HOME ASSIGNMENT REPORT ON

Applying Deep Neural Networks in the Healthcare Industry

FOR THE COURSE

Deep Learning (IC4263, ET4232)

TYPE OF ASSIGNMENT

Design

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DATE OF SUBMISSION: 25 November 2020

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Applying Deep Neural Networks in the Healthcare Industry to detect Pneumonia from chest x-ray images – A System Design in the field of Biomedical Sciences and Medicine for the course Deep Learning (IC4263, ET4232)

Preface (Aim and Objective)

"Deep learning" is a subset of machine learning which primarily focuses on artificial neural networks, which aim to replicate the way the human brain processes data and creates patterns for decision making. Advancements in computing technology on both hardware and software fronts have led to a boom in popularity of deep learning among enthusiasts and professionals alike. In deep learning models, data is filtered through a cascade of multiple layers, with each successive layer using the output from the previous one to inform its results. Deep learning

models can become more and more accurate as they process more data, essentially learning from previous results to refine their ability to make correlations and connections. Deep learning is steadily finding its way into innovative tools that have high-value applications in the real-world clinical environment. Some of the most promising use cases include innovative patient-facing applications as well as a few surprisingly established strategies for improving the health IT user experience.

"Pneumonia" is an inflammatory infection of the alveoli - tiny air sacs inside the lungs. A person suffering from pneumonia will have fluids and pus buildup inside the alveoli, leading to difficulty breathing. Pneumonia is usually diagnosed with a combination of x-rays, blood tests and sputum culture.

Through this project, we aim to design a system that leverages deep learning techniques (in particular, "Convolutional Neural Networks") in order to detect cases of pneumonia from x-ray images with a sufficiently high accuracy.

Case Study

In 2017, 2.56 million people died from pneumonia, with almost 33% of them being children under the age of five years old. People at-risk for pneumonia also include adults over the age of 65 and people with preexisting health problems.[1]

CNNs are designed with the assumption that they will be processing images thus allowing the networks to operate more efficiently and handle larger images. As a result, some CNNs are approaching – or even surpassing – the accuracy of human diagnosticians.[6] when identifying important features in diagnostic imaging studies. In June of 2018, a study[4] in the Annals of Oncology showed that a CNN trained to analyze dermatology images identified melanoma with ten percent more specificity than human clinicians.

Researchers at the Mount Sinai Icahn School of Medicine have developed a deep neural network [5] capable of diagnosing crucial neurological conditions, such as stroke and brain hemorrhage, 150 times faster than human radiologists. The tool took just 1.2 seconds to process the image, analyze its contents, and alert providers of a problematic clinical finding.

Software Components and Specifications

We chose to implement our system using the python programming language, due to its increasing popularity and range of libraries that focus on data analysis, image processing and deep learning. In particular, we have utilized the Open Computer Vision and Tensorflow packages for image processing and deep learning, respectively.

Table 1: Software components used and their current versions

Software Component	*Version*
Python	3.8
keras	2.4.3
matplotlib	3.2.2
numpy	1.18.5
opencv-python	4.4.0.44
os	3.8
Pillow	7.2.0
scikit-learn	0.23.1
tensorflow-gpu	2.3.1
tkinter	3.8

The software packages utilized along with their versions are listed in table 1.

Design Methodology

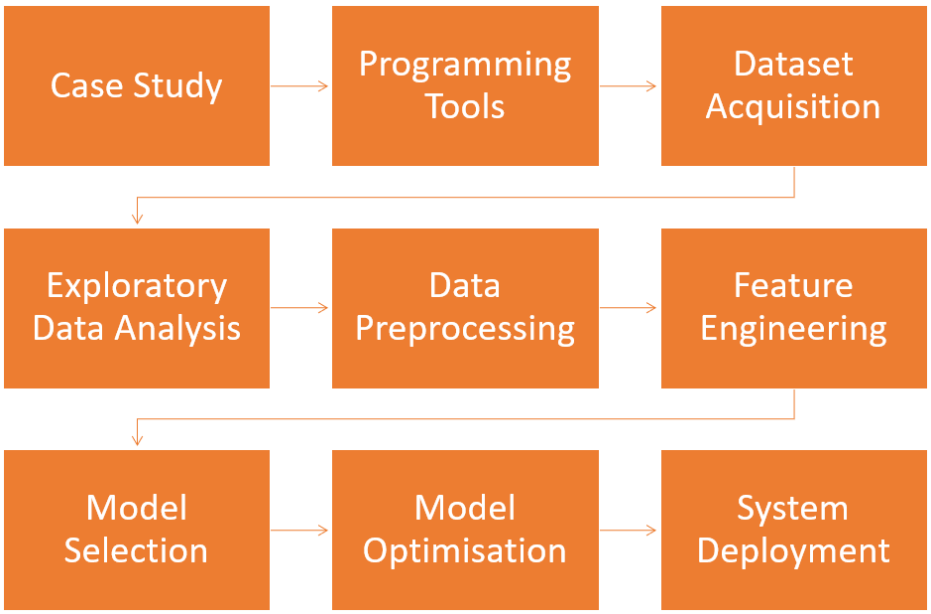

Figure 1: Block diagram indicating general flow of design.

Dataset acquisition

The dataset consists of 1,583 healthy x-rays and 4,273 x-rays from patients diagnosed with pneumonia. The dataset was compiled by Kermany, Daniel S. et al. [2] and is available online.[3]

Exploratory data analysis

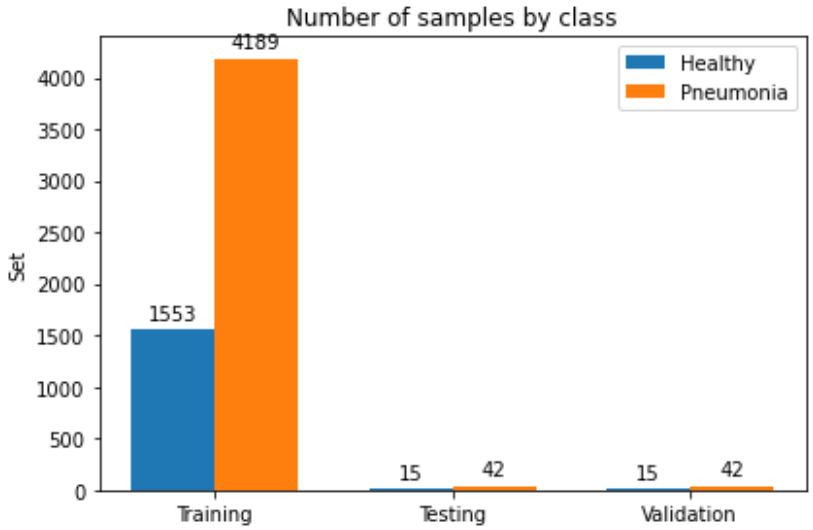

Figure 2: Number of samples per class

As shown in fig. 2, we split the data as 98% training, 1% testing and 1% validation. The training data is highly imbalanced, with the Pneumonia class having 2.69 times the number of samples as the healthy class. This can be remedied by up or down sampling the data, of which we do the former in the feature engineering step.

Data preprocessing

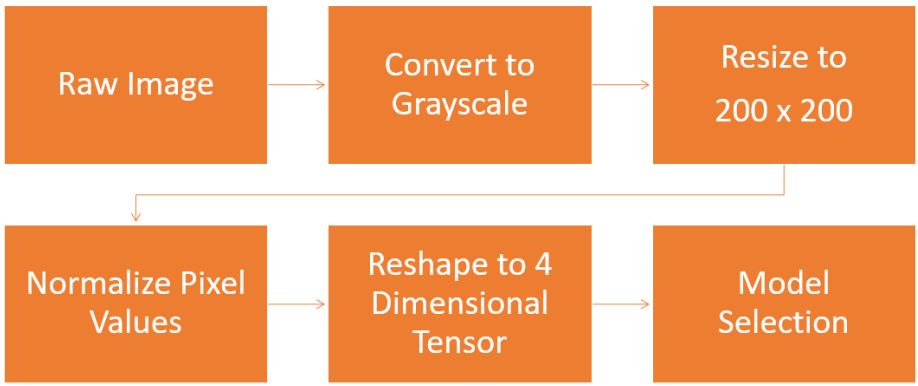

Figure 3: Data preprocessing process

Before training the network, we process the image as shown in fig. 3:

1) Convert to grayscale.

   This reduces the dimensionality of the input from 3 (red, green, blue) to 1 (single value representing intensity), leading to substantially smaller input without much loss in image information.

2) Resize to 200 x 200 pixels.

   Lower image sizes require less computing power and memory space, while still providing suitable model results. This step is done in order to reduce the pixel size of an image and that has several advantages e.g. It can reduce the time of training of a neural network as more is the number of pixels in an image more is the number of input nodes that in turn increases the complexity of the model.

3) Normalize the pixel values of the image from 0-255 to 0-1.

   Standardizing input to lie within the range of [0, 1] enhances the performance of gradient descent based optimizations, making them converge faster. It can also sometimes help you find better local optima i.e., improve model performance.

4) Reshape to a 4 dimensional vector of dimensions [n, 200, 200, 1], where n is the total number of samples in the set.

Applying these transformations will improve model performance and overall efficiency during both the training and prediction phases.

As such, the same process will be applied to new images for classification later.

Feature Engineering

As observed during the exploratory data analysis phase, our training classes have an uneven number of samples, i.e. they are “unbalanced”. Training a model on such a dataset can lead to over-sensitivity of the model towards one class. In this case, our model will be overly sensitive to pneumonia detections and will exhibit low accuracy when dealing with healthy cases.

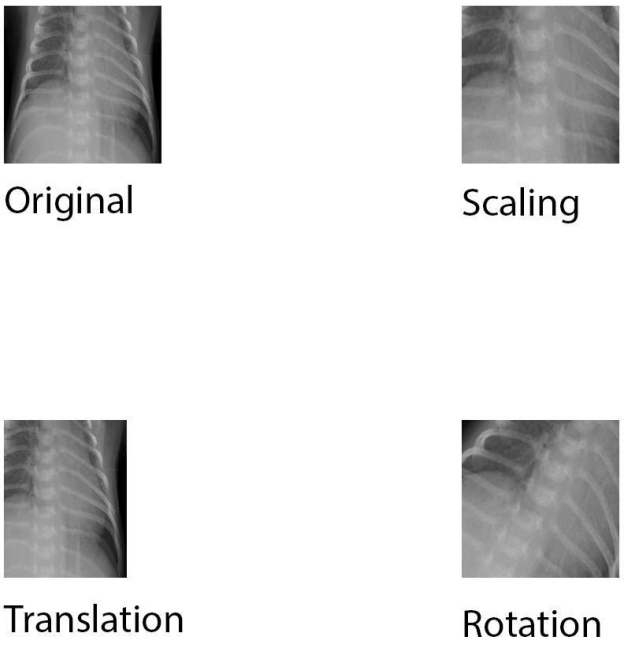

Figure 4: Transformations applied during image augmentation

To remedy this, we apply data augmentation where we generate new images by applying image transformations such as scaling, rotating, translating and zooming existing images of the set until the classes are balanced. Fig 4 shows a few examples of augmented images from our dataset.

Model Selection

Convolutional Neural Networks are a class of deep learning algorithms which are primarily applied to image processing tasks, which traditional machine learning models are not built to handle. A prominent feature of CNNs is “weight sharing”. We can extract useful attributes from an already trained CNN with its trained weights by feeding our data on each level and tuning the CNN for the specific task in a process known as “transfer learning”. Compared to ordinary Neural Networks, CNNs are less complex in nature and have a lower memory utilization. Their multi-layer-perceptron based architecture enables them to learn filters (which are normally hand engineered in traditional image processing algorithms) in order to efficiently extract features from images, even when faced with completely new data. The usage of CNNs are further motivated by the fact that they are designed to discern features from an image/video at different levels, similar to a human brain. This, along with the ease of access to deep learning frameworks made CNNs the obvious choice for this system.

Model Optimization

The performance of our model can further be optimized by adjusting the various hyper-parameters such as learning rate, number of hidden layers, momentum, etc.

Due to the degree of computational complexity of the network, we cannot apply grid search techniques. We instead utilize callbacks which automatically adjust the learning rate and weights of the system by continuously monitoring performance every epoch. We also include the "Adam" optimizer while defining the model, which implements a combination of gradient descent with momentum, along with RMSProp.

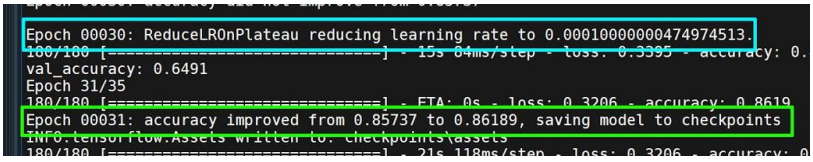

Figure 5: Verbose logs from the training process

Fig. 5 demonstrates the callbacks, reducing the learning rate (blue) and saving the best performing model (green) during the training process.

As opposed to grid search techniques, the use of callbacks generally cut down the time required for training while providing satisfactory results, and are thus more efficient when compared to manual tuning or grid search algorithms.

Performance Evaluation

The model built has a testing accuracy of 92.98%, and a loss of 0.23.

Table 2: Confusion matrix

Confusion matrix:		Predicted	
		Healthy	Pneumonia
Actual	Healthy	13	2
	Pneumonia	2	40

Table 3: Model performance metrics

Loss	0.230384544
Accuracy	0.929824561
Precision	0.952380952
Recall	0.952380952
F1 - Score	0.952380952

Table 2 shows the confusion matrix which can be further used to evaluate the model, the results of which are recorded in table 3.

System Deployment

We integrated our model into a GUI application using the tkinter framework for python, which enables the user to upload a chest x-ray image, which is then processed by the model and displays the predicted class along with the confidence value.

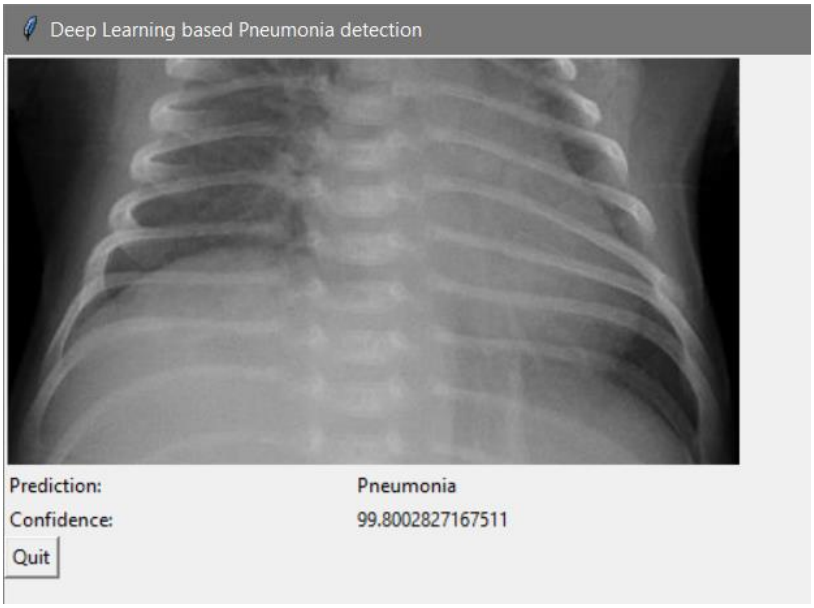

Figure 6: GUI implementation in tkinter

Merits, Limitations and Future Scope

The system designed thus far has a reported accuracy 92.98% and an F-1 score of 95,23%, which is well within the range of optimal performance for deep learning systems. We have also integrated the system into its an open source, standalone application, the benefits of which are multifold.

Since the backbone of the prediction model system is based on Tensorflow, the processing and prediction time ranges from 30 to 90 seconds, which can be reduced by optimizing the system and framework.

Like almost all systems in the deep learning field, the performance of this model can be improved by using a larger, more varied dataset. We can also improve performance by further tuning the model hyperparameters. In the future, this work can be expanded upon to detect other diseases (e.g. fibrosis, cancer) from other types of data, such as MRI or CT scans.

Conclusion

Through this project, we have utilized deep learning algorithms to create a model which can detect pneumonia from x-ray images with an F-1 score of 95.23%, and successfully deployed it into an application for easy use. While the results may seem promising, one must keep in mind that the error rate is still too high to fully replace professionals in the medical field. This model, like all machine learning models is not perfect, but is still useful and can serve as a preliminary guide in most situations. This system primarily serves as a demonstration of the progress made by deep learning in the past decade, and it will take several more decades for algorithms to reach the level of medical professionals.

Acknowledgement

We would like to thank Prof.(Dr.) Medha Wyawhare (class professor), Prof.(Dr.) Shripad Bhatlawande (Head of Department, Electronics and Telecommunication) Prof. Dr. (Mrs.) Shilpa Y. Sondkar (Head of Department, Instrumentation and Control) and Dr Rajesh Jalnekar (Director) for their constant guidance, and for giving us the opportunity and resources to perform this project.

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Appendix

Figures

Tables