Tri-Weekly Report (3/16/22~4/6/22)

Accomplishments

3/16/22~3/30/22

- For the MRI Tumor Image dataset, we applied two image augmentation methods, randomly rotation and horizontal flipping. As we explore the dataset, it is already cropped with its edges. Therefore, no need to crop the image again.
- Retrained SVM models with image augmentation, the results are improving:
  - SVM with PCA accuracy (unweighted):
    - Previously (no image augmentation on 80% variance): 74%
    - Now (with image augmentation on 80% variance, C=3.0, gamma=0.003636364, kernel=RBF): 93.27%
  - SVM with LBP accuracy:
    - Previously (no image augmentation, [8, 1] for LBP's P and R on 100% variance): 88.4%
    - Now (with image augmentation, [16, 2] for LBP's P and R on 100% variance, c=2.0, gamma=0.003597122, kernel=RBF): 92.4%
- Retraining CNN model with image augmentation, results improved with Dense Net 169
  - Pre data augmentation performance: 94%
  - Post data augmentation performance: 97% (3 More correctly classified images)
- Attempted to train a SVM model for FER-2013 dataset. However, it is very time consuming with a one-vs-one approach. Therefore, we utilized a one-vs-rest approach in order to cut down the computation requirement. Ideally, our SVM model should be a one-vs-one approach as the one-vs-rest approach could lead to imbalance problems for a few classes as the paper suggested [1].

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- Current implementation of CNN for FER-2013 dataset performs around 45% through simple CNN's under long computation time (over 1 hour and 30 min).

- Research performed on CNN structures utilized for FER-2013 classification, majority utilizing transfer learning with models such as Resnet yielding performances of 60% ~70%, other papers performing at most 73% accuracy utilizing CNN's only [2], [3].
- Current implementation of SVM for the FER-2013 dataset performs around 40% accuracy through PCA. The LBP version is around 22% accurate.
- Found another paper that utilized the same dataset with SVM classifier; however, they used a combination of Local Intensity Order Pattern (LIOP) and Histogram of Oriented Gradients (HoG) as feature selection method to achieve 63% accuracy [4].

Upcoming Goal

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- Continue training without cross validation SVM for FER-2013 dataset on GPU.
- Continue training CNN models utilizing current run times, optimizing for best model structure and weights
- Continue investigating methodologies for Intel GPU utilizing for CNN model training

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- Continuation to optimize computation times due to requiring more time for transfer learning of the CNN
- Apply similar CNN structures to those of papers performing at 60%+ accuracy, including transfer learning similar to MRI dataset.
- Apply the similar feature selection method as the paper discussed for the SVM for the FER-2013 dataset.

Issue & Barriers

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- Faced an issue of low performance of I/O when mounting Google Drive on Colab. We were able to overcome this by copying the dataset from Google Drive to Colab local machine then load the data through GPU.
- One major issue with the SVM model after moving forward with FER-2013, the next dataset, during spring break is that the cross validation with k-fold takes forever. Then we replaced Grid Search with Random Search so that computation time could be reduced. However, we had no luck with this approach. We tried the implementation of SVM in Nvidia Rapids' cuml library on GPU (with one-vs-rest decision boundary function) but it did not work well as it takes a very long time (more than 2 hours) to compute one fold. Therefore, the last hope could be the HPC.

- When attempting CNN testing for the FER-2013 dataset, while performance improved when transferring from Google Colab, time per epoch is currently 40 seconds/epoch resulting in testing a single fold (20 epochs) to be ~13 minutes resulting in over 1 hour of computation time utilizing CPU utilizing simple CNN structure with 6 layers (Convolution layer_1, Max Pooling layer, Convolution layer_2, Flatten layer, 2 Dense layers)

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- Computation time similar to before prevents multiple attempts at creating and testing CNN structures and weights.

Reference

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[1] Saeeda Saeed, Junaid Baber, Maheen Bakhtyar, Ihsan Ullah, Naveed Sheikh, Imam Dad and Anwar Ali Sanjrani, "Empirical Evaluation of SVM for Facial Expression Recognition" International Journal of Advanced Computer Science and Applications(IJACSA), 9(11), 2018. http://dx.doi.org/10.14569/IJACSA.2018.091195

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[2] Kaggle's Competition on Classification of FER-2013 Dataset https://www.kaggle.com/competitions/challenges-in-representation-learning-facial-expression-recognition-challenge/leaderboard

[3] A. Vulpe-Grigoraşi and O. Grigore, "Convolutional Neural Network Hyperparameters optimization for Facial Emotion Recognition," 2021 12th International Symposium on Advanced Topics in Electrical Engineering (ATEE), 2021, pp. 1-5, doi: 10.1109/ATEE52255.2021.9425073. https://ieeexplore-ieee-org.arktos.nyit.edu/document/9425073

[4] Kalsum, Tehmina et al. 'Localization and Classification of Human Facial Emotions Using Local Intensity Order Pattern and Shape-based Texture Features'. 1 Jan. 2021 : 9311 – 9331.