CM50265 - Group 1 - Cover Page

`Contribution grid submitted individually via Moodle and omitted from report.`

Model Links	
Model A	https://drive.google.com/file/d/1MaIDjs3kznC8Wxq9RpixRH_Bz4_IiXcl/view?usp=sharing
Model B	https://drive.google.com/file/d/1BuZmakWXkTTTTiMnITJOY3AWKmgM2fAO/view?usp=sharing
Notebook	https://colab.research.google.com/drive/1rFKfHzzp0lgjYBCbP1GG0Ttn77acamw2?usp=sharing

CM50265 - Assignment 1 - Group 1 Report

Age Estimation and Gender Classification CNN

Daniel Davis, James Whiffing

March 20, 2022

Contents

List of Figures

List of Tables

1 Our Model

1.1 Architecture

Our model architecture is shown in Fig **??**. It consists of a shared trunk with two convolutional layers with 64 3x3 kernels and relu activation followed by a 2x2 maxpooling layer and a batch-norm layer. It then has a convolutional layer with 128 3x3 kernels followed by a 2x2 maxpooling layer. The output of this trunk is sent to different branches for age and gender prediction. The age and gender branches have the same architecture except for the number of filters in their final convodlutional layers. Each branch has two convolutional-maxpooling-batchnorm blocks, the first with 64 3x3 convolutional filters and the second with 128 2x2 filters. They are then followed by another convolutional layer of 64 2x2 filters for gender and 128 2x2 filters for age. The output of this convolutional layer is then falttened and fed into a 3 layer dense MLP. The first layer has 128 node, the second 16 and the final layer is a single node for the output. The first and second layers use relu activation and the final layer uses no activation for age prediction and a sigmoid activation for gender prediction.

This architecture was chosen because the first layers of a CNN usually extract generic low-level features which are common to many images. Therefore using a shared trunk allows the network to use fewer parameters and helps reduce overffitting. The branches then allow the model to further extract higher level features specific to age or gender prediction. The batchnorm layers help to reduce overfitting. The dense layers also employ dropout and L2 regularisation to reduce overffitting. The dropout rate, regulartisation factor and the size of the final convolutional layer in the branches were chosen using hyperparameter tuning with keras.tuner.

1.2 Training

The model is trained to minimize a weighted average of losses from each branch. The loss for the gender prediction output is binary cross entropy because it is a binary classification problem and the loss for the age prediction is mean squared error because it is a regression problem. Mean squared error was chosen over mean absolute error in order to punish large errors more. than small ones. The average loss is weighted 1:50 towards gender prediction because the average gender losses seen during training were approximately 50 times smaller than the age losses. This weighitng was chosen so the model attempts to balance its training objectives without over-prioritising either age or gender. The model uses the Adam optimizer with a exponentially decaying learning rate.

The model is trained for 50 epochs but saves the weights from the epoch with the lowest validation loss. This is effectively using early stopping as a means to avoid overfitting.

1.3 Data

The model is trained on data from the training data provided. The training data is fed into the model using keras data generators. These generators split the data into a training and validation set using a validation split of 0.2. Data augmentation is performed to effectively increase the size of the dataset and prevent overfitting. The augmentations used are rotaion, zoom, and horizontal flipping. The augmentations were performed on both training and validation data.

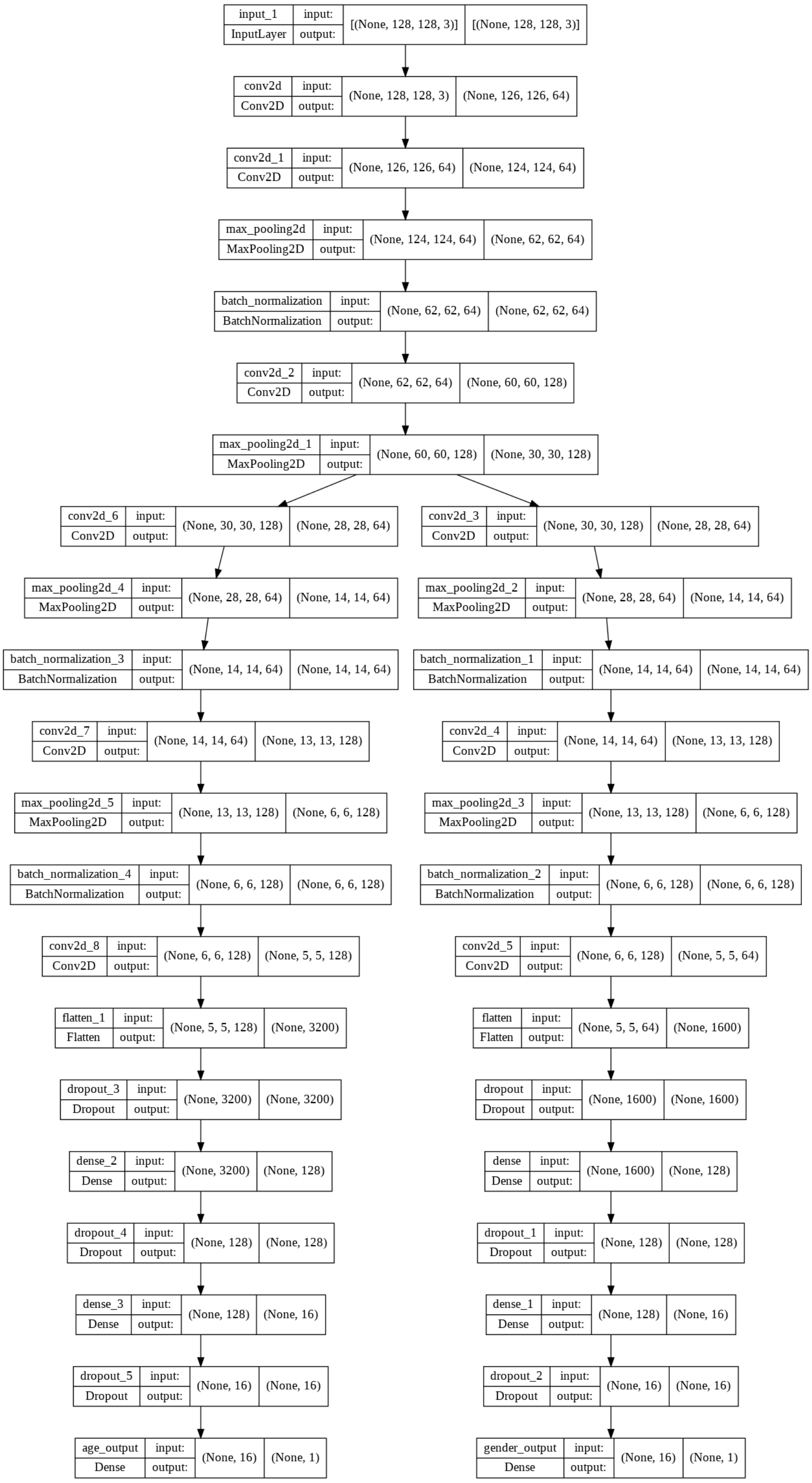


Figure 1: The architecture for our model.

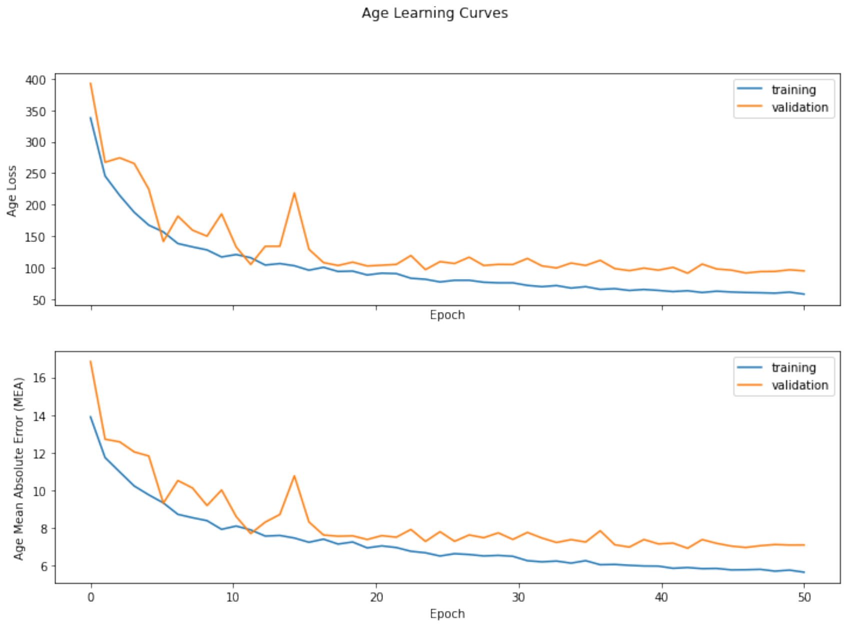


Figure 2: The performance on age predicition for our model.

1.4 Performance

The output of the final training epoch is below.

```
    Epoch 50/50
125/125 [==============================] - 41s 325ms/step - loss: 82.5588
- age_output_loss: 55.1034
- gender_output_loss: 0.1627
- age_output_mean_absolute_error: 5.5780
- gender_output_binary_accuracy: 0.9330
- val_loss: 131.3783
- val_age_output_loss: 90.0434
- val_gender_output_loss: 0.3111
- val_age_output_mean_absolute_error: 6.8350
- val_gender_output_binary_accuracy: 0.8821
```

Fig **??** and **??** show the training graphs. Our model shows good performance on both age and gender prediction. It achieves an accuracy of 93% for gender prediction and a mean absolute error of 5.6 for age prediction on the training data. However it can be seen that the model overfits slightly and achieves slightly lower performance on the validation data, with an accuracy or 88% for gender prediction and mean absolute error of 6.8 for age prediction. The gender branch can be seen to overfit to a greater extent than the age branch.

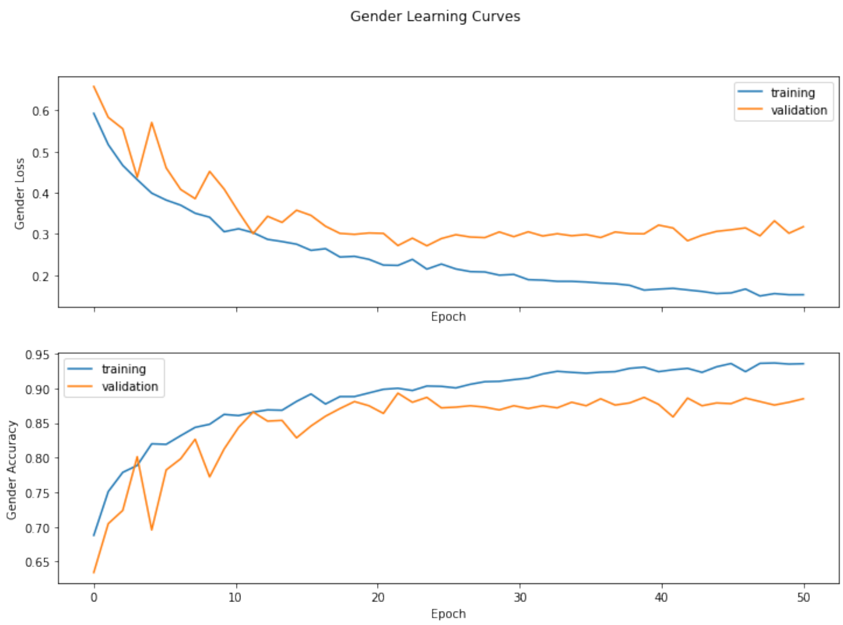


Figure 3: The performance on gender predicition for our model.

ModelB_AgeLearning_TunedHyperParams.png

Figure 4: The performance on age predicition for the finetuned model.

2 Pre-trained Model

2.1 Architecture

For our finetuned model we used ResNet50 as our base. This is because it is a relatively fast, lightweight and high performing model. We used weights trained on imagenet as our initialisation. The output of this base model was fed into a global average pooling layer and then a branch for each age and gender. Both branches used the same architecture as the dense layers in our model.

2.2 Training

The finetuned model was trained in the same manner as our model, with the same losses, loss weights, learning rate and optimizer. The model had a tendency to overfit quickly during training so we used early stopping to halt training once the validation loss increased for three consecutive epochs.

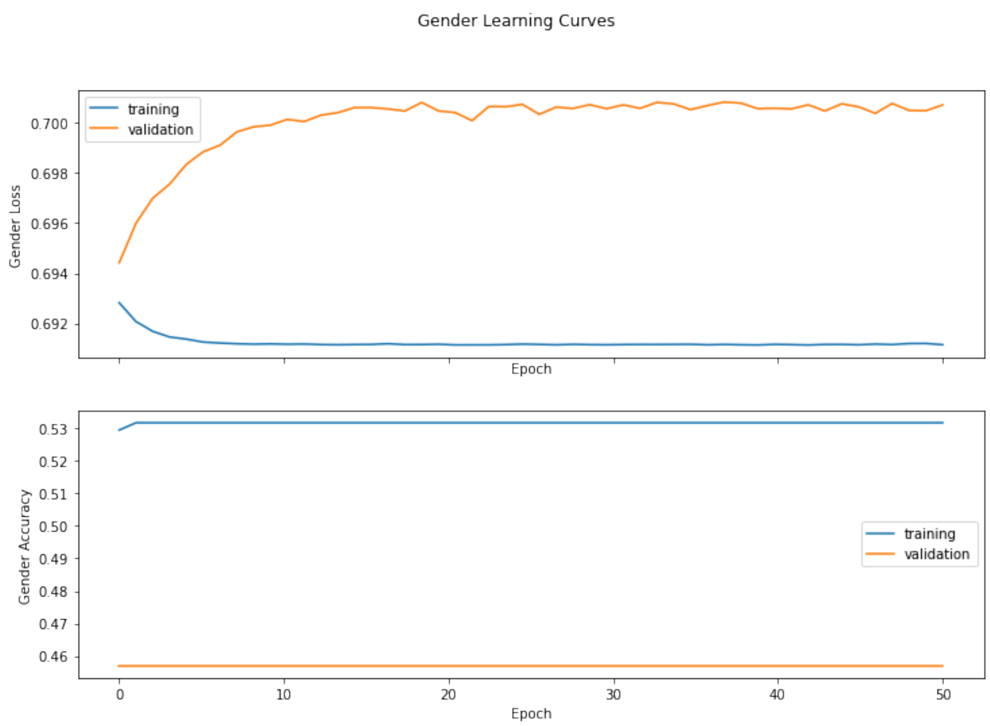
2.3 Performance

ModelB_GenderLearning_TunedHyperParams.png

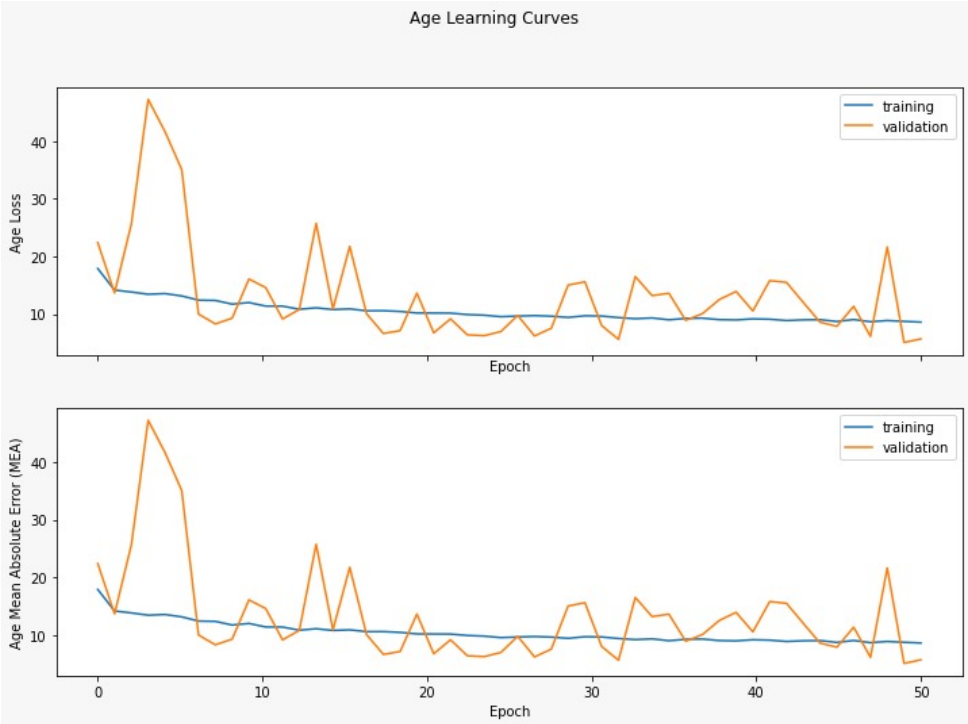
Figure 5: The performance on gender predicition for the finetuned model.

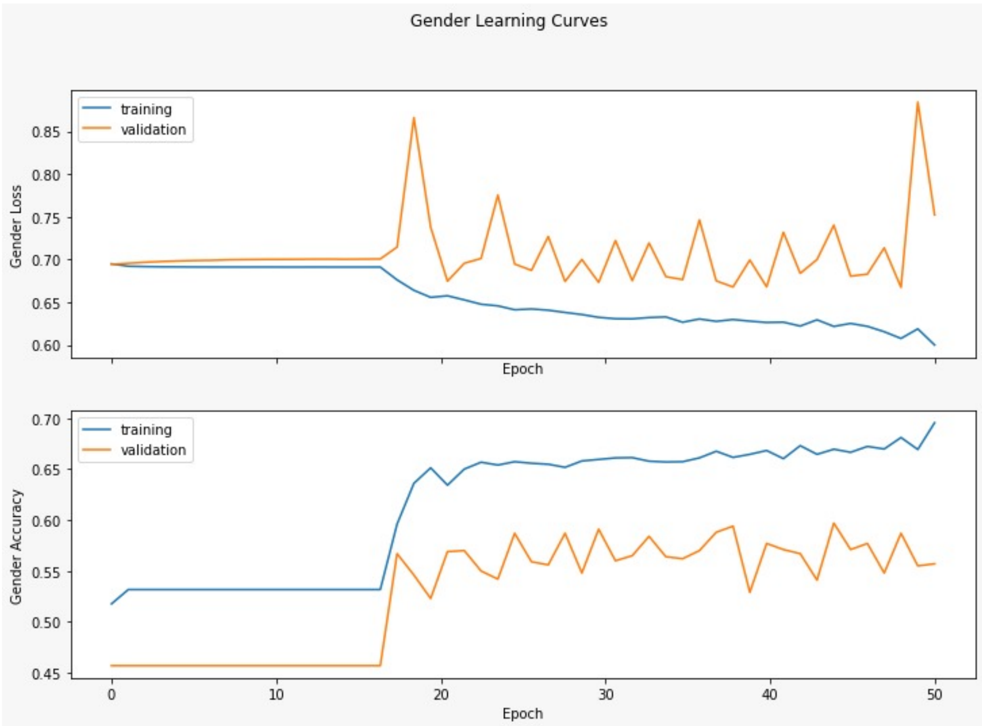
Model A Learning Curves - Greyscale Comparison

Greyscale Applied To Gender & Age Branches

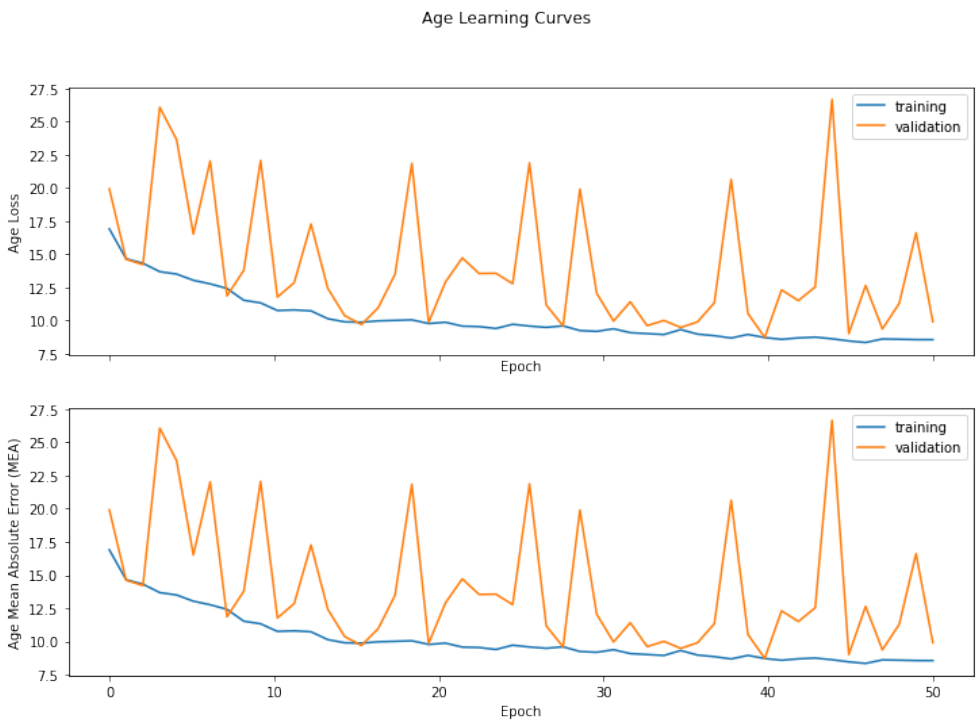


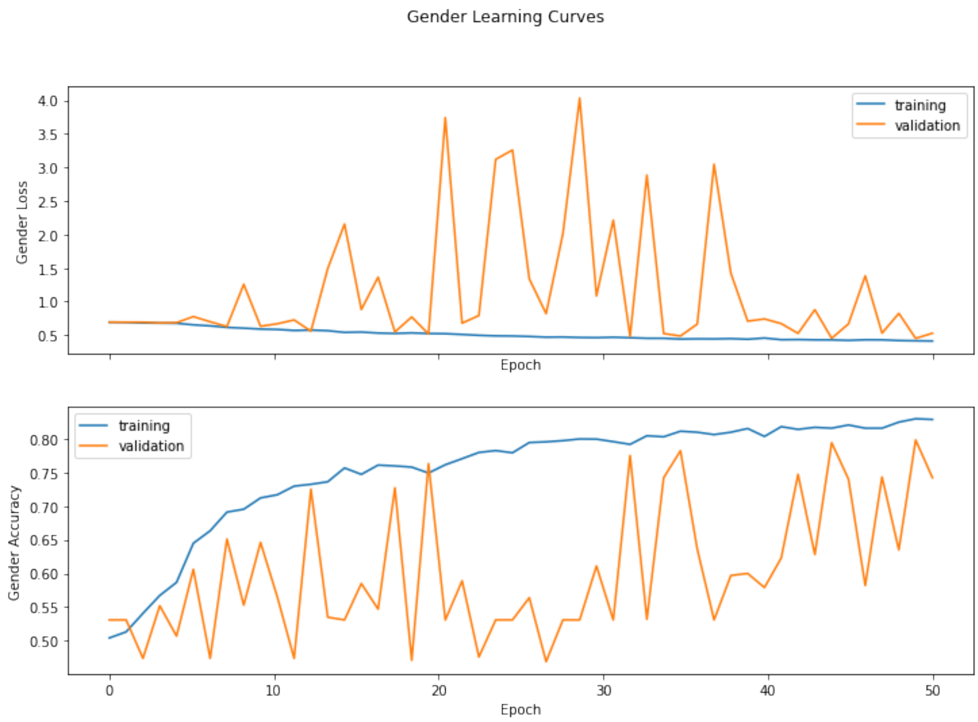
Greyscale Applied To Neither Branch





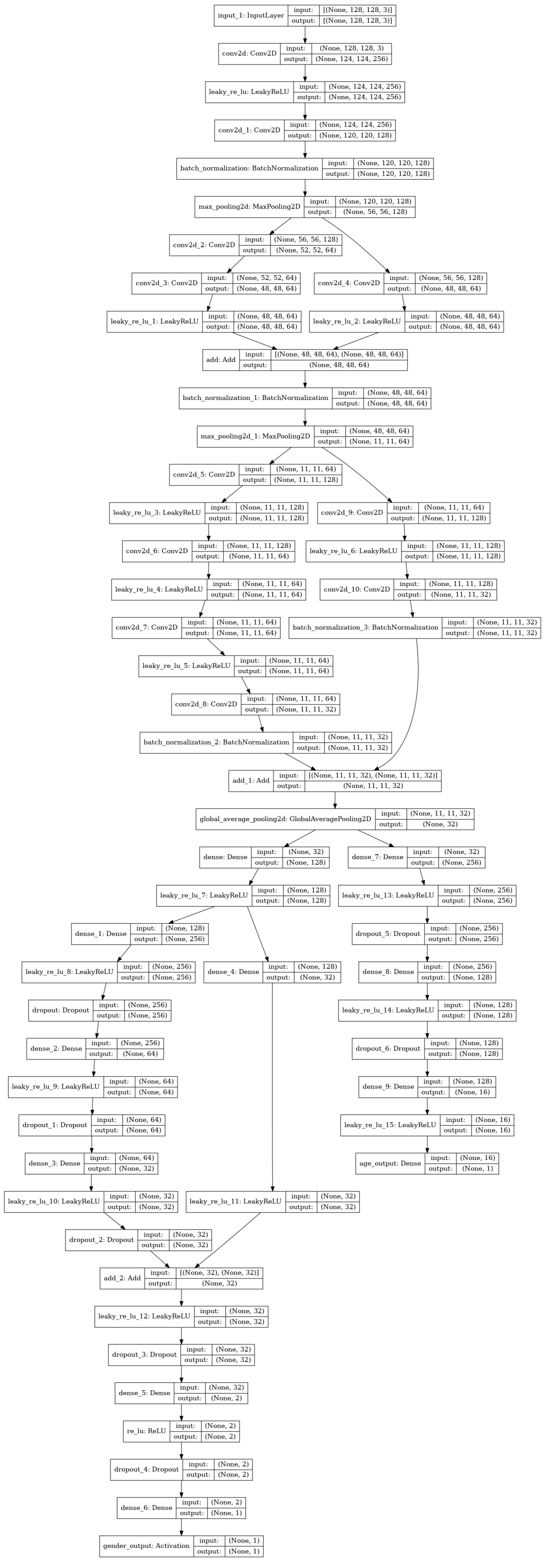
Greyscale Applied To Gender Branch Only



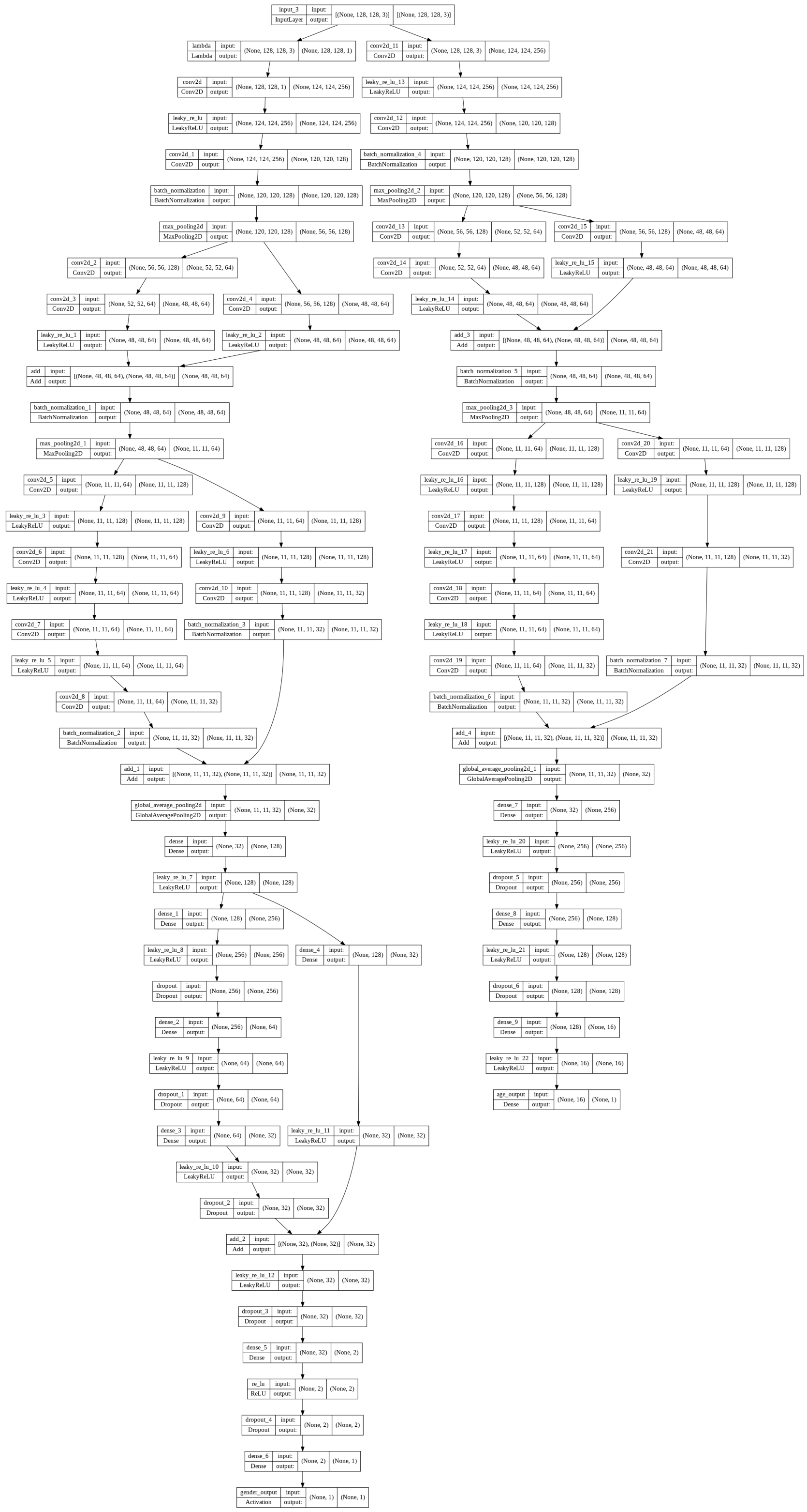


Original Model A Graphs

No Greyscale



Greyscale Applied To Gender Branch Only



Greyscale Applied To Both Branches