CHEST X-RAY PNEUMONIA IMAGE CLASSIFICATION WITH DEEP LEARNING

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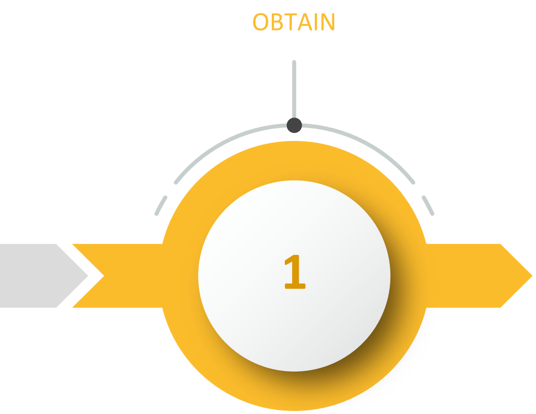
The Problem

- Globally, a child dies of pneumonia every 39 seconds.
- Pneumonia is the leading cause of morbidity and mortality in children younger than the age of 5, killing more children than HIV/AIDS, malaria, and measles combined.
- Chest X-rays are primarily used for the diagnosis of this disease. However, even for a trained radiologist, it is a challenging task to examine chest X-rays.

The Solution

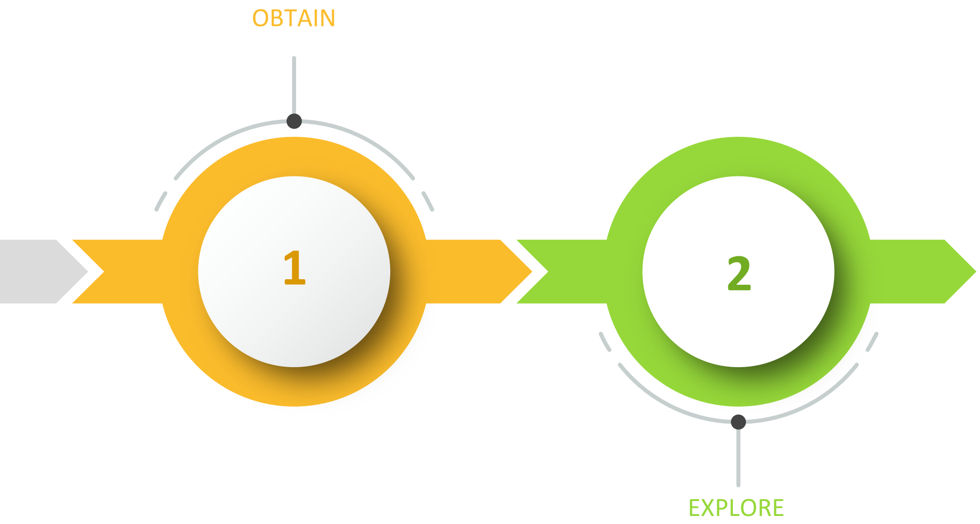
To solve this, deep learning (DL), a branch of machine learning (ML), is developed to detect hidden features in images which are not apparent or cannot be detected even by medical experts.

With AI system aiding medical experts in expediting the diagnosis, earlier treatment can be prescribed, resulting in improved clinical outcomes.

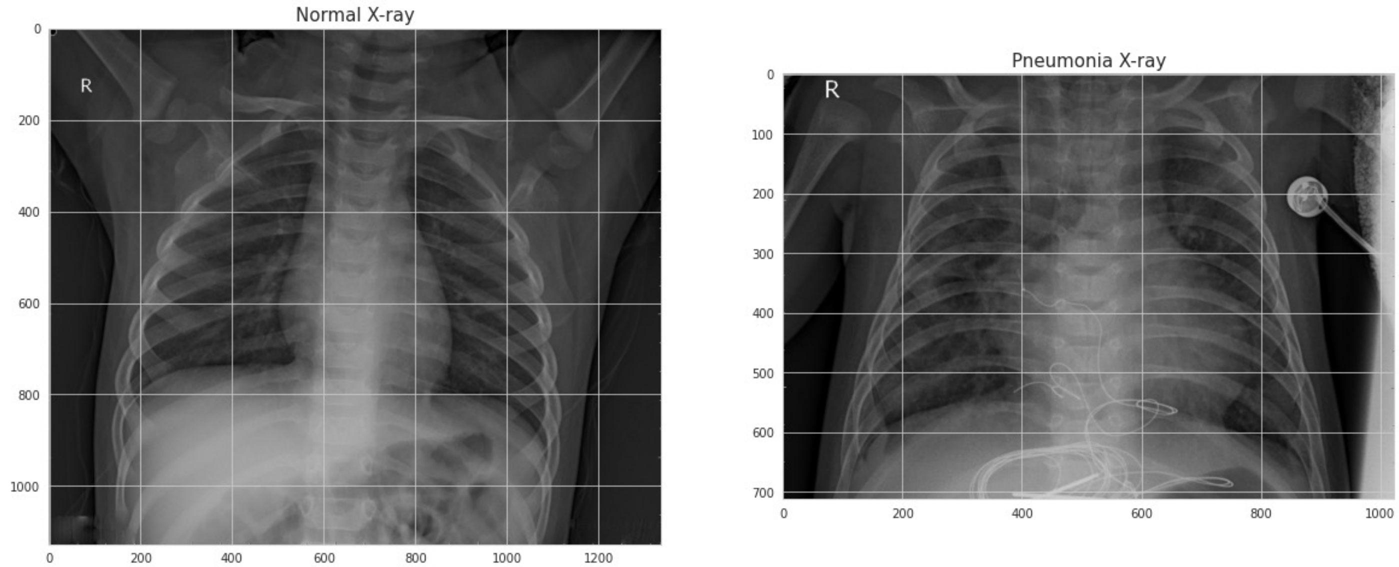


- Chest X-ray images (anterior-posterior) were selected from pediatric patients of one to five years old from Guangzhou Women and Children’s Medical Center.

- There are 5,863 X-Ray images (JPEG)
- 2 categories: Normal & Pneumonia



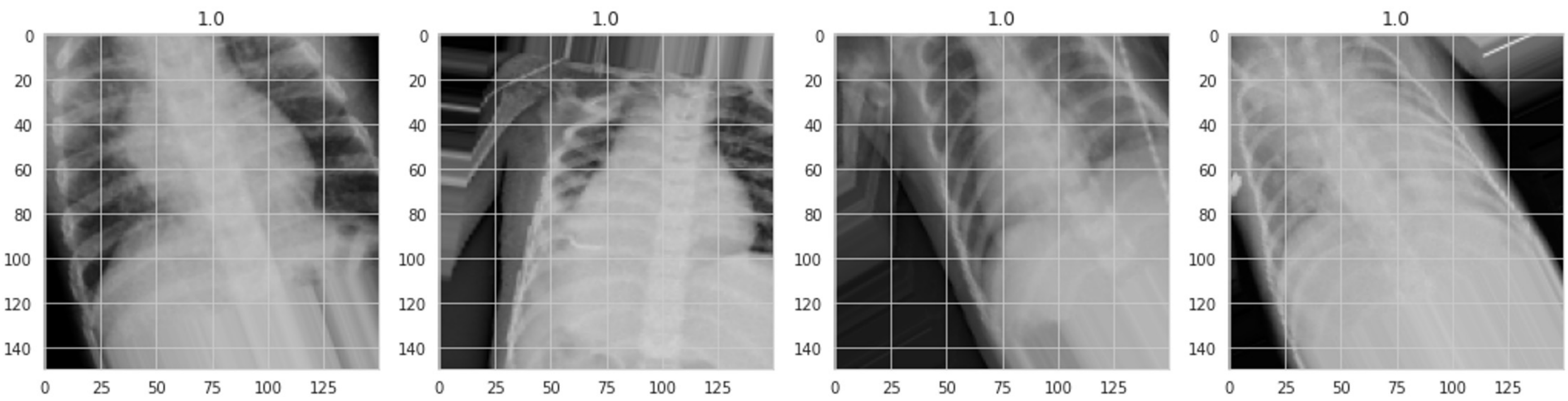
OBTAIN
1
2
EXPLORE

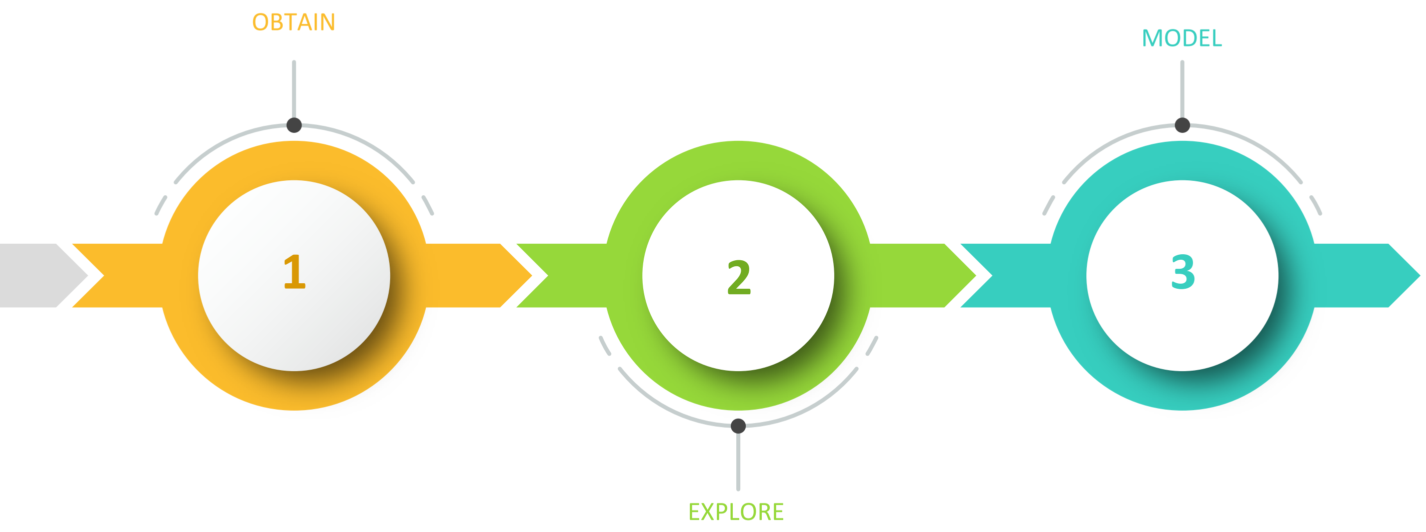

Normal X-ray
R
0
200
400
600
800
1000
0
200
400
600
800
1000
1200
Pneumonia X-ray
R
0
100
200
300
400
500
600
700
0
200
400
600
800
1000


X-ray Condition in Training Set
Count
4000
3500
3000
2500
2000
1500
1000
500
0
NORMAL
PNEUMONIA
Condition

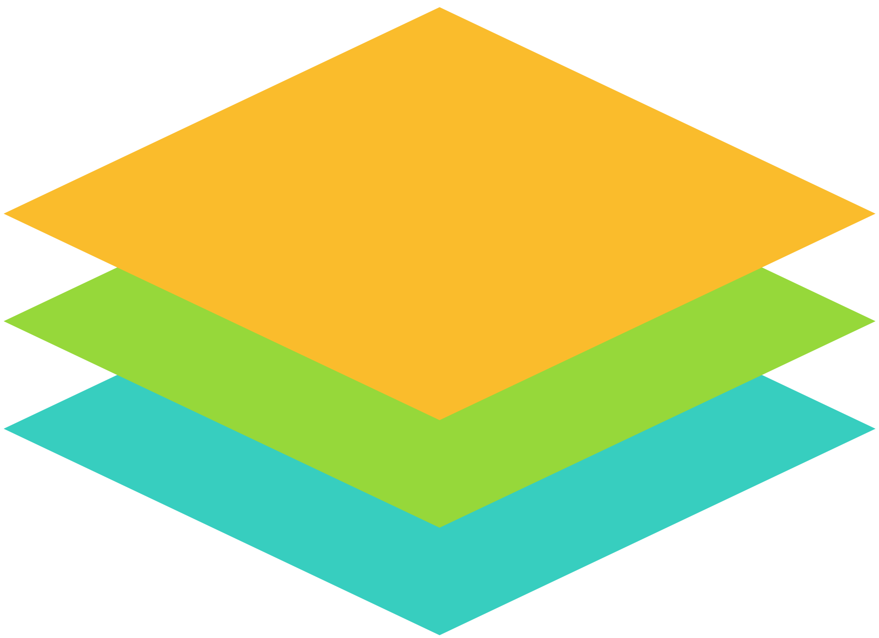
Data Augmentation

- To build a powerful image classifier using very little training data, image augmentation is usually required to boost the performance of deep networks.
- Image augmentation artificially creates training images through different ways of processing images, such as random rotation, shifts, shear and flips, etc. of each training instances



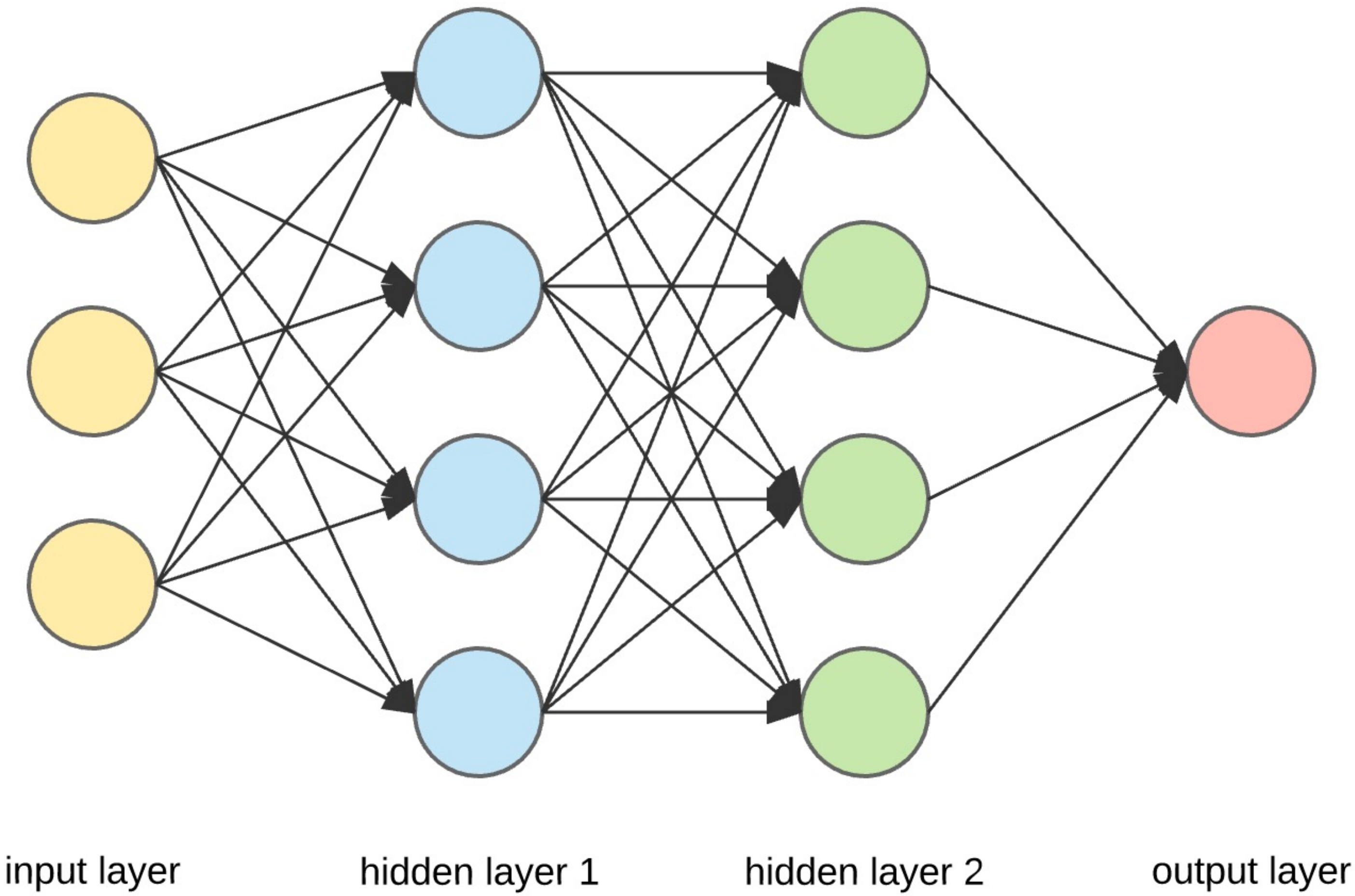

OBTAIN
1
2
EXPLORE
3
MODEL

Keras

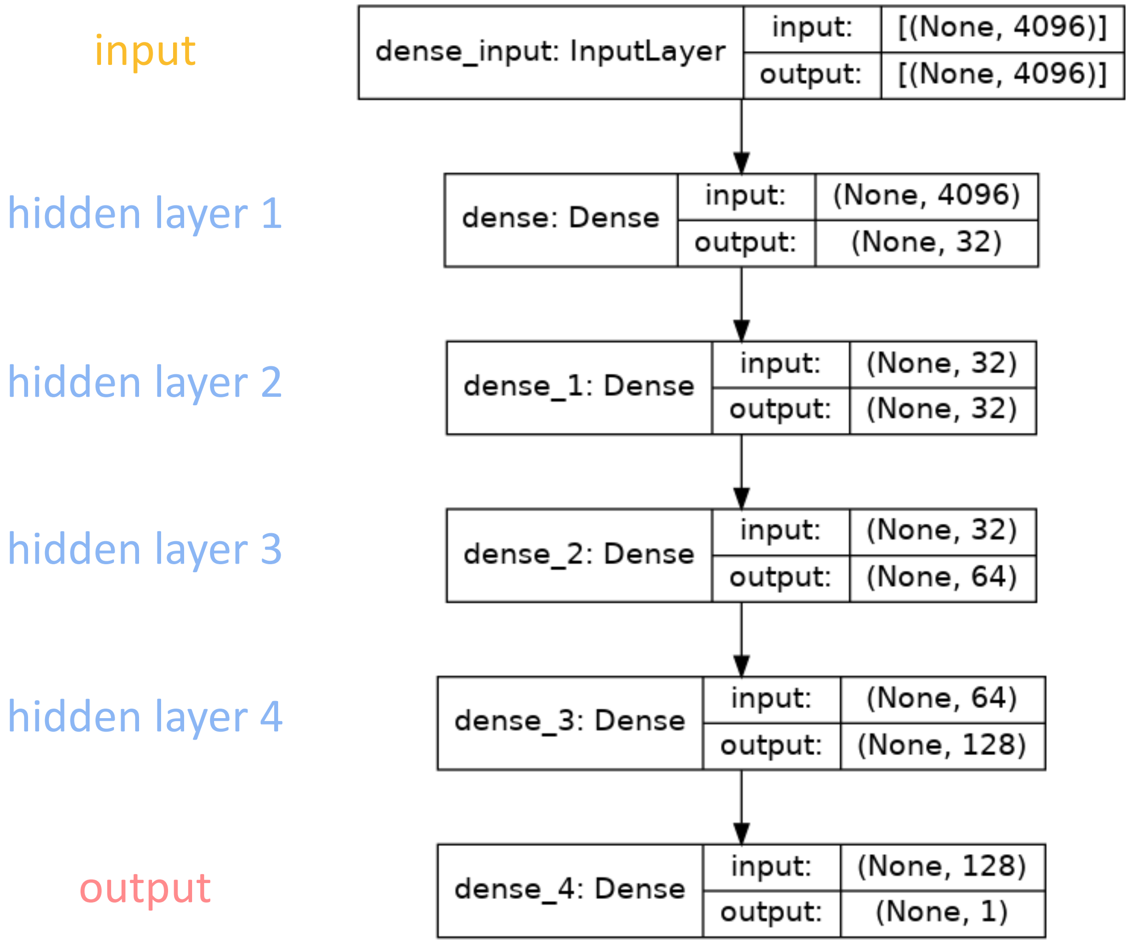


- MULTILAYER PERCEPTRON MODEL (MLP)
- CONVOLUTIONAL NEURAL NETWORK MODEL (CNN)
- TRANSFER LEARNING with VGG16 CNN MODEL

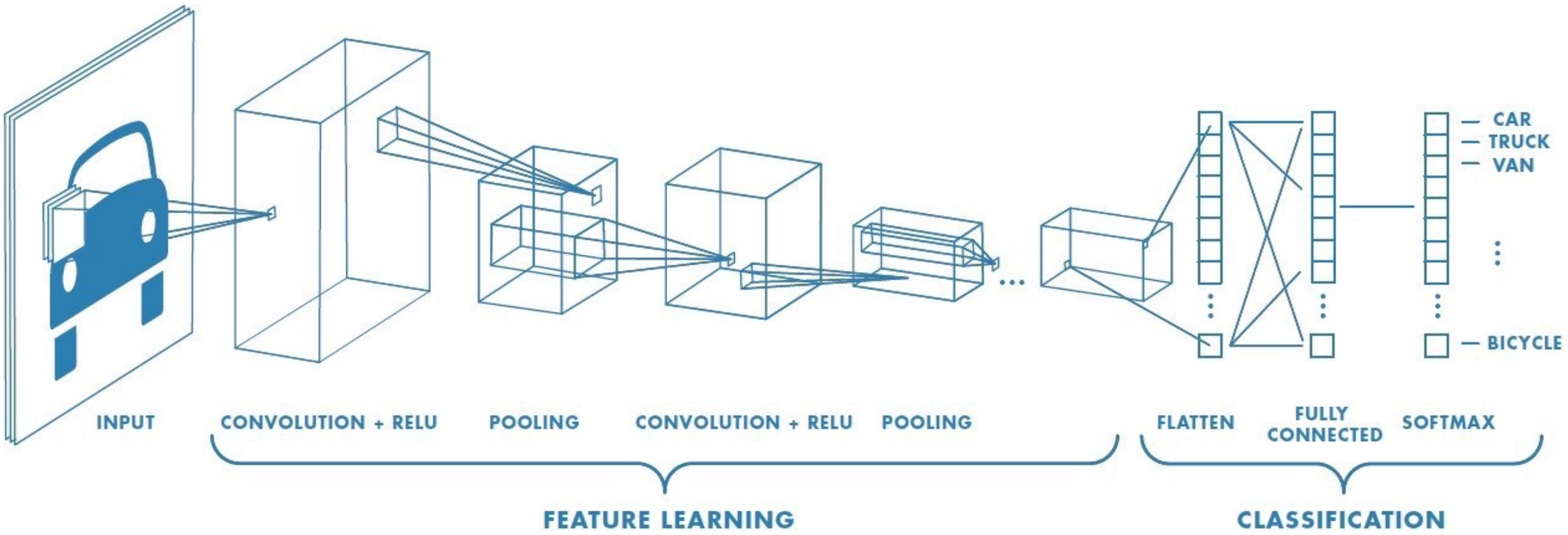
Multilayer Perceptron



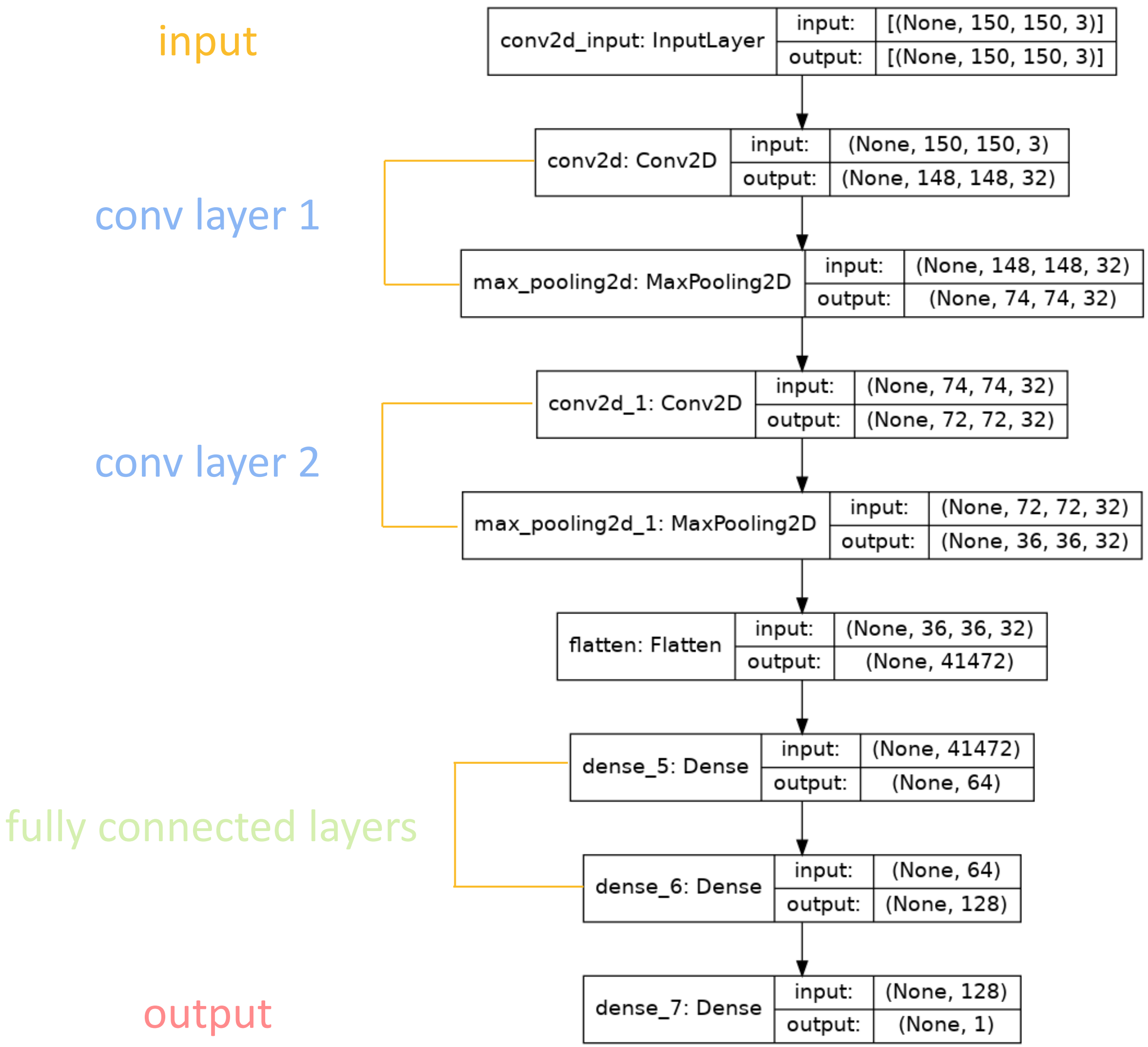
Multilayer Perceptron



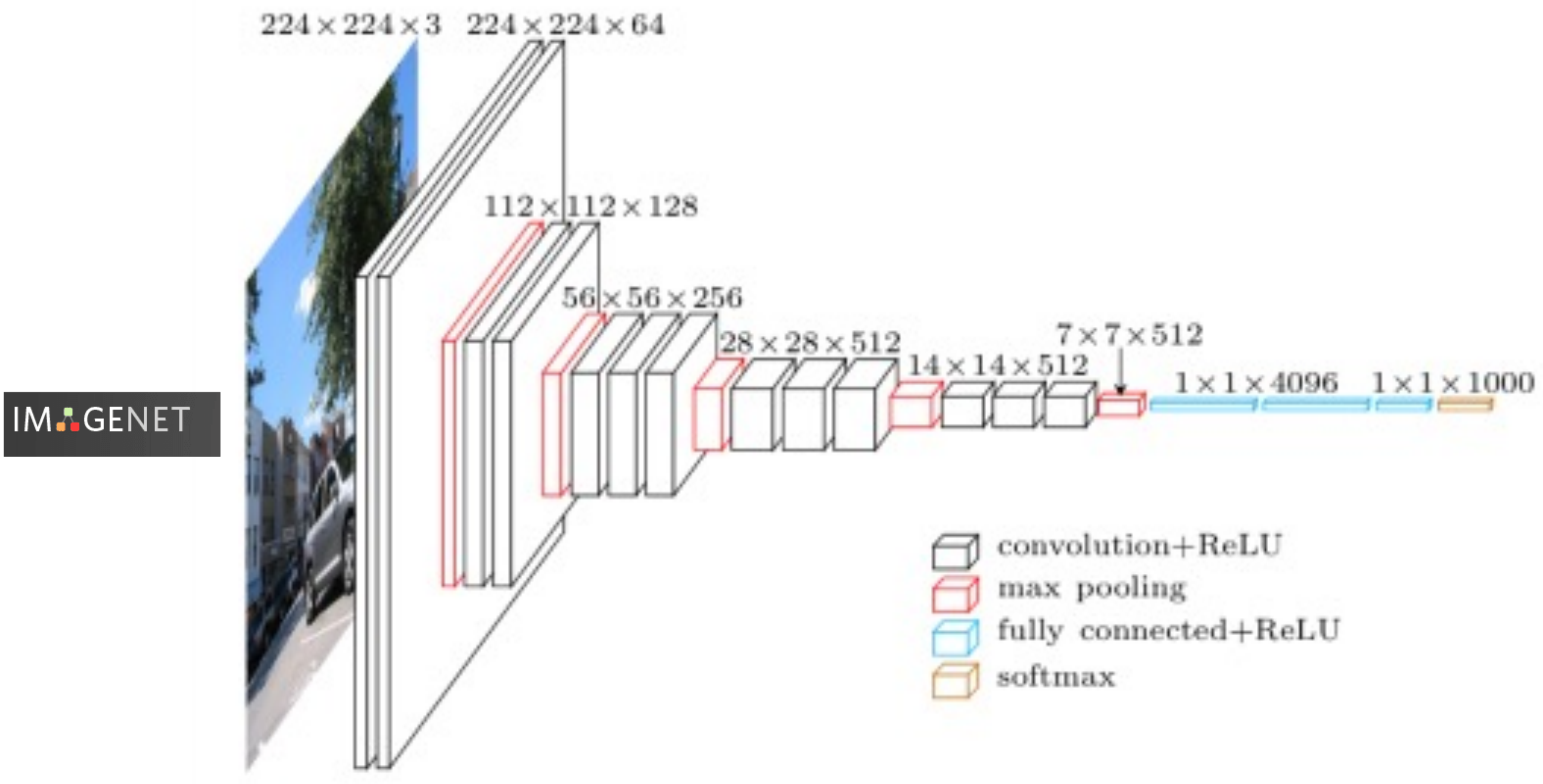
Convolutional Neural Network



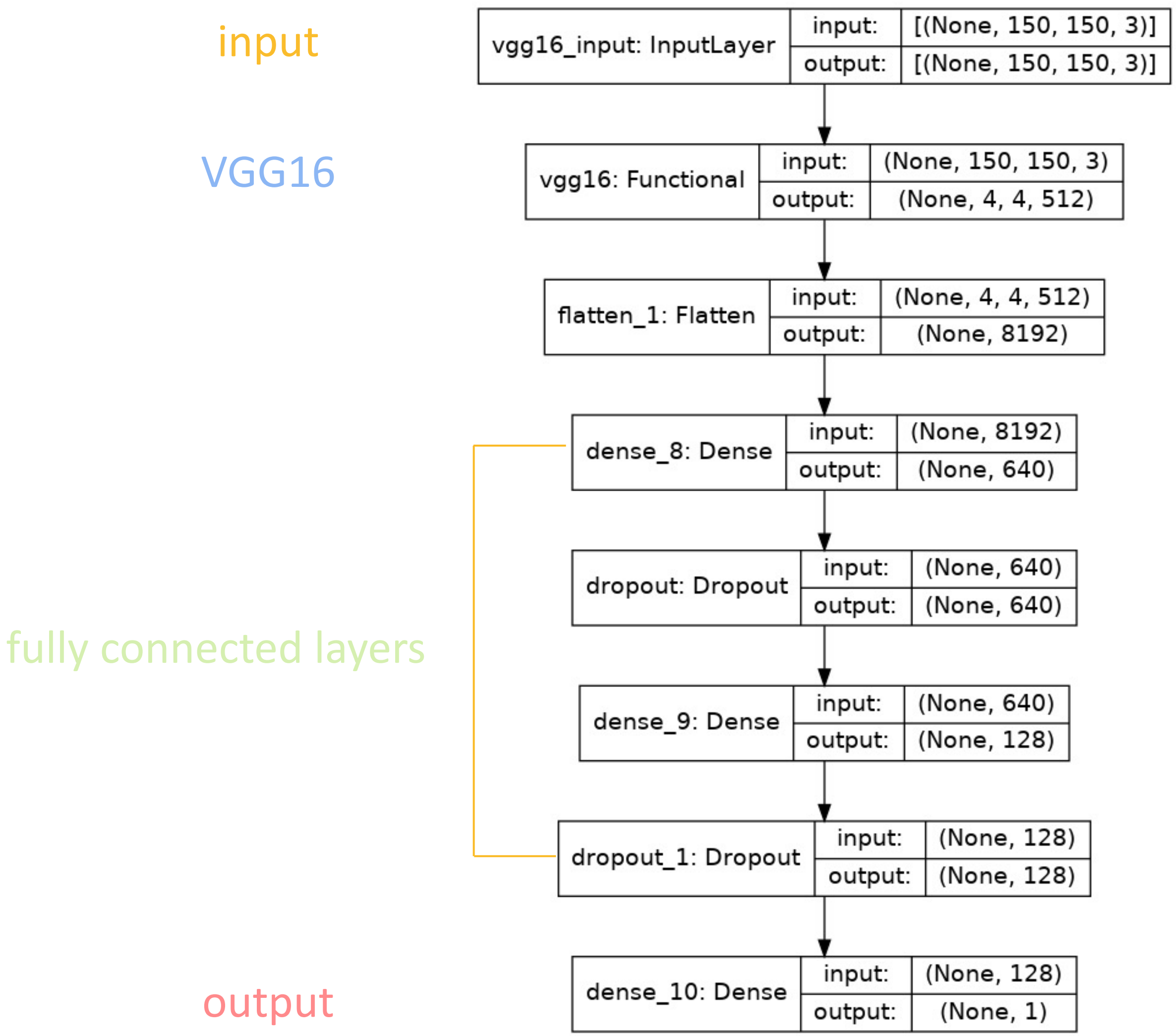
Convolutional Neural Network



Transfer Learning with VGG16

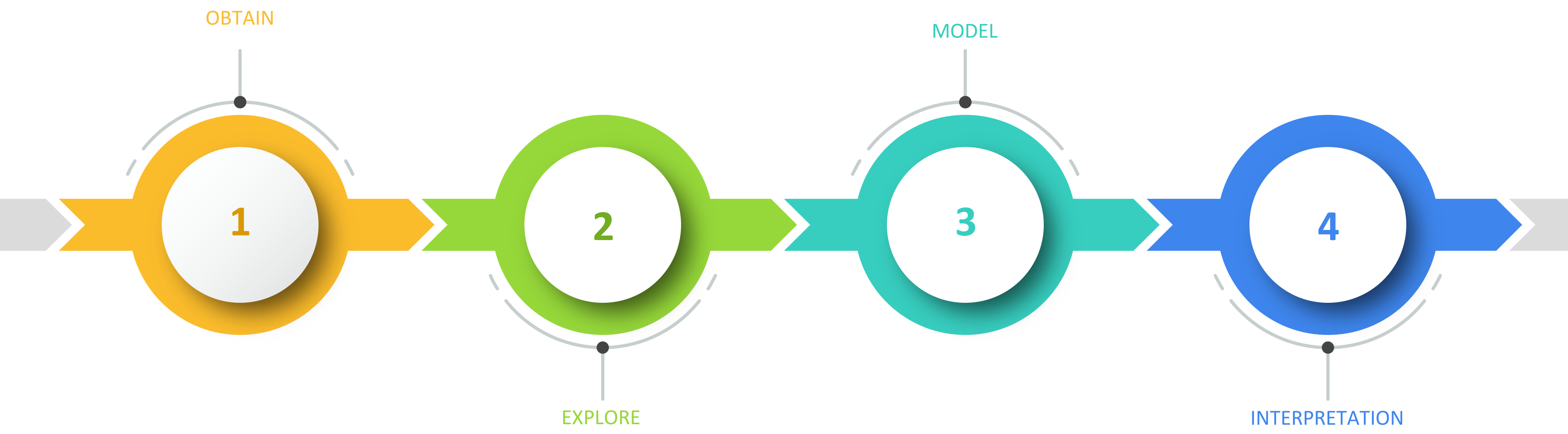


Transfer Learning with VGG16



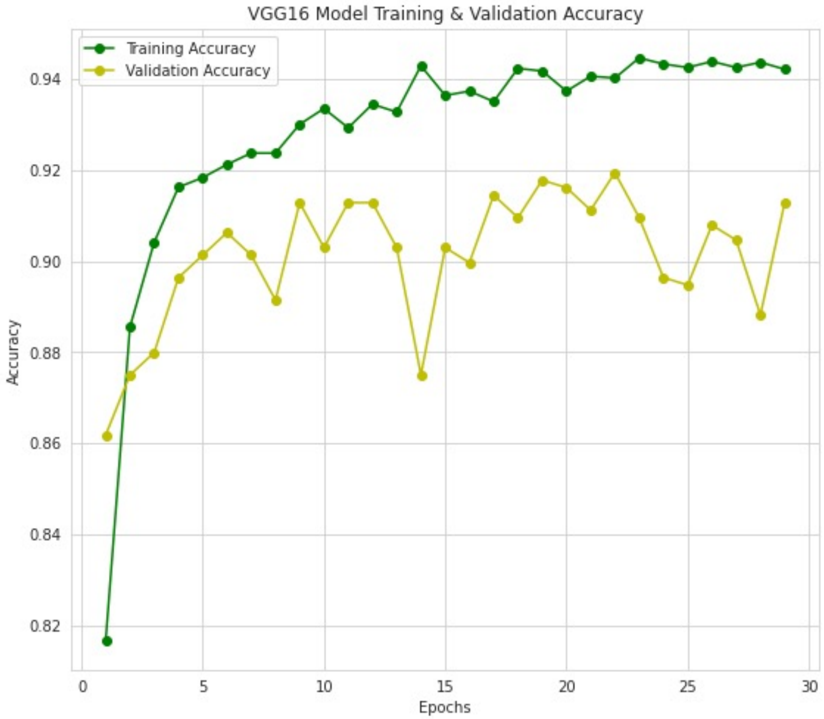
Summary of Key Findings

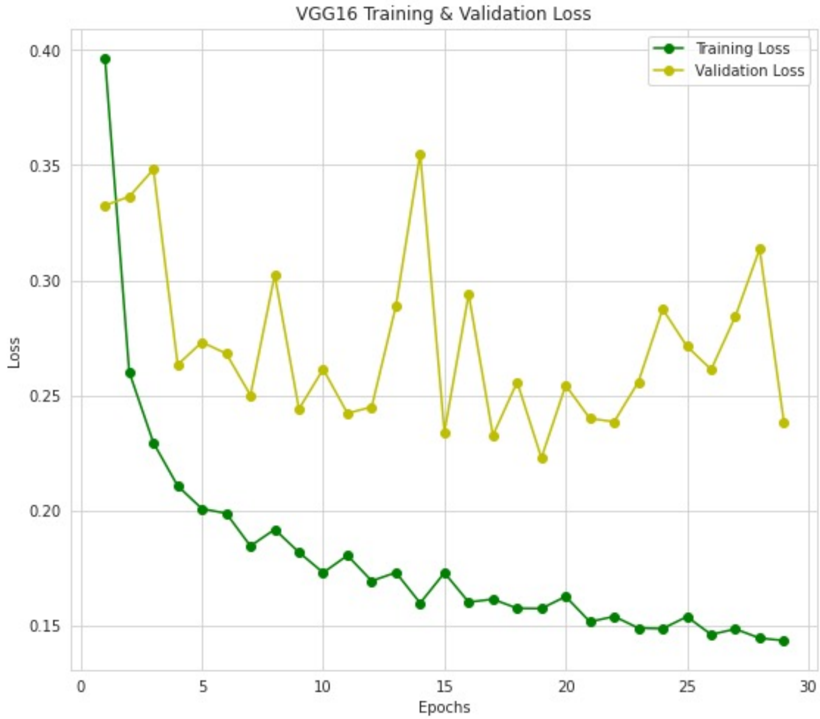
	Model	Accuracy	Precision	Recall	F1 Score	AUC
0	Multilayer Perceptron Model	0.79	0.84	0.74	0.75	0.74
1	Convolutional Neural Network Model	0.88	0.89	0.85	0.86	0.85
2	Transfer Learning: VGG16 CNN Model	0.92	0.91	0.90	0.91	0.90


OBTAIN
1
2
EXPLORE
MODEL
3
4
INTERPRETATION

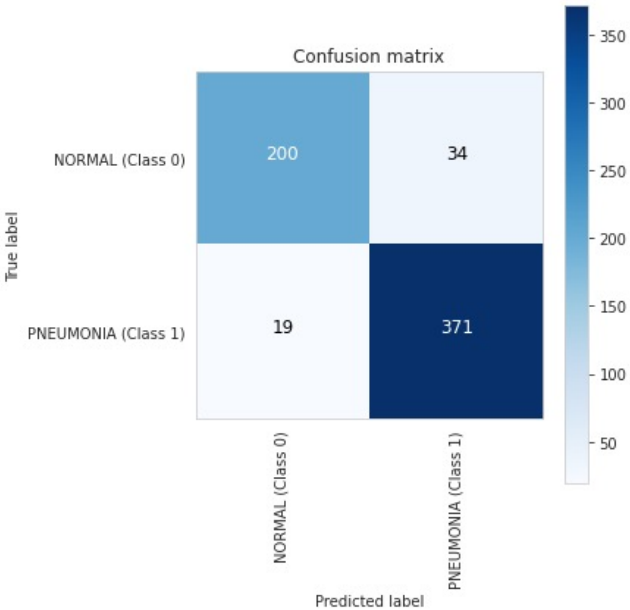
Best Model

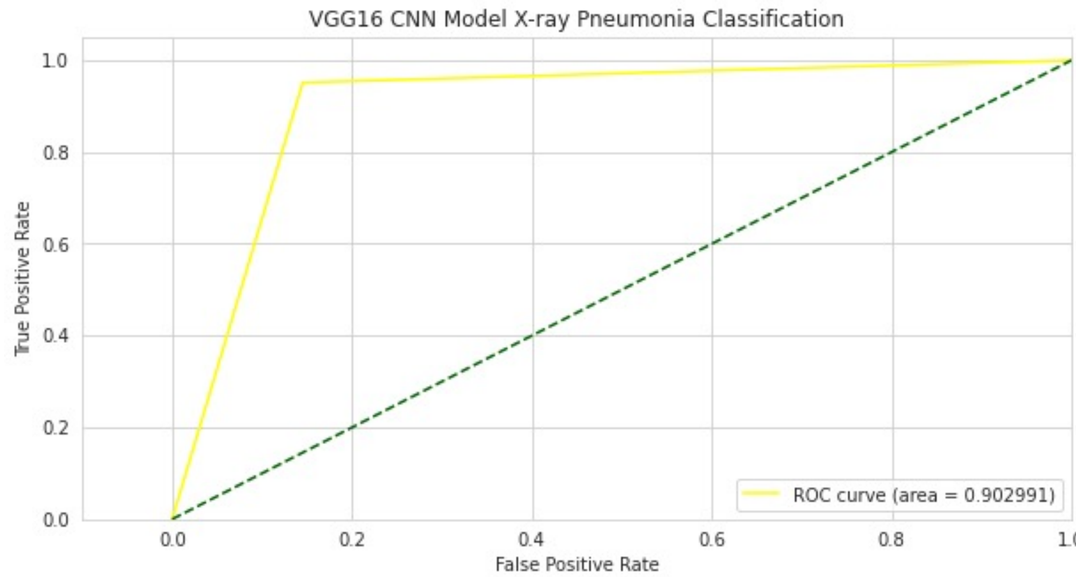
Transfer Learning with VGG16





Train accuracy = 95%
Validation accuracy = 92%





Accuracy of 92%
Recall/sensitivity of 90%
Precision/specificity of 91%
FN < FP
The area under the ROC curve of 90%

Future Work

1. Build a multi-class classification model to distinguish between Normal, Viral Pneumonia, and Bacterial Pneumonia
2. Combine CNN models with other classifiers such as Support Vector Machine (SVM)
3. Tune parameters such as learning rate, batch size, optimizer, number of layers, types of layer, number of neurons per layer, and the type of activation functions for each layer. GridSearchCV or RandomizedSearchSV can be used to achieve this.

Recommendations

Pneumonia are largely preventable in this age group and failure in long-term management or preventing it will result in increases of the risk of developing chronic pulmonary disorders in later adult life. Chang (2013) suggests:

1. Focus on solving problems that are associated with increased risk of pneumonia such as overcrowding, access to clean water, malnutrition, anemia, young maternal age, low birth weight, and exposure to tobacco smoke and other environmental pollutants
2. Invest in resources to collect data systematically, especially in poor countries
3. Develop a universally agreed diagnostic gold standard for childhood pneumonia, especially one that can also differentiate between bacterial and non-bacterial pneumonia, which is currently a major limitation in clinical research in this area

THANK YOU

APPENDIX

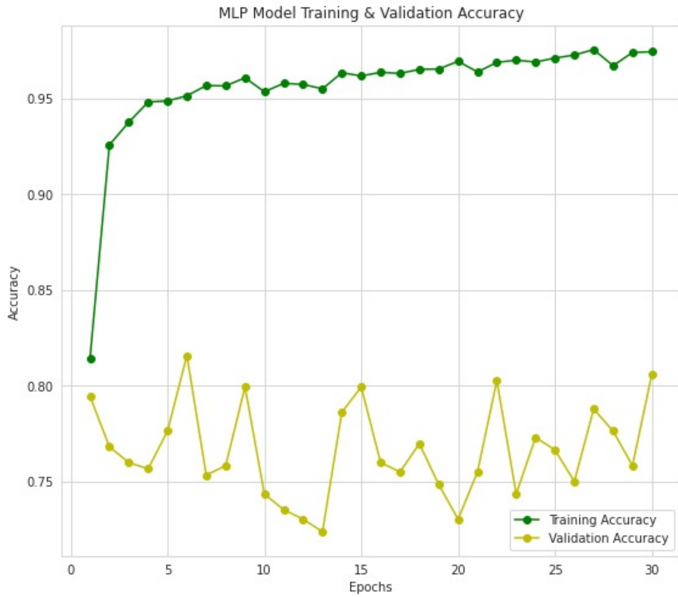
Reference

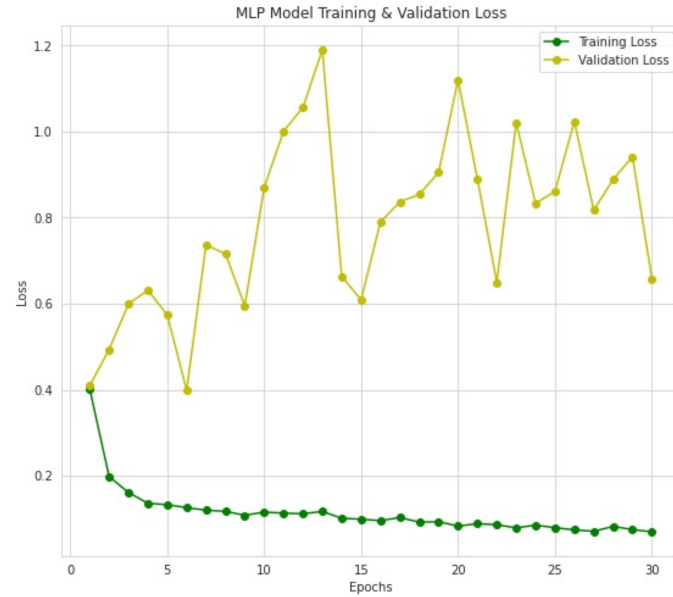
Chang, A. B., Ooi, M. H., Perera, D., & Grimwood, K. (2013). Improving the Diagnosis, Management, and Outcomes of Children with Pneumonia: Where are the Gaps?. *Frontiers in pediatrics*, *1*, 29. https://doi.org/10.3389/fped.2013.00029

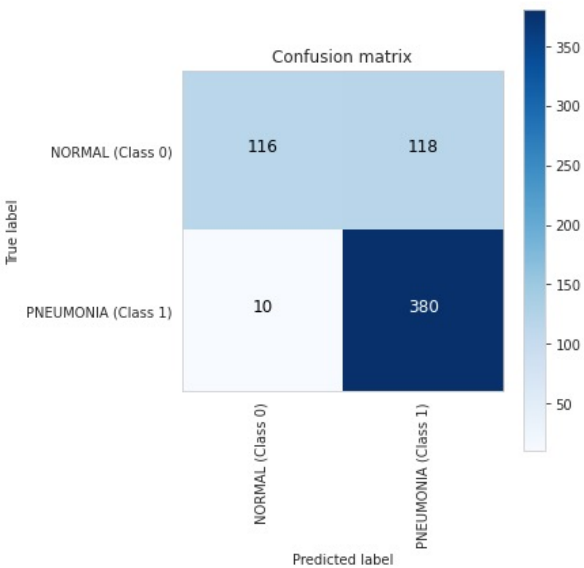
Geron, A. (2019). *Hands-on machine learning with Scikit-Learn, Keras and TensorFlow: concepts, tools, and techniques to build intelligent systems* (2nd ed.). O'Reilly.

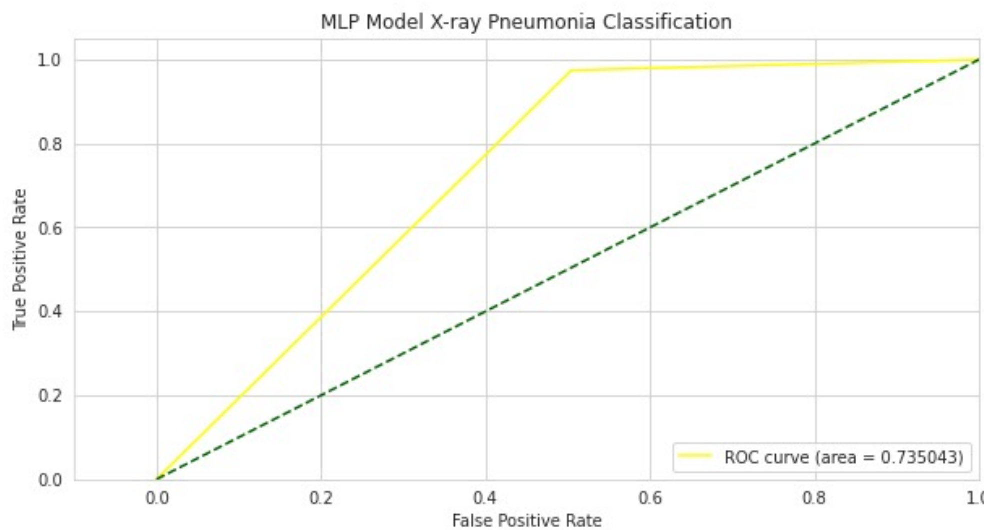
Kermany, D. S., Goldbaum, M., Cai, W., Valentim, C., Liang, H., Baxter, S. L., McKeown, A., Yang, G., Wu, X., Yan, F., Dong, J., Prasadha, M. K., Pei, J., Ting, M., Zhu, J., Li, C., Hewett, S., Dong, J., Ziyar, I., Shi, A., … Zhang, K. (2018). Identifying Medical Diagnoses and Treatable Diseases by Image-Based Deep Learning. *Cell*, *172*(5), 1122–1131.e9. https://doi.org/10.1016/j.cell.2018.02.010

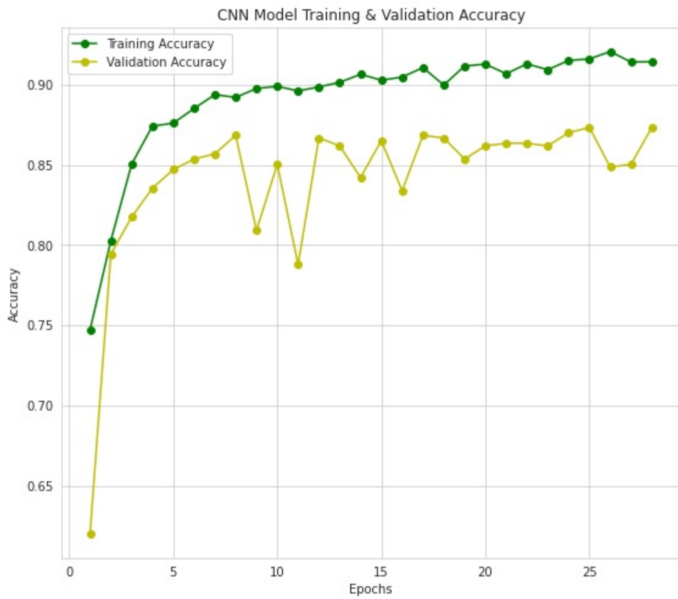
Unicef. (2021, April 07). Pneumonia in children statistics. Retrieved April 13, 2021, from https://data.unicef.org/topic/child-health/pneumonia/#:~:text=A%20child%20dies%20of%20pneumonia,of%20these%20deaths%20are%20preventable.

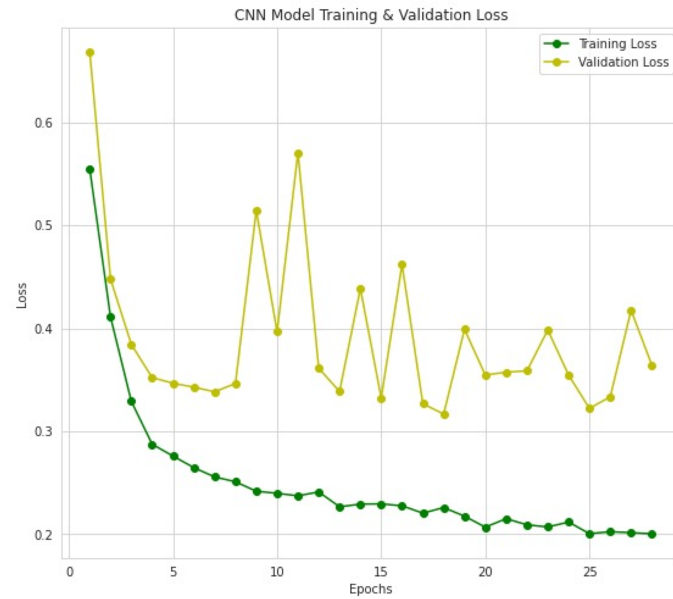

MLP Model Training & Validation Accuracy
Accuracy
Epochs
Training Accuracy
Validation Accuracy
0.95
0.90
0.85
0.80
0.75
0
5
10
15
20
25
30

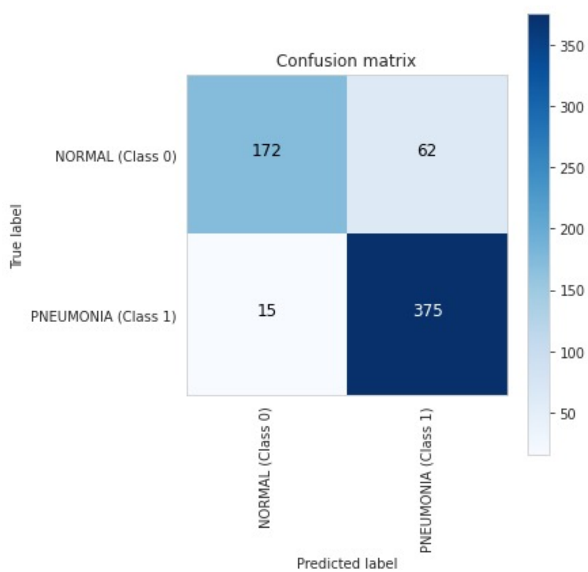

MLP Model Training & Validation Loss
Loss
Epochs
Training Loss
Validation Loss
1.2
1.0
0.8
0.6
0.4
0.2
0
5
10
15
20
25
30

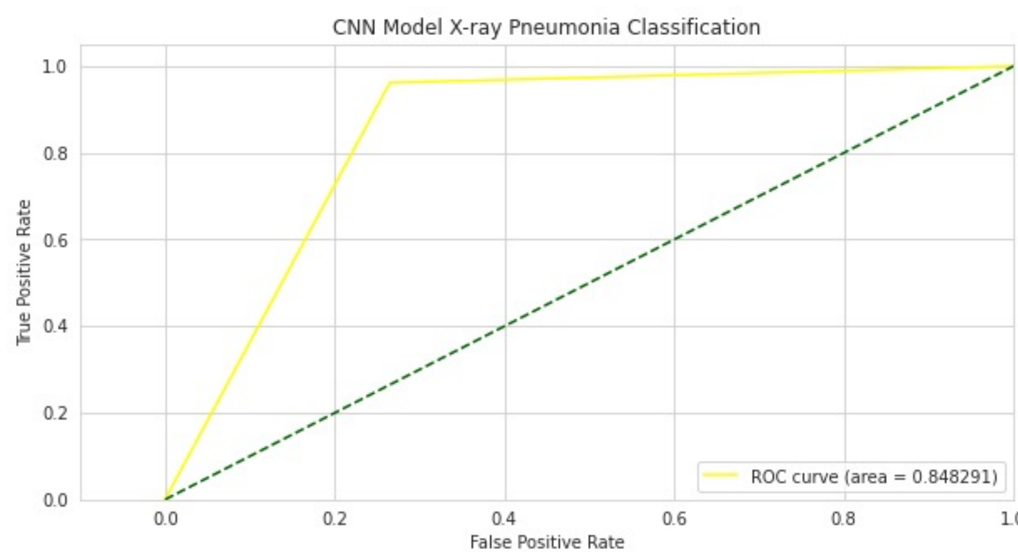

Confusion matrix
True label
Predicted label
NORMAL (Class 0)
PNEUMONIA (Class 1)
116
118
10
380
NORMAL (Class 0)
PNEUMONIA (Class 1)
350
300
250
200
150
100
50


MLP Model X-ray Pneumonia Classification
True Positive Rate
False Positive Rate
ROC curve (area = 0.735043)
1.0
0.8
0.6
0.4
0.2
0.0
0.0
0.2
0.4
0.6
0.8
1.0

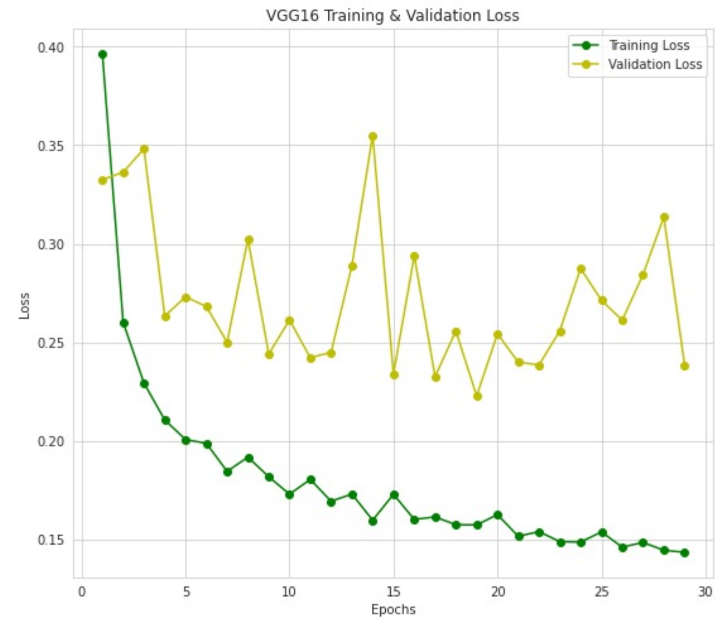

CNN Model Training & Validation Accuracy
Training Accuracy
Validation Accuracy
Accuracy
0.90
0.85
0.80
0.75
0.70
0.65
0
5
10
15
20
25
Epochs

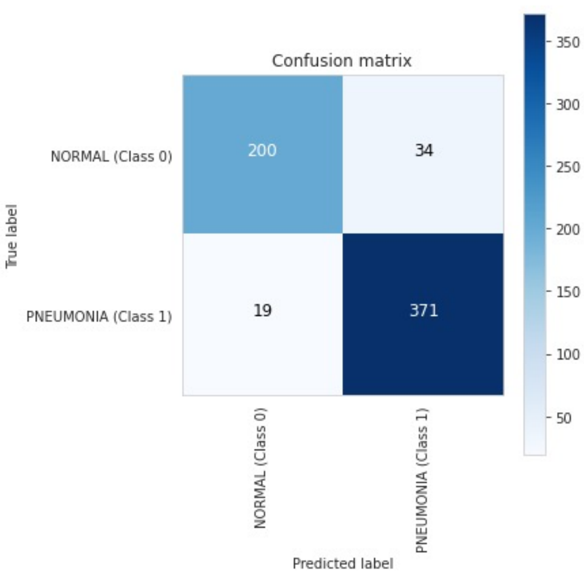

CNN Model Training & Validation Loss
Training Loss
Validation Loss
Loss
0.6
0.5
0.4
0.3
0.2
0
5
10
15
20
25
Epochs

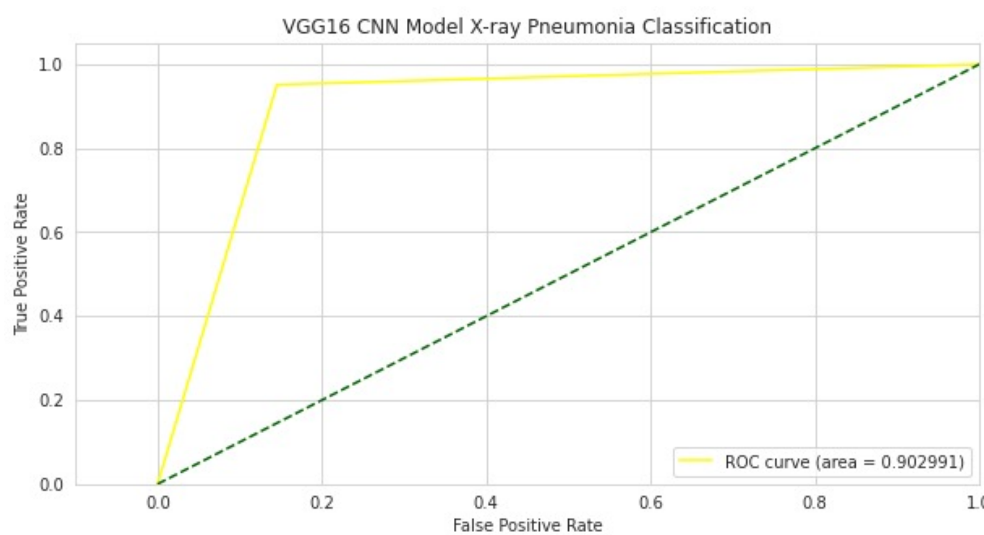

Confusion matrix
True label
NORMAL (Class 0)
PNEUMONIA (Class 1)
172
62
15
375
350
300
250
200
150
100
50
NORMAL (Class 0)
PNEUMONIA (Class 1)
Predicted label


CNN Model X-ray Pneumonia Classification
True Positive Rate
1.0
0.8
0.6
0.4
0.2
0.0
0.0
0.2
0.4
0.6
0.8
1.0
False Positive Rate
ROC curve (area = 0.848291)


VGG16 Model Training & Validation Accuracy
Training Accuracy
Validation Accuracy
Accuracy
0.94
0.92
0.90
0.88
0.86
0.84
0.82
0
5
10
15
20
25
30
Epochs


VGG16 Training & Validation Loss
Training Loss
Validation Loss
Loss
0.40
0.35
0.30
0.25
0.20
0.15
0
5
10
15
20
25
30
Epochs


Confusion matrix
NORMAL (Class 0)
PNEUMONIA (Class 1)
True label
200
34
19
371
NORMAL (Class 0)
PNEUMONIA (Class 1)
Predicted label
350
300
250
200
150
100
50


VGG16 CNN Model X-ray Pneumonia Classification
True Positive Rate
1.0
0.8
0.6
0.4
0.2
0.0
0.0
0.2
0.4
0.6
0.8
1.0
False Positive Rate
ROC curve (area = 0.902991)