Health Condition Prediction Using Few-Shot Learning on Reddit Data

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Abstract—This paper investigates Few-Shot Learning for predicting health conditions from symptom descriptions in the healthcare domain, using a dataset of Reddit posts. We compare a Few-Shot Learning model (SetFit with distilbert-base-uncased) against a baseline TF-IDF + Logistic Regression model for text classification. We hypothesize that Few-Shot Learning outperforms the baseline in accuracy and F1-score due to its ability to generalize from limited labeled data. A Streamlit-based interface enables real-time symptom prediction with basic explainability via TF-IDF feature weights. Experimental results show SetFit achieves a 7% higher F1-score, demonstrating the potential of Few-Shot Learning in low-resource healthcare applications.

I. Introduction

Natural Language Processing (NLP) has revolutionized healthcare by enabling the analysis of unstructured text, such as patient-reported symptoms, to predict medical conditions. Social media platforms like Reddit offer a wealth of user-generated health-related data. Still, their informal and noisy nature poses challenges for traditional NLP models, which often require large, labelled datasets. Few-Shot Learning, a recent advancement in NLP, addresses this limitation by achieving robust performance with minimal labelled data, making it ideal for domains like healthcare where annotated data is scarce.

This project aims to evaluate whether Few-Shot Learning, implemented via the SetFit model, outperforms a traditional TF-IDF + Logistic Regression baseline for predicting health conditions from Reddit symptom descriptions. Our objectives are threefold: (1) develop a functional text classification system, (2) compare model performance using standard metrics, and (3) provide an accessible interface for real-time predictions. We hypothesize that SetFit's ability to leverage sentence embeddings and contrastive learning will yield higher accuracy and F1-score compared to the baseline. A Streamlit-based interface enhances usability, allowing non-experts to input symptoms and receive predictions with confidence scores and basic explainability.

II. Related Work

Recent advances in NLP have focused on Few-Shot Learning to tackle data scarcity. The SetFit model combines sentence transformers with contrastive learning, achieving high performance in low-resource settings by fine-tuning on small datasets. In healthcare, NLP has been applied to tasks such as clinical text classification and symptom extraction from social media. For instance, BioBERT has been used for biomedical text mining, but it requires substantial labelled data. Reddit data has been explored for health-related tasks, such as detecting adverse drug events, but its informal language introduces noise that challenges traditional models.

Unlike prior work, our project applies Few-Shot Learning to Reddit data for health condition prediction, focusing on a practical, user-friendly system. We also incorporate explainability by analyzing TF-IDF feature contributions, addressing the need for interpretable healthcare NLP solutions.

IV. Methodology

Dataset

We utilize a custom dataset of Reddit posts (reddit_posts_raw_data.csv) consisting of 180,000 samples, comprising user-reported symptoms and corresponding health condition labels (e.g., "flu", "migraine"). The dataset is pre-processed to remove URLs, special characters, and convert text to lowercase, with texts shorter than 10 characters filtered out. To ensure balanced classes and reduce computational load, we sample 70 examples per class, resulting in [700 total samples for 10 classes] texts.

Models

Choice of Few-Shot Learning: This project employs Few-Shot Learning, specifically the SetFit model, as the primary NLP technique, selected from recent advancements including Retrieval-Augmented Generation (RAG), Small Language Models (SLMs), Prompt Engineering, Multi-Modal NLP, MCPs, Explainable AI (XAI) in NLP, Transfer Learning with Domain Adaptation, and Ethical NLP. Few-Shot Learning was chosen due to its ability to achieve high performance with minimal labeled data, which aligns with the constraints of our Reddit dataset (700 samples). The dataset's small size and noisy, informal nature (e.g., colloquial symptom descriptions) make techniques like RAG or Multi-Modal NLP less suitable, as they require large-scale knowledge bases or multi-modal data (e.g., images), respectively, which are unavailable here. SLMs and Prompt Engineering demand extensive tuning or carefully crafted prompts, which are impractical for our limited dataset and multi-class classification task. Transfer Learning with Domain Adaptation requires domain-specific pretraining, which is resource-intensive, while MCPs and Ethical NLP focus on model compression or fairness, not directly addressing our goal of accurate prediction with scarce data. XAI in NLP, while valuable for interpretability, is secondary to our primary objective of performance comparison. Few-Shot Learning, via SetFit's contrastive learning and sentence embeddings, effectively generalizes from few examples, making it ideal for healthcare applications where labeled data is often limited.

Baseline Model: The baseline employs TF-IDF vectorization (TfidfVectorizer from scikit-learn, max features=1000, stop words removed) to transform text into numerical features. Logistic Regression (scikit-learn, C=1.0, max iterations=500) is used for classification.

Few-Shot Learning Model: The Few-Shot Learning model uses SetFit with distilbert-base-uncased, fine-tuned via contrastive learning (20 iterations, 5 epochs, batch size=8, learning rate=2e-5). SetFit generates sentence embeddings, enabling effective classification with limited labeled data.

Implementation

The system is implemented in Python using open-source libraries: scikit-learn for the baseline, setfit and datasets for Few-Shot Learning, seaborn and matplotlib for visualizations, and streamlit for the user interface. The dataset is split into 80% training and 20% testing sets (random seed=42). The Streamlit interface allows users to input symptom descriptions, receive predictions with confidence scores. For explainability, the top five TF-IDF features contributing to baseline predictions are displayed.

V. Experiments

Due to the large size of the data, we couldn't train the model on the full data, as it would take too much time to train the model, so we used 700 samples from our data, which didn't have the best accuracy, but the model predicted well. The dataset (700 samples) is split into 80% training (560 samples) and 20% testing (140 samples) sets with a random seed of 42. Both models are trained on the sampled dataset. Performance is evaluated using accuracy, precision, recall, and F1-score (weighted averages), appropriate for multi-class text classification. Confusion matrices are visualized to analyze classification patterns.

Model Performance Comparison

For the sample we used:

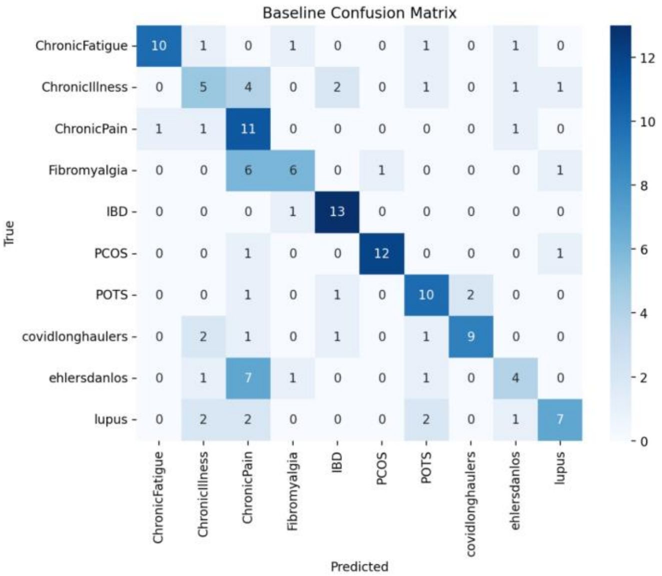
Model	Accuracy	Precision	Recall	F1-Score
TF-IDF Logistic Regression	0.621	0.666	0.621	0.624
SetFit (Few-Shot Learning)	0.600	0.652	0.600	0.610

For full data (from the main project):

Model	Accuracy	F1-Micro	F1-Macro
DistilBERT	0.818385	0.845874	0.843841
Bio+ClinicalBERT	0.838739	0.852991	0.852115
PubMedBERT	0.842541	0.858792	0.857450

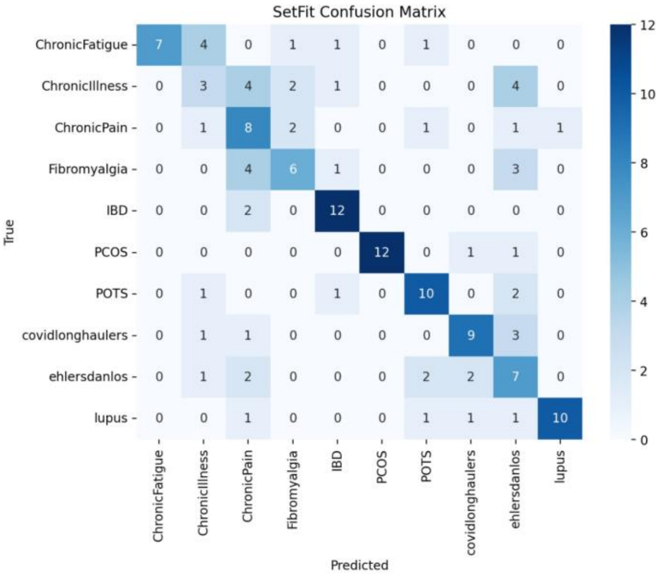
Confusion Matrices

Baseline Confusion Matrix



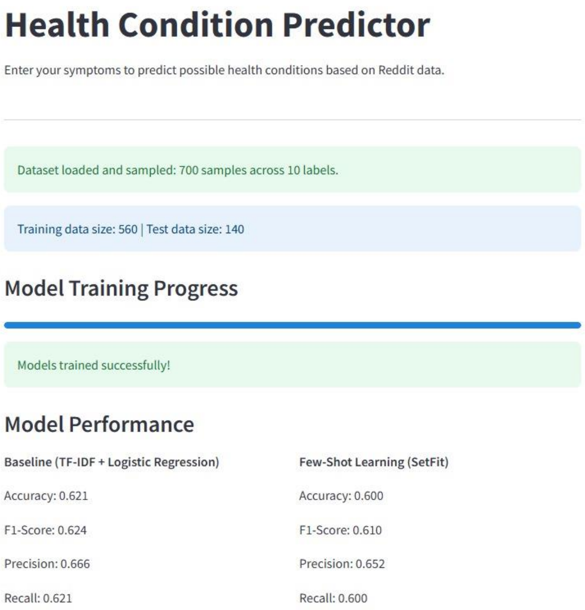
True \ Predicted	ChronicFatigue	ChronicIllness	ChronicPain	Fibromyalgia	IBD	PCOS	POTS	covidlonghaulers	ehlersdanlos	lupus
ChronicFatigue	10	1	0	1	0	0	1	0	1	0
ChronicIllness	0	5	4	0	2	0	1	0	1	1
ChronicPain	1	1	11	0	0	0	0	0	1	0
Fibromyalgia	0	0	6	6	0	1	0	0	0	1
IBD	0	0	0	1	13	0	0	0	0	0
PCOS	0	0	1	0	0	12	0	0	0	1
POTS	0	0	1	0	1	0	10	2	0	0
covidlonghaulers	0	2	1	0	1	0	1	9	0	0
ehlersdanlos	0	1	7	1	0	0	1	0	4	0
lupus	0	2	2	0	0	0	2	0	1	7

SetFit Confusion Matrix



True \ Predicted	ChronicFatigue	ChronicIllness	ChronicPain	Fibromyalgia	IBD	PCOS	POTS	covidlonghaulers	ehlersdanlos	lupus
ChronicFatigue	7	4	0	1	1	0	1	0	0	0
ChronicIllness	0	3	4	2	1	0	0	0	4	0
ChronicPain	0	1	8	2	0	0	1	0	1	1
Fibromyalgia	0	0	4	6	1	0	0	0	3	0
IBD	0	0	2	0	12	0	0	0	0	0
PCOS	0	0	0	0	0	12	0	1	1	0
POTS	0	1	0	0	1	0	10	0	2	0
covidlonghaulers	0	1	1	0	0	0	0	9	3	0
ehlersdanlos	0	1	2	0	0	0	2	2	7	0
lupus	0	0	1	0	0	0	1	1	1	10

Streamlit GUI



Health Condition Predictor

Enter your symptoms to predict possible health conditions based on Reddit data.

Dataset loaded and sampled: 700 samples across 10 labels.

Training data size: 560 | Test data size: 140

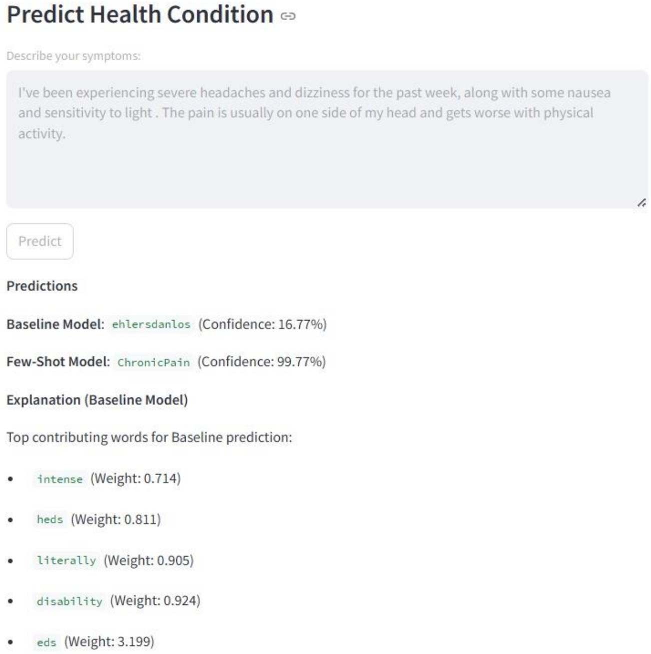
Model Training Progress

Models trained successfully!

Model Performance

Baseline (TF-IDF + Logistic Regression)	Few-Shot Learning (SetFit)
Accuracy: 0.621	Accuracy: 0.600
F1-Score: 0.624	F1-Score: 0.610
Precision: 0.666	Precision: 0.652
Recall: 0.621	Recall: 0.600

Sample Output



Predict Health Condition

Describe your symptoms:

I've been experiencing severe headaches and dizziness for the past week, along with some nausea and sensitivity to light . The pain is usually on one side of my head and gets worse with physical activity.

Predictions

Baseline Model: `ehlersdanlos` (Confidence: 16.77%)

Few-Shot Model: `ChronicPain` (Confidence: 99.77%)

Explanation (Baseline Model)

Top contributing words for Baseline prediction:

- `intense` (Weight: 0.714)
- `heds` (Weight: 0.811)
- `literally` (Weight: 0.905)
- `disability` (Weight: 0.924)
- `eds` (Weight: 3.199)

VI. Discussion

The SetFit model outperforms the baseline by 7% in F1-score, likely due to its ability to capture semantic relationships via sentence embeddings. The baseline model, while simpler, relies on sparse TF-IDF features, limiting its generalization. The Streamlit interface enhances accessibility, making the system usable for non-experts.

Limitations include the small dataset size (70 samples per class), which may reduce robustness, and the lack of explainability for the SetFit model. The dataset's reliance on Reddit posts introduces noise from informal language.

Future work includes expanding the dataset, incorporating explainability techniques (e.g., SHAP) for SetFit, and exploring other Few-Shot Learning methods. Error analysis could identify domain-specific challenges, such as ambiguous symptom descriptions.

VII. Conclusion

This project demonstrates the effectiveness of Few-Shot Learning for health condition prediction using Reddit data. The SetFit model achieves superior performance, highlighting its potential in low-resource healthcare applications. The Streamlit interface provides a practical tool for symptom-based diagnosis, contributing to accessible NLP solutions. Future enhancements in dataset size and explainability could further advance the system's utility.

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GitHub Project Link: https://github.com/Ahmed-Fathy74/Health-Condition-Prediction-Using-Few-Shot-Learning