Beloit College, DSDA390

SEIZURE VS NON-SEIZURE DETECTION USING MLP

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OVERVIEW

- Early detection of seizures can prevent injuries and provide better management for patients with epilepsy. Traditional methods may not be sufficient for real-time analysis

=> Build a ML model for binary classification to distinguish between seizure/non-seizure events from Bonn data

HOW DID I APPROACH

- **Prepare the data:** Preprocess the dataset, including feature extraction, normalization, and splitting into training and validation sets
- **Define the MLP model:** Create the model architecture using PyTorch
- **Train the model:** Set up the training loop, loss function, optimizer, and evaluation metrics
- **Evaluate performance:** Monitor the model’s performance

DATA PREPROCESSING

- Steps Involved:
  - **Load Dataset:** The data was loaded from CSV files
  - **Feature Normalization:** Scaled features using StandardScaler to ensure uniformity and avoid scale dominance during training
  - **Train-Test Split:** Divided the dataset into training and validation sets using train_test_split from scikit-learn

WHY MULTI-LAYER PERCEPTRONS?

- The dataset consists of tabular data, making MLP ideal
- MLP can scale easily to large datasets, making it suitable this growing data
- But also train moderate-size datasets faster (compared to more complex models like deep CNNs or RNNs)
- MLP can capture non-linear relationships in the data due to its non-linear activation functions (ReLU, Sigmoid)
- MLP is effective for classification

MODEL ARCHITECTURE

- **MLP** to classify the data into two classes: seizure or non-seizure
- **Input Layer:** Takes the features of the data
- **Hidden Layers:**
  - First hidden layer with 128 neurons
  - Second hidden layer with 64 neurons
  - Third hidden layer with 32 neurons
- **Output Layer:** One neuron with a sigmoid activation to predict the probability of the "Seizure" class
- **Activation Functions:** ReLU after each hidden layer and sigmoid for the output

TRAIN THE MODEL

```
Epoch 1/200, Loss: 0.6656, Accuracy: 0.6190
Validation Loss: 0.6967, Accuracy: 0.5000
Epoch 2/200, Loss: 0.5605, Accuracy: 0.7669
Validation Loss: 0.7529, Accuracy: 0.5400
Epoch 3/200, Loss: 0.4471, Accuracy: 0.7995
Validation Loss: 0.7837, Accuracy: 0.5300
Epoch 4/200, Loss: 0.3822, Accuracy: 0.8471
Validation Loss: 0.8017, Accuracy: 0.5600
Epoch 5/200, Loss: 0.3127, Accuracy: 0.9098
Validation Loss: 0.9238, Accuracy: 0.5800
Epoch 6/200, Loss: 0.2022, Accuracy: 0.9323
Validation Loss: 1.0110, Accuracy: 0.6300
Epoch 7/200, Loss: 0.1205, Accuracy: 0.9599
Validation Loss: 2.4914, Accuracy: 0.6300
Epoch 8/200, Loss: 0.0629, Accuracy: 0.9850
Validation Loss: 2.6878, Accuracy: 0.6500
Epoch 9/200, Loss: 0.0486, Accuracy: 0.9875
Validation Loss: 2.9061, Accuracy: 0.6400
Epoch 10/200, Loss: 0.0252, Accuracy: 0.9950
```

```
Epoch 195/200, Loss: 0.0000, Accuracy: 1.0000
Validation Loss: 5.4908, Accuracy: 0.6900
Epoch 196/200, Loss: 0.0000, Accuracy: 1.0000
Validation Loss: 5.4936, Accuracy: 0.6900
Epoch 197/200, Loss: 0.0000, Accuracy: 1.0000
Validation Loss: 5.4953, Accuracy: 0.6900
Epoch 198/200, Loss: 0.0000, Accuracy: 1.0000
Validation Loss: 5.4967, Accuracy: 0.6900
Epoch 199/200, Loss: 0.0000, Accuracy: 1.0000
Validation Loss: 5.5000, Accuracy: 0.6900
Epoch 200/200, Loss: 0.0000, Accuracy: 1.0000
Validation Loss: 5.5017, Accuracy: 0.6900
```

- Loss and Accuracy tracked for both Training and Validation sets
- **Pattern:**
  - **Training Loss:** Decreasing steadily -> model improvement
  - **Training Accuracy:** Increases to near 100% -> model is fitting well to the training data
  - **Validation Loss:** Initially fluctuates and increases -> overfitting
  - **Validation Accuracy:** Plateaus around 68%
- **Key Observations:**
  - The model performs well on the training set but struggles with generalization to the validation set, highlighting potential overfitting.

CLASSIFICATION REPORT

	precision	recall	f1-score	support
Non-seizure	0.71	0.70	0.71	50
Seizure	0.71	0.72	0.71	50
accuracy			0.71	100
macro avg	0.71	0.71	0.71	100
weighted avg	0.71	0.71	0.71	100

- The model performs well on non-seizure data but has slightly lower recall for seizure data
- Precision for seizure detection is better than recall

LIMITATIONS

- Limited understanding of Biology and Neuroscience hindered effective data interpretation and model design
- Training accuracy is near 100%, but validation accuracy stagnates at 68%
  - Model memorizes training data but fails to generalize well on unseen data
- The model may not provide clear insights into the decision-making process

IMPROVEMENTS

- Use regularization techniques (e.g., L2, dropout) and implement cross-validation
- Explore additional evaluation metrics (e.g., F1 score, ROC curve) that align with the application's goals
- Talk to domain experts and have a better understanding of the overall dataset

THANK YOU