Pneumonia is a widespread respiratory disease caused by viruses, bacteria, and fungi. Children and the elderly are at highest risk and the WHO estimated 15% of all deaths in children under 5 years is from Pneumonia (Ibrahim et al., 2021). COVID-19 epidemic has made the situation even worse and therefore correct and timely diagnosis of pneumonia is very important to ensure treatment can begin as soon as possible. The aims of this research is to explore a dataset of Xray images depicting normal (healthy) and pneumonia lungs. It is hypothesised images can be distinguished with high accuracy using deep learning.

**Method**

Dataset was downloaded from Kaggle and Jupyter notebook was used: keras API was used to augment images and build a convolutional neural network. The Xray images are from paediatric patients ranging from 1-5 years old.

D**ata augmentation**

The original training set had a balance ratio of ~ 1:3 with pneumonia as the dominant class. Therefore, to reduce the imbalanced training set, 700 images from the minority class in the training set were augmented. This was done using Keras’s ImageDataGenerator class.

**Under sampling majority class**

3000 images from the pneumonia class in the training set were sampled from a total of 3875 images. This further reduced the imbalance problem. The training set ended up consisting of 1541 samples from the normal class and 2250 samples from the pneumonia class.

**Validation set**

Considering the original dataset consisted of only 10 samples in the validation set for both classes, a new validation dataset was created. 500 samples were randomly sampled from the normal class and 700 samples from the pneumonia class and placed into the validation data sets.

**Convolutional neural network architecture: model 1**

Keras sequential API was used to stack the layers in the CNN. The first layer was a 2D convolutional layer with 32 filters and a filter size of 3 x 3. Max pooling was followed with a pool size 2 x 2 and 2 strides. The second 2D convolutional layer consisted of 64 filters and a filter size of 3 x 3. Max pooling was followed with a pool size of 2 x 2 and 2 strides. The CNN was then flattened before the final output layer. The output layer was fully connected and consisted of two nodes and the softmax function was used. Total trainable parameters were 420,226 and the activation function for each CNN layer was rectified linear unit. The model was then compiled with Adam optimizer with a learning rate of 0.0001 and the loss function was categorical cross entropy. The model was fitted with the training and validation data: both had a batch size of 10 and 10 epochs.

**Convolutional neural network architecture: model 2**

The second CNN model had the same architecture as model 1 except it had one extra 2D convolutional layer consisting of 96 filters and filter size of 3 x 3 followed by a max pooling layer with a pool size of 2 x 2 and 2 strides. Total trainable parameters were 224,738 and the activation function for each CNN layer was rectified linear unit. The model was also compiled with Adam optimizer with a learning rate of 0.001. The model was fitted with the training and validation data: both had a batch size of 10 and 15 epochs.

**Convolutional neural network architecture: model 3**

The third CNN model had the exact same architecture as the second model. The only difference was the learning rate was 0.0001 and there were 20 epochs.

**Results**

|  |  |  |  |
| --- | --- | --- | --- |
| Model | Training | Validation | Test |
| CNN 1 | 100 | 96 | 77 |
| CNN 2 | 96 | 91 | 76 |
| CNN 3 | 100 | 97 | 76 |

*Table 1.* Accuracy (%) on the training, validation, and test sets for each CNN model.

As can be seen from table 1, training accuracy was 100% for models 1 and 3 while validation accuracy was 96% for model 1 and 97% for model 3. The test set accuracy was 77% for model 1 and 76% for model 3. The only difference between these models was two extra layers were added too model 3 and 20 epochs were used in model 3 compared to 10 in model 1. Model 2 scored 96% on the training and 91% on the validation set but had similar test accuracy.

**Discussion**

In support with the hypothesis deep learning can be used to classify Xray images into normal and pneumonia classes with high accuracy was demonstrated. The first CNN model proved to be the optimal model considering it scored 100% classification accuracy on the training set and 77% on the test set which was higher than the other models. The extra layers and epochs added in models 2-3 only added computational costs for no accuracy gains. One limitation was under sampling the pneumonia images from the training set: this resulted in around a quarter of the images being discarded and therefore loss of information. In conclusion, the research demonstrated that convolutional neural networks can be an invaluable tool to classify Xray lung images of pneumonia with high accuracy. The implication of this is deep learning can assist with diagnosing pneumonia with more certainty and in a timely manner to ensure treatment can begin as soon as possible.

References

Ibrahim, A. U., Ozsoz, M., Serte, S., Al-Turjman, F., & Yakoi, P. S. (2021). Pneumonia

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