Predicting Dementia using Models

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Introduction

- Dementia affects much of the aging population
  - A set of symptoms representing a decline in cognitive ability, enough to disrupt daily life [1]
  - Only option is to manage symptoms
  - Early identification matters
- The Cookie Theft Picture Test [2]
  - Participants asked to explain what is occurring in the picture
  - Speech can be analyzed to identify onset dementia
  - Identification process *can* be automated using machine learning
- Project Purpose
  - Fine-tune different models to the purpose of identifying patients with dementia using Pitt Corpus [3]

Fig. 1 Boston Cookie Theft Picture [2]

Objective & Impact of Professor's Research

- **Goal:** Predicting dementia in patients early on and managing symptoms
- The lab also focuses on creating ways for robots to interact and assist humans in different ways
- Through researching the effectiveness of different ML models on predicting dementia, others can be assisted
- Hope to improve training with reduced training data

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Research & Learning

- **Use Pitt Corpus to train data**
  - A dataset containing audio and transcripts of different tasks for subjects
- **Use different NLPs**
  - BERT [4]
  - XLNet [5]
  - ALBERT [6]
- **Reducing Overfitting**
  - When model is too responsive to noise
  - Becomes good at predicting training data, but validation data is not predicted; not a generalization following is an example of overfitting:

Epoch	Training loss	Validation loss
8	0.08	1.57
9	0.04	1.79

- **Dropout**
  - One method to reducing overfitting
  - Involves removing neurons from the neural network while training

Methods

- **Models**
  - BERT BASE UNCASED [4]
    - Machine learning framework for NLP, including classification
  - XLNet BASE CASED [5]
    - Unsupervised language model for fine-tuning
  - ALBERT v2 [6]
    - A smaller version of BERT
    - Runs with similar results to BERT large model
- **Metrics**
  - Loss (L)
  - Accuracy (A)
  - Precision (P)
  - Recall (R)
  - F1 Score (F1)

Results

BERT Results

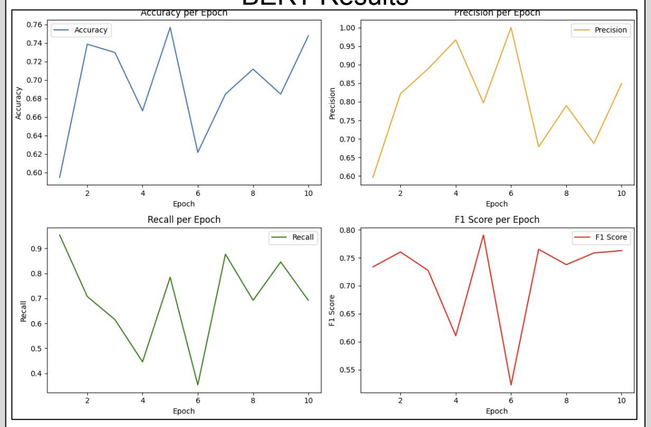

Fig. 2 BERT results showing metrics A, P, R, F1

XLNet Results

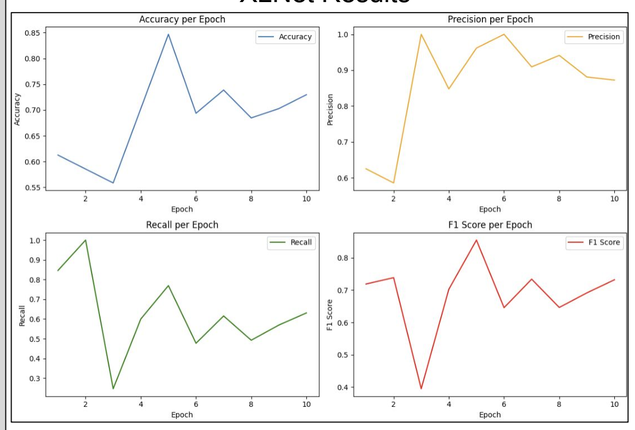

Fig. 3 XLNet results showing metrics A, P, R, F1

ALBERT Results

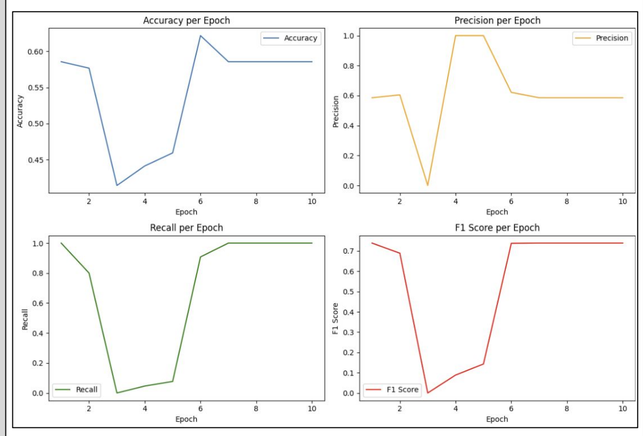

Fig. 4 ALBERT results showing metrics A, P, R, F1

Results Analysis

Model	E	L	A	P	R	F1
BERT	3	0.52	0.77	0.78	0.83	0.81
XLNet	5	0.48	0.85	0.96	0.77	0.85
ALBERT	6	0.66	0.62	0.62	0.91	0.74

Fig. 2-4 Validation Metrics

- BERT and XLNet overfit after epochs 3 and 5
- ALBERT stops improving after epoch 6

Next Steps for You & Advice to Future SHINE participants

- Incorporate audio files into the training and validation of data
- Improve model by doing further cleaning on the dataset
- Use other data from other tests, such as listing as many animals as possible, to further improve results
- To SHINE participants:
  - Get to know other students and other PhD mentors in your lab
  - Make connections with others, especially during the luncheon
  - Work hard and ask questions!

Citations

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4. Devlin, J., Chang, M. W., Lee, K., & Toutanova, K. (2018). Bert: Pre-training of deep bidirectional transformers for language understanding. arXiv preprint arXiv:1810.04805.
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6. Lan, Z., Chen, M., Goodman, S., Gimpel, K., Sharma, P., & Soricut, R. (2019). Albert: A lite bert for self-supervised learning of language representations. arXiv preprint arXiv:1909.11942.