Leveraging Deep Learning For Emotion Recognition & Detection

Scott Hameed

Springboard Capstone 3

Contents:

Summary (TL;DR)

- This project leverages Deep Learning to recognize and detect human emotions in images
- Human emotions are fundamental to our experience on our planet, as emotions affect everyone around us [1]
- One of the key inspirations for this project came from interacting with people; I realized that my interaction depends heavily on the emotions of the person I am interacting with
- A Convolutional Neural Network (CNN) was trained with multiple parameters to identify emotions in images of humans
- The following parametric tuning was then applied to improve accuracy which resulted in overall accuracy of 63%:
    - Increasing the number of Epochs
    - Decreasing batch sizes
    - Increasing the learning rate
- Future considerations for improving this Neural Network include:
    - Testing Gradient Descent with momentum as the optimizer
    - Testing different Loss functions
    - Updating the convolutional layers with varied parameters
- I am passionate about intelligent systems that can improve the life quality of people
- This project serves as a foundation for an ongoing project to build various computer vision and natural language processing functions that can then be used to create a personal assistant device such as a desktop personal assistant or personal robot
- This desktop assistant/personal robot is meant to be a consumer device to help improve the life quality of its customer

Business Problem

- A key problem in the domain of personal assistant/personal robot is to build a deeper connect with it's customer in a way that it enriches the life of the customer

- Current technology solutions are limited to offering helpful services to their customers but no commercial grade device has emotional support features that are persistent
    - There are however some social companion robots, however, they are focussed only on elder care [1]

- Emotion detection serves as a key component of the intelligence that needs to be persistent within the AI based system to create an emotional connection

- Humans innately use facial emotional expressions to infer emotions of others and this guides them to better interact with others

- Extensive research is being actively performed on the various areas of AI application towards emotion recognition [2]

- This project is a first step in the direction of defining algorithm that can focus on facial expressions to identify emotions

[1]: Carley Thornell. 6 AI innovations for those aging in place (Jul 2022). USA Today (link)
[2]: Anvita Saxena, Ashish Khanna, Deepak Gupta (2020). Emotion Recognition and Detection Methods: A Comprehensive Survey. Journal of Artificial Intelligence and Systems, 2, 53–79. (link)

Scope, Approach, Process, and Libraries

Scope:
- Define vision and approach
- Coding of the CNN
- Parametric optimization
- Report and presentation

Approach:
- Understanding existing research on image based emotion recognition and detection
- Determining the appropriate libraries
- Coding framework
- Optimization approach including variable identification and prioritization

Process:
- Setting up the Linux Ubuntu system (GPU drivers), CUDA, and CUDNN
- Installing the key libraries (See below)
- Coding and related troubleshooting
- Identifying baseline performance
- Leveraging prioritized parameters to tune performance

Libraries
- Tensorflow: Tensorflow is an end-to-end platform to develop and deploy machine learning algorithms
- Keras: an open source library for training and deploying machine learning algorithms
- Numpy: library for arrays and mathematical functions
- Pandas: library for reading, cleansing and analyzing data
- Sklearn: library for data processing and visualization

Neural Network & Algorithm Overview

- Convolutional Neural Network (CNN) was chosen for this project as it is the preferred neural networks for small scale image classification [1]
- CNN progressively extracts higher level representations of image contents
- CNN do not require pre-processing and instead uses raw pixels to derive features and infer the object
- Rectified Linear Units (ReLU) was the activation function used to introduce non-linearity into the model
- Adam Optimizer was used for the CNN as it has proven to be better in terms of general performance and parameters requires less tuning
- Using the Convolutional Neural Network (CNN), facial expressions were predicted with an accuracy of 61.7 percent

[1]: Mingxing Tan and Zihang Dai. Toward Fast and Accurate Neural Networks for Image Recognition (Sept ‘21). Google Research Blog (link)
[2] Akash Ajagekar, Wiki Entry. (Fall ‘21). Cornell University Computational Optimization Open Textbook (link)

Dataset Overview

- The data used is from the Kaggle FER2013 collection which has approx 35,9K 48x48 grayscale photos

- The faces in the photos are centered and roughly occupy the same amount of space in each image

- Each of the photos from the dataset represents one of the following emotions :
  - Anger
  - Disgust
  - Fear
  - Happy
  - Neutral
  - Sadness
  - Surprise

CNN & Algorithm Performance Summary (1 of 2)

- The baseline CNN using Adam optimizer performance is 56.9%

- The CNN using SGD optimizer performance is 33.5%

- Due to decreased SGD performance, the Adam Optimizer was selected and then further optimized using parametric tuning

- The Adam Optimizer CNN with highest achieved accuracy is 61,7% which is a 8.4% improvement compared to baseline of 56.9%

- The highest performing CNN has the following key parameters:
  - Batch Size = 16
  - Epoch = 60
  - Learning Rate = 0.0002

- **Optimization process key insights**
  - Increasing Epochs from 30 to 75 resulted in accuracy improvements, however, 60 is the max Epoch at which loss rates do not improve
  - Decreasing batch sizes resulted in accuracy improvements; we began with 64 and determined 16 is optimal
  - Adam Learning Rate accuracy is optimal when increased from 0.0001 to 0.0002. However, increasing further results in degradation

CNN & Algorithm Performance Summary (2 of 2)

Base Adam Model Performance Epochs:30, Batches :64, LR: 0.0001. Accuracy: 56.0%

	precision	recall	f1-score	support
0	0.469	0.463	0.466	501
1	0.000	0.000	0.000	45
2	0.336	0.075	0.123	477
3	0.754	0.872	0.809	921
4	0.405	0.582	0.477	617
5	0.791	0.586	0.673	406
6	0.510	0.601	0.552	622
accuracy			0.569	3589
macro avg	0.466	0.454	0.443	3589
weighted avg	0.551	0.569	0.543	3589

Optimization: Epochs Increased From 30-75 Accuracy: 60.7%

	precision	recall	f1-score	support
0	0.524	0.499	0.511	501
1	0.000	0.000	0.000	45
2	0.462	0.191	0.270	477
3	0.818	0.878	0.847	921
4	0.460	0.478	0.469	617
5	0.762	0.677	0.717	406
6	0.496	0.736	0.593	622
accuracy			0.607	3589
macro avg	0.503	0.494	0.487	3589
weighted avg	0.596	0.607	0.589	3589

Optimization: Batches Decreased From 64 To 16. Accuracy: 61.1%

	precision	recall	f1-score	support
0	0.543	0.491	0.516	501
1	0.667	0.044	0.083	45
2	0.471	0.241	0.319	477
3	0.817	0.848	0.832	921
4	0.501	0.464	0.481	617
5	0.634	0.798	0.707	406
6	0.517	0.707	0.597	622
accuracy			0.611	3589
macro avg	0.593	0.513	0.505	3589
weighted avg	0.604	0.611	0.595	3589

Optimization: LR Increased From 0.0001 to 0.0002. Accuracy: 61.7%

	precision	recall	f1-score	support
0	0.542	0.507	0.524	501
1	0.500	0.022	0.043	45
2	0.472	0.210	0.290	477
3	0.842	0.860	0.851	921
4	0.465	0.499	0.482	617
5	0.719	0.744	0.731	406
6	0.520	0.738	0.610	622
accuracy			0.617	3589
macro avg	0.580	0.511	0.504	3589
weighted avg	0.612	0.617	0.602	3589

Code Overview

- Code has 859 lines in a single Python File and also an associated Jupyter notebook
- Code has five main sections::
    1. **Libraries**
    2. **Data Processing & Setup**
    3. **CNN Model Setup**
    4. **Model Performance, Benchmarking, and Optimization**

- The explanation for each of the four code sections is shared in the next slides

Code Overview: 1. Libraries

- **Tensorflow:** Tensorflow is an end-to-end platform to develop and deploy machine learning algorithms
- **Keras:** an open source library for training and deploying machine learning algorithms
- **Numpy:** library for arrays and mathematical functions
- **Pandas:** library for reading, cleansing and analyzing data
- **Sklearn:** library for data processing and visualization

Code Overview: 2. Data Processing & Setup

- The data used is from the Kaggle FER2013 collection which has 35887 48x48 grayscale labeled emotion photos
- Below is the chart showing the data distribution by label:

- The data was split into approximately following subsets:
  - Training: ~80%
  - Test: ~10%
  - Validation: ~10%

```
(29068, 48, 48, 1)
(3589, 48, 48, 1)
(3230, 48, 48, 1)
```

Code Overview: 3. CNN Model Setup

- The Emotion Recognition and Detection CNN is composed of the following types of layers including their counts:

Layer Type	**Overview**	**Count**
Convolutional 2D layer	Performs convolution through scalar multiplication of inputs and weights	6
Batch Normalization	Layer to normalize data between layers using mini batches to speed up training	7
Max Pooling Layer	Takes the max values from batch input and summarizes into a feature map	5
Dropout	Masking layer that nullifies the contribution of some neurons towards the next layer to prevent overfitting	7
Dense	It is the network layer that takes input from all neurons in preceding layer and passing it as input to the next layer	3
Flatten	This layer takes the multiple pooled feature maps and and flattens it into a long vector	1

- Below is the parameter summary for the baseline Convolutional Neural Network (CNN)

```
=================================
Total params: 5,810,183
Trainable params: 5,805,191
Non-trainable params: 4,992
_________________________________
```

Code Overview: 4. Model Performance, Benchmarking, and Optimization

- Code runs the CNN Adam model and computes the training and validation accuracy, loss, and confusion matrix
- We then build a Stochastic Gradient Descent Optimization model leveraging the same parameters as the CNN
- Code runs the SGD Model and computes the training and validation accuracy and loss
- We then apply parametric based changes to further optimize the Adam based CNN. Below is the list:
    - Increasing Epochs from 30 to 50
    - Increasing Epochs from 50 to 75
    - Decreasing Batch Size from 64 to 32
    - Decreasing Batch Size from 32 to 16
    - Decreasing Batch Size from 16 to 8
    - Increasing Adam Learning Rate from 0.0001 to 0.0002
    - Increasing Adam Learning Rate from 0.0001 to 0.0009
    - Increasing Adam Learning Rate from 0.0001 to 0.001
    - Increasing Adam Learning Rate from 0.0001 to 0.002

Key Challenges & Learnings For Future

Key Challenges:

- GPU based acceleration ran into several issues:
  - GPU identification by Ubuntu ran into issues due to driver incompatibilities and lack of clear documentation
  - Tensorflow GPU installation using both Nvidia and Tensorflow installations had gaps and resulted in failure to correctly install
  - Even after resolution of Tensorflow-GPU issues using Conda install, Tensorflow caused severe issues resulting in extremely low accuracy of the neural network (~20%)
- The workaround for Tensorflow-GPU issues was to choose the Non-GPU version of Tensorflow, however, due to significant other issues around Ubuntu/Tensorflow, the recommended approach was to use a new system
- Macbook M1 (ARM) was then used to replace the Ubuntu Desktop
- Despite the relatively new nature of Tensroflow on M1 (ARM), it performed well on the Mac but the CNN training time significantly increased

Key Learnings For Future :

- It’s critical to not continue investing time into a systems problem that continues to worsen over time (cut losses)
- Always be willing to change an OS/system in sticky situations including using online compute (Colab et al)
- The Ubuntu system is being replaced as it has caused many issues and there is a high probability that these would continue despite clean installs

Future Enhancements & Optimizations

- Implement video camera frame capture to test and validate emotions
- Leverage Gradient Descent with Momentum for further optimization
- Experiment with other Loss Functions especially Dice Coefficient
- Update parameters for the Convolution layers
- Leverage other larger datasets for emotions

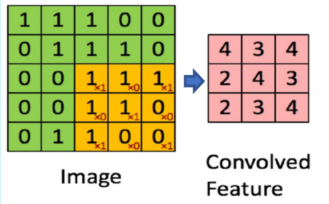
Project Resources

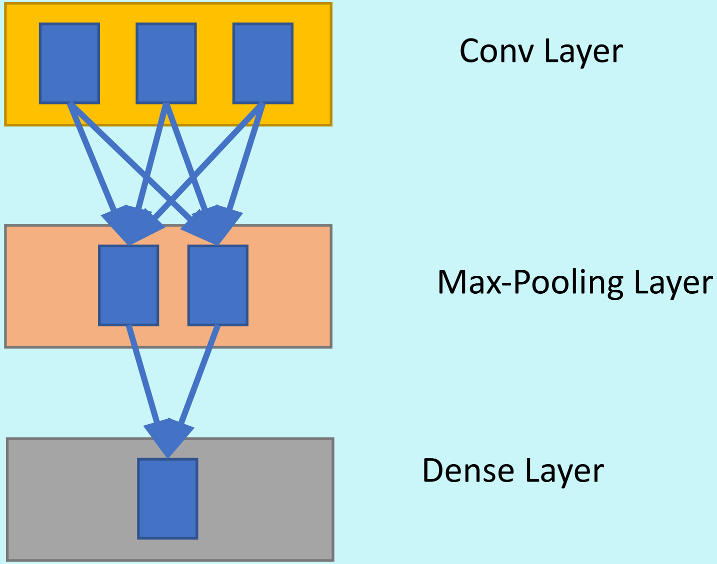
Project Resources

- Github repository homepage (Link)
- Jupyter Notebook (Link)
- Python code file (Link)
- Project report (Link)

Appendix: CNN Visualized

CNN Visualized (1 of 2)





[1]: Mingxing Tan and Zihang Dai. Toward Fast and Accurate Neural Networks for Image Recognition (Sept 2021). Google Research Blog (link)

CNN Visualized (2 of 2)