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CNNs for Detecting Pneumonia from X-ray Images

Abstract

More than 2,000 children die from pneumonia every day[7]. In underdeveloped countries where access to medical treatment is limited, pneumonia is more common and likely to have serious implications. To improve diagnostics, a convolutional neural network model was used to classify pneumonia in pediatric chest x-rays. The performance and effectiveness of the model were evaluated, and it was found to have high accuracy in prediction and a high confidence level, with 98% accuracy and an AUC of 0.996. Process augmentation using deep learning algorithms can analyze medical data from individual patients and provide personalized diagnostics, resulting in a potential savings of over $300 million annually in Nigeria's patient costs.

Considering Pneumonia Detection as an Image Detection Problem

Pneumonia is the leading cause of death in children 5 and under. Pneumonia is an infection of the tiny air sacs of the lungs, called alveoli. In a person with pneumonia the alveoli are filled with pus and fluid, which makes breathing painful and reduces the oxygen intake. Pneumonia is caused by a number of different infectious agents, including viruses, bacteria and fungi.

In areas of the world where access to medical treatment is compromised, malnutrition is present, or environmental factors like pollution affect the health of the lungs, pneumonia is far more common and likely to have serious implications. In sub-Saharan Africa and South Western Asia, pneumonia death rates are more than 10x that of the United States[8].

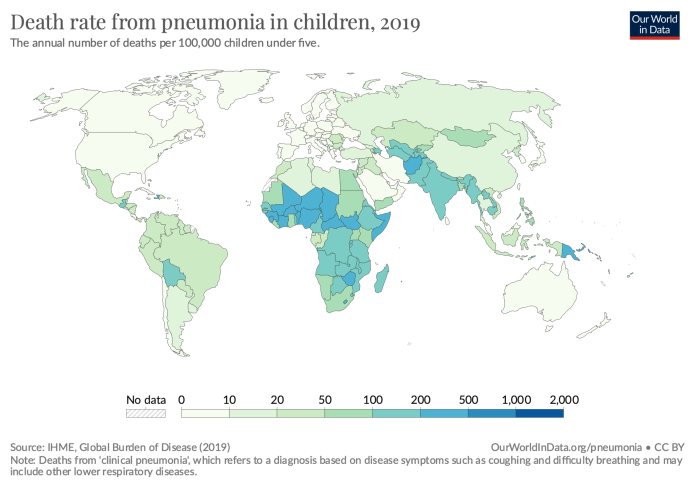

Figure 1: Pneumonia Death Rate by Country

A convolutional neural network model was used to classify pneumonia in pediatric chest x-rays. Convolutional neural networks are ideal for use in this case due to the model's ability to learn and recognize spatial patterns in the input image data.

Novel Aspects of the Model

The model was trained on 80% of 2897 diagnosed x-rays. The Convolutional Neural Network was designed to contain three convolutional layers with 50% drop out rate to prevent overfitting of filters. Each convolutional layer contains 64 filters with a kernel size of 3x3 to identify spatial patterns. Pooling was applied to lower computational load as 2x2 max pooling in each layer. After a batch of 12 input images, back propagation is used to adjust the model weights. The activation function used was ReLU, Rectified Linear Unit, for the purpose of computational efficiency and to prevent gradient problems.

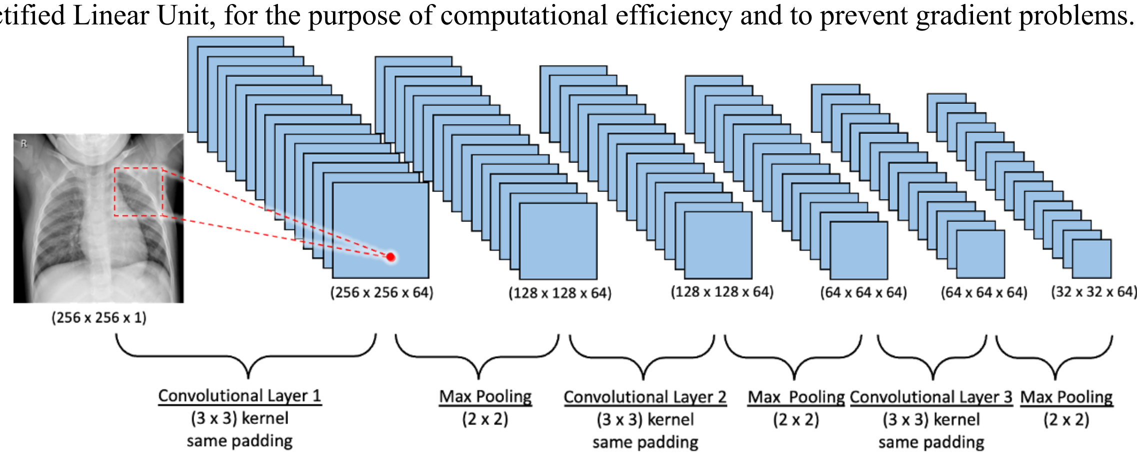

Figure 2: CNN Layer Structure

Process augmentation is implemented, which involves applying various image processing techniques to the original image such as rotating, flipping or cropping, this helps generate more diverse training data and improve the generalization of the deep learning model, augmentation also helps to prevent overfitting.

Performance and Effectiveness of the model

Deploying the deep learning model in underdeveloped countries has great potential for disrupting the current trends in high pediatric pneumonia complications. Since the model has high accuracy in prediction and a high confidence level, 98% accuracy and AUC of 0.996, it can assure the model's ability to improve diagnostics through process augmentation.

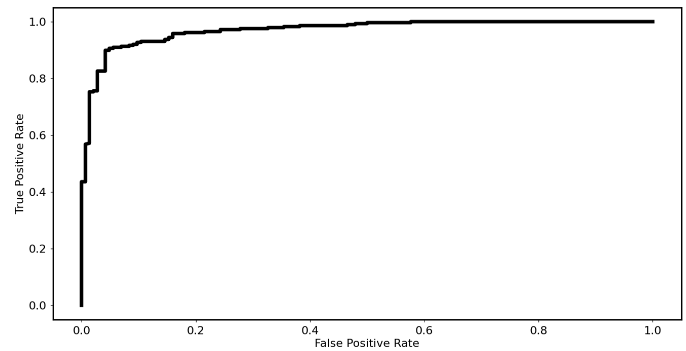

Figure 3: Model AUC Curve

Benefits of Process Augmentation using Deep Learning

Deep learning algorithms can analyze medical data from individual patients and provide personalized diagnostics. According to the [NCBI] paper, the median cost of pneumonia outpatient treatment in Nigeria is estimated to be $17. Thus, our analysis assumes that the cost of pneumonia diagnosis to a patient, despite actual infection (False Positive), would be that of outpatient treatment. Conversely, the inpatient treatment of pneumonia, prescribed in more severe cases, has a median cost of $272[5]. Therefore, if the patient is misdiagnosed as healthy when positive for pneumonia (False Negative), the assumption is that on average an undiagnosed case will develop to a more severe case that would require inpatient treatment. According to [UNICEF], Nigeria's annual death toll as a result of pneumonia in children under the age of five is more than 160,000[4]. Furthermore, the case stipulates that almost all the fatal cases of pneumonia are preventable with proper treatment. The number of cases in Nigeria is estimated to be 4 million based on a 4% death rate[6]. Compared to the current diagnosis accuracy of our naive model, our model has the potential to save over $300 million annually in Nigeria's patient costs. It is important to note that our baseline model, which provides treatment to all potential cases of pneumonia, is impractical due to constraints on medical supplies. Additionally, based on a 25%-time reduction due to process augmentation in the x-ray review process, radiologist salary savings yields an estimated annual savings of $180,000 (Exhibit 2). Additionally, process augmentation improves throughput resulting in a timelier diagnosis and decreases burden on the health care system. Further, the use of deep learning could aid in the diagnosis of cases not detected in traditional diagnostic method or that appear infrequently.

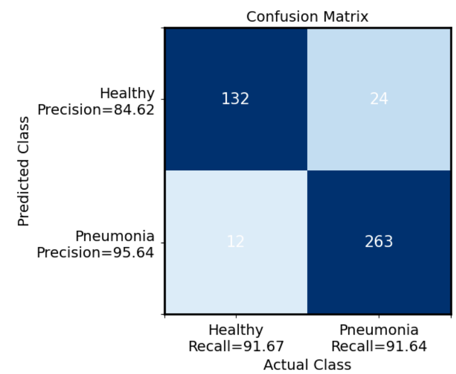

Figure 4: Model Confusion Matrix

Moving forward, the goal is to begin implementation in Nigeria, the country with the highest pneumonia death toll before expanding through Sub-Saharan Africa. Our costs associated with this process would require further model training ($300K), system implementation ($1.2 M), and personnel training($500K).

Conclusion

Our model, which has high accuracy and a high confidence level, has the potential to save over $300 million annually in Nigeria's patient costs. While further model training, system implementation, and personnel training are required, the potential benefits of implementing deep learning algorithms in pneumonia diagnosis are significant and should be considered as a viable solution for improving healthcare outcomes.

Appendix

Exhibit 1

Table A1. Cost Benefit Analysis

	Cost of FP	Cost of FN	Cost of TP	Cost of TN	FP	FN	TP	TN	FP Rate	FN Rate
Model CNN 16:1	$17	$272	$0	$0	12	24	263	132	0.027842	0.055681
Baseline: 21% cases diagnosed	$17	$272	$0	$0	0	340	91	0	0.000000	0.790000
Baseline: 21% nonPneumonia Treated/Treat All	$17	$272	$0	$0	340	0	91	0	0.790000	0.000000
Naïve: Pneumonia Undiagnosed	$17	$272	$0	$0	0	144	287	0	0.000000	0.334107

	Predicted number of cases	Annual FP	Annual FN	Annual Cost FP	Annual Cost FN	Cost of FP and FN
Model CNN 16:1	4,000,000	111368.9095	222723.4313	$1,893,271	$60,580,773	$62,474,045
Baseline: 21% cases diagnosed	4,000,000	0	3160000	$0	$859,520,000	$859,520,000
Baseline: 21% nonPneumonia Treated/Treat All	4,000,000	3160000	0	$53,720,000	$0	$53,720,000
Naïve: Pneumonia Undiagnosed	4,000,000	0	1336426.914	$0	$363,508,121	$363,508,121

Exhibit 2

Process Augmentation
300 radiologists in Nigeria[3]
15 minutes average X-ray review time
5 minutes Review Reduction

Table A2. X-Ray Review Process Augmentation Time Spent Calculation

Radiologists	300
Review Time (min)	20
Augmentation Reduction (min)	5
Cases	160000
Current time spent reviewing (hrs)	177.78
Time reduction (hrs)	133.33
Time saved (hrs)	44.44
Monthly Pay	$2,200
Total Saved Annual	$183,333

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