



# Deep Learning–Based Hospital Admission Prediction from Spanish Psychiatric Electronic Health Records

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# Table of Contents

**1** Introduction

**3** Dataset Description

**5** Models & Dataset Split

**7** Results

**2** State of the Art

**4** Methodological pipeline

**6** Solution Overview & Optimization

**8** Conclusions & Future Work

# About us:



## UNIVERSITY OF LEÓN

A public university with a strong commitment to teaching, research and innovation.

- High-quality education and research
- Excellence in Engineering and Data Science
- Interdisciplinary collaboration
- International outlook and impact

## ALBA LAB

We develop and apply **Artificial Intelligence** to solve real healthcare challenges and improve people's lives.

**CLINICAL NLP**

Extracting knowledge from clinical texts and EHRs.

**PREDICTIVE ANALYTICS**

Building models to predict outcomes and support decisions.

**KNOWLEDGE GRAPHS**

Structuring and linking biomedical knowledge.

**CLINICAL DECISION SUPPORT**

Developing intelligent tools to support healthcare professionals.

**OUR MISSION**

Transforming clinical data into actionable medical knowledge through AI, to enable better decisions and better care.



**100+** PUBLICATIONS

**50+** CONFERENCES

**NATIONAL & INTERNATIONAL COLLABORATIONS**

**COMPETITIVE RESEARCH PROJECTS**

**REAL-WORLD IMPACT**

# About us: ALBA members



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# Introduction



## 1 in 7 people

Living with a mental disorder worldwide

≈ 1.1 billion people (WHO 2021)



## High clinical risk

Severe psychiatric disorders are associated with:

- ☹️ Increased suicide risk
- ❤️ Physical comorbidities
- ⬇️ 10–20 years reduced life expectancy



## Limited access to care

Long waiting times and shortage of specialists can delay treatment and increase hospitalization risk.



## Documentation Complexity

Spanish psychiatric notes present additional challenges (**figurative language**, **abbreviations**, **inconsistency**).



## Narrative Language

Extracting structured data from Spanish psychiatric notes presents **unique linguistic and domain-specific difficulties**.



## Main Goal

Early and objective identification of **high-risk patients** can **optimize healthcare resources** and **improve the decision-making process**.

# State of the art

How can we automatically identify which patients need to be hospitalized based on their clinical notes?



NLP in medicine has advanced in **automatic document classification**, **risk prediction**, and analysis of Electronic Health Records (EHRs).



**Deep Learning** models and **Transformer-based architectures** (BERT, EHR-BERT, BiLSTM) outperform traditional methods in clinical prediction and medical text analysis.



In psychiatry, AI has been applied to **text classification**, clinical entity **extraction and normalization**, and prediction of mental health crises using multimodal approaches.



Mental health-specific models, such as **Guardian-BERT**, can detect subtle **linguistic signals** associated with clinical risk (e.g., suicidal ideation).



Research on **Spanish psychiatric texts** is still limited, and no studies were found on **hospitalization prediction** using unstructured clinical notes with deep learning models.



This work addresses this gap by **evaluating advanced NLP models** to automatically classify psychiatric clinical notes based on the need for patient hospitalization.

# Dataset information

## DATA EXAMPLE

MC 1 | APC 2 | APF 3 | DX 4 | TTF 5 | TTA 6

Mujer de 25 años diagnosticada de **esquizofrenia simple** con varios ingresos en Unidad de Cuidados Especiales (último en 2013). Seguimiento en Centro de Salud Médico de José Aguado en tratamiento con **leponex 100(0-0-1/2)**, **abilify 10 miligramos (1-0-0)** y **escitalopran 1 (0-1/2-0)**. Acude a urgencias refiriendo **oir voces** de 5 días de evolución, en forma de insultos y amenazas. ESTADO PSICOLÓGICO DEL PACIENTE: consciente, orientada. escasamente colaboradora. Inhibición psicomotriz. Mal contacto visual. Discurso pobre con aumento numero latencia de respuesta. Alucinaciones auditivas. Ideación delirante autorreferencial. No ansiedad- No ideas de muerte. No autoagresividad/heteroagresividad. IMPRESIÓN DIAGNÓSTICA: **ESQUIZOFRENIA SIMPLE PLANIFICACIÓN: Abilify 10 miligramos: 1 comprimido por la mañana y otro medio en la comida Heipram 10 miligramos: 1 comprimido a la hora de la comida. Resto tratamiento igual Consulta preferente en Centro de Salud Médico.** En caso de no mejoría volver a urgencias.



### Data source:

Complejo Asistencial Universitario de León (CAULE).

### Original state

500 clinical notes from psychiatric emergencies in **free text without structure** and completely anonymized data.

### Preprocessing stage

Cleaning, spelling correction and **manual NER labeling** to ensure the quality of the set.

### Final result

**409 valid records** after the debugging process, ready for model training.

# NER Entities Identified in the Data

Clinical notes were annotated with six categories of key clinical entities to structure patient information.



## Chief Complaint (MC):

Main reason for the psychiatric consultation.



## Clinical History (APC):

Relevant past medical or psychiatric conditions (diagnoses, surgeries...).



## Pharmacological History (APF):

History of previous treatments with medications and other substances.



## Diagnosis (DX) :

Psychiatric disorder(s) identified by the clinician according to guidelines.



## Pharmacological Treatment (TTF):

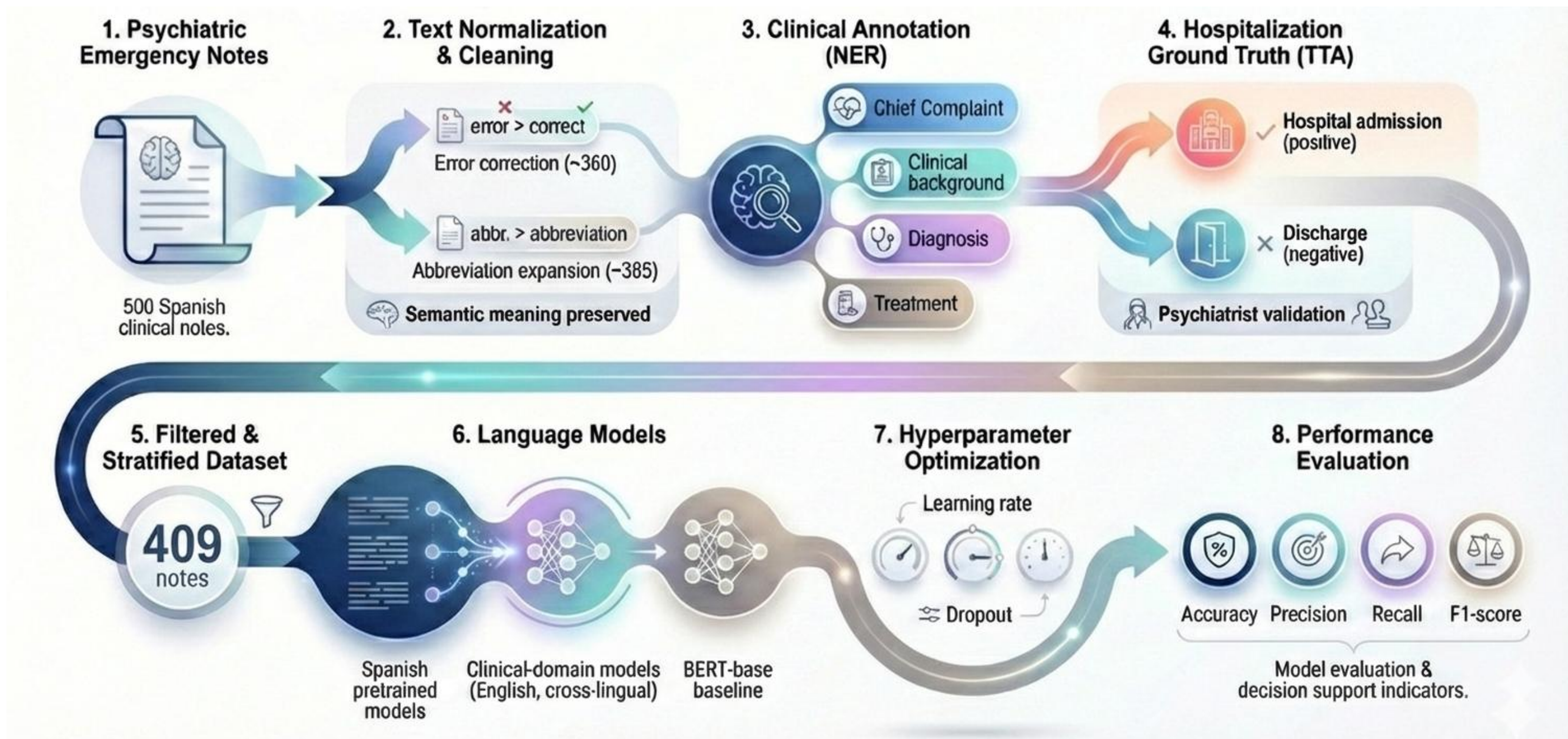
Medications currently prescribed for psychiatric treatment.



## Action-Based Treatment (TTA):

Non-pharmacological interventions, such as hospitalization or discharge.

# Methodological pipeline



# Models & Dataset split

## BERT Base

BERT base model pretrained with a general English corpora. Available **cased** and **uncased** versions

## BERT Beto

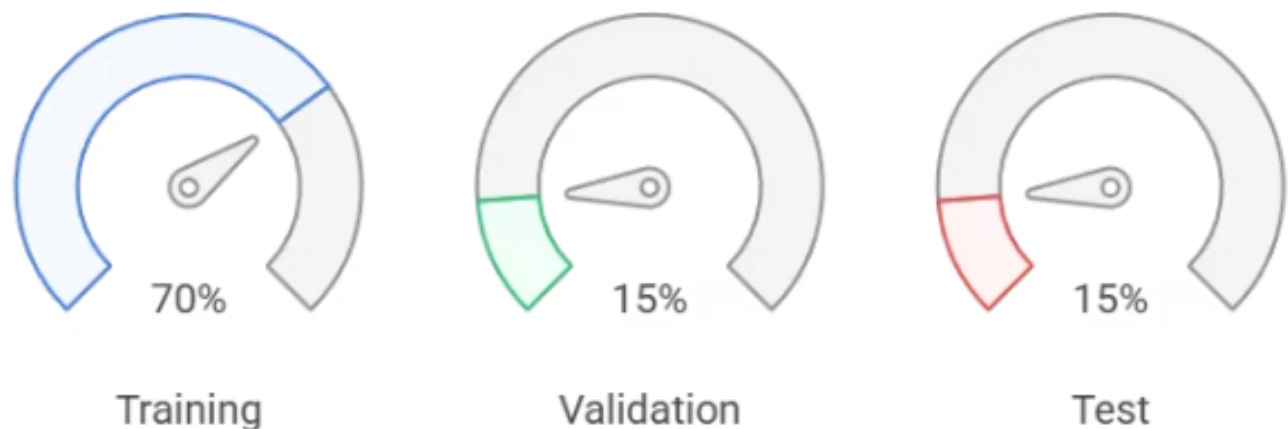
BERT base model pretrained with a general Spanish corpora. **cased** and **uncased** variants

## Clinical BERT

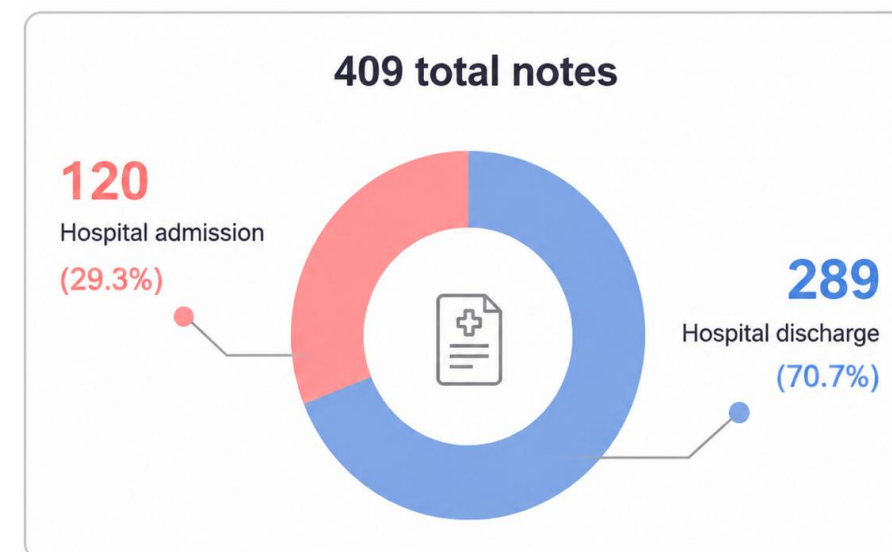
Domain specific BERT pretrained with EHRs and without **cased** or **uncased** versions.

## Dataset distribution

**Stratified split** to maintain the proportion of samples from each class among the fine-tuning process.



## Data imbalance



<span style="color: red;">●</span> Hospital admission	120 notes	29.3%
<span style="color: blue;">●</span> Hospital discharge	289 notes	70.7%

# Solution Overview & Optimization

## Main Approach

Classification using the full text of the clinical note as written, without additional structural processing

### Baseline





Using the models with their default configuration, such as learning rate, train epochs for the fine-tuning.

### Grid Search

Testing different configurations for each model in order to obtain the best results in the fine-tuning process.

## Hyperparameter Search Space

Values explored during results optimization.

Hyperparameter	Values Explored
 Batch size (per device)	{8, 16}
 Learning rate	{ $2e^{-5}$ , $1e^{-5}$ , $3e^{-5}$ }
 Number of epochs	{3, 4}
 Weight decay	{0.0, 0.01}

# Results overview



## Model performance comparison

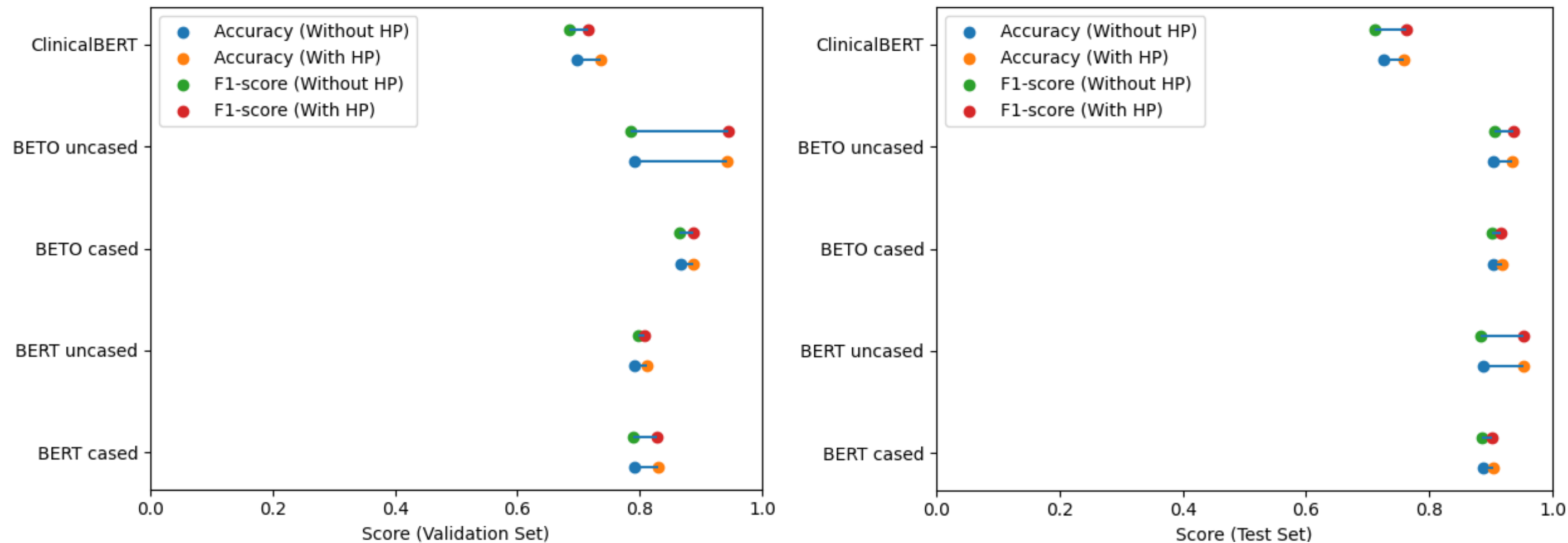
Comparison of the models using two approaches: default configuration and optimized configuration (With Hyperparameters).

Metrics reported on validation and test sets:

- Accuracy: proportion of correct predictions.
- F1-score: harmonic mean between precision and recall.

Model	Method	Validation		Test	
		Accuracy (higher is better)	F1-score (higher is better)	Accuracy (higher is better)	F1-score (higher is better)
Clinical BERT	Default configuration	69.8%	68.4%	72.6%	71.1%
	With Hyperparameters	<b>73.6%</b>	<b>71.5%</b>	<b>75.8%</b>	<b>76.3%</b>
BETO (uncased)	Default configuration	79.2%	78.6%	90.3%	90.5%
	With Hyperparameters	<b>94.3%</b>	<b>94.4%</b>	<b>93.5%</b>	<b>93.6%</b>
BETO (cased)	Default configuration	86.8%	86.4%	90.3%	90.1%
	With Hyperparameters	<b>88.7%</b>	<b>88.7%</b>	<b>95.2%</b>	<b>95.2%</b>
BERT (uncased)	Default configuration	79.2%	79.7%	88.7%	88.4%
	With Hyperparameters	<b>83.0%</b>	<b>82.5%</b>	<b>93.5%</b>	<b>93.5%</b>
BERT (cased)	Default configuration	79.2%	79.0%	88.7%	88.6%
	With Hyperparameters	<b>83.0%</b>	<b>82.9%</b>	<b>90.3%</b>	<b>90.1%</b>

# Results



□ The graph on the left compares the performance of the validation set, while the graph on the right compares the performance of the test set.

# Conclusions & Future Work

## Key findings



### 1. Hyperparameter optimization consistently improves performance

Particularly in BETO uncased, with large gains in validation (Accuracy: 0.792 → 0.943; F1-score: 0.786 → 0.944).



### 2. BETO cased with optimization achieves the best test performance

It reaches the highest results on the independent test set (Accuracy: 0.952; F1-score: 0.952), showing strong generalization.



### 3. Language alignment is crucial

Spanish-pretrained models (BETO, BERT) outperform ClinicalBERT, indicating that linguistic alignment has more impact than domain pretraining alone.



### 4. Transformer models are effective

After tuning, BETO uncased, BERT uncased and BETO cased surpass 0.93 in both Accuracy and F1-score on the test set.



## Limitations

- **Relatively small dataset:** Although carefully curated, the dataset size (409 EHRs) may limit model capacity.
- **Single-center data:** All notes come from a single institution, which may restrict generalizability.
- **Free-text and binary classification only:** The study does not include structured variables or multi-class scenarios.



## Future work

1



### Expand to multi-center datasets

Evaluate models across different institutions to assess cross-institutional robustness and generalizability.

2



### Explore hybrid architectures

Combine structured clinical variables with unstructured text to leverage complementary information.

3



### Evaluate ensemble strategies

Investigate ensemble and stacking approaches to enhance stability and predictive performance.

4



### Extend to more complex scenarios

Study multi-class predictions (e.g., length of stay, discharge destination) and early risk stratification models.



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