Project Report (October 15, 2021)

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ABSTRACT

We discuss the various techniques and approaches that we have incorporated in our methodology to improve the classification results by **5.5%** for the problem of measuring severity of age related macular degeneration. We try different preprocessing techniques and attempt to reduce the data imbalance issue with the aid of augmentation.

Data Pre-processing

- We extract **green channel** from the RGB data image as it visually sound information of fovea and exudates which are required for classification.
- Different techniques experimented on the extracted green channel to **adjust the contrast** of the image:
  - **Adaptive thresholding:** It is unable to retain information and distinguish the exudates from the rest of the fovea features.
  - **Histogram equalization:** We tried variations of histogram equalization like Adaptive Histogram Equalization and CLAHE but the exudates get distorted to a great extent.
  - **Contrast stretching:** We stretch the pixel values ranging from 40 to 190 as majority information lies in this range. This gives best vizualization of exduates so far.

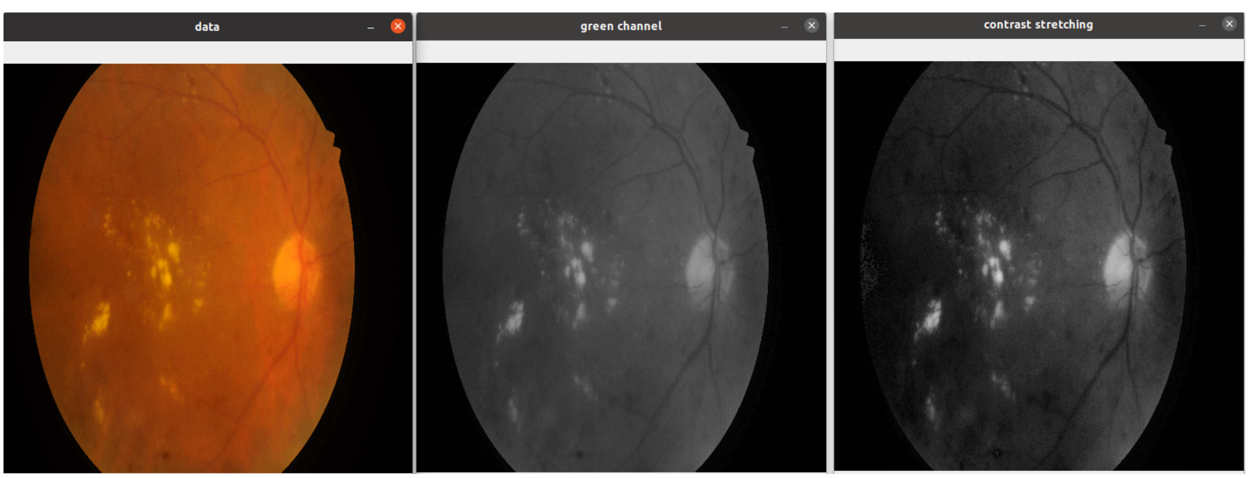

Figure 1. Data, Green Channel Extraction, Contrast Stretching (Left to Right)

Data Augmentation

We implement online augmentation and offline augmentation to enhance the dataset.

- **Offline Augmentation**
  - Label 1 has only 58 datapoints. To increase the number of datapoints we perform different types of augmentation to generate and store more data.

– Augmentation techniques include horizontal flip, vertical flip, brightness, contrast and rotation.
– The label 1 data is increased four-folds thus making a total of 290 datapoints.
– Fig 2 shows the dataset post augmentation. Datapoints across label 0, 1 and 2 are now almost equally distributed.

```
----------------Dataset-----------
IDRiD Testing Set  : 103
IDRiD Training Set  : 413
drive  : 31
messidor2  : 80
augData Label1  : 232
Total datapoints:  859



----------------Labels------------
Label  0 :      295
Label  1 :      290
Label  2 :      274
Total datapoints:  859
```

Figure 2. Dataset post augmentation

- **Online Augmentation**
  We apply augmentation during training which introduces the model to more variations in the dataset so that the results are generalized.

Methodology

- **EfficientNet-B3** (12M parameters) is implemented to be trained for this 3-class classification problem.
- We use pre-trained **ImageNet** weights and train the entire network over the dataset.
- The optimizer that we have used is **Adam optimizer** with a learning rate of **5e-4**.
- The batch size found optimal is **8**.

Result Comparison

- Table 2 demonstrates our results compared to other methods. Our model performs significantly better after addition of augmentation and pre-processing techniques.
- We obtain an accuracy of **93.6%** which surpasses majority of the methods listed in the table.

Discussion

- Despite the mentions of heavy data pre-processing in literature review we find that the model performs better on original data. This shows neural networks do a better job of feature extraction by themselves for better performance and hence we can do away with pre-processing completely.

Method	No. of datapoints	Classes	Accuracy
Ours (augmentation)	627	3	**93.6%**
Ours (augmentation & preprocessing)	627	3	92.4%
Zapata et al	306,302	2	86.3%
Gonzalez-Gonzalo et al	134,421	2	85.9%
Burlina et al	133,821	2	91.6%
Grassmann et al	120,656	13	63.6%
Bhuiyan et al	116,875	4	**96.1%**
Govindaiah et al	116,875	4	86.1%
Ting et al	108,558	2	88.8%
Keenan et al	59,812	2	**96.5%**
Peng et al	59,302	6	67.1%
Keel et al	56,113	2	**96.5%**
Burlina et al	5664	4	79.4%
Phan et al	279	2	87.7%
Kankanahalli et al	2772	3	81.8%
Mookiah et al	784	4	90.2%

Table 1. Classification Results

Method	Accuracy	No. of datapoints	Classes
Ours	**93.6%**	627	3
Burlina et al	79.4%	5664	4
Govindaiah et al	86.1%	116,875	4
Kankanahalli et al	81.8%	2772	3
Mookiah et al	90.2%	784	4
Bhuiyan et al	**96.1%**	116,875	4

Table 2. Classification Results (3 or 4 number of classes)

- The results improved significantly from 88.1% to 93.6% after increasing datapoints through augmentation. Thus we see improvement in accuracy with more data, justifying the requirement of more data to improve our model.
- Since we are facing compute issues for self supervised pretraining (cpc V2 model), we are going to try basic self supervised pretraining i.e. training an autoencoder for the pretrained weights.
- We also need unlabelled AMD data for trying the semi supervised algorithm mentioned in previous report.
- We will try to train segmentation and classification in a multi-task learning setup to observe enhancement in performance once good baseline results are obtained. Compute remains a concern.