Personality recognition of images using EmotionGCN

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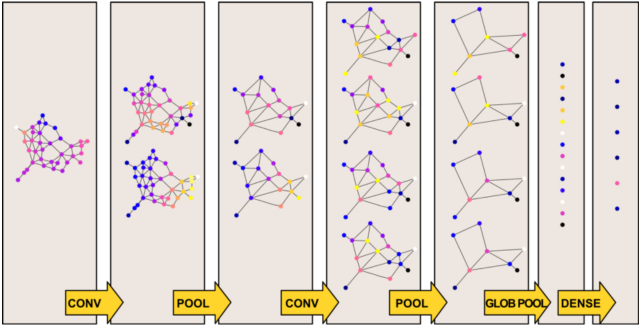

Figure: A GCN layer takes the node representation and the adjacency matrix as the input and outputs the new node presentation after the convolution operation on the graph.
Image-ref:
https://towardsdatascience.com/graph-convolutional-networks-deep-99d7fee5706f

Challenges faced

Facial Emotion detection - Personality recognition

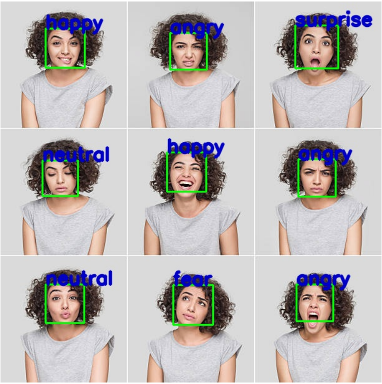

Figure: The state-of-the-art CNN algorithm modelled with limited number of classes of image is difficult to identify a particular emotion clearly as there are correlations between multiple human emotions which are difficult to identify in one go.

Challenges faced

State of the art CNN network for peronality recognition

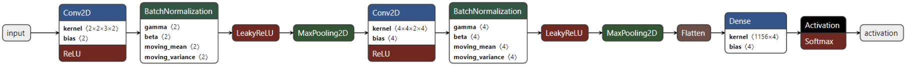

Figure: The traditional CNN network used for image emotion (personality) recognition has multiple layers and The number of layers in CNN should be high to get better performance, which requires high computational cost. Hence, it is also difficult to fine tune for a specific application.

Proposed Method

Single layer graph convolutional network

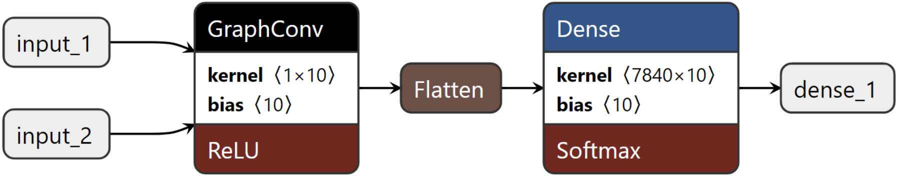

Figure: The graph extracted from the emotion dataset image pixels is converted to a sparse adjacency matrix and then feed to the graph convolutional layer. From this the final weight matrix $\mathrm{W} = \mathcal{G}\,(\mathrm{W}_p,\ \mathrm{g})$ can be determined. Then these weights are normalized by flattening it. finally, the distribution can be obtained by feeding the normalized weights to a dense layer $\hat{y} = \mathrm{Softmax}\,(\mathrm{W} \otimes \mathrm{f}_i)$ to get the distribution. This method considers only 4 classes of emotion, such as angry, happy, sad, surprise.

EmotionCNN model

Ground truth distribution

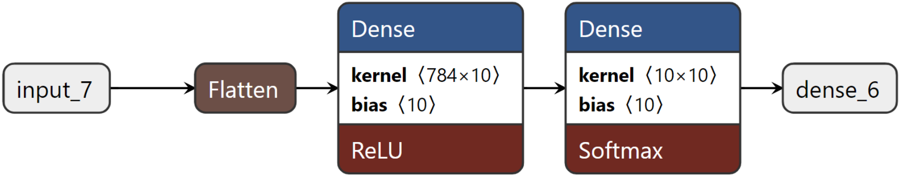

Figure: After finding the distribution, the comparison will be done with the ground truth distribution. Here, the output of fully connected CNN with 2 dense layers is considered as the ground truth.

EmotionGCN model

Multi layer graph convolutional network

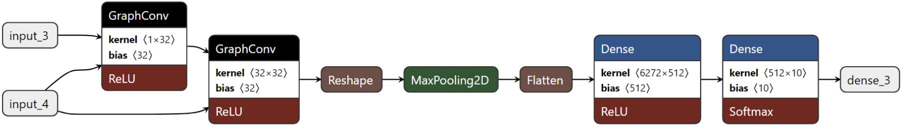

Figure: The performance of the model increases by increasing the the number of GCN layers with normalization of weight matrix obtained. Or better fitting is possible by training each emotion with a single layer GCN network. The common form of operation in GCN layer is $f\left(\mathrm{H}^{(l)}, \mathrm{A}\right) = \sigma\left(\mathrm{AH}^{(l)}\mathrm{W}^{(l)}\right)$. For a two layer GCN with softmax output, the resulting function will be $Z = \text{Softmax}\left(\widetilde{A}\sigma\left(\widetilde{A}XW^{(0)}\right)W^{(1)}\right)$. Where, $\widetilde{A}$ is the normalized adjacent matrix $\hat{\mathrm{D}}^{-\frac{1}{2}}\hat{\mathrm{A}}\hat{\mathrm{D}}^{-\frac{1}{2}}$.

Implementation

Pixels to graph conversion for classes 1 and 2

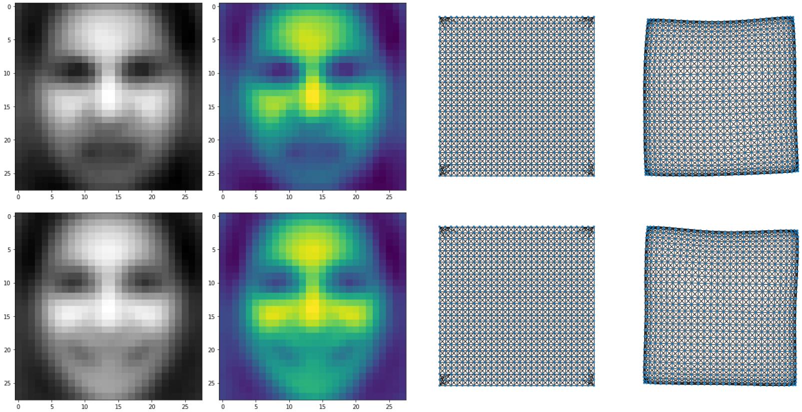

Figure: Sample images of 'anger' and 'happy' classes converted to graphs with number of nodes 784 and number of edges 3198 each, and these graphs should be non-directed and there shouldn't be self loops.

Implementation

Pixels to graph conversion for classes 3 and 4

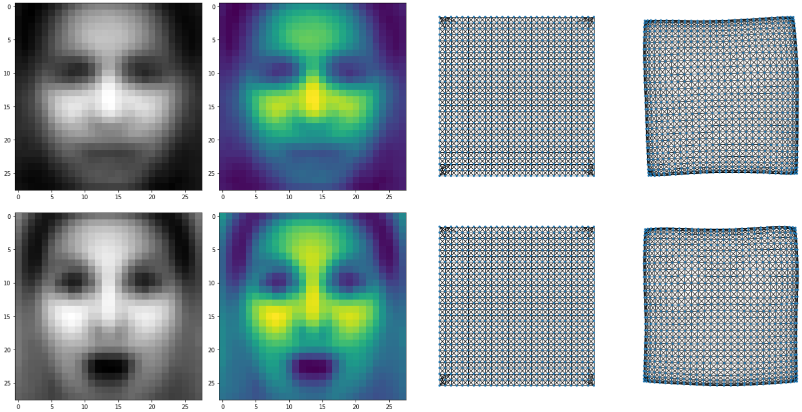

Figure: Sample images of 'sad' and 'surprise' classes converted to graphs with number of nodes 784 and number of edges 3198 each, and these graphs of 4 classes will be fed to the GCN.

Implementations

Distributions of class 1 and 2

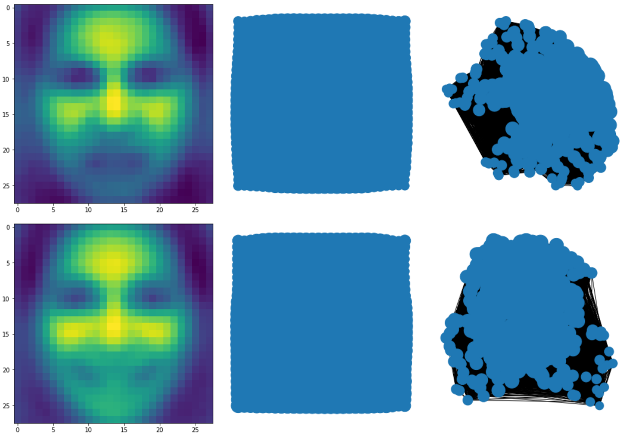

Figure: The final graph distribution of emotions formed by the training of class 'angry' and class 'happy' respectively.

Distributions of class 3 and 4

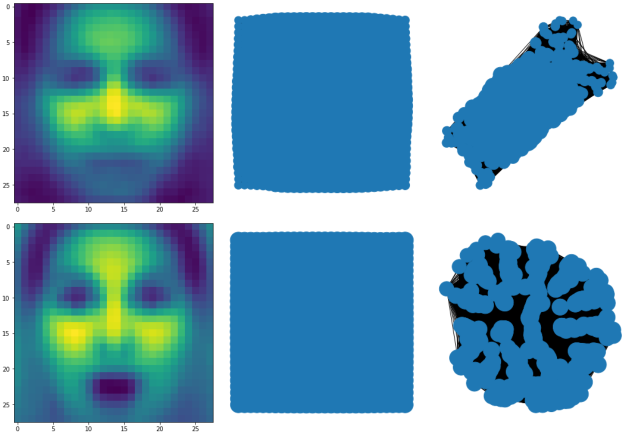

Figure: The emotion correlation graph distribution formed by the training of class 'sad' and class 'surprise' respectively, considering the coordinate matrix and pairwise distance.

Implementations

Distributions of class 3 and 4

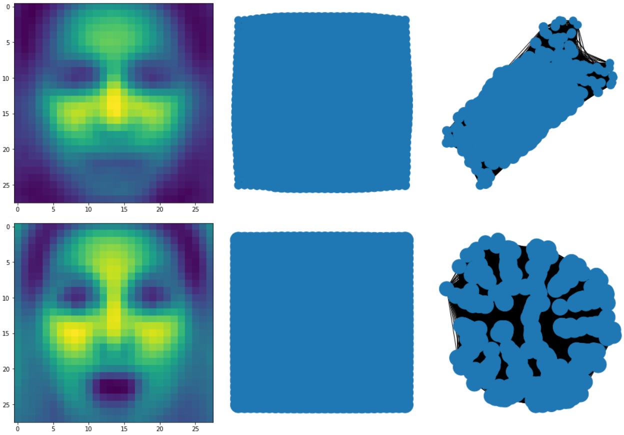

Figure: The emotion correlation graph distribution formed by the training of class 'sad' and class 'surprise' respectively, considering the coordinate matrix and pairwise distance.

Observations

Emotion wheel	Correlation graph edges	Emotion efficiency
Angry	250706	0.4496240601503759
Happy	267144	0.5168
Sad	242263	0.4047244094488189
Surprise	300470	0.7196850393700788

Table: Performance of GCN in emotion wheel

Performance metrics

Confusion matrix for personality recognition using CNN

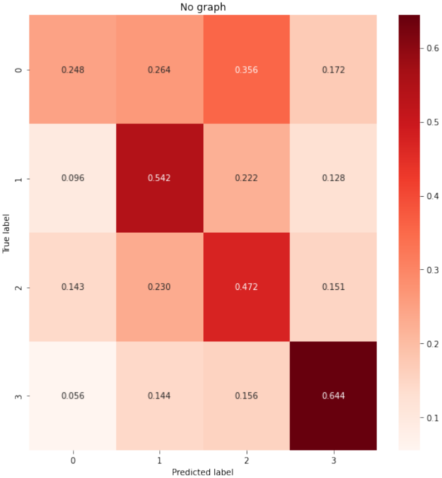

Figure: 0 - angry; 1 - happy; 2 - sad; 3 - surprise

Performance metrics

Confusion matrix for personality recognition using GCN

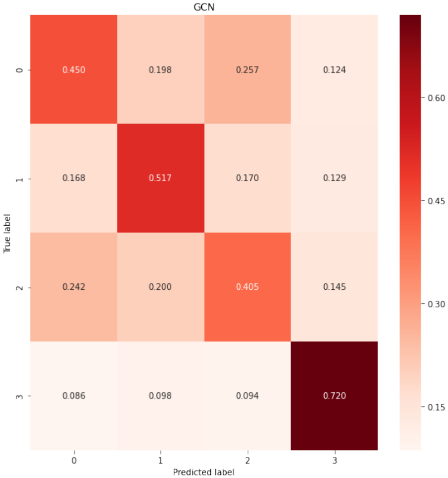

Figure: 0 - angry; 1 - happy; 2 - sad; 3 - surprise