Project Presentation

CS613

Alzheimer's Classification using OASIS Dataset

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Overview

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- Related Works
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Problem

We classified various phases of Alzheimer’s Disease.

Alzheimer’s is a neurodegenerative disorder

- Loss of memory & reasoning
- eventually Dementia

Need of capable Machine Learning models for Alzheimer’s

- Identify trends in pre-disease symptoms
- Drug development
- Quality of Life

Data Source

OASIS Alzheimer's Detection Dataset, a take on Marcus et. at OASIS-1.

Source: https://www.kaggle.com/datasets/ninadaithal/imagesoasis

80,000 (498x258) brain MRI images of 461 patients, classified into **four** labels based on the provided metadata and Clinical Dementia Rating (CDR) values on Alzheimer's progression.

Dataset Size: 1.3 GB

Data Preprocessing

Due to class imbalance, we had to reduced our data set as follows:

- For binary classification: 488 images from the non-demented class labeled not Alzheimer's, and from all other 3 classes we took 162 images from each and labeled as Alzheimer's. **Class Prior: 50%.**
- In multiclass moderate dementia class had 488 images, so we randomly sampled 488 images from each class. **Class Prior: 25%.**
- Downsampled it and worked with two feature dimensions of images one being 1/8 of the size of the image which is (64x32) and the other being 1/4 which is (128x64).
- Modified the image to get blurred images and separately applied canny edge detection to get the edges.

Related Works

- **Challis et al.:**
  - Used Bayesian Gaussian Linear Regression for brain analysis.
  - achieved 75% accuracy in distinguishing mild dementia from normal brains.
  - 97% accuracy in mild dementia from Alzheimer's.
- **Subramoniam et al:**
  - Used Resnet 101 for feature extraction.
  - Labels (non-demented, mild, very mild, and moderate).
  - Achieved accuracy of 95.32% using CNN along with a dense layered Deep Neural Network (DNN).
- **Knox et al.:**
  - Used separately trained Auto-Encoders for feature extraction on a localized hippocampal MRI dataset.
  - Gaussian Naive Bayes for classification.
  - Accuracy of around 80% in classifying extracted features of brain images.

Related Works (cont'd)

- **Fulton et al.:**
  - Proposed using Resnet-50 for detecting Clinical Dementia.
  - Employed Gradient Boosting for Alzheimer's analysis, achieving 91% accuracy on a minimal mental state exam data.
  - Achieved a remarkable 99% accuracy in 3-class classifications of Dementia using Resnet-50.
- **Durate et al.:**
  - Transfer Learning techniques with VGG16 on a small dataset.
  - Applied SVM and other approaches.
  - Conducted binary classification for Alzheimer's detection.
  - FP Priori performed best with 71%.

Models (2 Dimensions: 128x64 & 64x32)

- Binary Classification (Alzheimer's-Not Alzheimer's)
  - Logistic Regression
  - LDA
    - PCA (Time Complexity)
- Multiclass Classification(Non Demented, Very Mild, Mild, Moderate)
  - MultiLDA (PCA (Time Complexity))
    - Normal
    - Blur
    - Canny Edge
  - K Nearest Neighbours
    - Normal
    - Blur
    - Canny Edge

Models (cont'd)

- Multiclass Classification
  - Naive Bayes
    - Normal
    - Blur
    - Canny Edge
  - 1 vs 1 Approaches
    - 1vs1 Logistic Regression
      - Normal
      - Blur
      - Canny Edge
    - 1vs1 LDA
      - Normal
      - Blur
      - Canny Edge

Models (cont'd)

- Ensemble (Mean Ensemble)
  - KNN (Canny Edge)
  - 1 vs 1 LDA (Normal)
  - 1 vs 1 Logistic Regression (Normal)

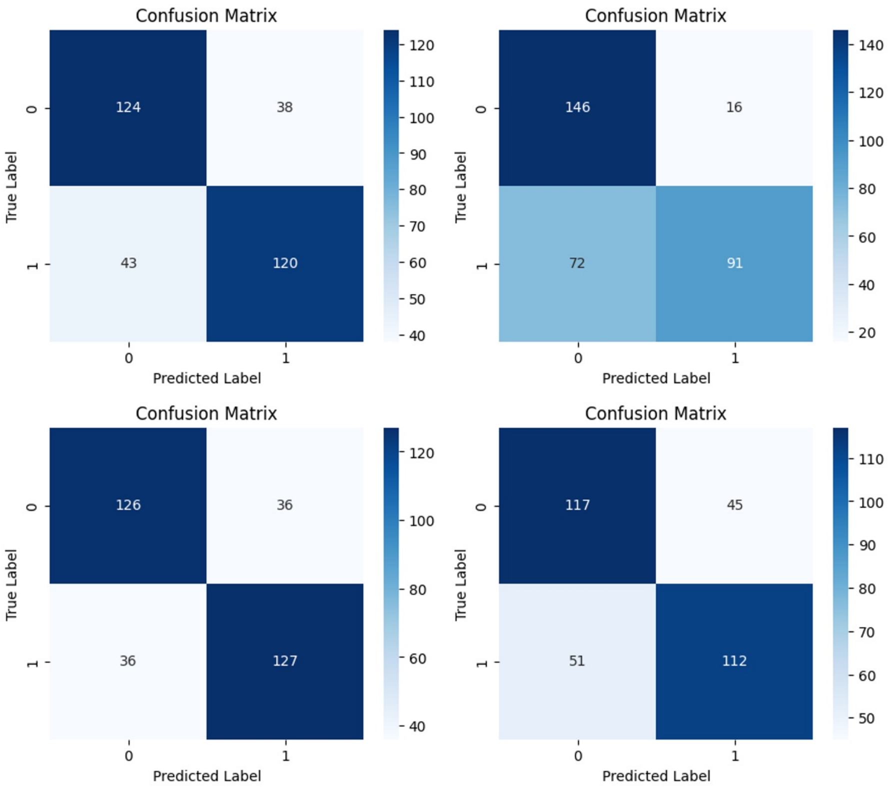
Experiments and Results

Binary Classification

	LDA(PCA)	
	64x32	**128x64**
	0.7046153846	0.7784615385
	Log Regression	
	64x32	**128x64**
BINARY	0.7292307692	0.7507692308

Confusion Matrix of Binary Models with the upper 2 being logistic regression in 128x64 and 64x32 respectively and the bottom 2 are of LDA respectively.

0:Alz
1:Not_Alz

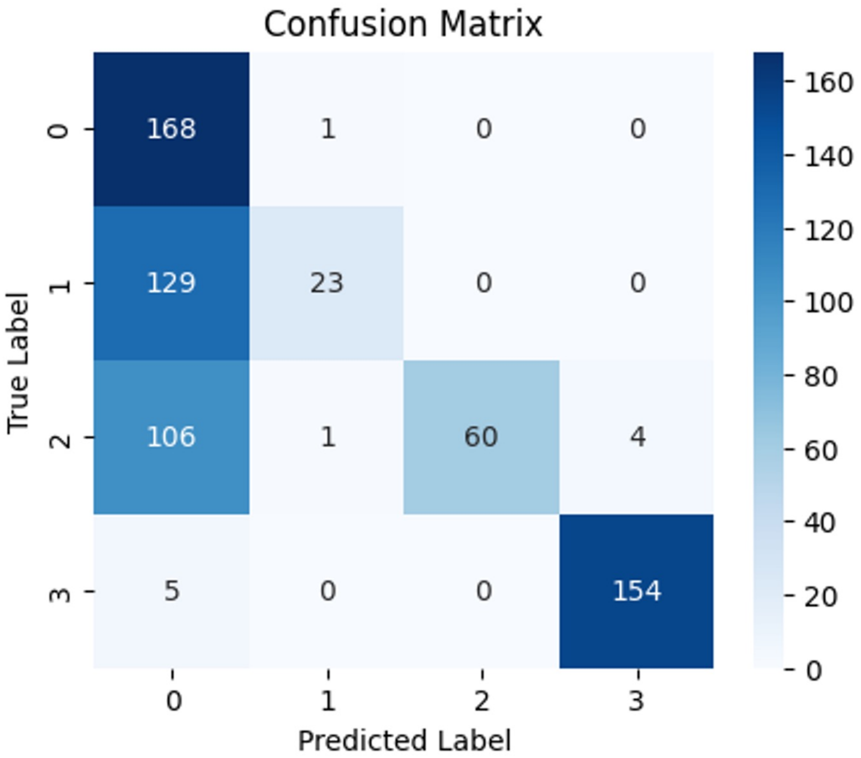


MultiClass Classification

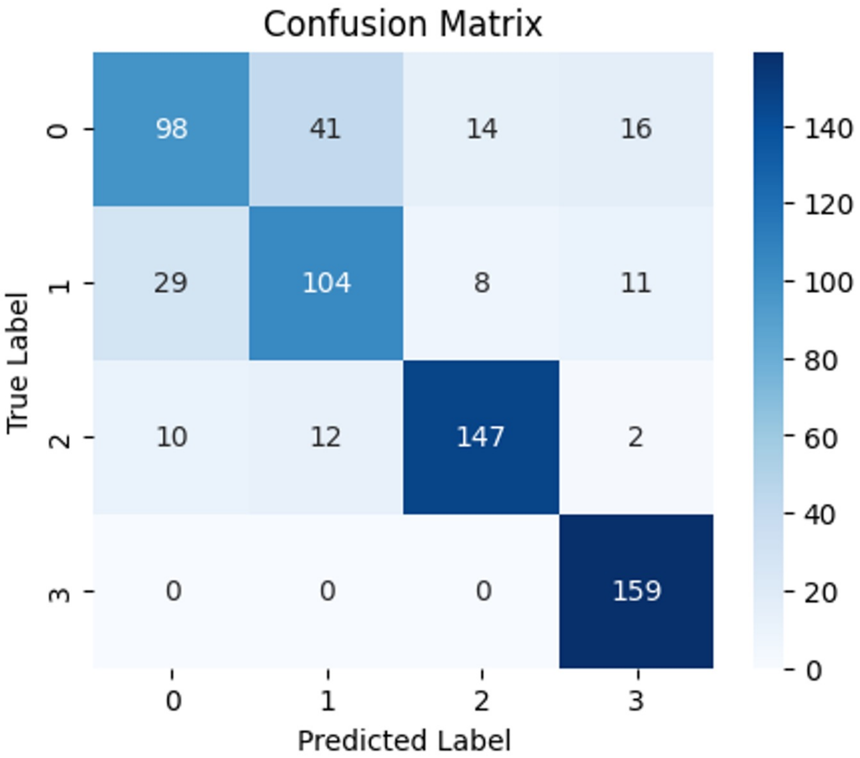
Multi class LDA(PCA)		
	64x32	**128x64**
Normal	0.465437788	0.490015361
Blur	0.4500768049	0.4792626728
Canny	0.4700460829	0.4869431644
Naïve bayes		
	64x32	128x64
Normal	0.6651305684	0.6651305684
Blur	0.6835637481	0.6912442396
Canny	0.5975422427	0.5960061444
KNN		
	64x32	128x64
Normal	0.6205837174	0.6221198157
Blur	0.6159754224	0.6205837174
Canny	0.7603686636	0.7803379416

Comparison of Confusion Matrix (KNN)

0:Non,
1:VMild,
2:Mild,
3:Moderate



Normal



Canny

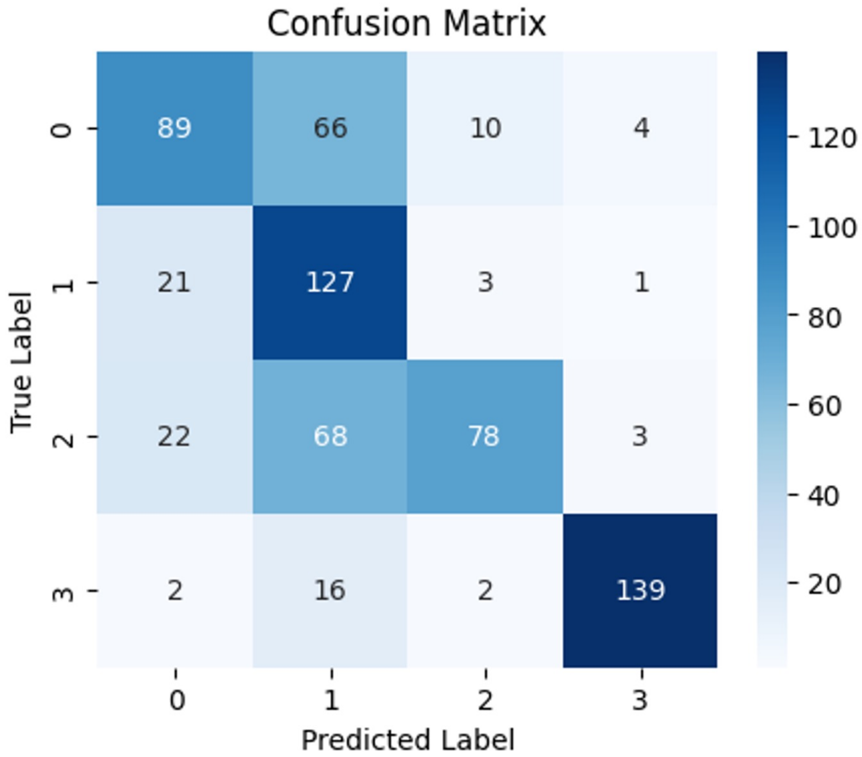
Comparison of Confusion Matrix (KNN)

Reason for Increased Accuracy:-

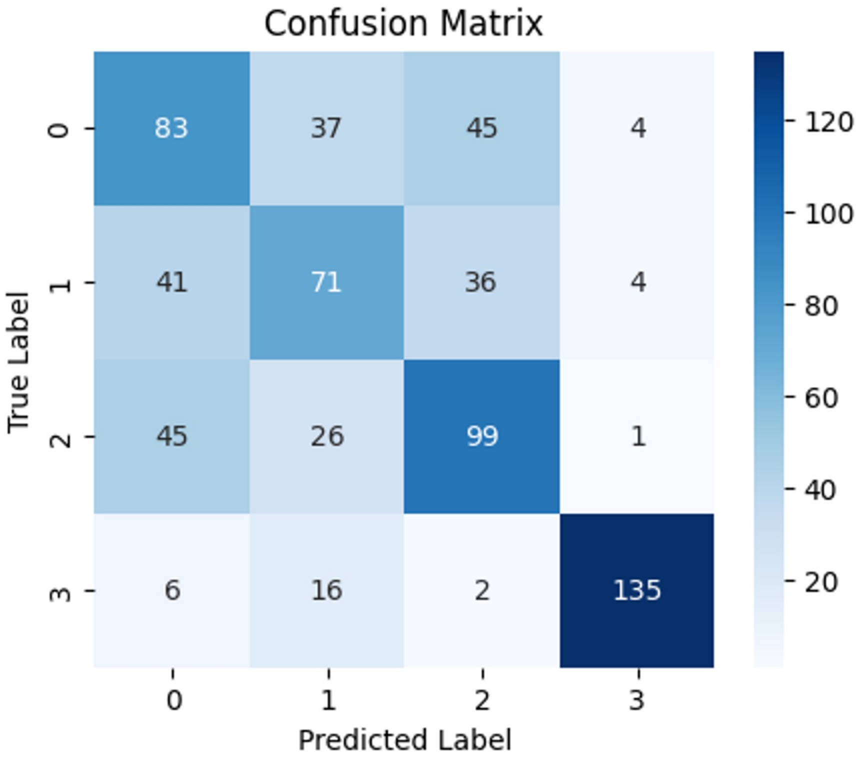
- Edge Reducing Noise
- Decreasing Similarity
- Suitable for KNN

Comp'n of Confusion Matrix (Naive Bayes)

0:Non,
1:VMild,
2:Mild,
3:Moderate



Normal



Canny

Comp’n of Confusion Matrix (Naive Bayes)

Reason for Decreased Accuracy:-

- Denial of Feature Independence.
- Not so ideal for probabilistic models.

1 vs 1 Models

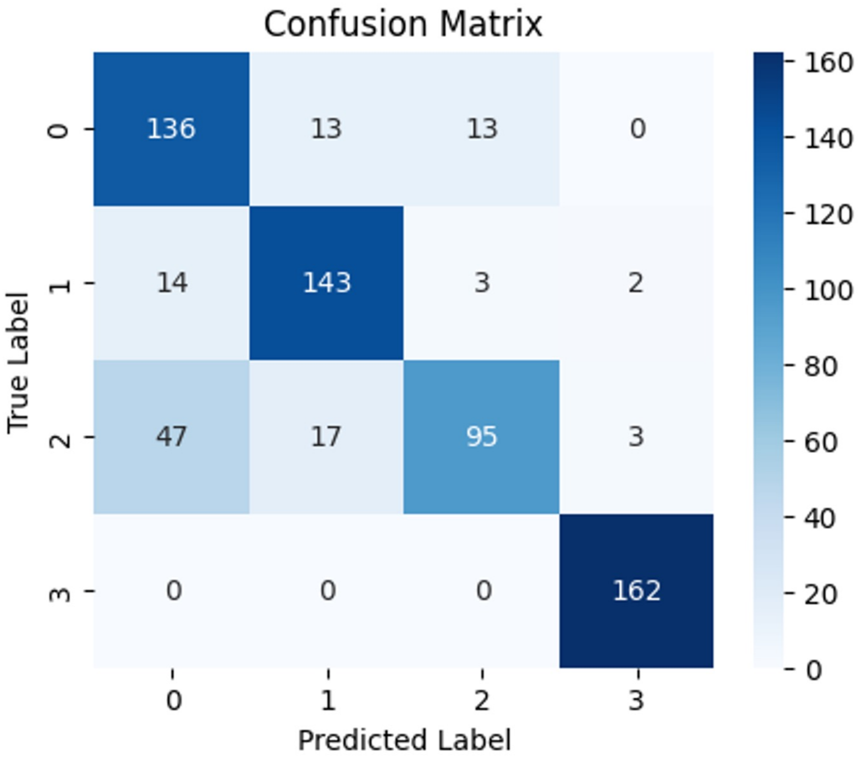
ONE vs ONE	LDA(PCA)		
		64x32	128x64
	Normal	0.7561728395	0.774691358
	Blur	0.7361111111	0.7608024691
	Canny	0.6682098765	0.612654321
	Log Regression		
		64x32	128x64
	Normal	0.8194444444	0.8271604938
	Blur	0.8086419753	0.8179012346
	Canny	0.7299382716	0.774691358

Ensembling Results

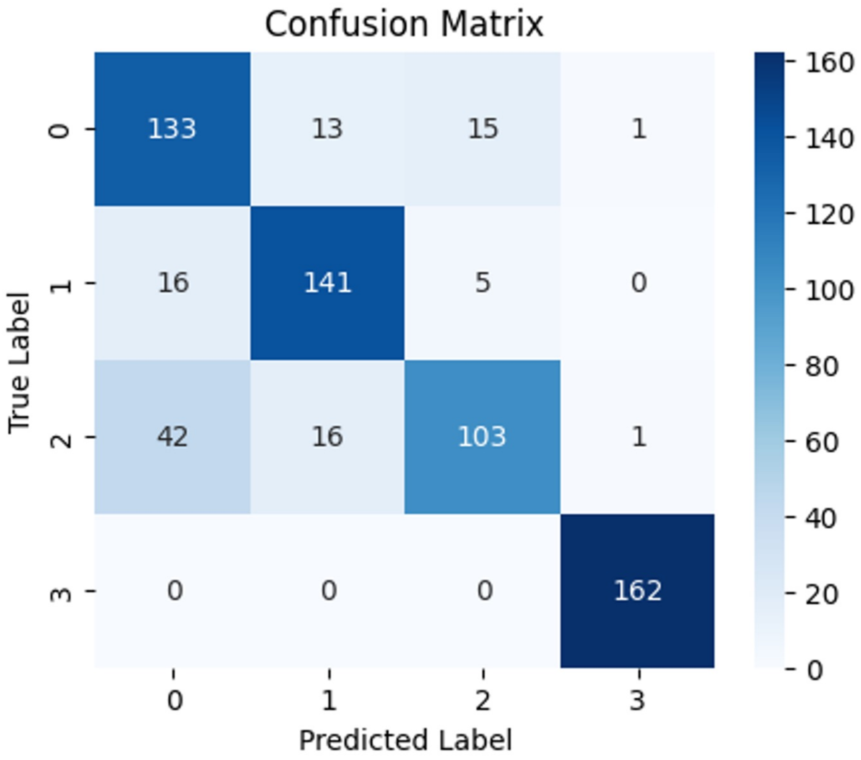
- **For 64x32:**
  - **Ensemble Accuracy:** 82.72%
  - **Ensemble Precision:** 83.57%
  - **Ensemble Recall:** 82.72%
  - **Ensemble F1-score:** 83.14%
- **For 128x64:**
  - **Ensemble Accuracy:** 83.18%
  - **Ensemble Precision:** 83.77%
  - **Ensemble Recall:** 83.18%
  - **Ensemble F1-score:** 83.48%

Confusion Matrix of Ensembles

0:Non,
1:VMild,
2:Mild,
3:Moderate

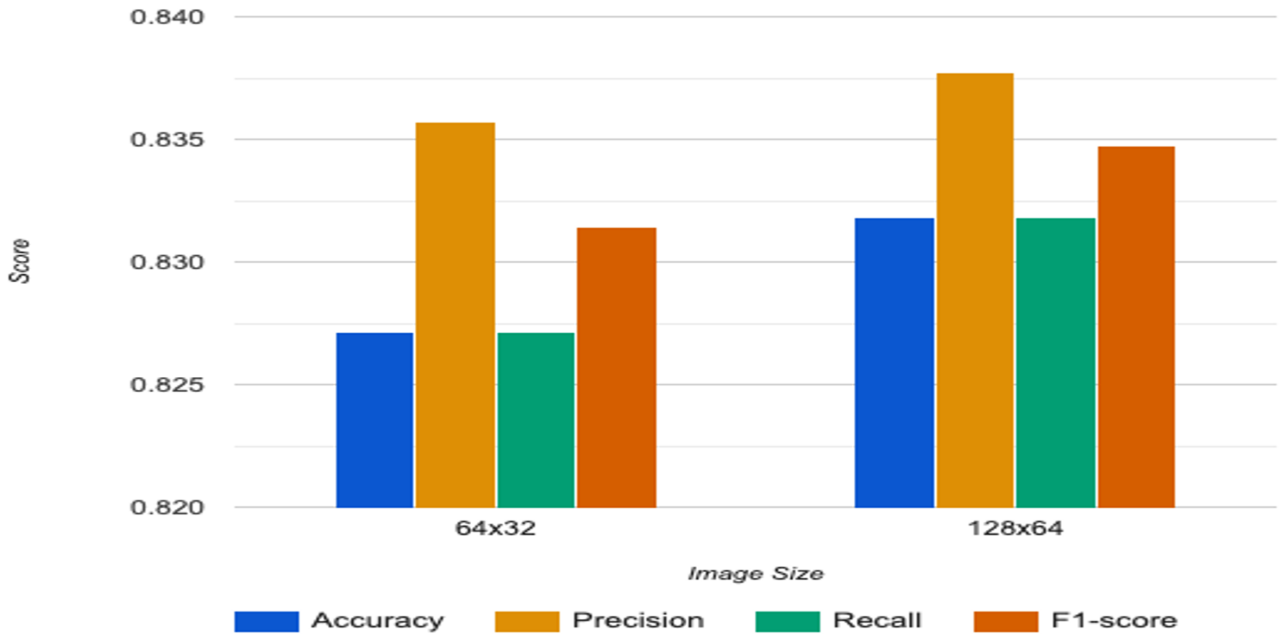


(64x32)



(128x64)

Ensembling Results



Conclusion

In 64x32 image size, KNN with Canny (76%), 1vs1 LDA (75.6%), and 1vs1 Logistic Regression (81.9%) Ensembled to 82.72%.

In 128x64 image size, KNN with Canny (74.5%), 1vs1 LDA (77.5%), and 1vs1 Logistic Regression (82.7%) Ensembled to 83.18%.

Increase in Accuracy in both image dimensions!!

Likely, Classifiers are accurate and have diverse errors.

Future Works

- Data Merging and Augmentation
- Using Image in Real Dimension (Computationally Heavy)
- Auto-Encoders (Deep Learning)
- Image Classification (Deep Learning-Tensorflow)

References

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Thank You