Syslab Final Report

NeuroTech: An AI Assistant for Schizophrenia Diagnosis

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Yilmaz - Period 1

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Abstract

This project explores a novel multimodal approach for predicting brain disorders by integrating functional MRI (fMRI) data and clinical text using deep learning. Specifically, I employed a convolutional neural network (CNN) to analyze 400 features extracted from fMRI scans **[1]**, while a fine-tuned BioBERT-based transformer model processed associated clinical notes. These two modalities produced independent probability predictions, which could be combined using a weighted average, highlighting the value of combining imaging and textual data to inform neuropsychiatric diagnostics.

I. Introduction

In neuropsychiatric care, clinicians often rely on both brain imaging and written diagnostic reports to understand and classify patient conditions. However, computational models tend to focus on only one of these modalities. **[8]** This project aims to bridge that gap by developing a system that can learn from both imaging and textual data, making diagnostic predictions based on a more complete clinical context. The idea originated from reviewing limitations in current clinical workflows, where radiographic data may suggest one finding, while subjective written assessments suggest another. By modeling both simultaneously, I aimed to build a classifier that benefits from the objectivity of fMRI scans and the nuance of narrative text.

My model combines a CNN that processes static 400-dimensional brain connectivity vectors with a transformer-based NLP model that extracts semantic patterns from clinical descriptions. **[13]** The probability outputs of both models are averaged to produce a final prediction. This method improves robustness and mimics the way human clinicians synthesize multiple forms of input before reaching a diagnosis.

II. Background

Many prior models analyzing brain disorders rely solely on one data source—either imaging or text. On the imaging side, CNNs are frequently used to detect spatial patterns in MRI scans. For text, transformer architectures like BERT have shown exceptional performance in clinical NLP tasks such as named entity recognition and condition classification. However, few systems combine these two sources of information. **[9]** imaging data comes from the COBRE dataset, which includes resting-state fMRI scans of individuals diagnosed with schizophrenia as well as healthy controls. The fMRI signals were processed into 400-dimensional vectors, each representing functional connectivity between predefined brain regions. **[1]** In contrast, my NLP component used a collection of clinical notes, either from public sources or generated to align with imaging labels. These notes were tokenized and passed through a BERT-based model fine-tuned for binary classification. **[13]** This approach builds on recent work in multimodal machine learning, a field that emphasizes combining data from diverse sources to improve performance in complex tasks like diagnosis and prognosis.

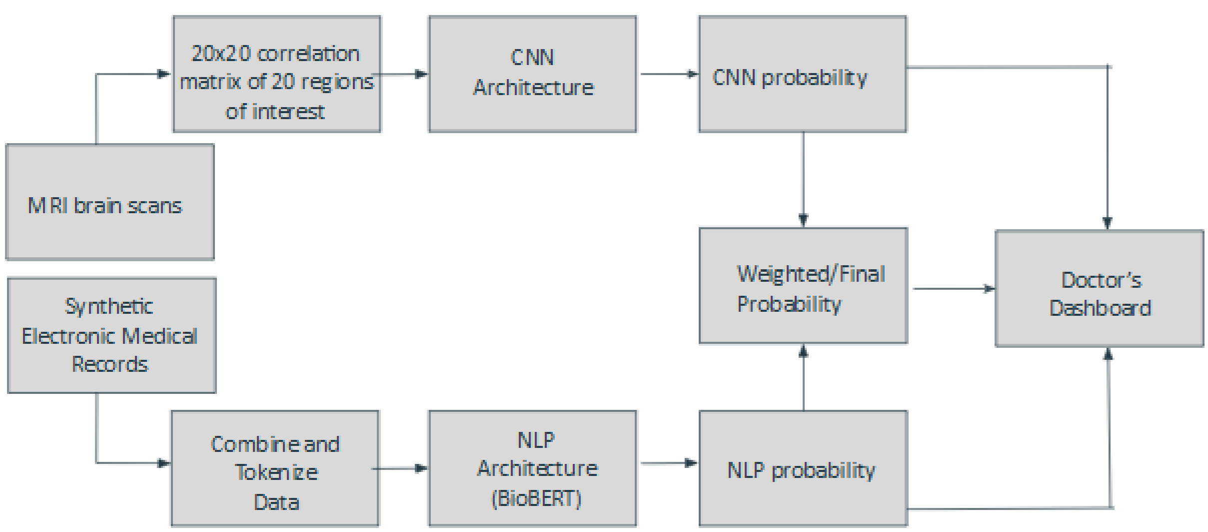

Fig. 1: Systems Architecture Flowchart

III. Applications

This multimodal model has several potential applications. In a clinical setting, it could serve as a diagnostic assistant, helping clinicians make more informed decisions by combining textual and imaging analysis. In research, it offers a powerful tool for investigating links between brain activity and behavioral descriptions. Finally, in medical education, it can be used to demonstrate the value of integrating objective data with clinical narratives.

IV. Methods

Architecture Overview

The system is composed of two parallel models. The first is a CNN that receives a 400-dimensional fMRI feature vector and returns a probability score between 0 and 1. The second is a fine-tuned BERT model that analyzes clinical notes and outputs a similar probability. These are averaged using predefined weights to yield the final prediction.

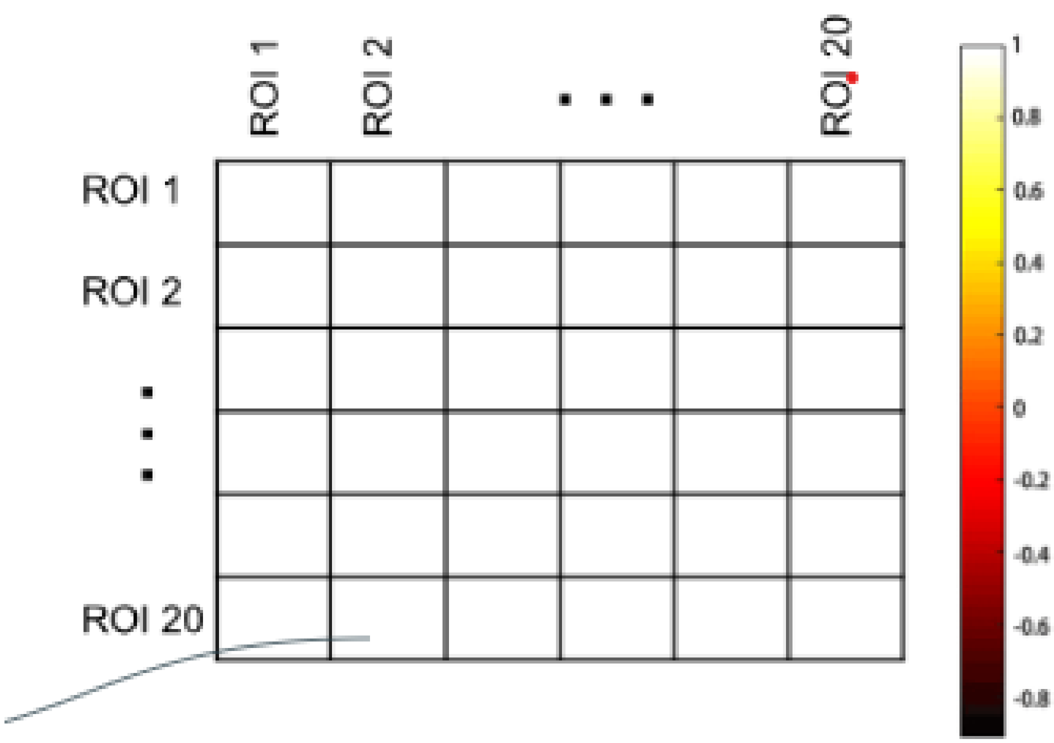

Fig. 2: CNN input data

CNN model

The CNN architecture includes three fully connected layers:

```
self.lin1 = nn.Linear(400, 64)
self.dropout1 = nn.Dropout(0.4)
self.lin2 = nn.Linear(64, 32)
self.dropout2 = nn.Dropout(0.4)
self.lin4 = nn.Linear(32, 1)
```

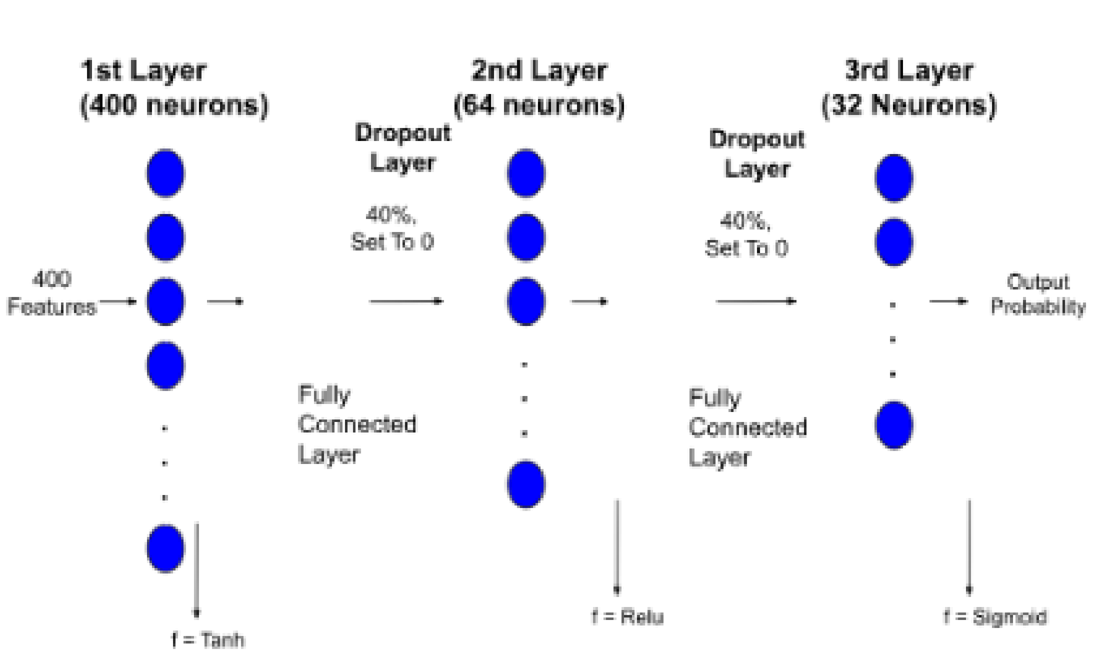

Fig. 3: CNN Architecture

The model applies a tanh activation after the first layer to introduce smooth nonlinearity, followed by a ReLU activation for positive sparsity. The final layer uses sigmoid to output a probability suitable for binary classification. Dropout layers with a 0.4 rate are used to prevent overfitting by randomly deactivating neurons during training.

NLP Model

The NLP model uses BERT, a transformer pretrained on large corpora and fine-tuned on my classification task. Texts are tokenized using BERT's tokenizer, passed through transformer layers, and reduced to a pooled output that is fed into a binary classification head. The output is again a probability between 0 and 1.

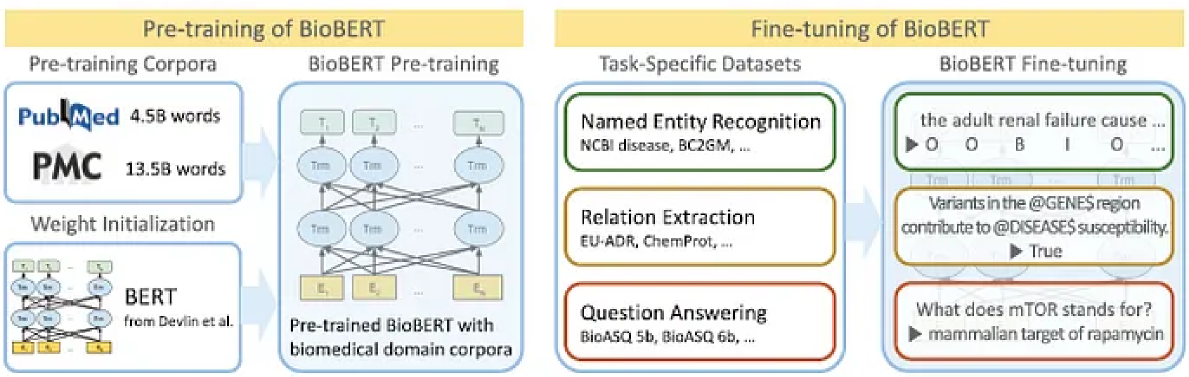

Fig. 4: BioBERT NLP base architecture

Fusion Strategy

To merge predictions, I compute a weighted average of the CNN and NLP outputs:

final_prob = w_cnn * prob_cnn + w_nlp * prob_nlp

The weights are chosen based on each model's validation performance to reflect relative reliability.

Training and Evaluation

Models were trained using the Binary Cross Entropy loss function. Accuracy and confusion matrices were used as performance metrics. I also split the dataset into training, validation, and test sets using a 50/50 ratio. Each modality was trained independently before being evaluated together via fusion.

V. Results

On individual validation sets, the CNN and BERT models each achieved accuracies around 90-97%. The confusion matrix showed that the fusion model had fewer false positives and false negatives, particularly reducing errors in schizophrenic subject classification.

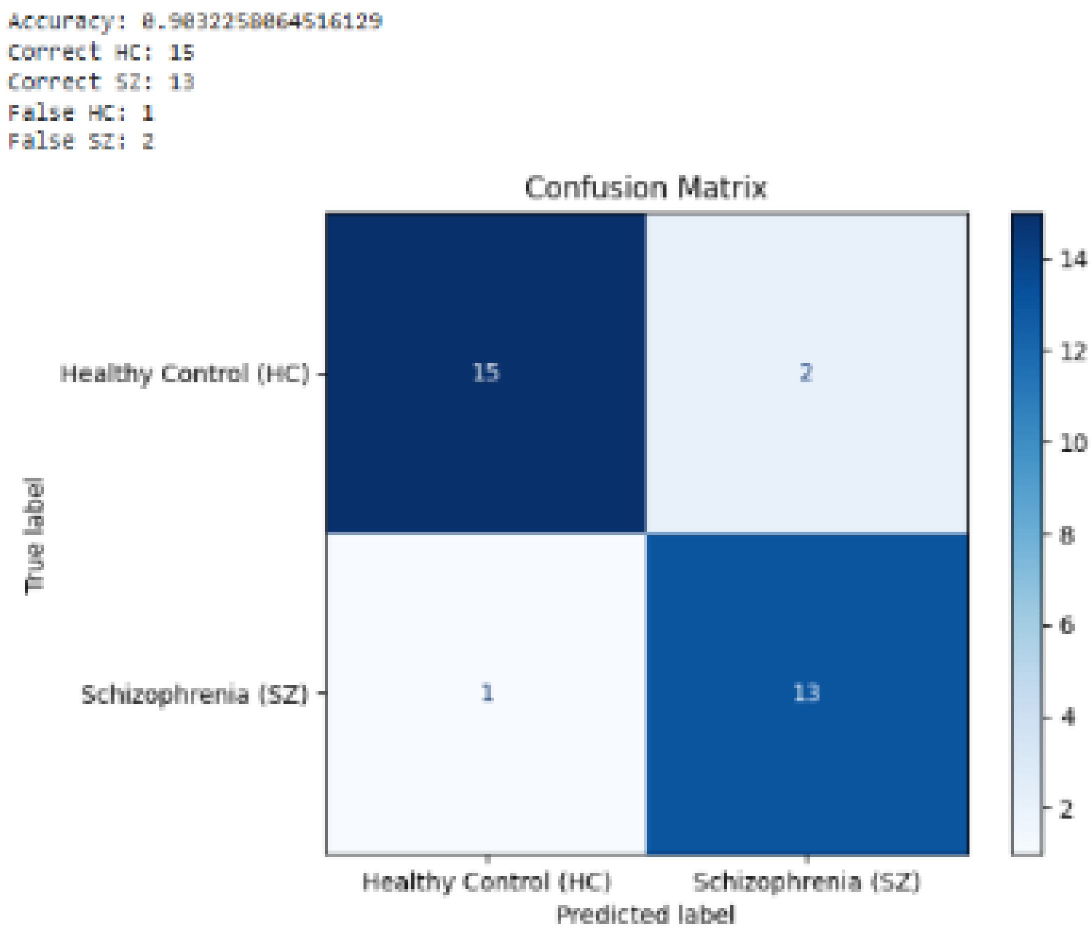

Fig. 5: CNN Output

```
Training the model on synthetic data...
[57/57 07:51, Epoch 3/3]
```

Epoch	Training Loss	Validation Loss
1	0.675900	0.475052
2	0.322600	0.044813
3	0.074000	0.013892

```
Evaluating the model on test data:
[19/19 00:27]
{'eval_loss': 0.01389189250767231, 'eval_runtime': 28.6163,

Predicted Probability of Schizophrenia for the new patient:
0.9791
```

Fig. 6: NLP Output

VI. Limitations

The most significant limitation of this project was the limited availability of high-quality, matched text and imaging data. my NLP dataset was partially synthetic, which may have introduced biases. Additionally, my fusion strategy—simple weighted averaging—could be improved with more dynamic or learnable fusion mechanisms. Finally, due to GPU and memory constraints, I were unable to train larger versions of my models or test more complex ensembling techniques.

VII. Conclusion

This project demonstrates the benefits of multimodal learning in neuropsychiatric diagnosis. By combining CNN-based fMRI analysis with BERT-based clinical text classification, I created a robust system capable of accurate predictions. my results underscore the complementary nature of objective and subjective data and present a promising direction for future AI-assisted healthcare tools.

VIII. Future Work and Recommendations

Future extensions should include training on larger, real-world clinical datasets, especially for the text component. I also recommend exploring attention-based fusion mechanisms that dynamically adjust the importance of each modality. Additional classification granularity (e.g., mild vs. severe disorder) could also be added. Finally, a web-based front-end would make this tool accessible for clinical testing and broader feedback.

References

[1] https://figshare.com/articles/dataset/COBRE_preprocessed_with_NIAK_0_12_4/1160600

[2]https://www.cambridge.org/core/journals/psychological-medicine/article/computing-schizophrenia
[3]https://www.sciencedirect.com/science/article/pii/S0957417422013835
[4]https://www.nimh.nih.gov/health/statistics/mental-illness
[5]https://www.who.int/news-room/fact-sheets/detail/schizophrenia
[6]https://www.ncbi.nlm.nih.gov/pmc/articles/PMC11024310/#B29
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[8]https://www.sciencedirect.com/science/article/pii/S1746809421005140?via%3Dihub
[9]https://www.sciencedirect.com/science/article/pii/S0957417422013835?via%3Dihub
[10]https://www.sciencedirect.com/science/article/pii/S092099641730302X?via%3Dihub
[11]Hugging Face BERT: https://huggingface.co/transformers/
[12]PyTorch: https://pytorch.org/

[13] GitHub Repo: https://github.com/danceyboi07/Schizophrenia