Brain cancer gene expression using Neural Networks

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For Machine Learning for Biomedical Informatics

Images have been taken from sources cited on the slides.

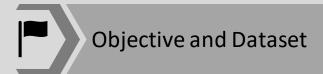
Code available on: https://github.com/ShivikaPrasanna/brain_cancer_gene_expression.git

Outline:



Introduction

- Level of gene expression depends on factors
 - Type of cell
 - Developmental stage of the organism
 - Presence of external signals or environmental stimuli
- Regulation of gene expression critical for maintaining proper balance of proteins and other molecules within cells



Goal:

Predict the class of gene expression in Brain Cancer dataset

- SBCB lab focuses on the computational analysis of biological structures
- Curated Microarray Database (CuMiDa) containing 78 cancer datasets curated from 30,000 studies
 - Provide standardized preprocessing and benchmark results
 - Facilitate machine learning studies in cancer research



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The use of artificial intelligence, particularly machine learning, creates new opportunities for analyzing large volumes of biological data

Machine Learning and Biological Data Analysis

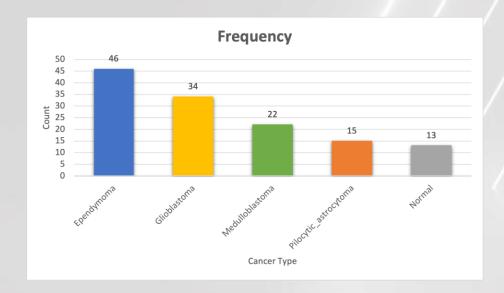
Big data analytics Translational data science Feature selection Predictive models

Source: https://sbcb.inf.ufrgs.br/



Objective and Dataset

- GSE50161 on brain cancer gene expression:
 - 5 classes
 - 54,676 genes
 - 130 samples
- Distribution of the 5 classes:



	samples	type	1007_s_at	1053_at	117_at	121_at	1255_g_at	1294_at	1316_at	1320_at	
0	834	ependymoma	12.498150	7.604868	6.880934	9.027128	4.176175	7.224920	6.085942	6.835999	
1	835	ependymoma	13.067436	7.998090	7.209076	9.723322	4.826126	7.539381	6.250962	8.012549	
2	836	ependymoma	13.068179	8.573674	8.647684	9.613002	4.396581	7.813101	6.007746	7.178156	
3	837	ependymoma	12.456040	9.098977	6.628784	8.517677	4.154847	8.361843	6.596064	6.347285	
4	838	ependymoma	12.699958	8.800721	11.556188	9.166309	4.165891	7.923826	6.212754	6.866387	
125	959	pilocytic_astrocytoma	12.658228	8.843270	7.672655	9.125912	5.495477	8.603892	7.747514	5.828978	
126	960	pilocytic_astrocytoma	12.812823	8.510550	8.729699	9.104402	3.967228	7.719089	7.092496	6.504812	
127	961	pilocytic_astrocytoma	12.706991	8.795721	7.772359	8.327273	6.329383	8.550471	6.613332	6.308945	
128	962	pilocytic_astrocytoma	12.684593	8.293938	7.228186	8.494428	6.049414	8.214729	7.287758	5.732710	
129	963	pilocytic_astrocytoma	12.397722	8.843524	8.825100	8.551541	5.002072	8.547894	6.920827	5.738159	
130	130 rows × 54677 columns										

1 data.samples.count()

130

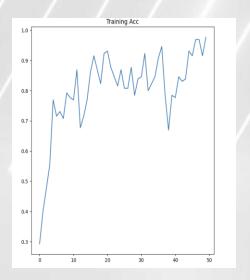
1 data.type.unique()

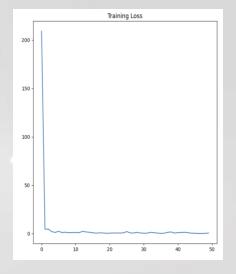


Benchmark Comparison

- Model:
 - Train-test split of 100-0
 - ResMLP (Sequential)
 - Dense layer (Activation: ReLU)
 - Batch normalization
- Optimizer: Adam
- Loss: Sparse Categorical Cross Entropy
- Model Training Parameters:
 - Epochs: 50
 - Batch size: 16

Laye	r (type)	Output Shape	Param #
dens	e (Dense)	multiple	55988224
	h_normalization (BatchN lization)	multiple	4096
sequ	ential (Sequential)	(None, 4096)	153147392
dens	e_23 (Dense)	multiple	20485





Our Model

- Neural Network
- Model definition:
 - Train-test split of 90-10 due to small size
 - Sequential model
 - 4 dense layers (16, 8, 4, 1 units)
 - Activations:
 - Layers 1-3: ReLU
 - Layer 4: Sigmoid

```
# Define the model architecture
model = Sequential()
model.add(Dense(16, activation='relu', input_dim=X_train.shape[1]))
model.add(Dense(8, activation='relu'))
model.add(Dense(4, activation='relu'))
model.add(Dense(1, activation='sigmoid'))

# Compile the model
model.compile(loss='binary_crossentropy', optimizer='adam', metrics=['accuracy'])
```



Loss: Binary Cross Entropy

• Optimizer: Adam

Metrics: Accuracy

```
1 # Compile the model
2 model.compile(loss='binary_crossentropy', optimizer='adam', metrics=['accuracy'])
```



- Model Training Parameters
 - Early Stopping

Monitor: loss

• Patience: 10

Mode: min

Model Checkpoint

Monitor: loss

- Save best model with min loss
- Learning Rate

Monitor: loss

• Factor: 0.1

Mode: min

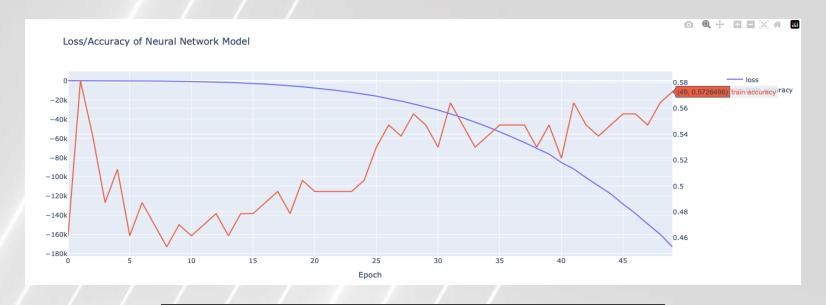
earlyStopping = tf.keras.callbacks.EarlyStopping(monitor='loss', patience=10, verbose=0, mode='min', restore_best_weights=True)
mcp_save = tf.keras.callbacks.ModelCheckpoint('.mdl_wts.hdf5', save_best_only=True, monitor='loss', mode='min')
reduce_lr_loss = tf.keras.callbacks.ReduceLROnPlateau(monitor='loss', factor=0.1, patience=7, verbose=1, min_delta=1e-4, mode='min')



1 model.summary()						
Model: "sequential"						
Layer (type)	0utput	Shape	Param #			
dense (Dense)	(None,	16)	874832			
dense_1 (Dense)	(None,	8)	136			
dense_2 (Dense)	(None,	4)	36			
dense_3 (Dense)	(None,	1)	5			
======================================						



Metrics	Value
Training Accuracy	0.57
Test Accuracy	0.61
Epochs	50
Batch size	16



```
1 score, acc = model.evaluate(X_test, y_test, batch_size=32, verbose=2)
2 print("Accuracy: ", acc)

1/1 - 0s - loss: -1.3199e+05 - accuracy: 0.6154 - 99ms/epoch - 99ms/step
Accuracy: 0.6153846383094788
```

Conclusion

- Neural networks can be used to classify the gene expression
 - Into 3 classes for Brain Cancer dataset due to extreme class imbalance, namely ependymoma, glioblastoma, medulloblastoma
- Data was split into 90-10 due to dataset size
- Model developed had fewer layers to accommodate the data size
- Multiple experiments were carried out to finalize the best model
 - SMOTE for additional synthetic data points yielded similar test accuracy of 59%
 - Smaller model of 2 layers yielded test accuracy of 60%
- Hyperparameter tuning on the batch size, epochs and split ratio