproducibility and its broader applicability across different research settings and

medical domains

**Demographic and Textual Bias:** The processed data are in free-text format, written by healthcare staff, which introduces significant variability. This variability is not only present between different services within the same health facility but also across various centers. Factors such as the content of clinical notes, the medical abbreviations used, writing styles, and the level of detail in documentation can differ greatly from one source to another. Such differences could potentially impact the performance of our models, making it essential to test and adapt our approach to data from diverse sources.

## Comparison with Prior Work

Comparing the performance of our models with those documented in the literature presents challenges because our models are specifically fine-tuned to pseudonymize French-language clinical notes. Consequently, it is not feasible to apply them to the English-language databases traditionally used for benchmarking, such as i2b2 [33], MIMIC II [34], and MIMIC III [35].

In addition to these differences in benchmarking context, there are also divergences in the methodologies used for de-identification. Historically, de-identification of medical records has evolved from rule-based systems, which rely on predefined rules, regular expressions, and dictionaries, to more sophisticated machine learning approaches. Rule-based methods, while easy to implement and interpret, often fall short in handling the variability and unpredictability inherent in unstructured clinical texts. On the other hand, machine learning-based approaches offer more flexibility and adaptability, particularly when dealing with large and diverse datasets. These models can learn patterns directly from the data, making them more effective in identifying PII that deviate from standard formats. However, their effectiveness is heavily dependent on the quality and quantity of annotated data available for training. Moreover, machine learning models typically require significant computational resources and expertise in model tuning, which can be a barrier to adoption, particularly in resource-constrained settings.

Our proposed model leverages these advanced machine learning techniques, specifically fine-tuned for the French language. This focus allows our model to effectively capture and manage the linguistic intricacies specific to French clinical notes, such as frequent abbreviations and unstructured text entries, which are common in emergency department settings.

Additionally, our results demonstrate that while our model performs comparably to those trained on English-language corpora, certain challenges persist, particularly in the detection of location-based PII. This is likely due to the complexity introduced by variations in PII forms, such as acronyms and abbreviations, as well as the presence of typing errors, which are less predictable and harder to model.

Therefore, to compare performance metrics accurately, it is necessary to assess the complexity of clinical texts from these databases against those used in our study. In the Multimedia Appendix 1, we include examples of clinical notes from our dataset to demonstrate that PII can appear randomly within the text, in an unstructured manner, and that these PII, along with the rest of the text, often include numerous abbreviations. This tendency towards abbreviation is explained by the unique demands of emergency department settings, where nurses are required to perform efficient, real-time data entry into the hospital's information system. As a result, our dataset more closely aligns with MIMIC II, which features unstructured clinical notes made by nurses, as opposed to i2b2, where each type of information is distinctly separated, preventing the amalgamation of multiple PII within single sentences.

As shown in Multimedia Appendix 3, our results (overall F1-score of 0.9673) are on par with previous studies

on english clinical text corpus that used an algorithm including models using self-attention [17,24,35,36]. The Multimedia Appendix 4 summarizes study results that examined recall variations according to PII categories. These figures consistently show that the relative weakness of these algorithms, ours included, lies in a small number of errors concerning locations. Our dataset presents additional challenges for PII identification due to the presence of multiple variations of PII, including acronyms, abbreviations, and typing errors. Specifically, of the 44 notes with failed identification, 15 involved abbreviations or acronyms, and 2 contained typing errors.

## Future work

We aim to enhance the detection capabilities of PII in our medical notes by fine-tuning our model with newly annotated data. To achieve this, we plan to generate artificial clinical notes using commercially available APIs, such as GPT-4. These large language models, much more powerful than ours, can produce realistic notes containing PII and annotations, which will facilitate the training process and increase data diversity.

By generating a substantial volume of these artificial data, we can ensure equitable representation of different PII categories and evaluate two key aspects: identifying the optimal amount of clinical notes needed to achieve the highest possible accuracy and recall, and comparing the effectiveness of models fine-tuned with real data versus those fine-tuned with artificially generated data.

Using this newly developed model based on artificial data, we aim to make it available as an open-source resource, benefiting the broader community. Additionally, this foundation will enable us to create a multilingual model capable of processing both English and French clinical notes. This multilingual model will allow us to perform performance comparisons against literature benchmark datasets such as i2b2 and MIMIC. The performance of these refined models will be evaluated using our corrected test set, along with newly annotated data from various emergency services.

This study is currently focused on data from an emergency department in France. In the subsequent phases, our goal is to extend this methodology to other services across France, with the ambition of creating a national French observatory on trauma. However, it is important to consider the potential for demographic biases in our model's performance.

By diversifying data sources, we aim to enhance the model's generalizability. If biases are identified in this process, we plan to retrain the model, either by using a specific portion of data from each service or by integrating synthetic data to mitigate these biases.

We intend to extend our methodology to other types of sensitive documents, such as medico-legal records, to evaluate the generalizability and effectiveness of our approach in protecting personal information across various domains.

We are also considering integrating explainability methods, similar to those used by Arnaud et al. [38], to enhance the transparency of our model in PII detection. These techniques, based on transformer models and interpretability approaches like LIME, which have already proven effective on triage note data similar to ours, could strengthen user trust and facilitate the adoption of our technologies in clinical settings.

Through this comprehensive approach, we aim to enhance the value and applicability of our models, contributing to the development of privacy-preserving technologies in the healthcare domain and strengthening the security of patients sensitive information.

## Ethical considerations and practical implementations

The use of small to moderate-sized models is a key consideration in our approach. These models are generally capable of running on GPUs with at least 16 GB of VRAM, making them suitable for use on personal computers or within local infrastructures. This is particularly advantageous for institutions with limited resources, as it allows them to manage data privately and securely without relying on extensive external infrastructure. However, while local deployment ensures better control over sensitive data, it can also be time-consuming and may introduce challenges related to the interoperability of different systems.

One of the main challenges of this pipeline is its implementation across all participating emergency services, given that not all institutions may be equipped to efficiently manage these new procedures. The rationale behind implementing this process is rooted in a data-sharing initiative aimed at establishing a national observatory, which necessitates enhanced protection for the information being used.

At this stage, centralizing the data in a dedicated center with the necessary computational resources remains the simplest solution. This would allow for secure, controlled, and efficient management of patient data. Alternatively, the process could be implemented directly within health data warehouses (HDWs), enabling these facilities to store and apply the de-identification process locally. Regardless of the approach, it is imperative that the use of this pipeline on health data is conducted within a legally and digitally controlled framework, authorized by the relevant authorities.

Given the potential risks of data re-identification, especially when dealing with unique clinical histories, we emphasize that pseudonymization alone is insufficient and should be accompanied by additional protection and security measures to prevent unauthorized access to sensitive data.

## Conclusion

Our research underscores the significant capabilities of generative NLP models, with Mistral 7B standing out for its superior ability to de-identify clinical texts efficiently. Achieving notable performance metrics, Mistral 7B operates effectively without requiring high-end computational resources. These methods pave the way for a broader availability of pseudonymized clinical texts, enabling their use for research purposes and the optimization of the healthcare system.

## Acknowledgments

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## Abbreviations

**BERT:** Bidirectional Encoder Representations from Transformers

**BLEU:** BiLingual Evaluation Understudy

**EHRs:** Electronic Health Records

**GDPR:** General Data Protection Regulation

**GPT:** Generative Pre-trained Transformer

**HIPAA:** Health Insurance Portability and Accountability Act

**LLM:** Large Language Model

**NER:** Named Entity Recognition

**NLP:** Natural Language Processing

**PHI:** Personal Health Information

**PII:** Personal Identifying Information

**qLoRA:** quantized Low-Rank Adaptation

**SmoE:** Sparse Mixture of Experts

**TARPON:** Traitement Automatique des Résumés de Passages aux urgences pour un Observatoire National (in english : Automatic Processing of Emergency Department Visits Summaries for a National Observatory)

## Data Availability

The data set and model's weights are not available because of patient privacy restrictions.

## Authors' Contributions

Conceptualization and design: EL, CGJ, AFM. Annotation: BC, OD, EL, DR, CGJ. Analysis and interpretation: OD, CGJ, EL. Manuscript drafting: OD, EL, AGA. Critical revision: All authors. Provision of study material: CGJ. Supervision: EL.

## Conflicts of Interest

None Declared.

## Multimedia Appendix 1

In the provided document, the upper section presents an original clinical text as it was written by a nurse or hospital staff. The section below displays the same note after correction, rendered in proper French.

For this first example (Textbox 1), identifying data have been pseudonymized. The location (LOC) of the original note has been replaced with 'Clinique du Louvre'.

Textbox 1. Example of french nursing notes

**Original note** : tft de la cl du louvre pour pec dune fracture du col femoral droit patient sous plavix transféré du louvre pour orthopédiste pour prise en charge d'une fracture du col du fémur

**Manual transcription without abbreviations:** Transfert de la clinique du Louvre pour prise en charge d'une fracture du col femoral droit patient sous plavix transféré du Louvre pour orthopédiste pour prise en charge d'une fracture du col du fémur

For this second example (Textbox 2) we change the date, the name of the Doctor and the Location.

Textbox 2. Example of french nursing notes

**Original note** : chutes à repet trauma lombaires sans deficit plaie 2 pieds car a marchè sur debris verre ( a rv pour irm cerebrale à cl du louvre )- a resulttas bacterio aurait inf urinaire pas encore ttè (sa fille a resultats en salle d'attente) 01/01/2000 22:22 - docteur Dupond, interne retrouvé au sol dans les toilettes à 17h, vu pour la derniere fois à 10h par la femme de ménage. contexte d'infection urinaire, avec ecbu positif à e.coli, sensible à la rocéphine (ecbu dans le dossier). arrive avec 39 de température.

**Manual transcription without abbreviations:** Chutes à répétition, traumatisme lombaires sans déficit, plaie des 2 pieds, car a marché sur des débris verre (à rendez-vous pour irm cérébrale à clinique du Louvre)- A des résultats bacterio, elle aurait infection urinaire pas encore traitée (sa fille à les résultats en salle d'attente) 01/01/2000 22:22 - docteur Dupond, interne retrouvé au sol dans les toilettes à 17h, vu pour la dernière fois à 10h par la femme de ménage. Contexte d'infection urinaire, avec ecbu positif à e.coli, sensible à la rocéphine (ecbu dans le dossier). Arrive avec 39 de température.



## Multimedia Appendix 2

In the corrected data, there are 2056 non-anonymous anamneses (compared to 2066 in the original test set) and 944 anonymous anamneses (compared to 935 in the original test set), indicating that 9 anamneses were misannotated by our experts.

### Recall, precision and F1 statistics

The Table 1 presents a comparative analysis of model performance, measured by recall, precision, and F1 score, at epoch 7 on both the original and post-hoc test sets. Bold values indicate improvements in the corrected versions of the Mistral 7B, Mixtral 8x7B, and LLaMa2 7B models, highlighting the effectiveness of fine-tuning.

*Table 1: Comparative analysis of fine-tuned model performance at epoch 7 for original test set and post-hoc test set*

Model	Clinical Notes			
	Recall	Precision	Recall	F1
Mistral 7B	0.9326	0.9721	0.9625	0.9673
Mistral 7B <sup>P</sup>	0.9465	0.9732	0.9630	0.9681
LLaMa2 7B	0.6888	0.9596	0.8041	0.8750
LLaMa2 7B <sup>P</sup>	0.7932	0.9583	0.8026	0.8736
Mixtral 8x7B	0.6417	0.9852	0.7655	0.8616
Mixtral 8x7B <sup>P</sup>	0.7620	0.9819	0.7625	0.8584

<sup>P</sup>: Post-hoc test set

The corrected version of Mistral 7B shows improvement in all metrics, especially precision, which increased to 0.9588. Mixtral 8x7B and LLaMa2 7B corrected models also exhibit slight enhancements, with notable increases in precision and F1 score, demonstrating the positive impact of model corrections.

### Recall for PPI categories

The Table 2 provides a comparative analysis of the recall performance for different PPI categories (NAME, TEL, DATE, and LOC) evaluated at epoch 7 across both the original and post-hoc test sets for the Mistral 7B, Mixtral 8x7B, and LLaMa2 7B models, along with their corrected versions.

*Table 2: Comparative analysis of fine-tuned model performance at epoch 7 for original test set and post-hoc test set. Recall PII*

Model	NAME	TEL	DATE	LOC
Mistral 7B	0.9914	1.0	0.9725	0.9026
Mistral 7B <sup>P</sup>	0.9914	1.0	0.9744	0.9037
LLaMa2 7B	0.9276	0.8787	0.8627	0.5553
LLaMa2 7B <sup>P</sup>	0.9255	0.8787	0.8624	0.5557
Mixtral 8x7B	0.9148	0.909	0.7941	0.5464
Mixtral 8x7B <sup>P</sup>	0.9106	0.909	0.7937	0.5426

<sup>P</sup>: Post-hoc test set

The results do not show significant differences in recall for the various PPI categories between the original and corrected versions of the test set. The recall rates across NAME, TEL, DATE, and LOC categories remain relatively stable, indicating that the corrections made to the models have not

drastically altered their ability to correctly identify these PPI categories.



## Multimedia Appendix 3

Table 5: Comparison with previous work

Authors	Corpus (N)	Language	Precision	Recall	F1	Notes
Grouin et al. (2013) [39]	Cardiology set (62)	FR	94.8 <sup>b</sup>	89.4 <sup>b</sup>	92.1 <sup>b</sup>	Medina-CFR
	Foetopathology set (10)		89.1 <sup>b</sup>	86.5 <sup>b</sup>	87.8 <sup>b</sup>	Medina-RB
			75.4 <sup>b</sup>	58.5 <sup>b</sup>	65.9 <sup>b</sup>	Medina-CFR
			72.0 <sup>b</sup>	72.6 <sup>b</sup>	72.3 <sup>b</sup>	Medina-RB
Chazar et al. (2014) [40]	French discharge letters (508)	FR	79.6	98.1	87.9	Pattern matching. Use a list of authorized words
Catelli et al. (2020) [41]	SIRM (50)	IT	-	-	85.61	Bert-base (IT) cased
		IT	-	-	94.49	mBERT Cased
		IT	-	-	83.17	Bi-LSTM-CRF : BPEemb (IT) + Fair (IT)
		EN IT	-	-	86.19	Bi-LSTM-CRF : Multi-BPEemb + Fair multi fast
Berg et al. (2020) [42]	neurology unit clinical (-)	SW	96.07 <sup>c</sup>	92.82 <sup>c</sup>	94.4 <sup>c</sup>	token binary evaluation optimized for F1 model
Ahmed (2020) et al. [17]	i2b2 (1304)	EN	98.74	95.85	97.28	GRU
			99.01	95.12	97.08	GRU-GRU
			98.74	95.27	96.98	LSTM-GRU
	MIMIC-II (486)	EN	98.03	98.41	98.22	Self-attention
			81.82	66.23	73.21	GRU
			80.00	71.00	75.23	GRU-GRU
			85.14	68.18	75.72	LSTM-GRU
			89.20	82.90	85.90	Self-attention
			89.20	82.90	85.90	Self-attention
	MIMIC-III (891)	EN	99.94	100	99.97	GRU
			99.93	99.99	99.96	GRU-GRU
			99.94	99.99	99.96	LSTM-GRU
			99.95	98.78	99.36	Self-attention
Syed et al. (2022) [43]	i2b2 (-)	EN	94.89	95.96	93.84	Input Embeddings+Bi-LSTM+CRF
			92.99	93.50	93.25	
			93.86	93.37	94.31	without mixed domain pre-training
	CoNLL-2003 (-) internal corpus (100)		96.23	94.51	95.36	with mixed domain pre-training
Meaney et al. (2022)	2014-i2b2 (486)	EN	96.69	96.81	96.75	Roberta-Large
			96.62	96.27	96.44	Albert-XXLarge fine-tuned
			95.10	95.33	95.22	Roberta-Base fine-tuned

						95.53	95.34	95.43	Bert-Large fine-tuned
						93.87	93.85	93.86	Albert-Base fine-tuned
						93.80	94.40	94.10	Bert-Base fine-tuned
Tchouka (2022)	et al. [44]	HNFC (375)		FR.		94.6a	94.9a	94.7a	NER hybrid system
Liu Z. (2023)	et al.	2014-i2b2 (50)		EN		-	-	-	Accuracy 0.99 Explicit prompt GPT-4
						-	-	-	Accuracy 0.929 Explicit prompt ChatGPT
Liu L. (2023)	et al. [37]	2014-i2b2 (-)		EN		98.92 <sup>a,c</sup>	97.66 <sup>a,c</sup>	98.29 <sup>a,c</sup>	BiLSTM-CRF (RoBERTA).
		CardiacAI (40)				95.19 <sup>a,c</sup>	93.47 <sup>a,c</sup>	94.32 <sup>a,c</sup>	BiLSTM-CRF (RoBERTA).
		CardiacAI (60)				94.87 <sup>a,c</sup>	95.26 <sup>a,c</sup>	95.07 <sup>a,c</sup>	BiLSTM-CRF (RoBERTA).
Liu J. (2023)	et al. [25]	OpenDeid (700)		EN		95.58 <sup>a,b</sup>	92.42 <sup>a,b</sup>	93.97 <sup>a,b</sup>	fine-tuned BioBERT
						95.82 <sup>a,b</sup>	91.98 <sup>a,b</sup>	93.86 <sup>a,b</sup>	fine-tuned Clinical BioBERT
						95.87 <sup>a,b</sup>	92.22 <sup>a,b</sup>	94.01 <sup>a,b</sup>	fine-tuned Discharge Summary BioBERT
						97.84 <sup>a,b</sup>	95.92 <sup>a,b</sup>	96.87 <sup>a,b</sup>	fine-tuned Discharge Summary BioBERT + cascading rules
						95.59 <sup>a,b</sup>	89.35 <sup>a,b</sup>	92.37 <sup>a</sup>	LSTM GloVe+PMC+word2vec-OpenDeID corpus word embeddings.
Our	Model	French notes (3000)	nursing	FR		97.32	96.30	96.73	fine-tuned Mistral 7B model with LoRA

## Multimedia Appendix 4

Table 1 : Comparison of Recall for PII with previous work

Authors	Method	L.	NAME		DATE		LOC		TEL		Info
			R (%)	N	R (%)	N	R (%)	N	R (%)	N	
Grouin et al [39]	MEDINA-RB	FR	90.7 – 92.7	314 <sup>s</sup>	87.1	238 <sup>s</sup>	12.5-100	81 <sup>s</sup>	100	8	NAME : Last Name (205) and First Name (109) LOC : HOSPITAL (43), TOWN(22), ZIP(8), ADDRESS(8)
	MEDINA-CRF	FR	88.3-89,0		94.6		12.5-75.0		75.0		
Tchouka et al [44]	FlauBERT-MEDINA	EN	99.8	-	86.7	-	57.3-95.1	-	97.9	-	LOC : ORGANIZATION + LOCATION
L Liu et al [37]	BiLSTM-CRF (RoBERTA)	EN	95.83	528	96.92	65	50.0	6	85.71	35	Dataset Cardiac AI (N = 600)
Our work	Mistral-7B qLoRA	+ FR	99.14	555	97.25	607	90.26	715	100	100	

S : sum of entities

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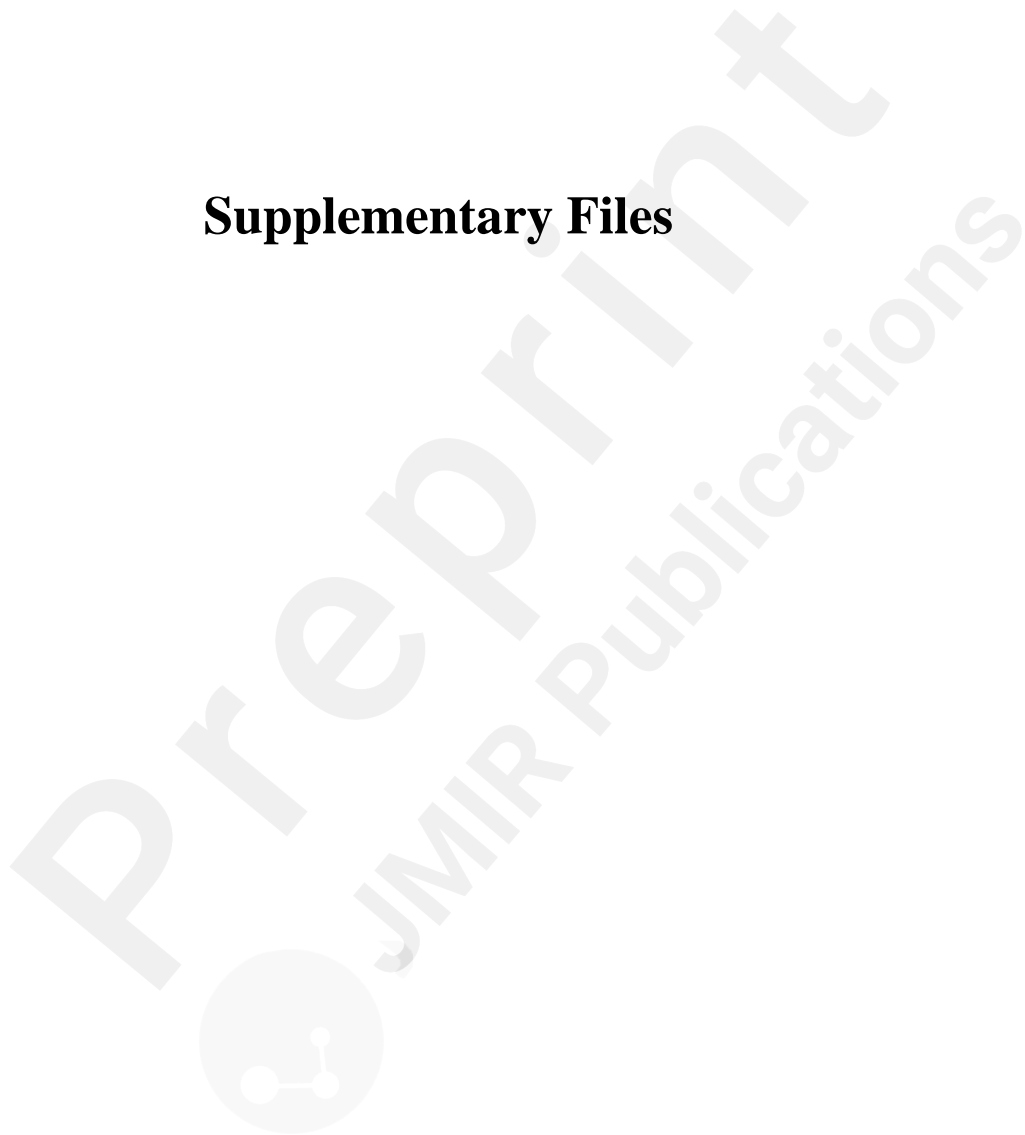
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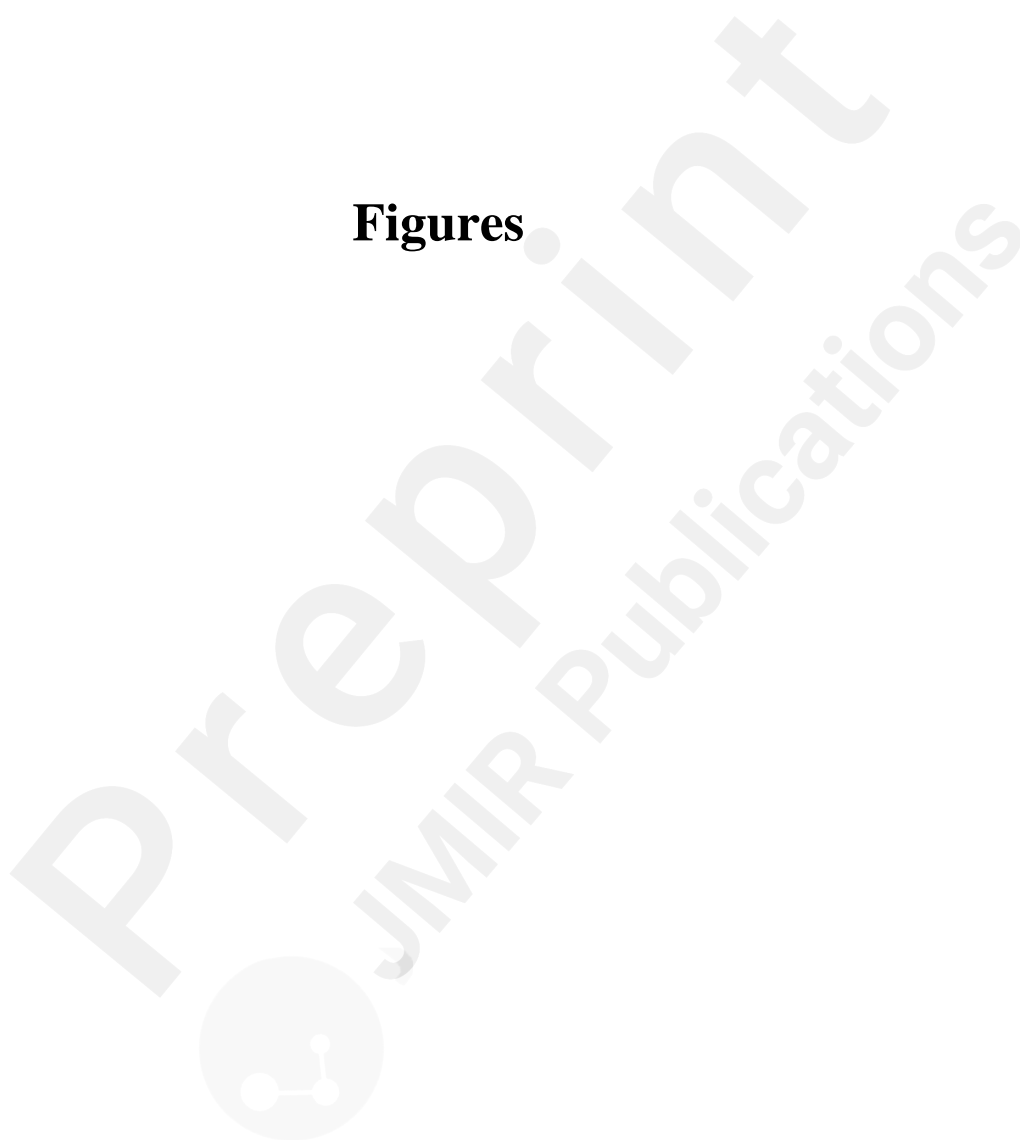
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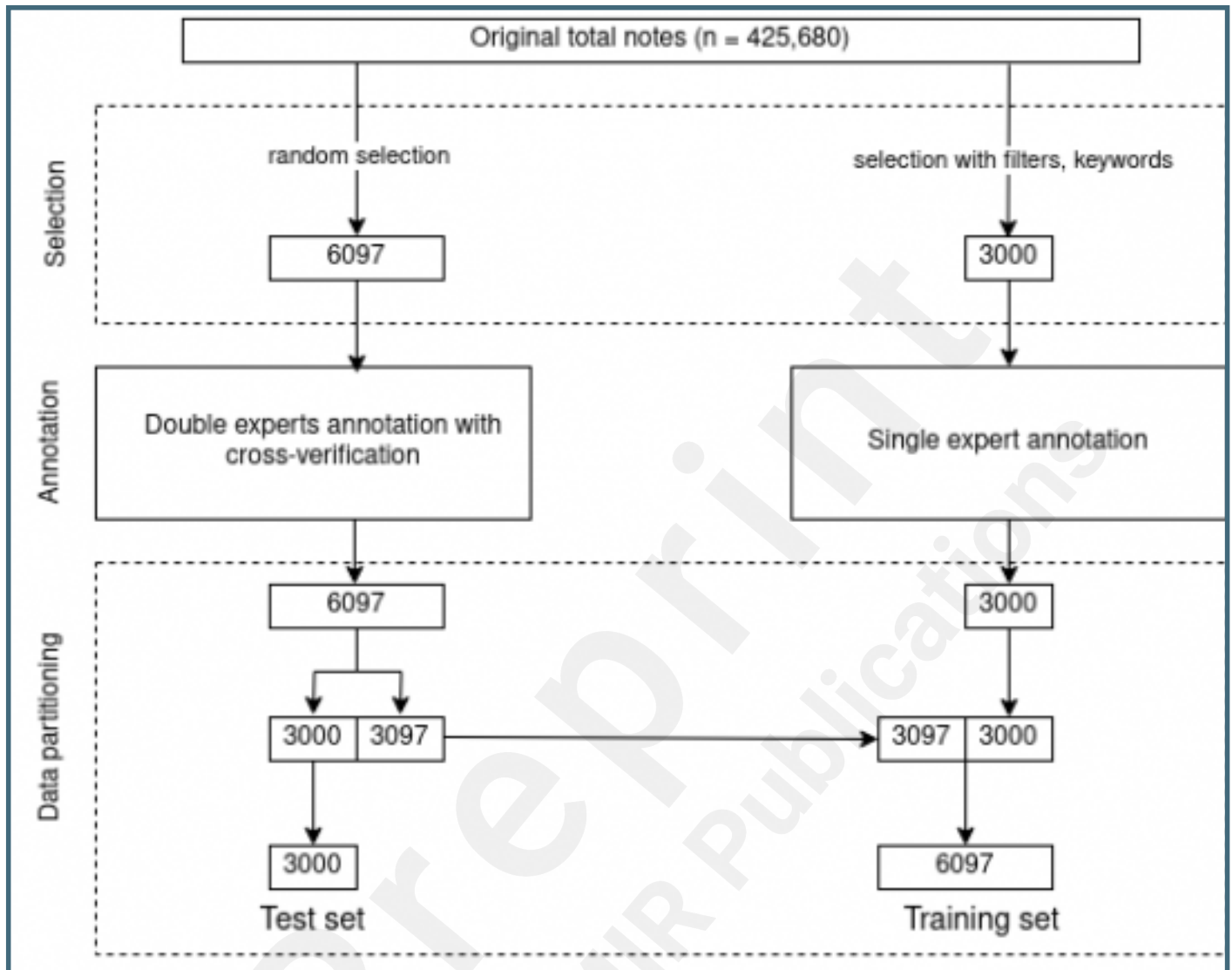
## Supplementary Files



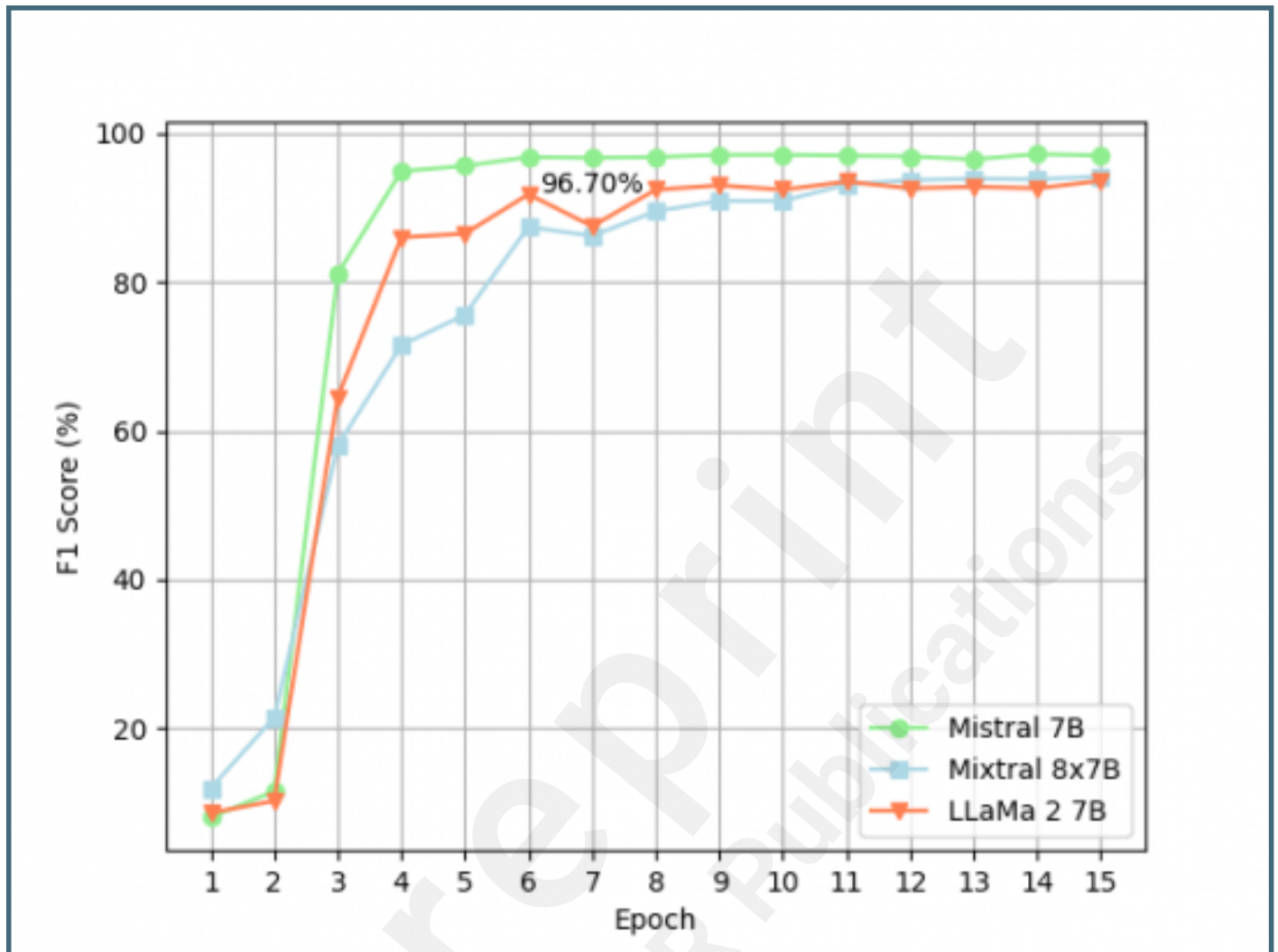
## Figures



Data Preparation: Annotation and Splitting into Training and Test Sets.

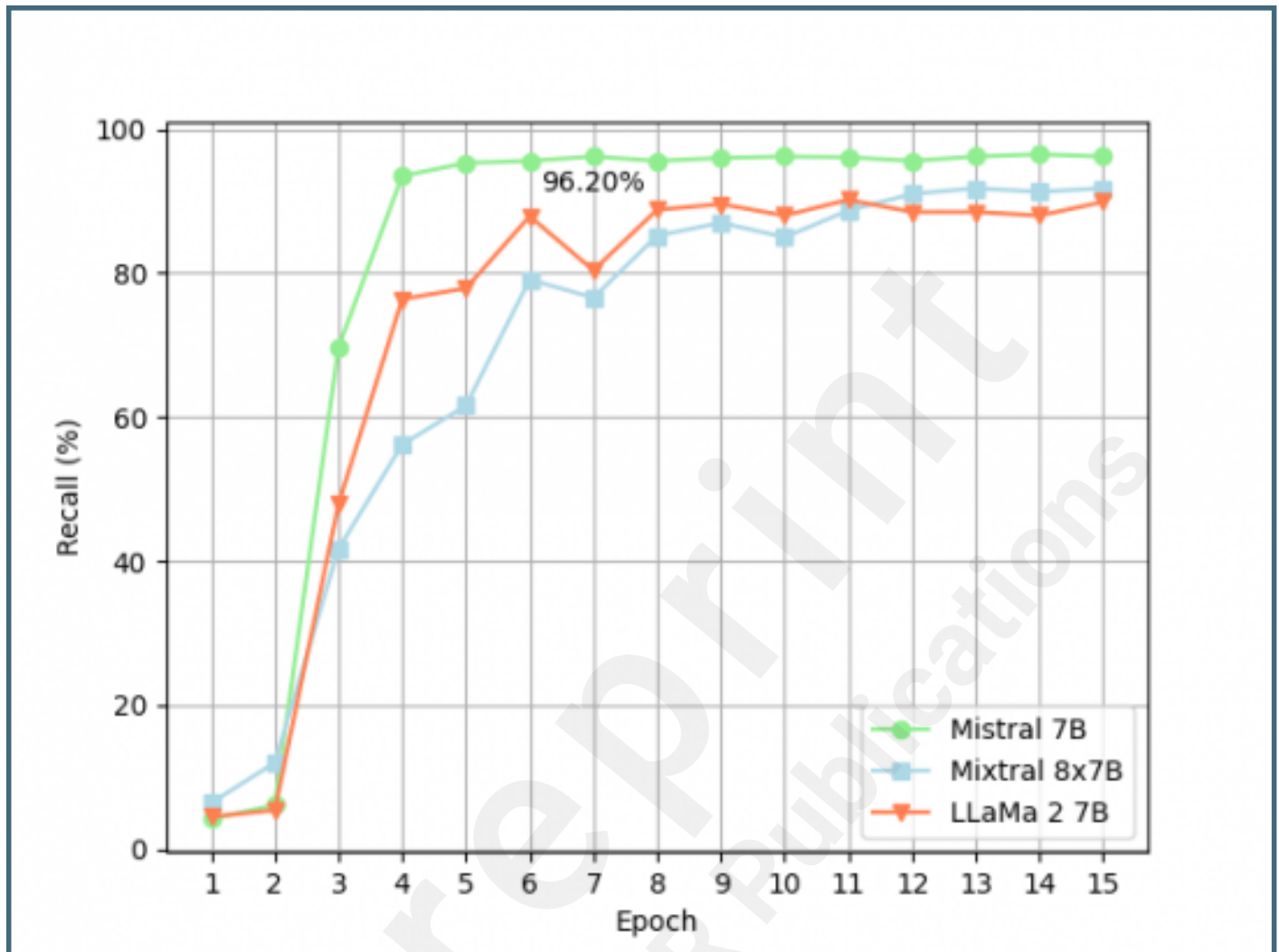


Plot of F1-score by epoch : PII as statistical unit.

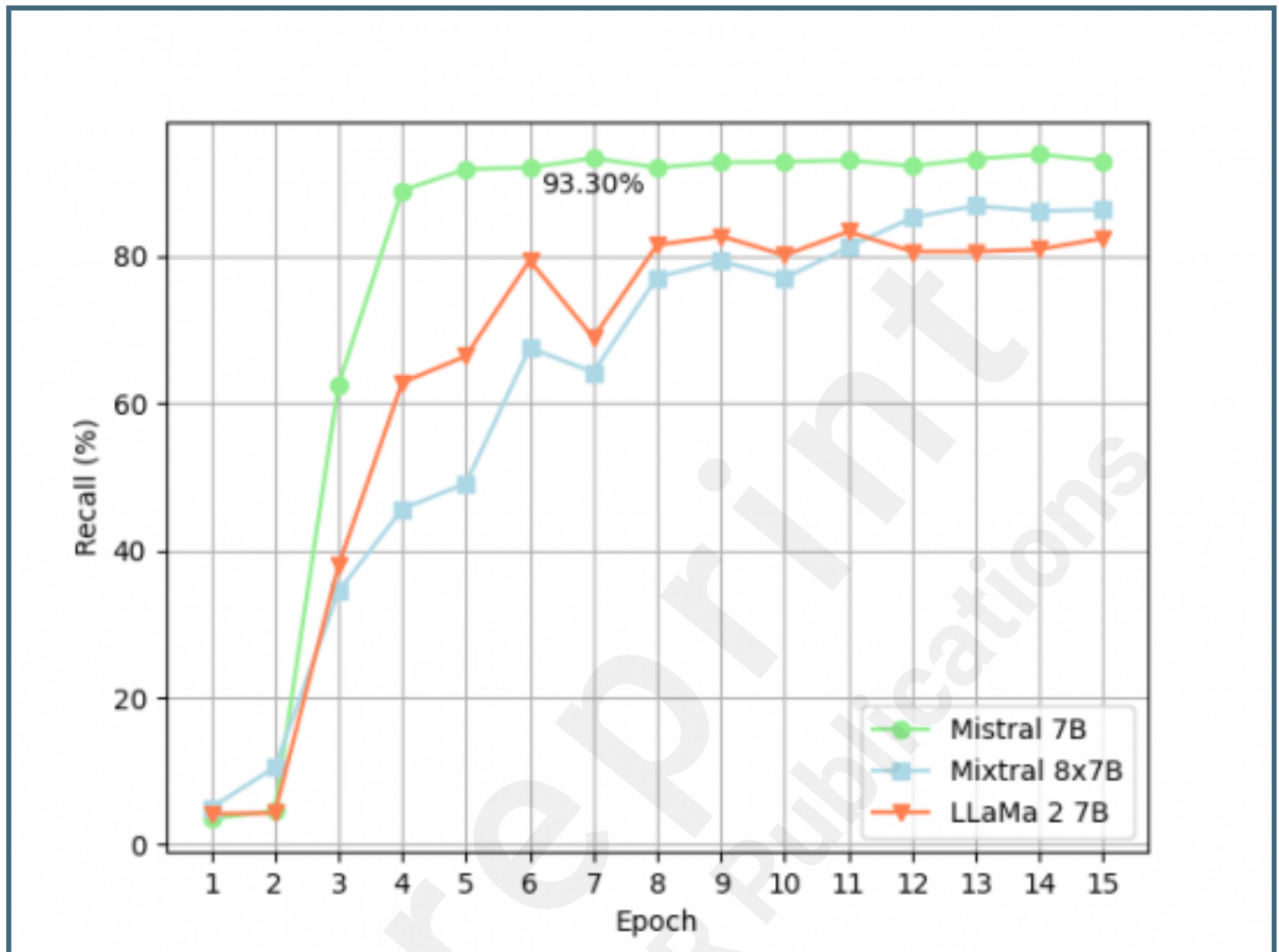




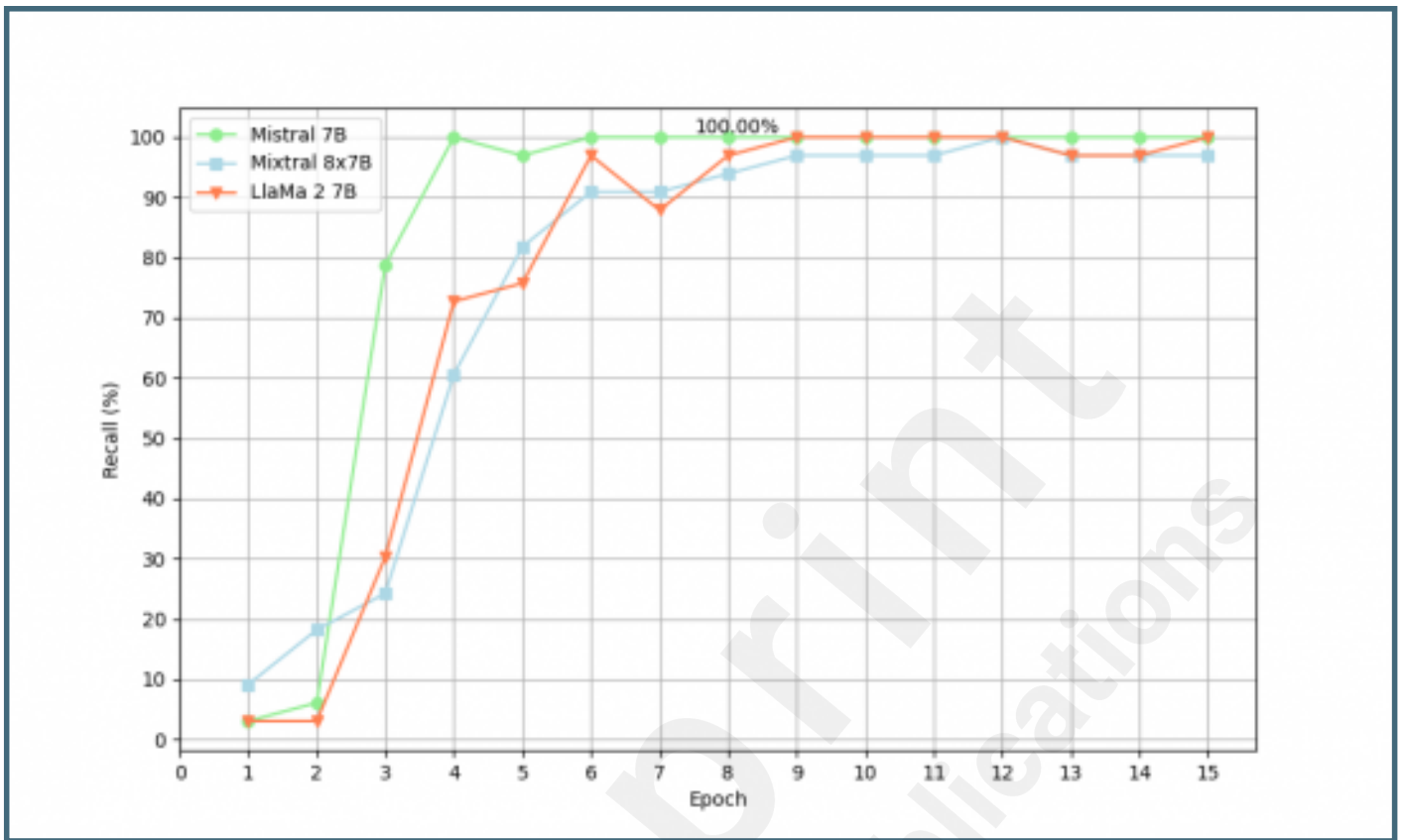
Plot of Recall by epoch : PII as statistical unit.



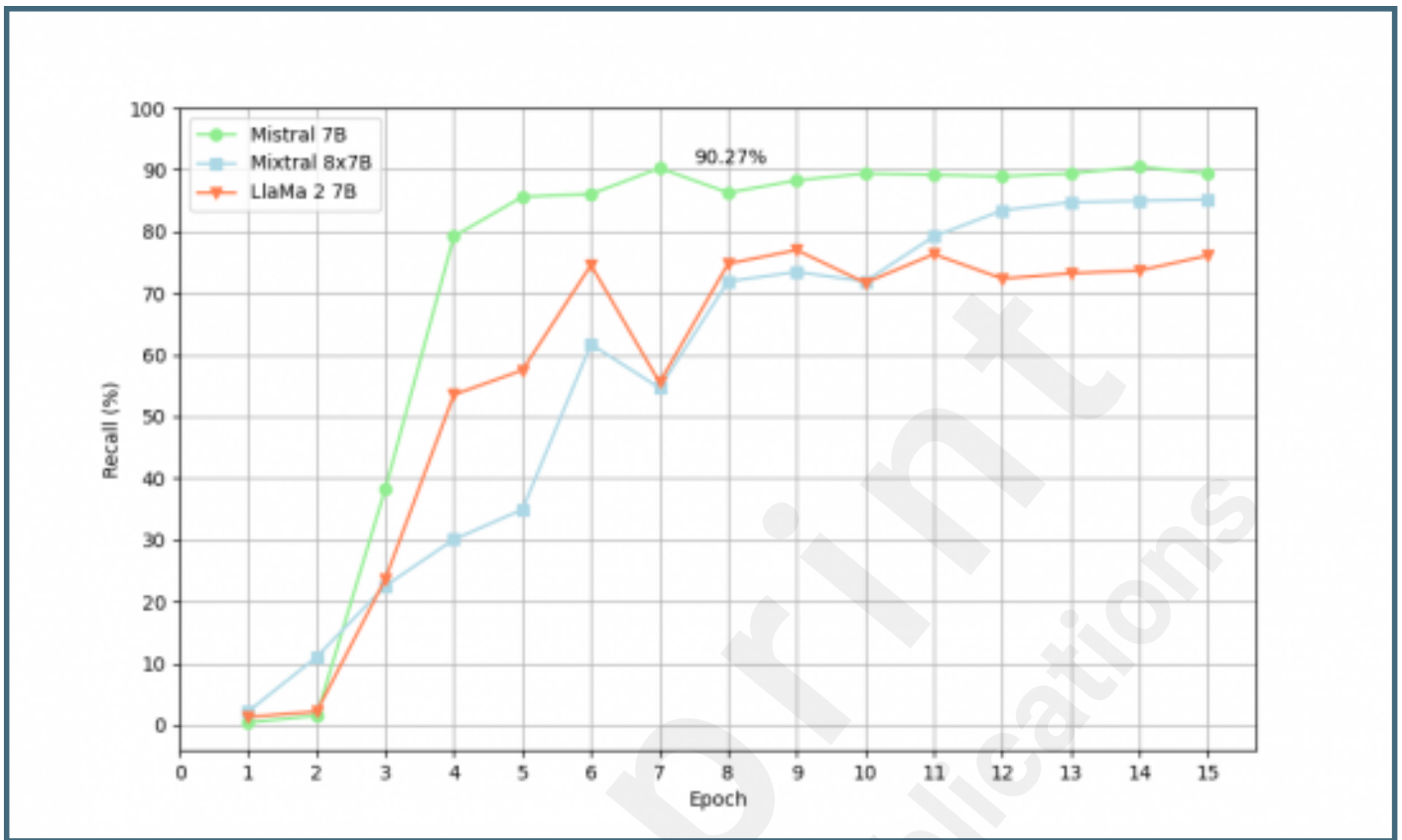
Plot of Recall by epoch : clinical note as statistical unit.



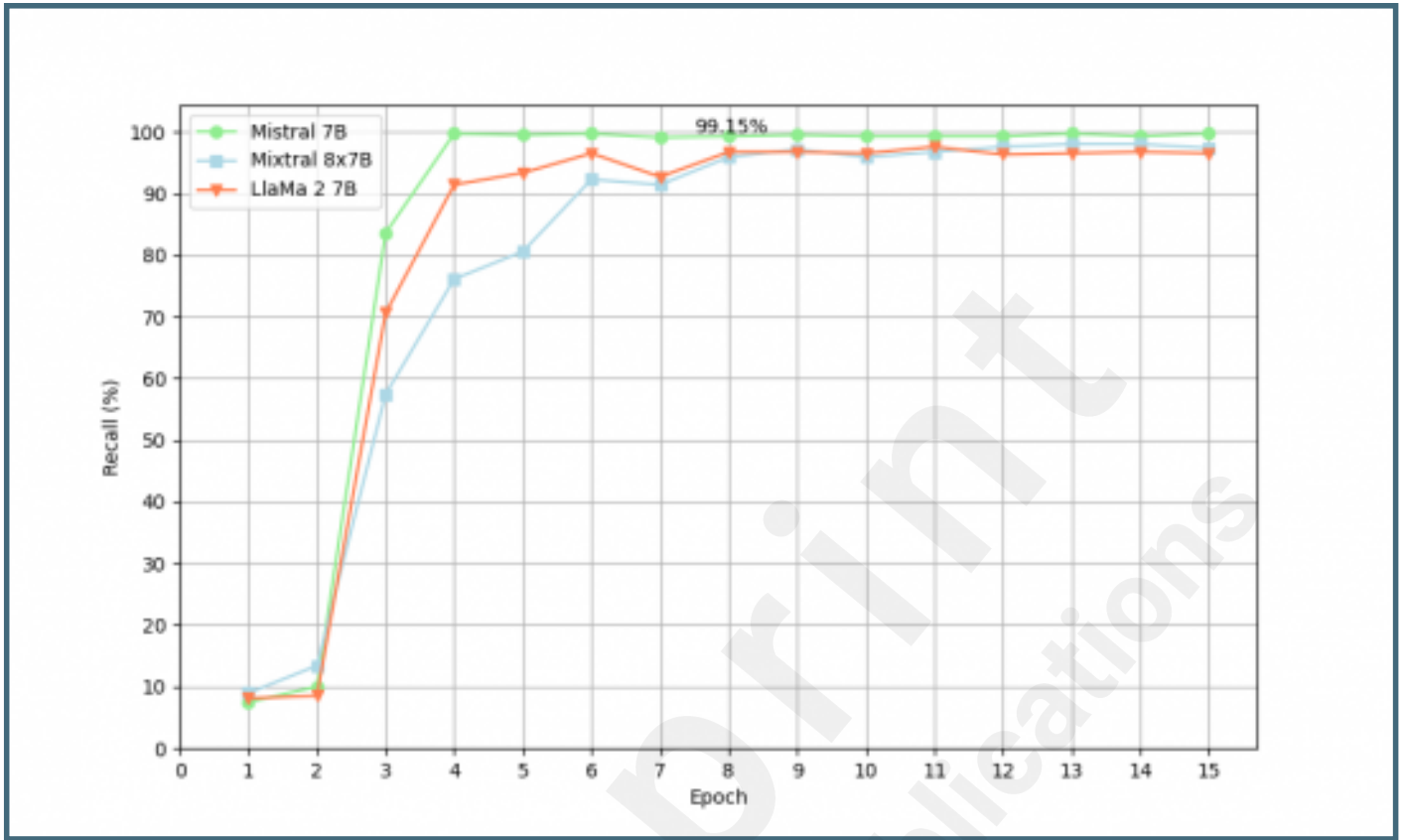
Plot of Recall by epoch for PII : TEL.



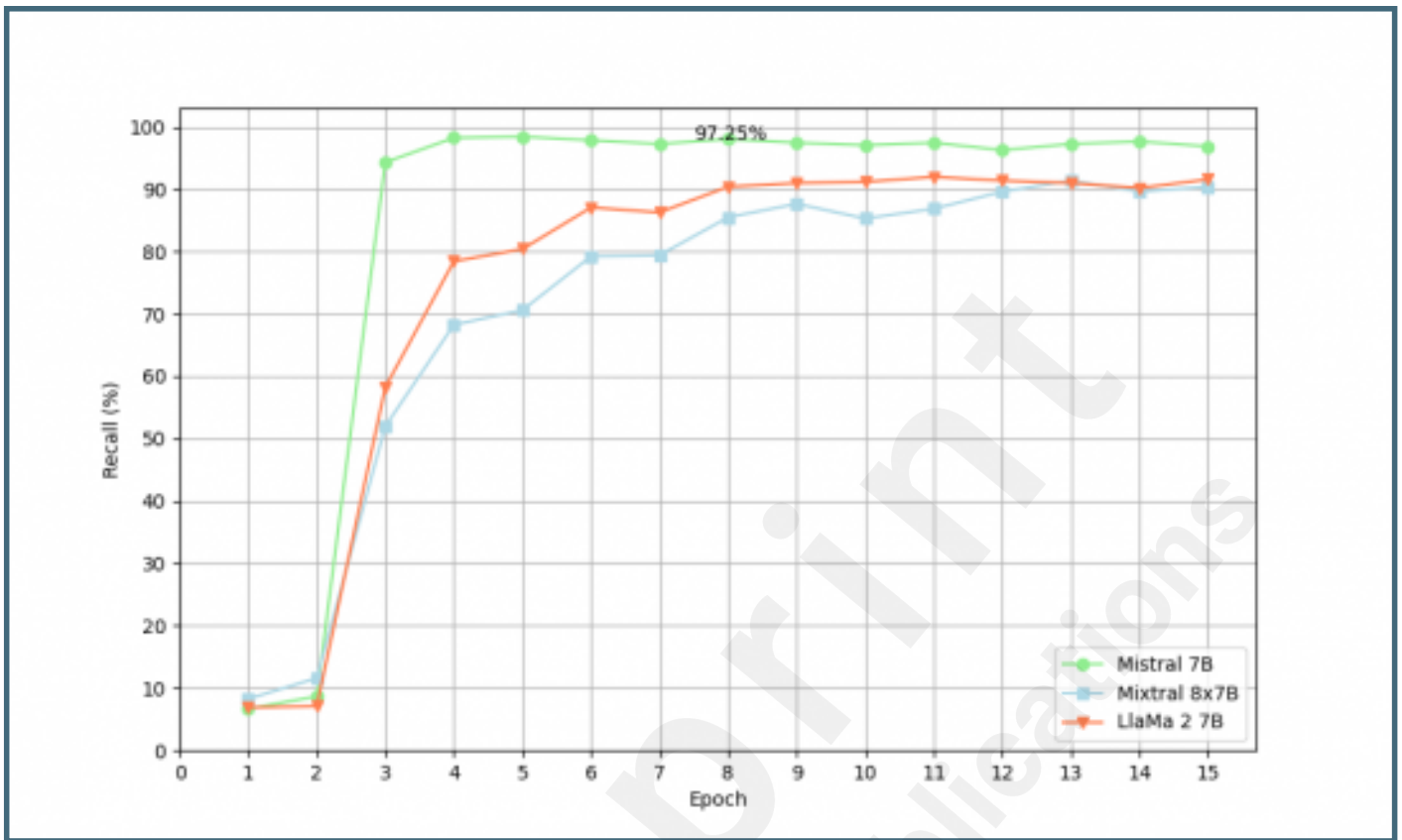
Plot of Recall by epoch for PII : LOC.



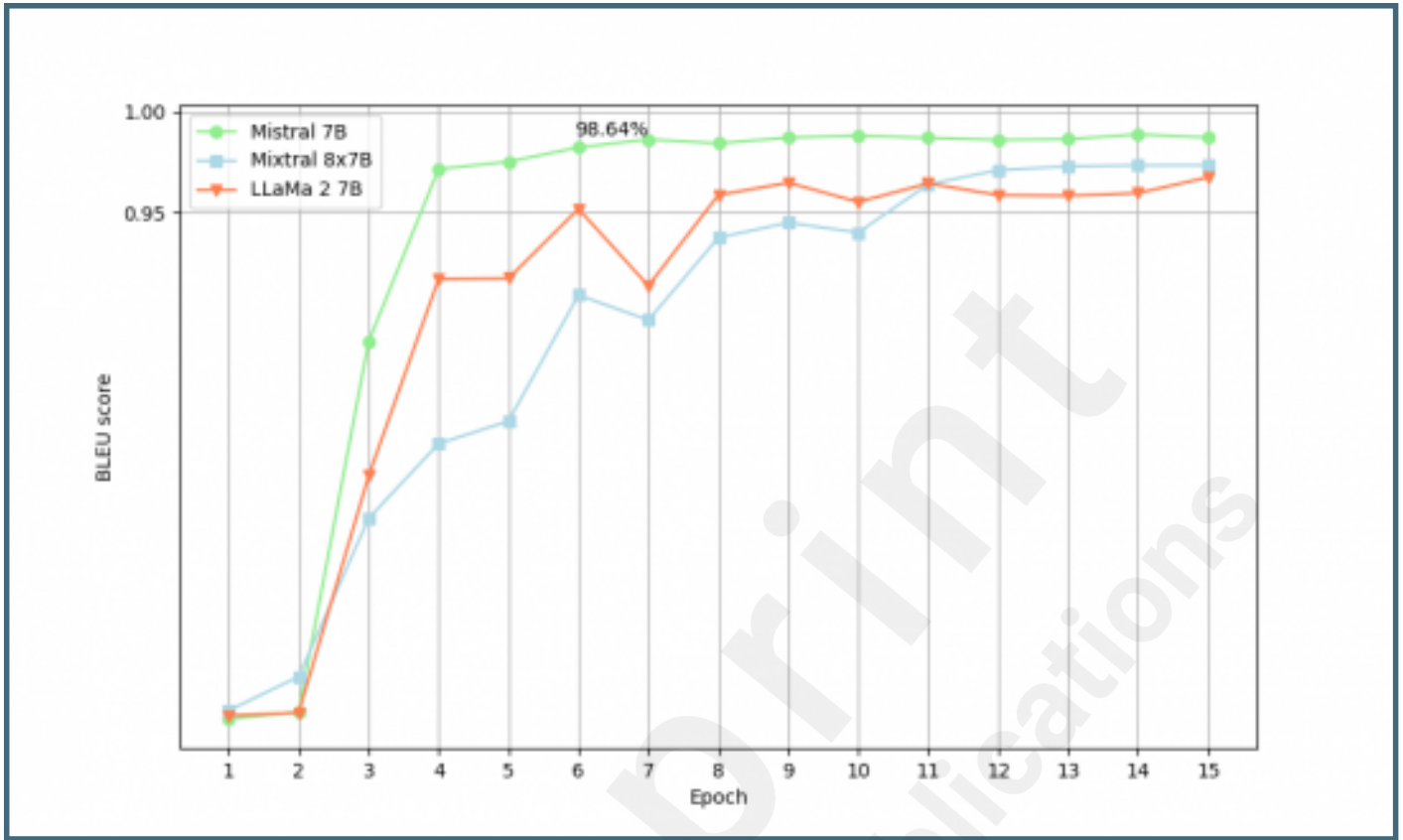
Plot of Recall by epoch for PII : NAME.



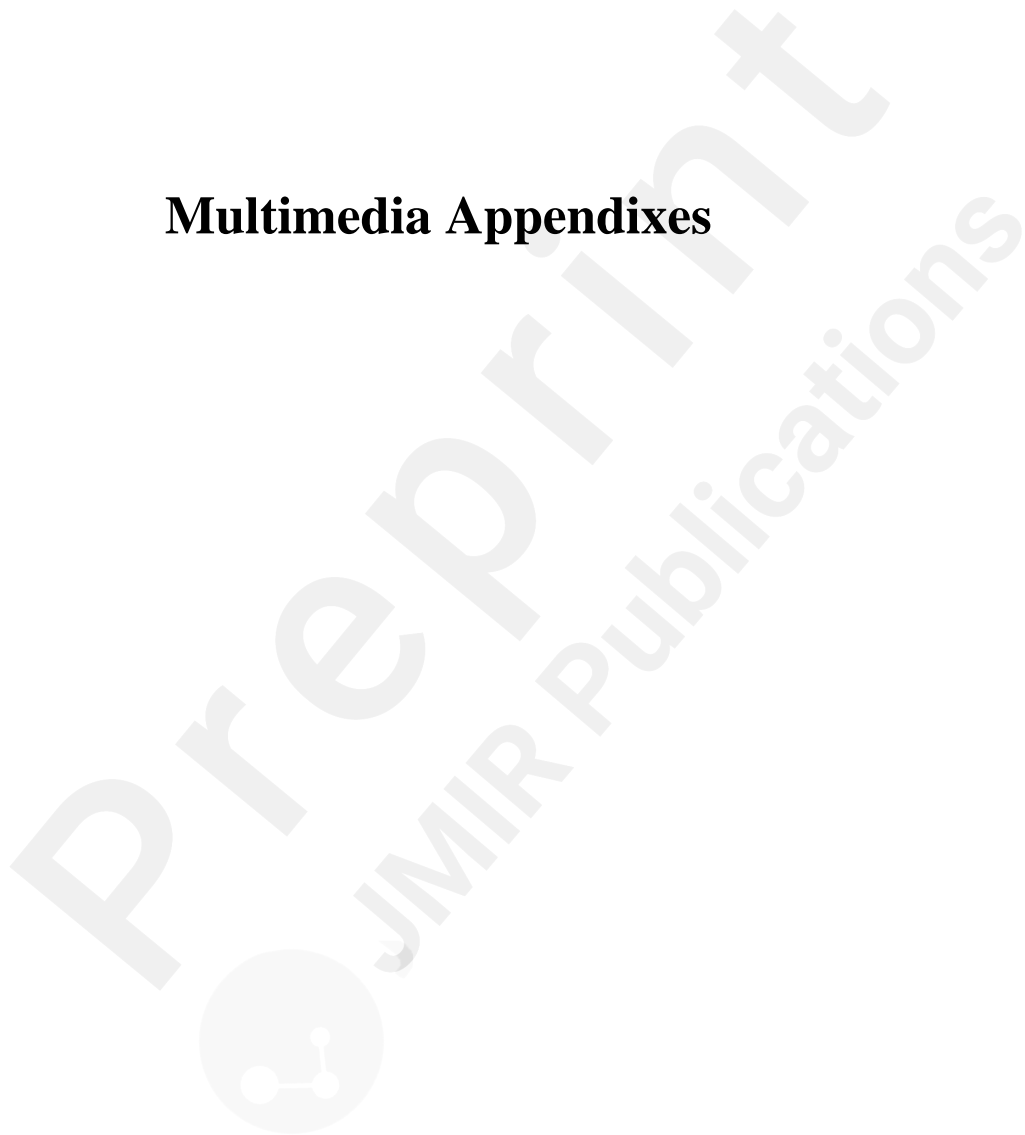
Plot of Recall by epoch for PII : DATE.



Plot of BLEU score by epoch : clinical note as statistical unit.



## Multimedia Appendixes





Examples of french nursing notes.

URL: <http://asset.jmir.pub/assets/1225fd668d368cc83054469f5a46c510.docx>

Analysis of Performance Evaluation on corrected Test set.

URL: <http://asset.jmir.pub/assets/a4ec12704de6f18e3bddbe4d96db13d0.docx>

Comparative Table of Statistical Results from Previous Studies.

URL: <http://asset.jmir.pub/assets/2e3d42df59d4331e6e4757123e85b2f1.docx>

Comparative Table of Recall Across PII Categories from Previous Studies.

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