Bone Age Prediction

Individual Report

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1. Introduction

A bone age study helps doctors estimate the maturity of a child's skeletal system. It's usually done by taking a single X-ray of the left wrist, hand, and fingers. It is a safe and painless procedure that uses a small amount of radiation. A child's bone age (also called the skeletal age) is assigned by determining which of the standard X-ray images in the atlas most closely match the appearance of the child's bones on the X-ray. A difference between a child's bone age and his or her chronological age might indicate a growth problem

The bone age study can help evaluate how fast or slowly a child's skeleton is maturing, which can help doctors diagnose conditions delay or accelerate physical growth and development. This test is usually ordered by pediatricians or pediatric endocrinologists

2. Individual Work

The Individual work I have done for this project can be categorized into the following.

- Data preprocessing
- Data visualization
- Built 2 models, model 1(Simple MLP model) and model 2 (CNN model)

2.1 Data preprocessing

I have used CV2 to resize all the images to 50*50. I used image data generator to generate more images. The number of training images before using data generator were 10088 and I generated 20,176 using image data generator (Doubled the training images using image data generator). The following parameters were used in image data generator.

rotation_range=20,

width_shift_range=0.2,

height_shift_range=0.2,

zoom_range=0.3,

horizontal_flip=True,

brightness_range=[0.5, 1]

2.2 Data Visualization

The csv file contained the gender of the child along with their bone age, so I visualized the data to get a better understanding.

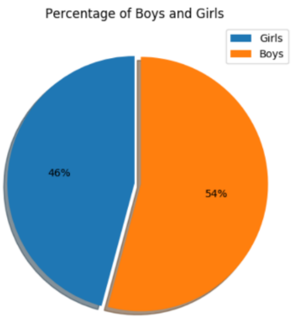


Figure 1.1

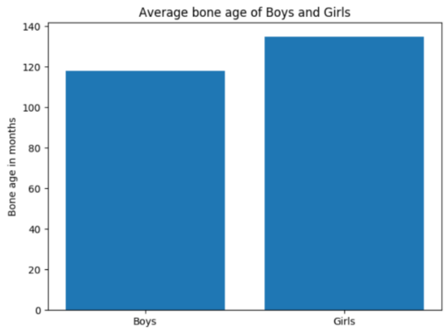


Figure1.2

From figure 1.1 we can observe that the total number of boys and girls in the dataset are almost equal. Figure 1.2 depicts the average bone age of boys and girls it was observed that the average bone age of girls was around 138 month and the average bone age of boys was 118 months.

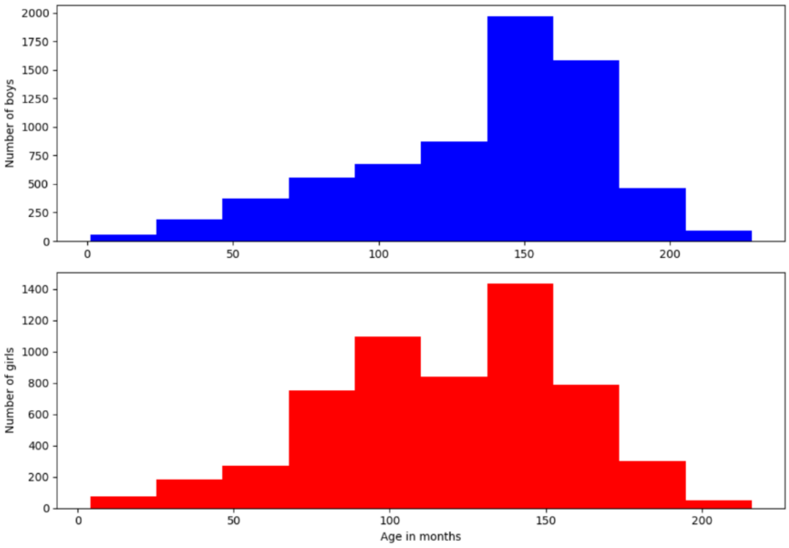


Figure 1.3

Figure 1.3 demonstrates the number of observations for each bone age for both girls and boys. It was seen that for boys bone age of 150 months had the highest number of observations (1900), It was the same case with girls as well bone age of 150 months had the highest number of observations (1300). For girls we had the least number of observations for bone age of 200 months while for boys it was 225 months.

2.3 Data Modelling

I have built 2 models in this project. The 1st model is a simple MLP, while the 2nd is a CNN Model. Since I am trying to predict the bone age which is a continuous value I have used Mean squared error and Mean absolute error as our metrics to evaluate the model.

Model 1 Architecture:

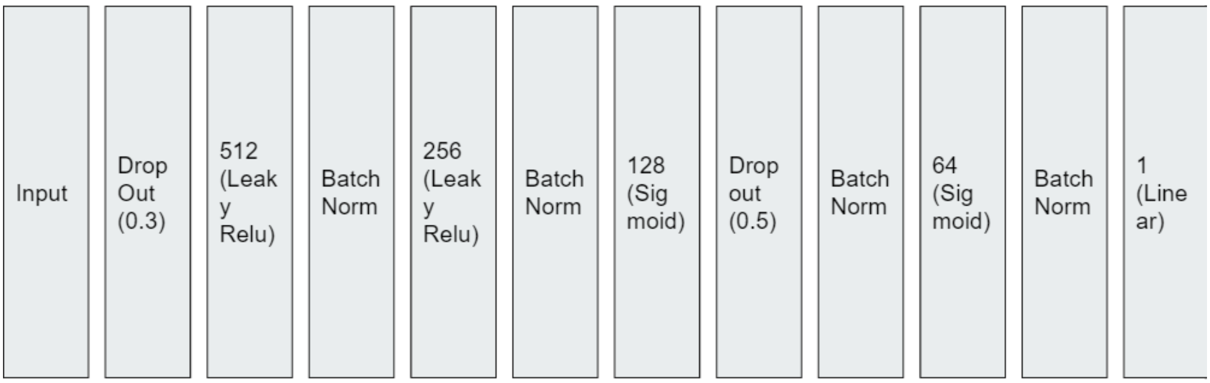


Figure 2.1

Figure 2.1 describes the simple MLP model's architecture. I have used a dropout in the 1st layer and 7th layer. There is a batch normalization layer in 3,5,8 & 10. Layers 2 & 4 have 512 and 256 neurons respectively and they have Leaky Relu as the activation function. I have used Laeky relu to overcome the dead activation problem in Relu. Layer 6 & 9 have 128 and 64 neurons with Sigmoid as the actication unit and the last layer is a linear layer with 1 neuron as the target is a continuous value.

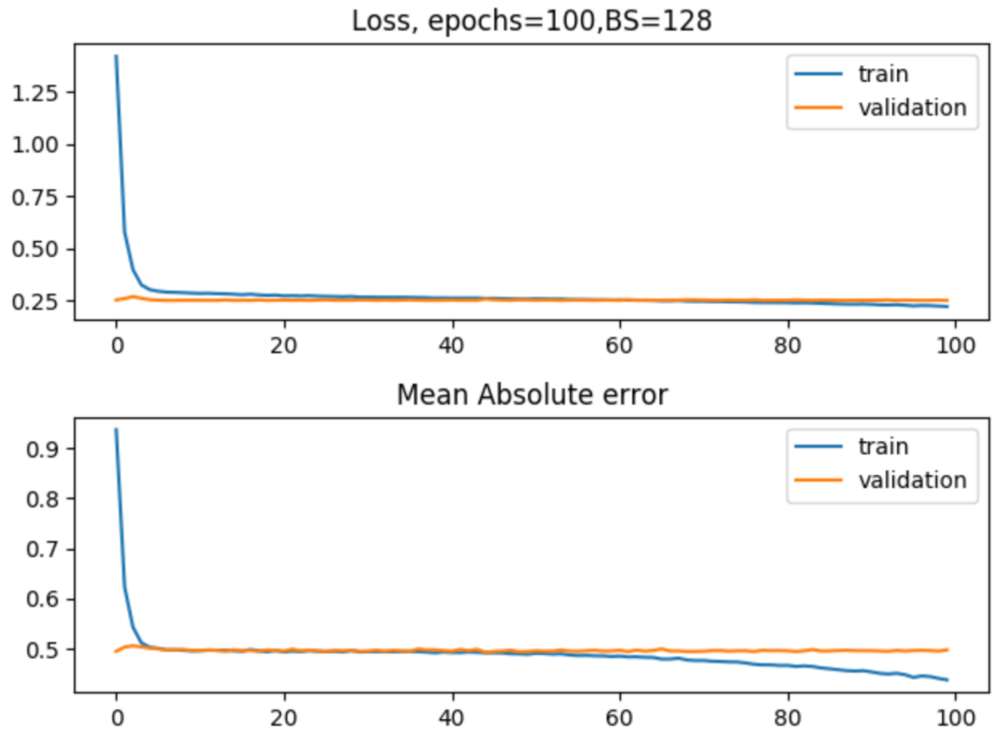


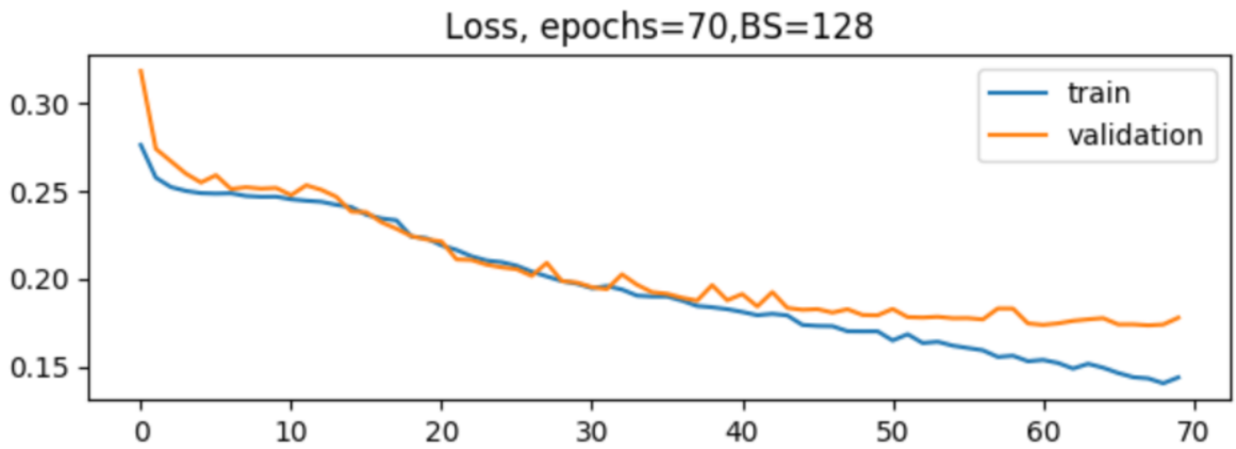
Figure 2.2

Figure 2.2 shows that the training loss and Mean absolute error were almost constant which indicates that this model is not good enough to solve the problem. To have better results I used a CNN model next.

Model 2 Architecture:

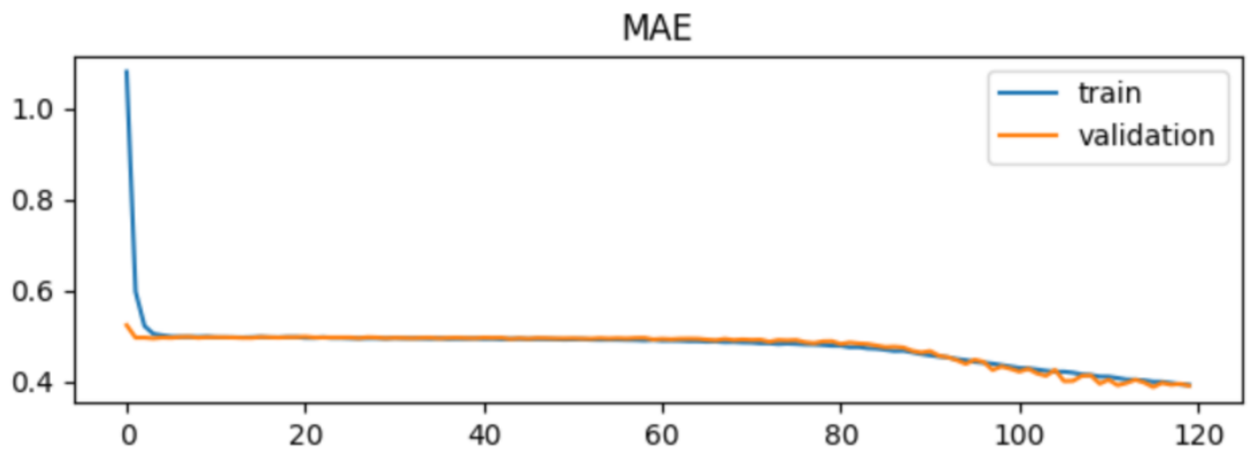
Layer (type)	Output Shape	Param #
conv2d_7 (Conv2D)	(None, 50, 50, 32)	896
conv2d_8 (Conv2D)	(None, 48, 48, 32)	9248
max_pooling2d_4 (MaxPooling2	(None, 24, 24, 32)	0
dropout_7 (Dropout)	(None, 24, 24, 32)	0
conv2d_9 (Conv2D)	(None, 24, 24, 64)	18496
conv2d_10 (Conv2D)	(None, 22, 22, 64)	36928
max_pooling2d_5 (MaxPooling2	(None, 11, 11, 64)	0
dropout_8 (Dropout)	(None, 11, 11, 64)	0
conv2d_11 (Conv2D)	(None, 11, 11, 128)	73856
conv2d_12 (Conv2D)	(None, 9, 9, 128)	147584
max_pooling2d_6 (MaxPooling2	(None, 4, 4, 128)	0
dropout_9 (Dropout)	(None, 4, 4, 128)	0
flatten_3 (Flatten)	(None, 2048)	0
dense_8 (Dense)	(None, 512)	1049088
dropout_10 (Dropout)	(None, 512)	0
dense_9 (Dense)	(None, 1)	513

The model 2 architecture is more robust than that of the model 1 architecture, as we can see there are more number of layers and also this model was trained for larger number of epochs. A total of 16 layers were used in the CNN model. This model has more number of dropout layers compared to the simple MLP model. Also, there are three max-pooling layers in layer 3,7 & 11 respectively. The drop out layers were placed immediately after the max-pooling layers at 4,8 & 12 respectively. The CNN model results seem to be more reliable.



Number of epochs

From the figure above we can clearly see that the validation loss is decreased as the number of epochs increased also. The validation loss decreases as the training loss decreases, this is a good indication that this CNN model is learning well.



Number of epochs

We can also see that the validation Mean absolute error also starts to coincide with the training mean absolute error as the number of epochs were increased.

3. Results

- The best model I have obtained is the CNN model. The CNN model has a validation loss of 0.17, validation MAE of 0.34 and validation MSE of 0.18
- The least performed model as expected was model 1 (the simple MLP model)

4. Summary & Conclusions

- The custom-built Convolutional Neural Network worked quite well on the train and test data, however, it could not achieve any further improvement in its performance. Therefore, it was finally decided to employ a pre-trained model for our project.

5. References

- **https://kidshealth.org/en/parents/xray-bone-age.html**