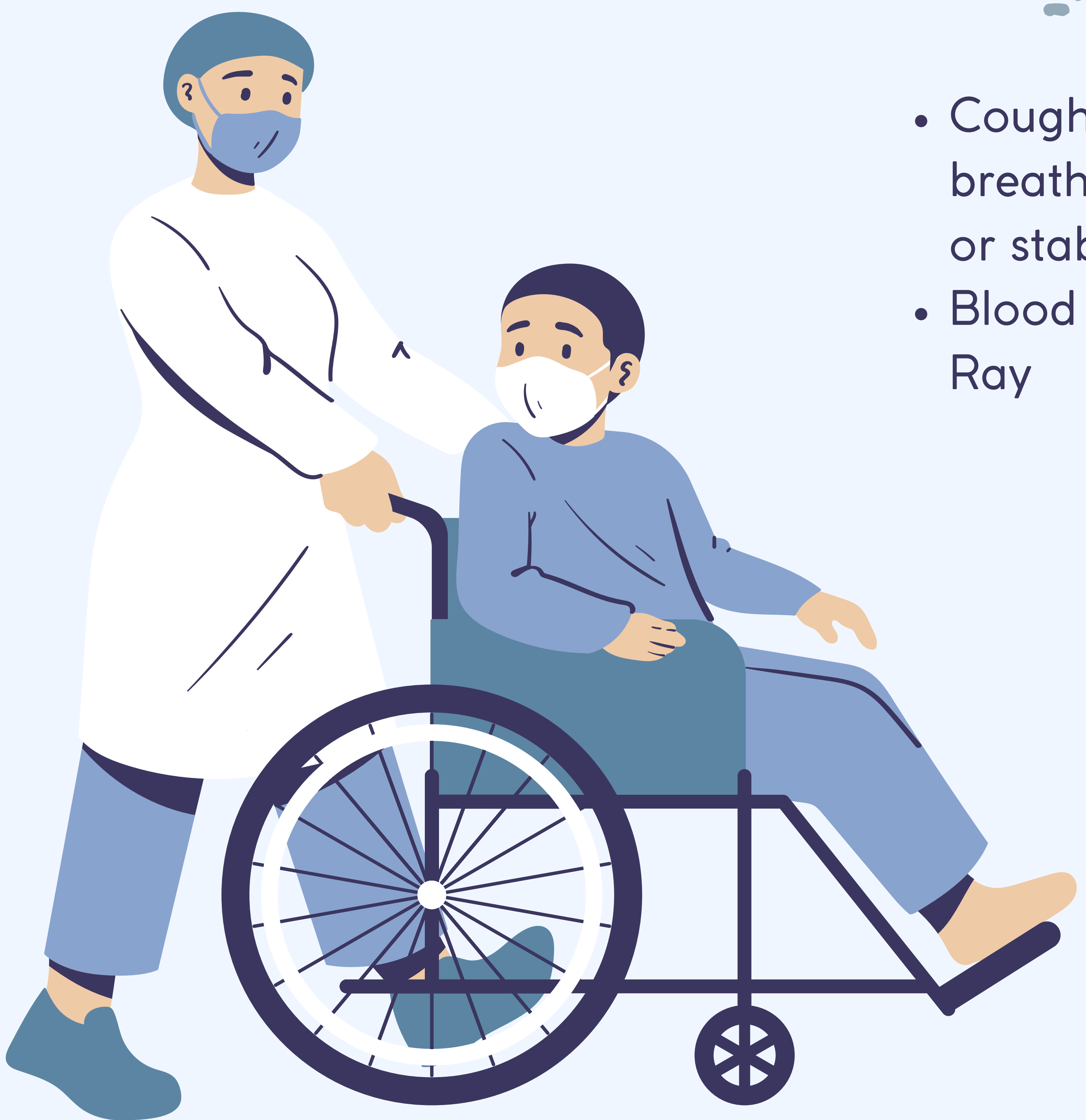
Patient Pneumonia Detection

General Medical Background



What?

- Infection (caused by bacteria, virus, or fungi) in one or both lungs --> Alveoli fill with liquid
- ~1.5 million adults diagnosed per year in the US

Diagnoses

- Cough, high fever with chills, fast breathing, shortness of breath, sharp or stabbing chest pain
- Blood test, sputum culture, chest X-Ray

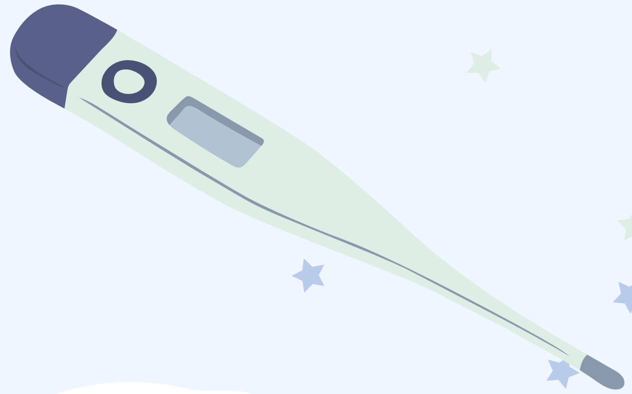
Why?

- Acute respiratory distress, pleural effusion, lung abscesses
- ~ 50,000 deaths per year
- False Positive --> given unneeded medication
- False Negative --> patient not treated, could develop complications

Diagnosing Pneumonia

- Pneumonia symptoms are very similar to other illnesses, making **misdiagnosis common**.
- About **12%** of patients were inappropriately diagnosed with pneumonia in a study across 48 hospitals in Michigan.
- **1 in 8** patients are misdiagnosed.
- A DL preventative diagnosis can save hospitals rooms and time of doctors for more dire cases.

Objective



Highly Accurate Image Classification Model

Correctly detect pneumonia in chest X-rays which can help ensure patients receive the care they need.

Data Preprocessing

Dataset

- Binary outcome variable: Normal vs. Pneumonia
- 5856 images
  - training: 3513 images
  - testing: 1171 images
  - validation: 1172 images
- Resized to (64,64)
- Normalized pixel values to be between 0 and 1
  - divided image size by 225
- Expand dimensions to retain consistency in shape for deep learning.

Normal

Pneumonia

The Models

Model Objectives

Determining the best model to detect Pneumonia

Using extensive deep learning models, we aim to implement the model that can most accurately detect a case of pneumonia within a patient.

Meeting the human benchmark

With a pulmonary specialists knowledge, they can accurately predict a patient with pneumonia with a rough 90% accuracy. We want a model that can closely predict a specialists accuracy.

Metric Used

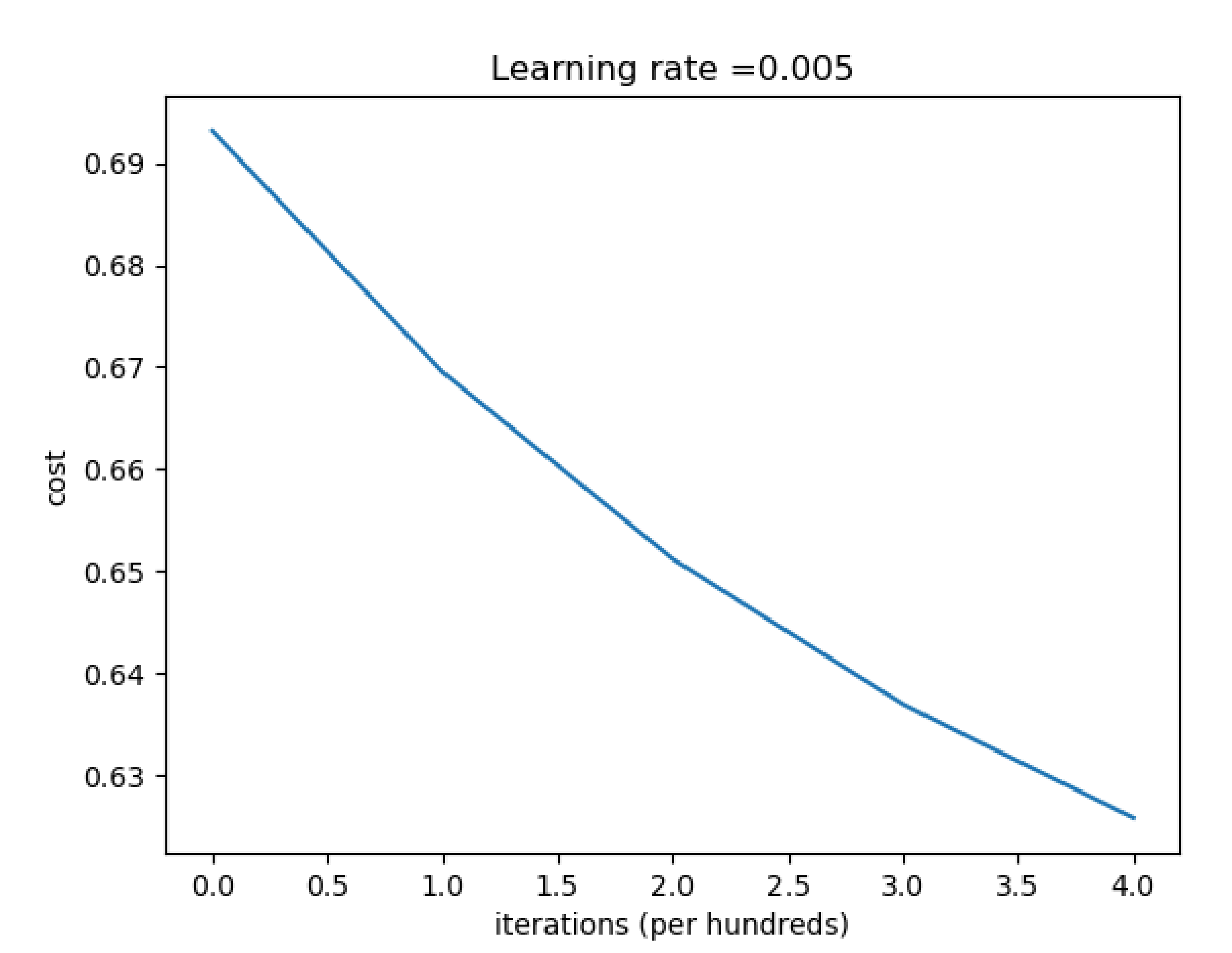
For our models, we will prioritize our accuracy and Recall metrics. Accuracy to determine how our model is performing and recall to see how accurate the models perform for detecting pneumonia.

Logistic Regression - No Hidden Layers

Training Set	
Iteration	**Cost**
0	.6931
100	.669 5
200	.6512
300	.6370
4000	.6258

- For our logistic regression, found having a learning rate of .005 to be our most optimal rate.
- we would want to improve our accuracy using different models.

Training Accuracy	72.92%
Testing Accuracy	73.89%
CV Accuracy	72.16%

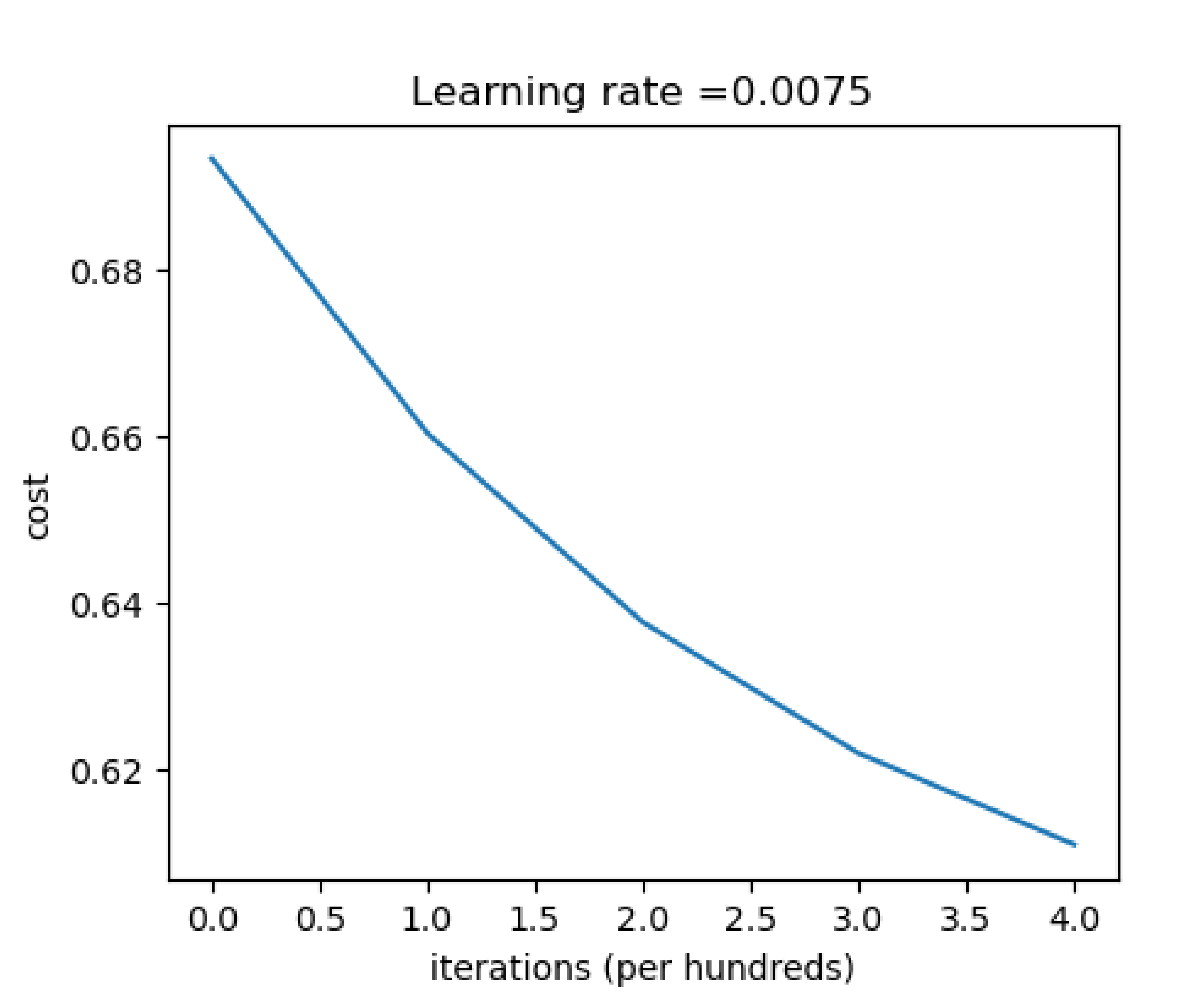


Deep NN - 2 hidden layers, 4 hidden units

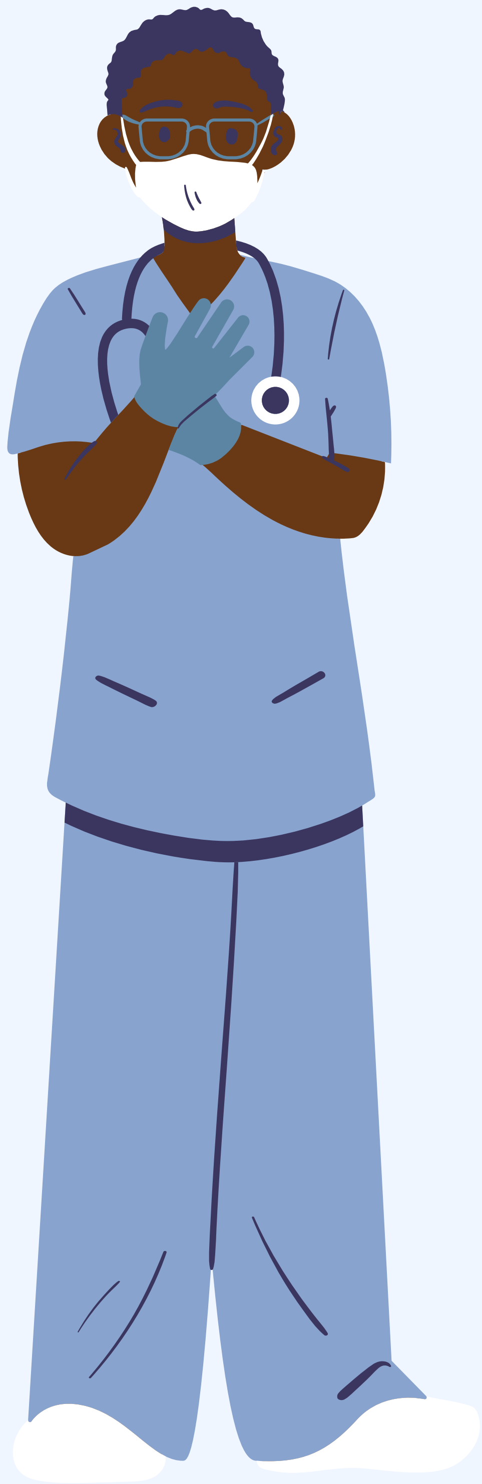
Training Set	
Iteration	**Cost**
0	.6931
100	.6602
200	.6375
300	.6218
400	.6109

- With a Deep Neural Networks model and using learning rate = .0075, our cost gradually decreases with each iteration.
- From our final results, we are having a consistent accuracy of 72 - 73%.

Training Accuracy	72.92%
Testing Accuracy	73.89%
CV Accuracy	72.16%

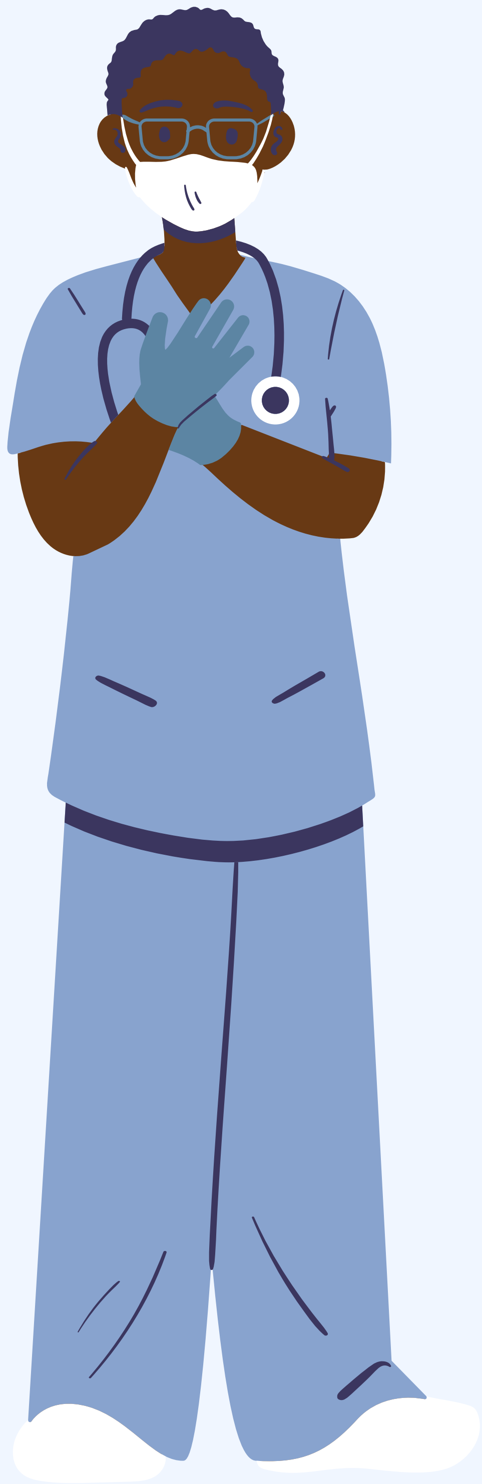


Model Optimizations



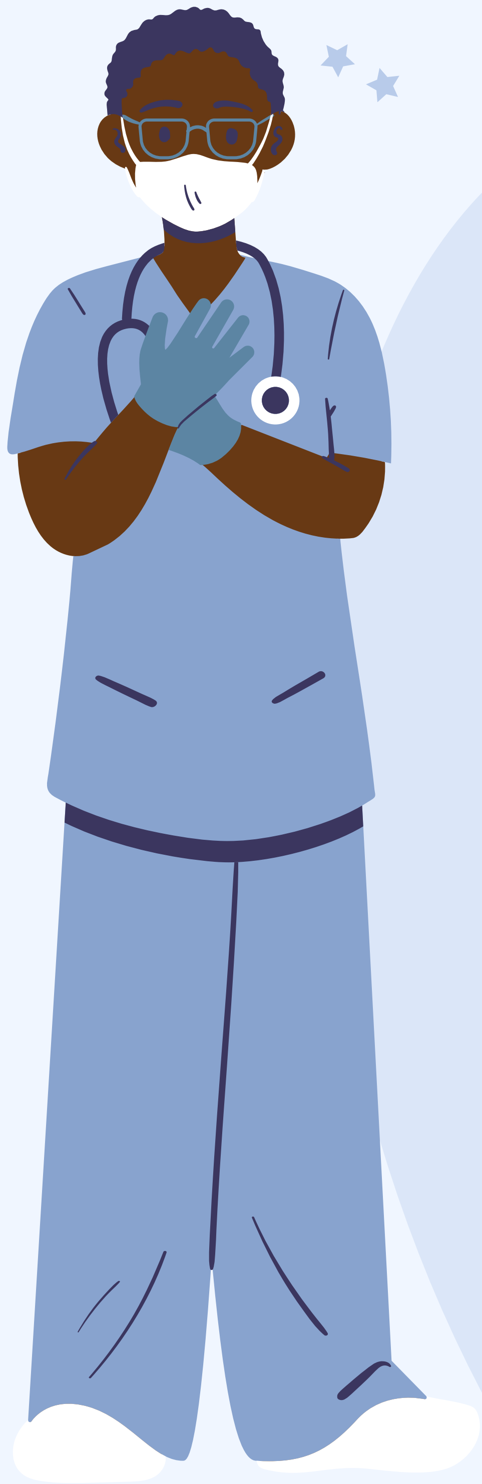
Algorithm	Training Accuracy	Training Recall	CV Accuracy	CV Recall
Model	89.90%	95.90%	88.64%	97.98%
Model Fit w/ Validation	91.74%	96.14%	91.72%	98.93%
Changing NN	93.08%	96.84%	94.53%	98.22%

Best Optimization – Changing NN Iterations



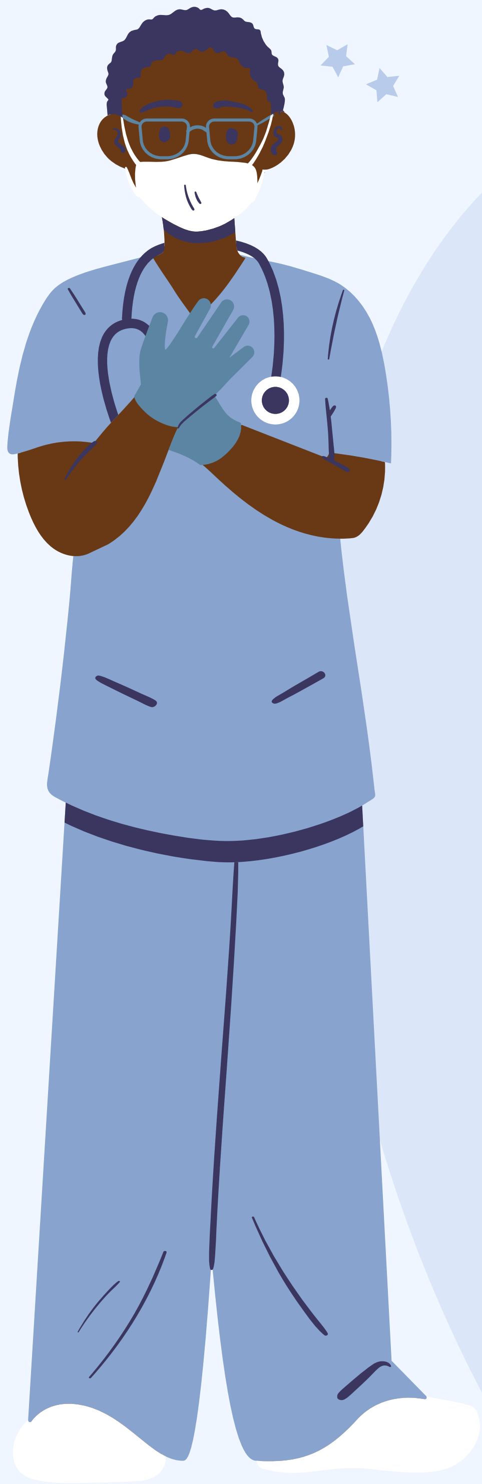
Epoch	Training Accuracy	Training Recall	CV Accuracy	CV Recall
2	77.63%	90.01%	87.36%	94.91%
4	88.76%	94.93%	90.44%	97.40%
6	91.32%	96.17%	93.08%	97.04%
8	93.08%	96.84%	94.53	98.22%

L2 Regularization



Lambda	Train Accuracy CV Accuracy	Train Recall CV Recall
0.001	91.65% 92.47%	98.47% 99%
0.002	93.52% 94.68%	97.82% 97.91%
0.003	93.25% 94.97%	97.23% 97.71%
0.004	93.7% 94.33%	95.78% 96.08%
0.005	93.67% 94.34%	97.02% 97.07%

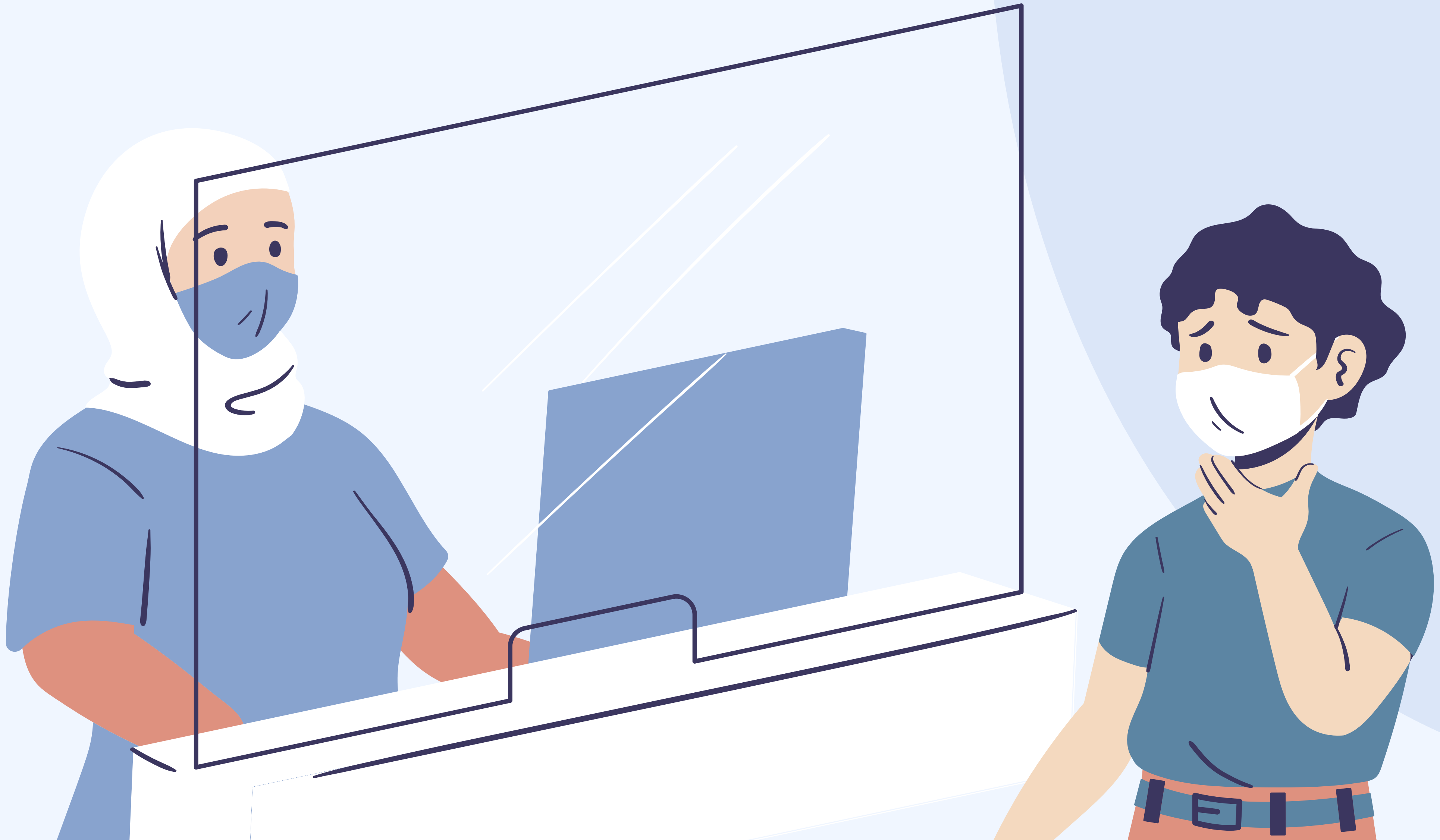
Dropout Regularization



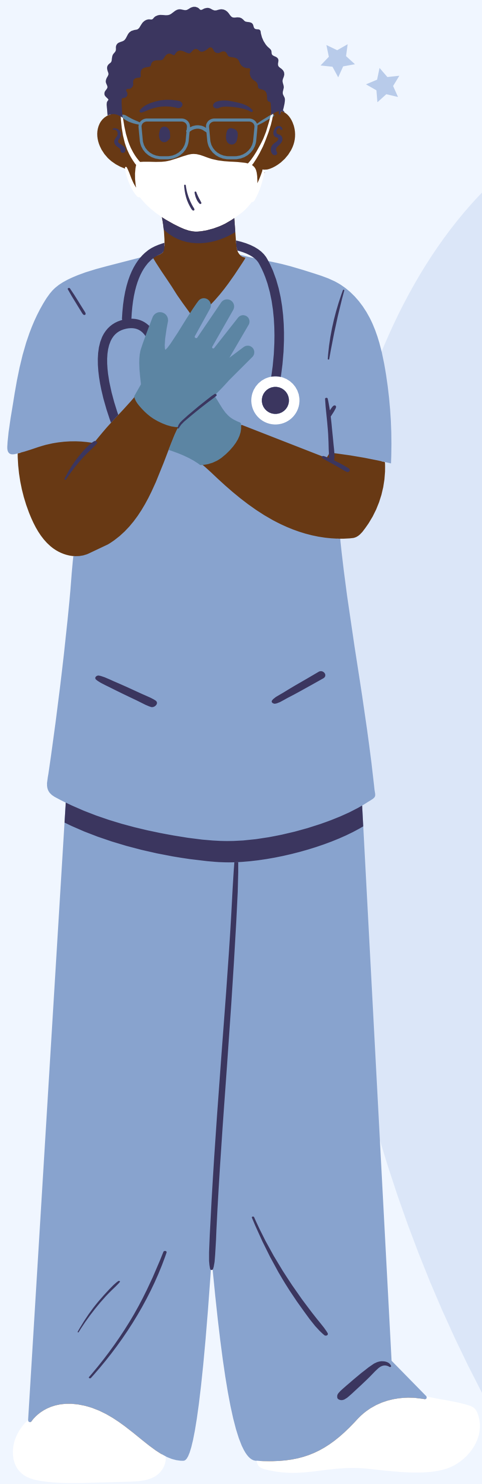
Dropout Rate	Train Accuracy	Train Recall	CV Accuracy	CV Recall
0.5	92.28%	97.58%	93.28%	98.2%
0.6	73.82%	1	72.53%	1
0.4	90.05%	98.78%	90.10%	99.21%
0.3	91%	97.54%	91.9%	98.11%
0.2	73.82%	1	72.53%	1

L2 & Dropout Regularization

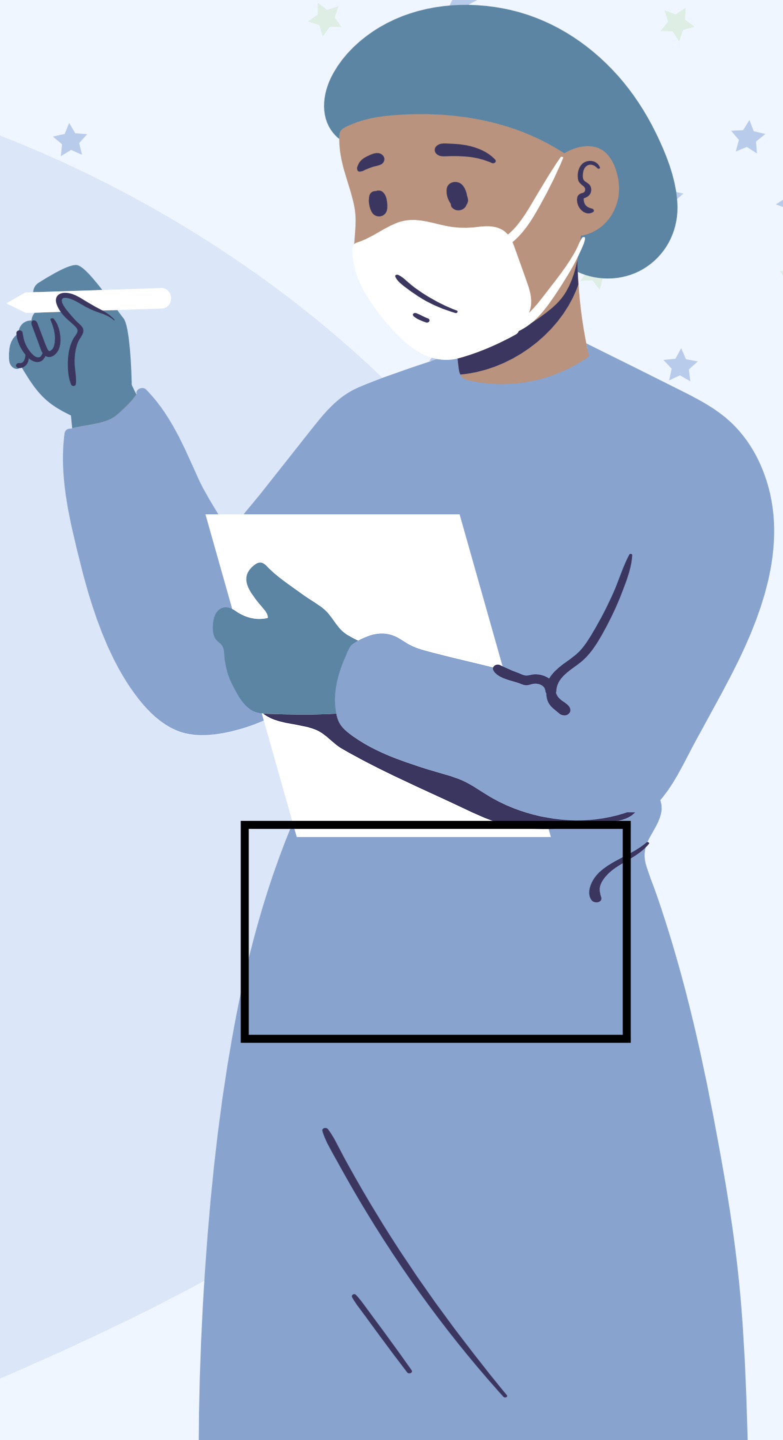
Lambda	Dropout Rate	CV Accuracy	CV Recall
0.001	0.2	92.66%	99%
0.003	0.4	86.94%	99.4%
0.004	0.5	94.48%	97.77%
0.005	0.6	84.13%	99.4%



Batch Normalization



Batch	CV Accuracy	CV Recall
Default	81.96%	99.57%
momentum - 0.98 epsilon - 0.002	89.17%	96.42%
momentum - 0.97 epsilon - 0.003	41.41%	19.33%
momentum - 0.96 epsilon - 0.004	72.58%	1
momentum - 0.95 epsilon - 0.005	27.5%	0.00034%



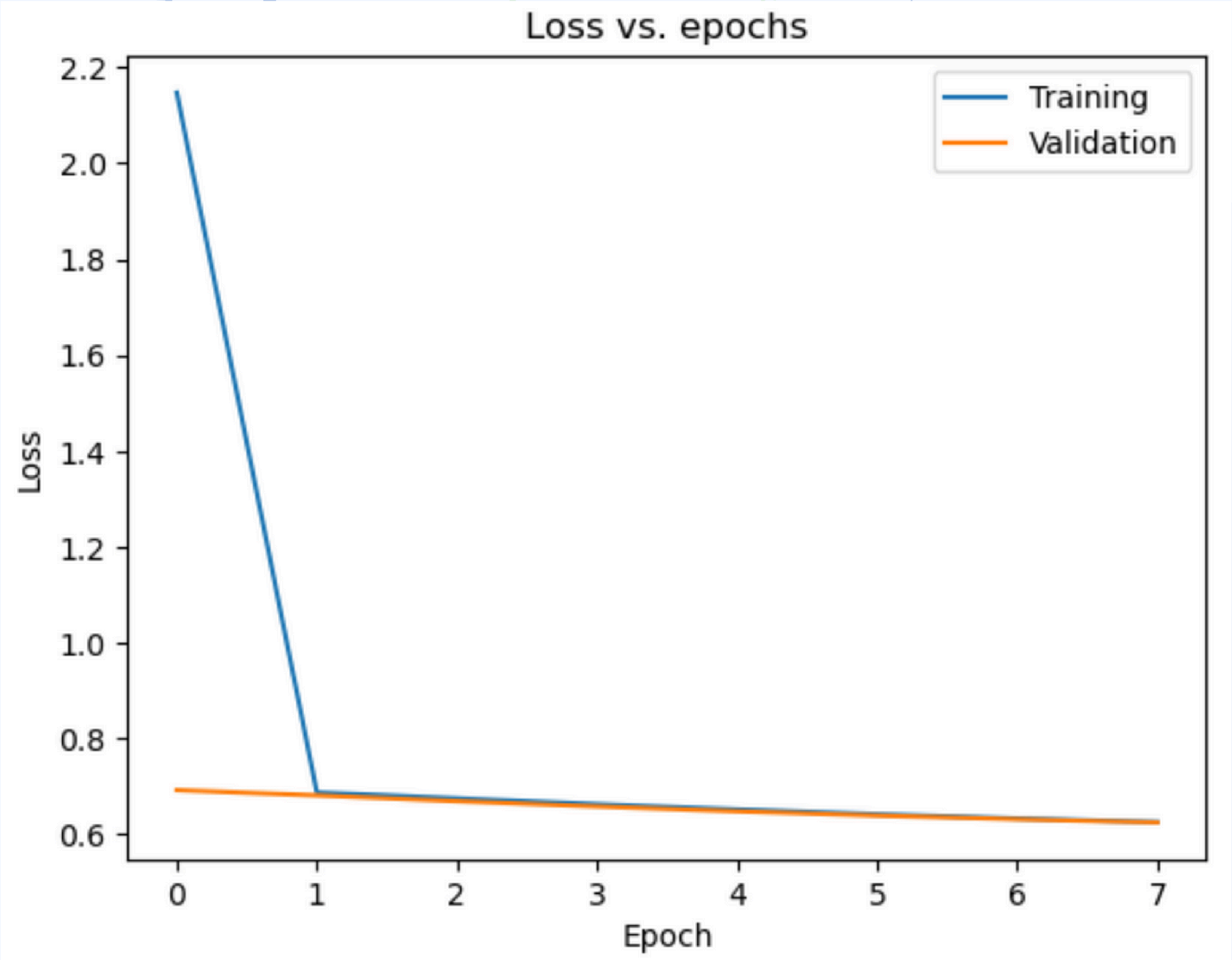
Batch Normalization & Dropout Rate

Momentum	Epsilon	Beta initializer	Gamma Initializer	Dropout Rate	CV Accuracy	CV Recall
Default	Default	Default	Default	0.5	80.76%	99.87%
0.95	0.005	mean=0.0, stddev=0.05	0.9	0.5	84.49%	80.93%
0.90	0.010	mean=0.0, stddev=0.06	0,8	0.5	80.49%	77.52%
0.92	0.015	mean=0.0, stddev=0.07	0.7	0.5	78.85%	99.29%
0.97	0.006	mean=0.0, stddev=0.08	0.6	0.5	73.26%	1

Combinations

Model	Training Accuracy	CV Recall
Baseline with L2 Regularization	93.42%	98.93%
L2 Regularization & Dropout	94.87%	97.86%
L2 Regularization and Batch Normalization	81.63%	99.88%
L2 Regularization, Batch Normalization, and Dropout	94.10%	93.13%
Increased Complexity with L2, Batch Normalization, and Dropout	35.33%	10.41%

Early Stop



CV Accruacy	72.53%
CV Recall	1

Best Model

L2 Regularization + Dropout

Model	Train Accuracy	Train Recall	CV Accuracy	CV Recall	Test Accuracy	Test Recall
L2 Regularization + Dropout	0.9487	0.9709	0.9487	0.9786	0.9301	0.9650

TESTING DATASET		Predicted	
		Normal	Pneumonia
Actual	Normal	257	49
	Pneumonia	29	837

- Based on the models explored, the combination of **L2 Regularization + Dropout** performed the **best**
- Good **balance** between high accuracy and recall
- Much **improved** compared to logistic regression which hovered around **70%** accuracy.

VGG Model

Model	Train Accuracy	Train Recall	CV Accuracy	CV Recall	Test Accuracy	Test Recall
VGG using CONV layers	0.9555	0.9887	0.9406	0.9689	0.9429	0.9757

TESTING DATASET		Predicted	
		Normal	Pneumonia
Actual	Normal	262	44
	Pneumonia	23	843

- **High rate** of true positive (TP) to minimize misdiagnosis.
- Good **balance** between recall and accuracy.
- VGG competes well with our other existing models, but is also **computationally expensive**.

Business Implications

Managerial Benefits

Accuracy/Efficiency &
Scalability/Automation

Enhanced Decision Making

Quality and Medical
Compliance
Standardization

Competitive/First Mover
Advantage

Cost Implications

The associated cost of an occupied hospital bed can be $1k to $3k per day in the US (Worldmetrics.org).

31.1% of pneumonia cases were among children and adolescents (<18 years) *$900 - $2.6k*
44.8% were among non-elderly adults (18-64) *$2.2k - $3k*
24.1 were among elderly adults (>= 65 years) *$4k - $5k*
(Jwatch.org)

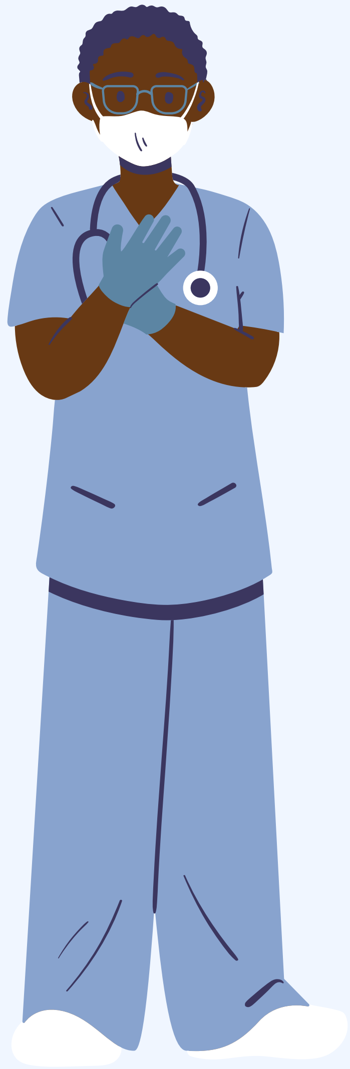
Age group	Cost per episode (US$)
	Mean
< 1 y	2621.9
1 y	1255
2–4 y	923
5–17 y	910.2
18–49 y	2177.7
50–64 y	3478.3
65–74 y	4025.8
75–84 y	4605.1
≥ 85 y	4993

Efficiency Gains with Economies of Scale
&
Readmission Costs

Conclusion

COST SAVINGS:

- Cost of a misdiagnosis is around **$2-5k** (diagnostics, bed occupancy, etc.)
- Actual misdiagnosis rate is at 12%, our model can predict up to 95% **(8% reduction)**
- For every 1,000 cases, hospitals can save up to **$20-50k** annually *(not including costs for readmissions.*
- Better diagnoses can lead to appropriate treatments reducing the likelihood of readmission:
  - Assuming readmission cases cost $15,000 per case, total savings (from 25 cases) can reach $375,000.



REVENUE GAINS:

- Reduced time to diagnosis (ability to handle more patients):
  - A 10% increase in patient throughput with each additional patient bringing in $5k can result in over **$500,000 annual** revenue.
- Faster patient turnover and reduced operational costs:
  - Assuming a 0.5 day reduction in diagnostic process can save $2,000 a day **(up to $1 million annually)**

Potential Savings up to **$2 million annually**

Thank You!