MEMORANDUM

To: The Gates Foundation
From: The Revolutionaries Foundation – Founder and CEO: Giulia Neves Monteiro
Subject: Funding Proposal for Pneumonia Detection in Children in Uganda

Executive Summary

This memo proposes a funding request of $2,000,000 to support the implementation of a deep learning model designed to improve pneumonia diagnosis in children under 5 years old in Uganda. Given the limited availability of radiologists, diagnostic resources, and substantial health expenditures, our initiative aims to leverage Convolutional Neural Networks (CNNs), an advanced machine learning technique, to develop a predictive model that accurately diagnoses a patient with pneumonia based on their X-rays. By utilizing CNNs to enhance the accuracy of pneumonia classifications, our approach focuses on improving the diagnostic process and augmenting healthcare capabilities, ensuring reduced health costs and reliable patient care. $1M of the funding would be used to further develop the model, cover the maintenance costs, the costs to augment it even further to achieve an accuracy score of 100%, specially to account for some low resolution X-ray images in certain regions. The other $1M would be used to assist the lower income households in Uganda in the initial years of the adaptation of our model that end up being misdiagnosed. Given that the number of misdiagnosed cases are very low for our model, once we achieve 100% accuracy the remaining funding would be used to assist all possible lower income household with children under 5 with pneumonia.

Background

Pneumonia remains the leading infectious cause of death among children globally, accounting for an alarming 22% of deaths in children below 5.[1] The burden is particularly heavy in Uganda where it is the 2nd leading cause of death for children under 5.[2] A study revealed that only 58% of symptomatic children received evaluation by healthcare providers, contributing to misdiagnosis and inadequate treatment.[3] Factors like healthcare worker quality, the type of healthcare professional involved, and the overall availability of healthcare services further exacerbate the issue. This led to delays in treatment and potential fatalities, whereas a third of deaths occur at home and half in hospitals.[6] The economic implications of pneumonia are profound; in Uganda, the average societal cost per episode estimated at USD$42, while hospitalized cases can reach an average of USD$62 and ambulatory cost USD$16 per episode.[4] Hospital stays last between 3.2 to 12.9 days, incurring treatment costs beyond many families' means. Travel expenses compound these costs, requiring families to journey long distances for care. To cope, 39% of caregivers end up spending over 40% of their non-food household budget on a single pneumonia episode.[4] Addressing these economic challenges is essential to alleviate the financial strain on vulnerable households, especially since it is one of the main reasons why families end up taking longer to address their children's health issues.

Model Development and Evaluation

The model was built utilizing a dataset of approximately 2,900 X-ray images from pediatric patients to train and validate our predictive model, ultimately testing it against 200 additional cases in Kaggle. We completed more than 50 tests using different key architecture designs, documenting each change and its respective accuracy and AUC scores. Some parameters that we explored to ultimately arrive at our current best performing model with a Kaggle AUC score of 99.71% was the number of layers, filters, and epochs, batch size, kernel size, dropout value, and learning rate. Our current model has 3 convolutional (2D) layers, all of which have a dropout layer and only one has max pooling. The last layers of the model contain flatten, dense, and dropout layers. We also only used the parameterized model since they are often more computationally efficient and require fewer training data to estimate parameters compared to the non-parametric model.[8] But ultimately, what assisted the most in improving our scores was the use of data augmentation; this makes sense since augmentation enhances a model's ability to handle unseen data, reduces data dependency, and handles overfitting.[7] Furthermore, compared to the initial starting point, our current model has adjusted data augmentation values. We reduced the values for rotation, width, height, shear, and zoom ranges to better account for smaller X-ray images.

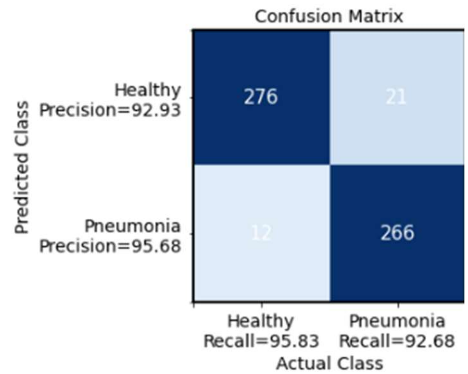
Furthermore, the following covers some hyper parameter modifications that assisted in achieving our best model thus far: Increasing the number of layers to 3 allowed for a deeper network, thus capturing more complex patterns. Increasing number of filters to 64 as more is usually better for a model. Leaving kernel size at 5, changing it didn't improve our accuracy since increasing it can sometimes capture more context but would decrease precision. Lowering dropout value to 0.3 to retain more information during training. Reduced max pooling to 2 to preserve more spatial information. Increased batch size to 25 since it helps with convergence. Lastly, increased number of epochs to 25 so the model would have more training rounds. The image below shows three examples of the accuracy scores and some hyper parameters used, the more complete version of the table is included in figure 1 in the appendix.

Dropout	NumLayers	numFilters	kernelSize	dropout val	MaxPooling	batchSize	LR	epochs	Epoch#	EpochACC	EpoccAUC	KaggleScore
Yes	3	64	5	0.3	2	32	0.0001	25	23	93.22	98.5	**0.9971**
Yes	3	64	5	0.3	2	32	**0.00001**	25	21	**94.61**	98.28	0.9887
Yes	3	64	5	0.3	2	**64**	0.0001	25	23	94.09	**98.65**	0.99

In some health disparate countries, radiologists are less than 85% accurate at detecting pneumonia. Our models have reached outstanding accuracy scores above 98% in Kaggle by systematically optimizing its parameters and closely monitoring performance metrics, such as accuracy and AUC scores. It is generally recognized that higher AUC values equate to fewer deaths. It is also of extreme importance to have highly accurate model to make up for the image quality degradation in X-rays from some regions; this is a limitation to keep in mind since our model may currently have 99.71% accuracy, but may be reduced 1-4% in X-rays with lower quality.

Cost Benefit Analysis

	TP	TN	FP	FN	Total Cost
Model	266	276	12	23	$ 2,114,275
Naïve-All Pneum	289		288		$ 6,042,314
Naïve- All no Pneum		288		289	$23,332,669



Based on data from the Uganda National Institute of Public Health, there were 753,978 pneumonia admissions between 2013-2021.[10] We conducted a cost benefit analysis considering that value as the number of instances, $62 as the false negative (FN) cost, considering this is the average hospitalization cost, and $16 as the false positive (FP) cost as this is the average ambulatory cost.[4] FP is when we diagnose as having pneumonia, but they do not, so they incur the ambulatory cost since they can do a mobile X-ray there, with no need of hospitalization. FN is when we say they do not have pneumonia but they actually do, this is considering the hospitalized cost since they were not treated in time and required needing to be at the hospital. This was a simplistic approach to the costs since there are many other additional costs that could be accounted for, such as transportation, cost of the death of the child for the FN cases where it was incorrectly diagnosed, cost of the doctor's time, and so forth. The level of detail for the costs is limited as there is few data covering this in Uganda. In addition, another limitation to this analysis is that there are many unreported cases that are not being taken into account.[2] We also calculated naïve models considering if all patients are diagnosed as not having pneumonia or as having pneumonia. The table above highlights the enormous difference in cost between scenarios, emphasizing the cost benefit of having highly accurate models. If dividing the total model cost by the number of years it refers to, the annual cost would be $234,919, which is covered in full by the portion of the funding dedicating to misdiagnosis. Additionally, the confusion matrix that was used in this analysis is included above and the ROC curve that shows the steep curve closer to the top-left corner, further highlighting the high performance of the model is found in figure 2 in the appendix.

Summary

Investing in this project will not only help us address urgent healthcare challenges but also contribute to the broader global effort to protect, prevent, and treat pneumonia effectively. [5] Your support in securing this funding will enable us to develop a robust predictive model that safeguards child health in Uganda. Pneumonia can be prevented with simple interventions. Our model would ensure high accuracy in diagnosing children, eliminating the need for many to be hospitalized if they simply take the X-ray beforehand and if they are healthy, it eliminate the hospitalization cost, saving time and money for the families and doctors. Lastly, part of the funding would directly assist the lower income households in Uganda to cover their healthcare expenditures, especially when being misdiagnosed.

Appendix

Figure 1 – Tracker of Different Architectural Designs and Scores

The top 3 highest accuracy, AUC, and Kaggle AUC scores are highlighted. In the hyper parameter column, whenever there was a change in hyper parameter, the cell was also highlighted. Please note, not all rows were included in the image below.

Data Augmentation	MaxPooling	Dropout	NumLayers	numFilters	kernelSize	dropout va	MaxPooling	batchSize	LR	epochs	use DA	ModelUsed	Epoch#	EpochACC	EpoccAUC	KaggleScore
No	Yes L1	Yes	**1**	**64**	**5**	**0.4**	**3**	**16**	**0.0001**	**3**	**FALSE**	Parameterized	0	92.35	96.69	0.9766
No	Yes L1	Yes	1	64	5	**0.3**	**2**	**32**	**0.1**	3	FALSE	Parameterized	1	93.39	98.5	0.9872
No	Yes L1	Yes	1	64	5	0.3	2	32	0.1	**5**	FALSE	Parameterized	4	93.74	98.19	0.9852
No	Yes L1	Yes	**2**	64	5	0.3	2	32	0.1	5	FALSE	Parameterized	4	94.09	97.66	0.9823
No	Yes L1	Yes	2	64	5	0.3	2	32	0.1	**10**	FALSE	Parameterized	5	93.91	98.09	0.9874
No	Yes L1	Yes	2	**128**	5	0.3	2	32	0.1	10	FALSE	Parameterized	2	93.04	97.84	0.9808
No	Yes L1	Yes	2	128	5	**0.2**	2	32	0.1	**7**	FALSE	Parameterized	2	94.26	97.99	0.9868
No	Yes L1	Yes	2	**64**	5	0.2	2	32	**0.01**	7	**TRUE**	Parameterized	5	86.96	94.81	0.9682
Yes	Yes L1	Yes	2	64	5	0.2	2	32	0.01	**10**	TRUE	Parameterized	3	93.57	98.03	0.9866
Yes	Yes L1	Yes	**3**	64	5	**0.3**	2	32	**0.001**	10	TRUE	Parameterized	7	93.74	98.4	0.9882
Yes	Yes L1	Yes	3	64	5	0.3	2	32	0.001	**20**	TRUE	Parameterized	15	93.57	98.21	0.9909
Yes	Yes L1	Yes	3	64	5	0.3	2	32	0.001	20	TRUE	Parameterized	12	93.04	98.19	0.9883
Yes	Yes L1	Yes	3	64	5	0.3	2	32	0.001	20	TRUE	Parameterized	11	93.91	98.08	0.9854
Yes	Yes L1	Yes	3	64	5	0.3	2	32	0.001	**25**	TRUE	Parameterized	5	93.39	97.81	0.9852
Yes	Yes L1	Yes	3	64	5	0.3	2	32	0.001	25	TRUE	Parameterized	13	93.22	98.13	0.9907
Yes	Yes L1	Yes	3	64	5	0.3	2	32	0.001	25	TRUE	Parameterized	15	93.56	98.16	0.9885
Yes	Yes L1	Yes	3	64	5	0.3	2	32	0.001	25	TRUE	Parameterized	17	93.56	98.37	0.9926
Yes	Yes L1	Yes	3	64	5	0.3	2	32	**0.0001**	25	TRUE	Parameterized	16	92.7	98.28	0.9961
Yes	Yes L1	Yes	3	64	5	0.3	2	32	0.0001	25	TRUE	Parameterized	22	93.91	98.34	0.9965
Yes	Yes L1	Yes	3	64	5	0.3	2	32	0.0001	25	TRUE	Parameterized	23	93.22	98.5	0.9971
Yes	Yes L1	Yes	3	64	5	0.3	2	32	0.0001	**30**	TRUE	Parameterized	29	93.04	98.23	0.9929
Yes	Yes L1	Yes	3	64	5	0.3	2	32	0.0001	30	TRUE	Parameterized	28	92.17	98.11	0.994
Yes	Yes L1	Yes	3	64	**3**	0.3	2	32	0.0001	**25**	TRUE	Parameterized	21	93.91	98.4	0.9914
Yes	Yes L1	Yes	3	64	3	0.3	2	32	0.0001	25	TRUE	Parameterized	19	93.56	98.29	0.9914
Yes	Yes L1	Yes	3	64	3	0.3	2	32	0.0001	25	TRUE	Parameterized	15	93.74	98.18	0.99
Yes	Yes L1	Yes	3	64	3	0.3	2	32	0.0001	25	TRUE	Parameterized	13	92.52	98.02	0.9915
Yes	Yes L1	Yes	3	64	**5**	0.3	2	32	**0.00001**	25	TRUE	Parameterized	21	94.61	98.28	0.9887
Yes	Yes L1	Yes	3	64	5	0.3	2	32	0.00001	25	TRUE	Parameterized	19	93.56	98.27	0.9857
Yes	Yes L1	Yes	3	64	5	0.3	2	**64**	**0.0001**	25	TRUE	Parameterized	23	94.09	98.65	0.99
Yes	Yes L1	Yes	3	64	5	0.3	2	64	0.0001	25	TRUE	Parameterized	19	94.44	98.47	0.99
Yes	Yes L1	Yes	3	64	5	0.3	2	64	0.0001	25	TRUE	Parameterized	11	93.04	98.15	0.987
Yes	Yes L1	Yes	3	64	5	0.3	2	64	**0.001**	25	TRUE	Parameterized	21	92.17	97.92	0.9862
Yes	Yes L1	Yes	3	64	5	0.3	2	64	**0.0001**	25	TRUE	Parameterized	21	94.09	98.57	0.9927
Yes	Yes L1	Yes	3	64	5	0.3	2	64	0.0001	25	TRUE	Parameterized	17	93.04	98.39	0.9903
Yes	Yes L1	Yes	**2**	64	5	0.3	2	64	0.0001	25	TRUE	Parameterized	17	94.09	98.61	0.9922
Yes	Yes L1	Yes	2	64	5	0.3	2	64	0.0001	25	TRUE	Parameterized	13	93.39	98.53	0.9942
Yes	Yes L1	Yes	2	64	5	0.3	2	64	0.0001	25	TRUE	Parameterized	12	90.61	98.29	0.9916

Figure 2 – ROC curve from Cost Benefit Analysis Model

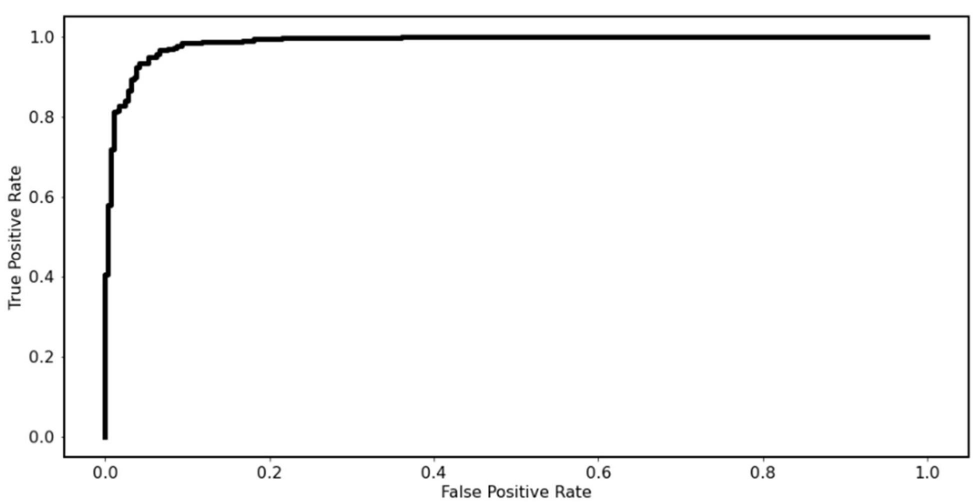


Figure 3 – Detailed Cost Benefit Analysis

Model	Pneumonia Detection in Uganda											
	TP	TN	FP	FN	FP Proportion	FN Proportion	Total FP Cost	Total FN Cost	Total Cost		FN Cost	$ 62
Model 1	261	278	10	26	0.02	0.05	$ 209,803	$ 2,113,761	$ 2,323,564		FP Cost	$ 16
Model 2	266	276	12	23	0.02	0.04	$ 250,890	$ 1,863,384	$ 2,114,275		Instances	753,978
Naïve All say p (FP)	287		288		0.50	-	$ 6,042,314	$ -	$ 6,042,314			
Naïve All no p (FN)		288		287	-	0.50	$ -	$ 23,332,669	$ 23,332,669			

References

Vocarium Code – file “Individual Assignment”:
https://vocproxy-1-13.us-west-2.vocareum.com/lab/tree/work/Individual%20Assignment.ipynb

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