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COVID or flu? That’s the question!

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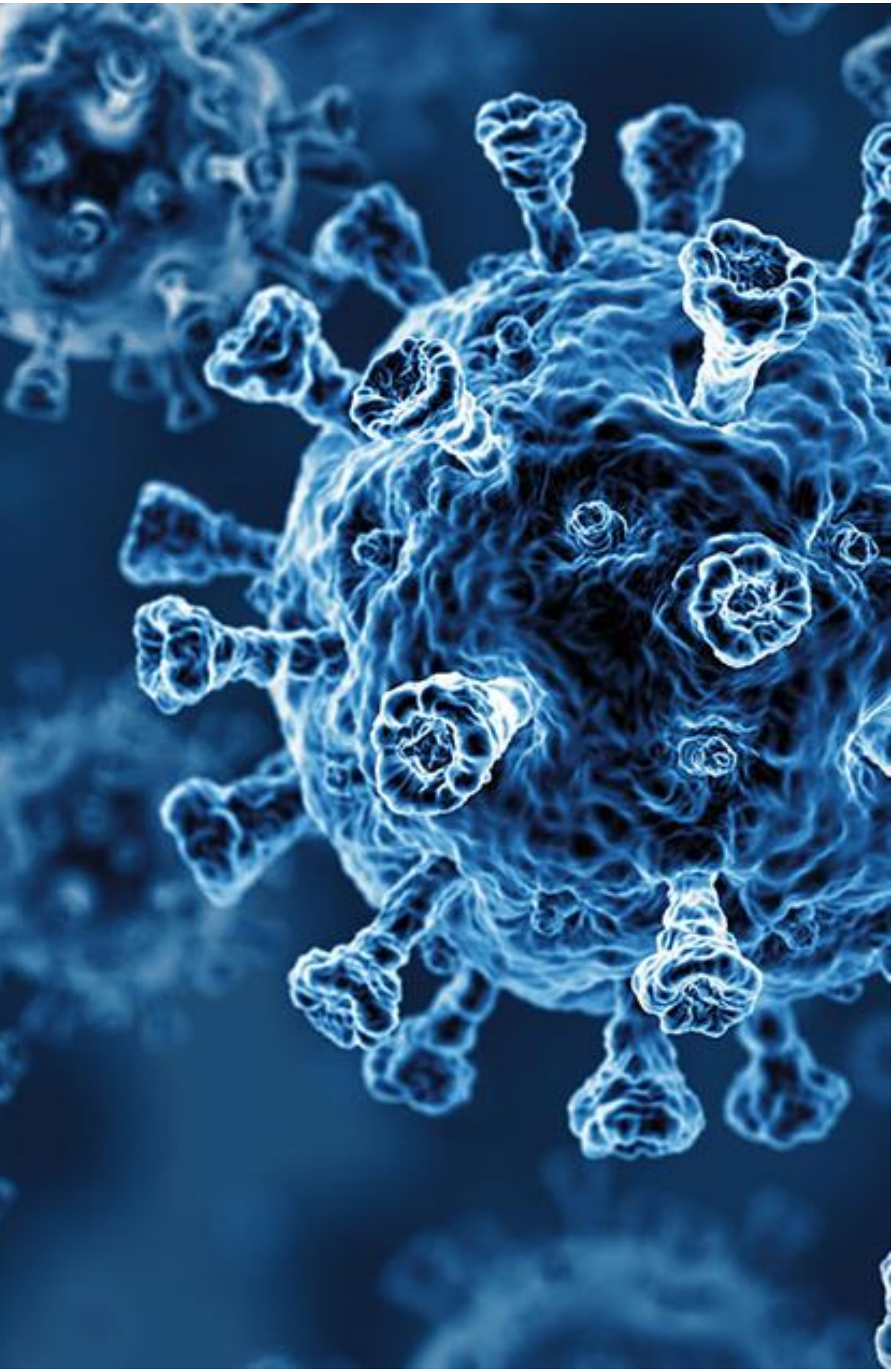
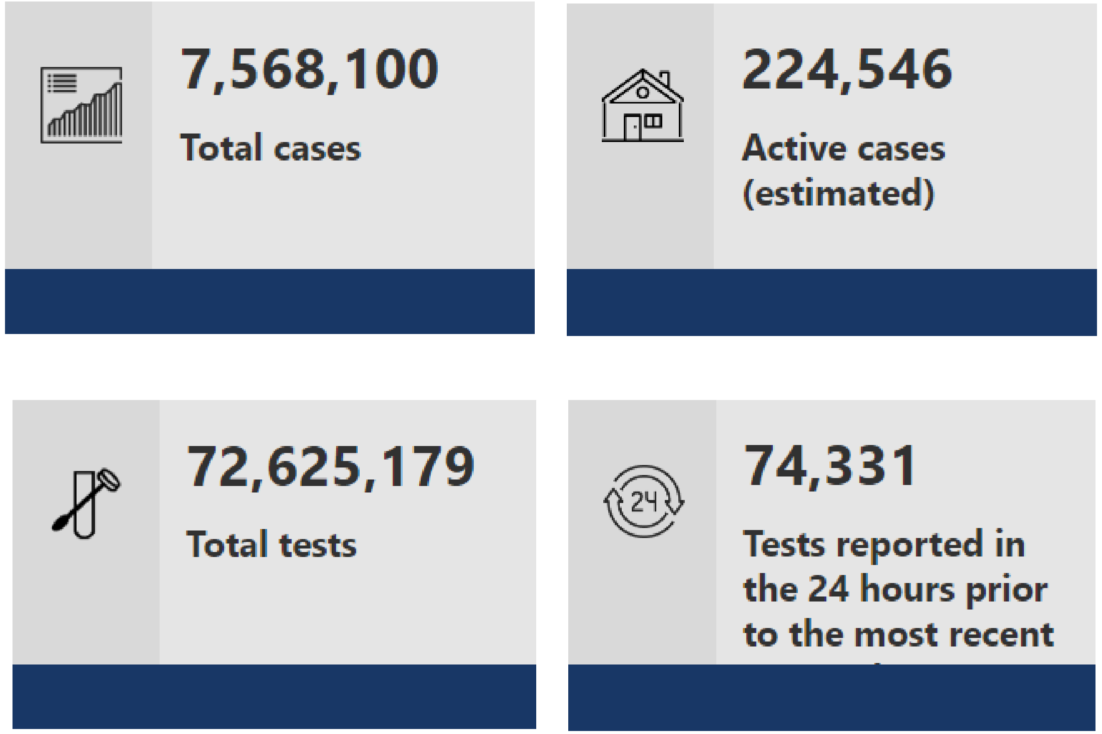


The Big Picture

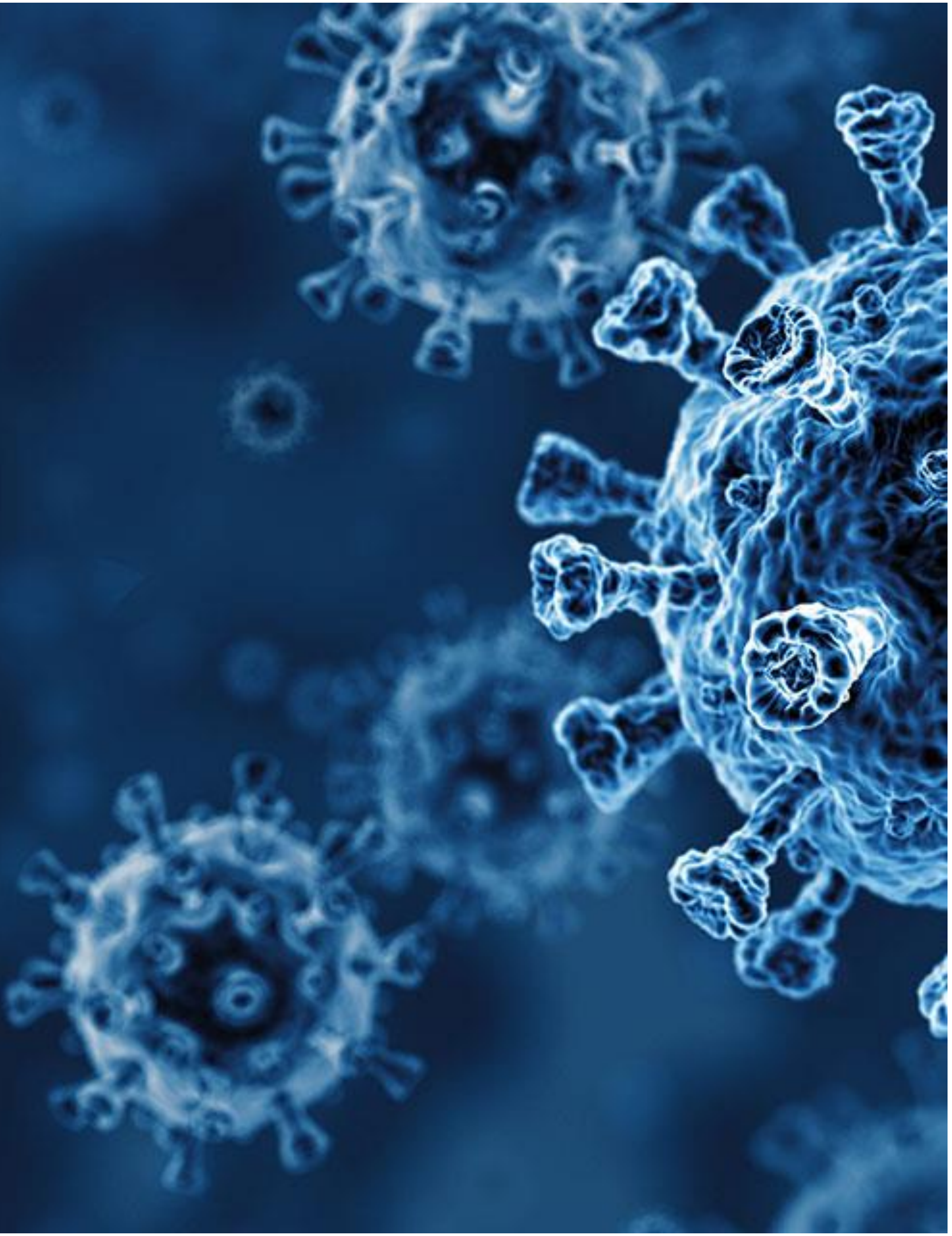
- COVID-19 is a deadly respiratory disease
  - Significant impact on healthcare, economy and lifestyle
- Important to conduct research into new ways of diagnosing COVID-19
  - To reduce burden on healthcare workers
  - To decrease test turnaround time
- Machine Learning can be used to detect COVID-19 in chest X-rays



COVID-19 Statistics in Australia as of 12 June 2022 [1]

Outline

Introduction



COVID-19 Diagnosis

- Several ways to detect COVID-19
  - PCR – accurate, but long turnaround time
  - RAT – result in 15 minutes, but less accurate

- Chest radiography is an alternative method
  - Requires analysis by radiographer
  - Similar respiratory diseases can be hard to distinguish

- Can use Machine Learning models to automatically detect and differentiate COVID-19 from other respiratory diseases in chest X-rays

Project Aims

- To develop Machine Learning models to classify chest X-ray images for
  - COVID-19
  - Viral Pneumonia
  - Normal patients
- To compare Machine Learning models for best classification
  - Evaluation Metrics

Theory – Chest Radiography

- Uses non-lethal ionising radiation to produce X-ray images
  - Brighter regions – dense structures such as bones & organs
  - Darker regions – mostly air
- Lungs are less transparent for patients with COVID-19 and Viral Pneumonia
  - Due to fluid build-up which increases lung density

Normal

Viral Pneumonia

COVID-19

Chest X-ray images [2]

Theory – Machine Learning

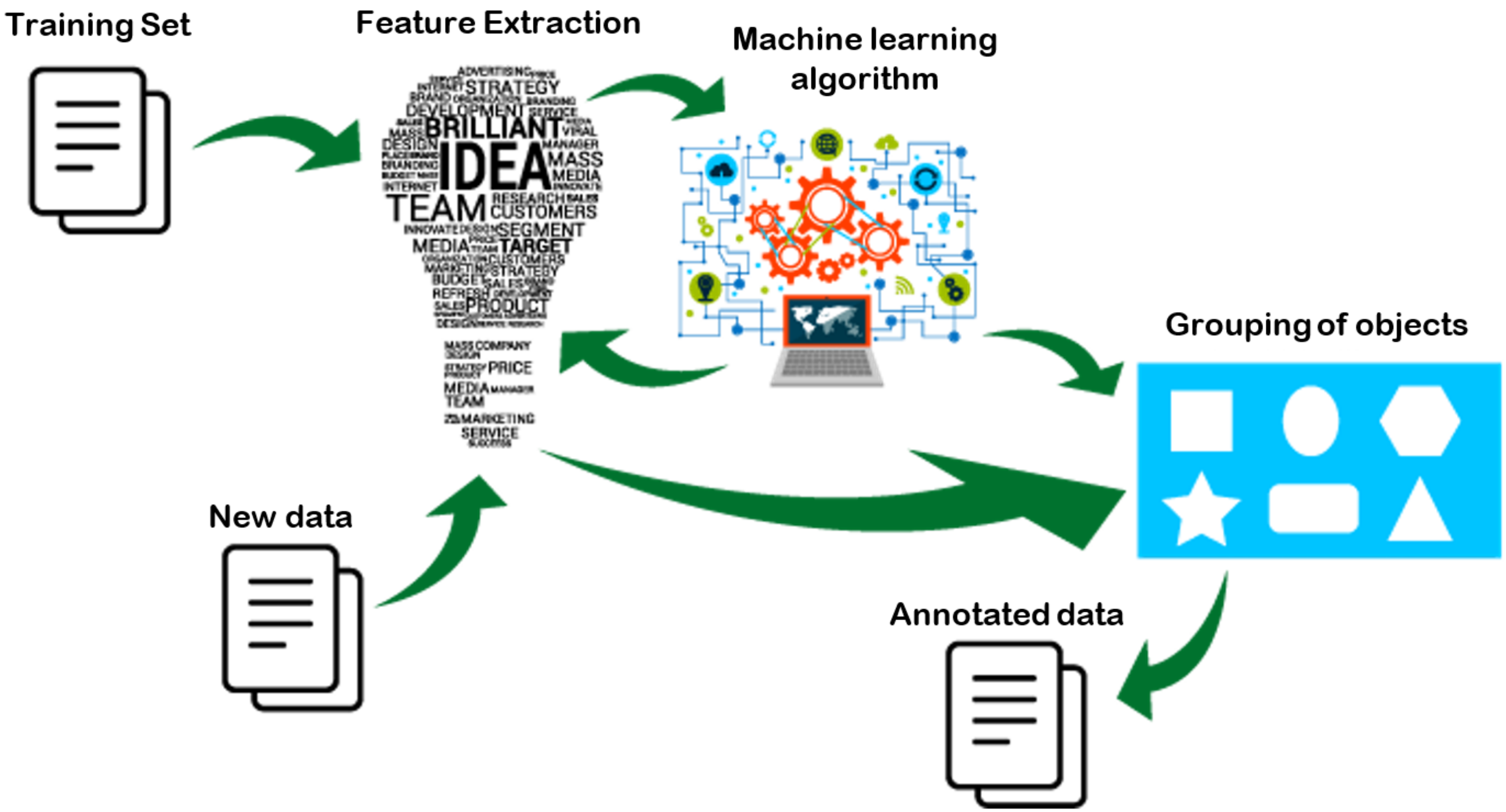
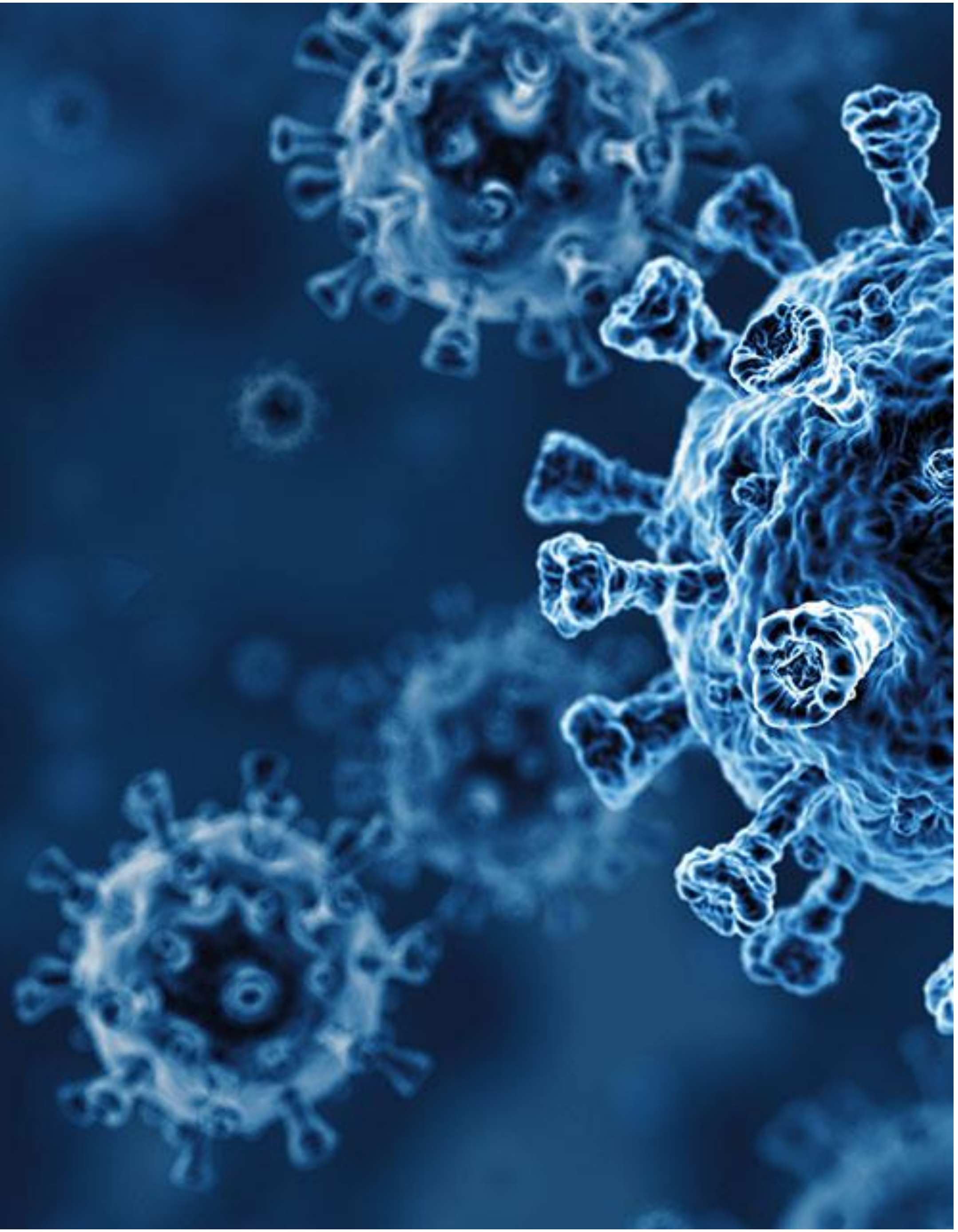


Figure 3: Diagram depicting different stages involved in a Machine Learning model [3]

Methodology



Outline

Data Collection:

- **Dataset A:** University of Montreal Dataset
- **Dataset B:** COVID-19 Radiography Database
- **Content:** Labelled chest X-ray images of COVID-19, Viral Pneumonia and Normal patients

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Data Preparation:

- **Data Pre-processing:** Resize images to 224 x 224 size. Normalise pixel intensity values to range of 0 to 1.
- **Data Augmentation:** Generate additional data by applying rotation, horizontal flipping, vertical shifting and horizontal shifting of chest X-ray images.

→

Develop Machine Learning models:

- **CNN architectures:** Custom CNN Model
- **Pre-trained models via Transfer Learning:** VGG-16, Inception-V3 DenseNet-121

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Evaluate Machine Learning models:

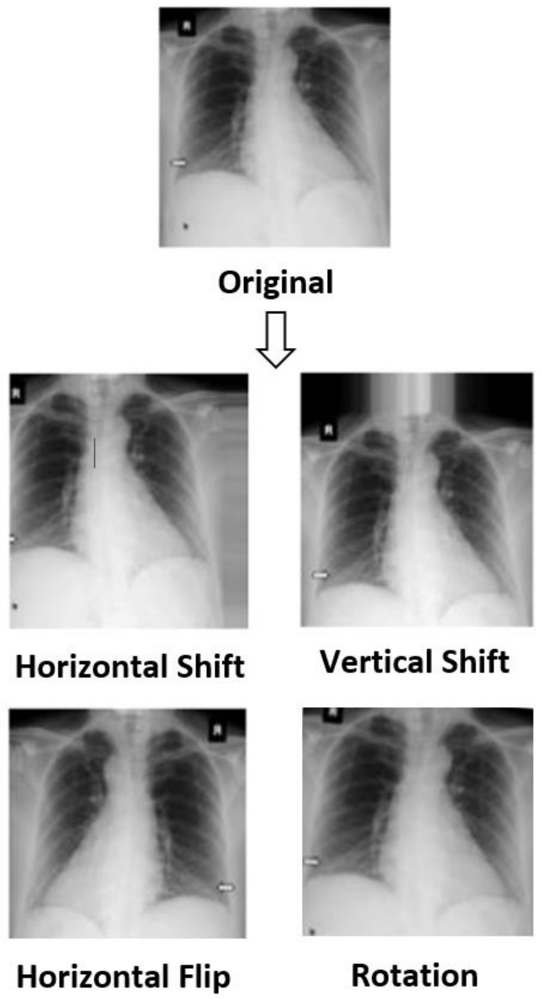
- **Testing set:** Use new 'un-seen' data in the testing set.
- **Evaluation metrics:** Use F1-Score, Precision, Recall and Accuracy as performance measures of ML models.
- Determine best performing model by comparing accuracy on test set.

Data Pre-processing

- Input images were in different sizes
- Images resized to 224 × 224 using the nearest neighbour resampling method
  - Transfer learning models required this size as the input
- Pixel intensity values normalised to a range of 0 – 1
  - To reduce the computational time

Data Augmentation

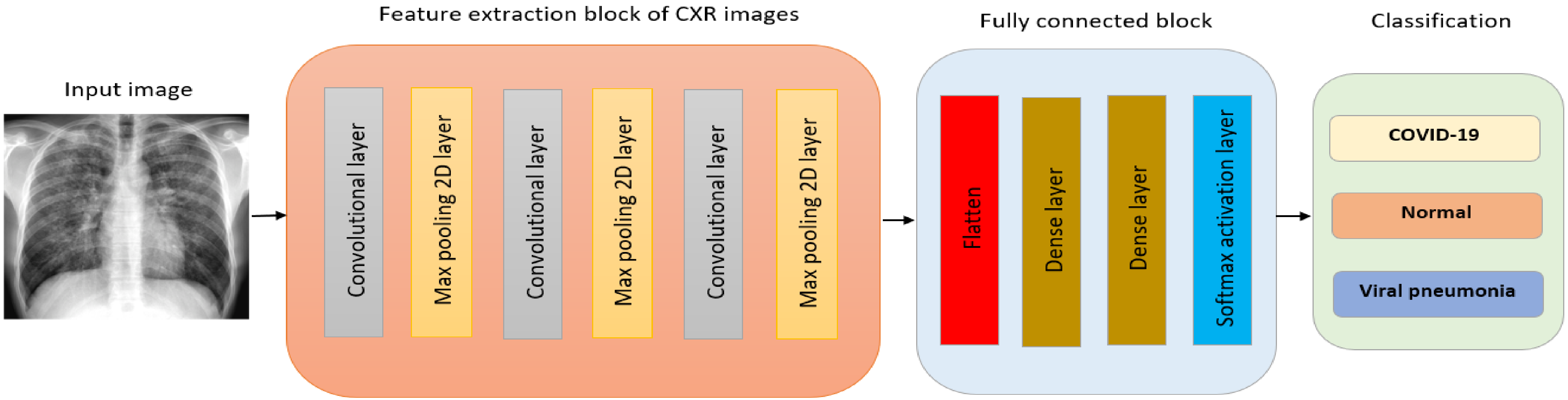
- Generating additional data by making slight variations such as rotating, shifting and flipping on existing data
  - Rotation in a range of ±20°
  - Vertical shift of ±20%
  - Horizontal shift of ±20%
  - Flipping Horizontally



Data Augmentation techniques used [2]

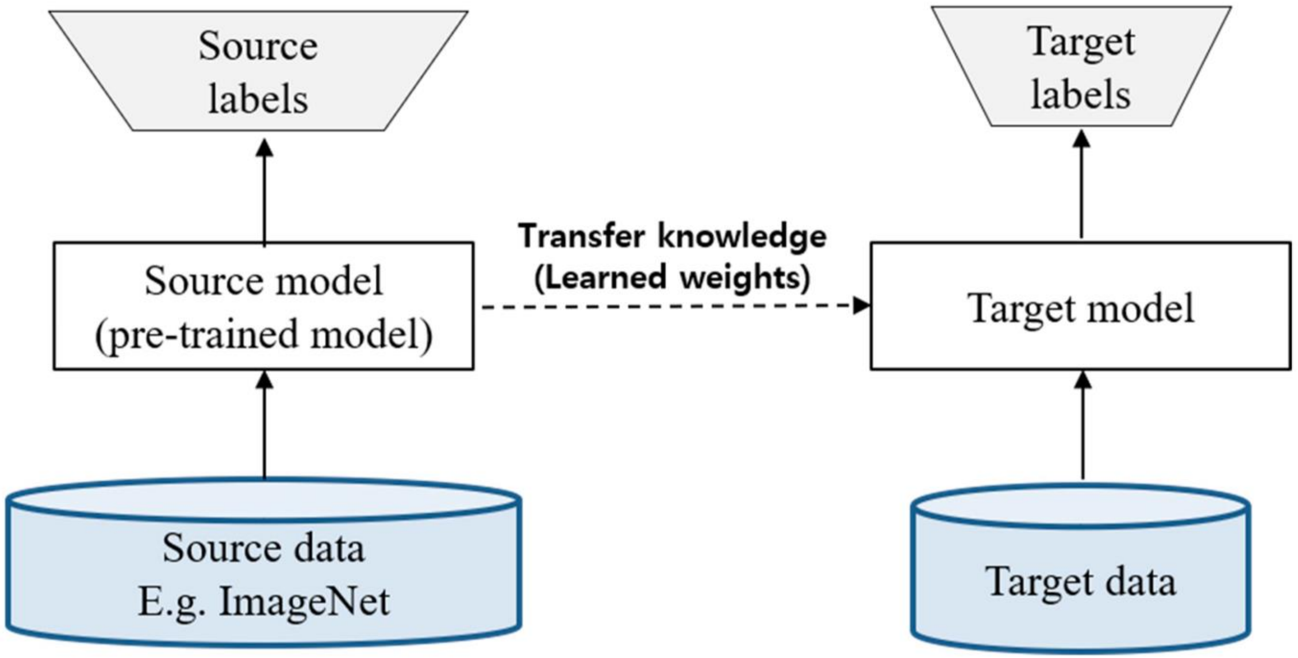
Convolutional Neural Networks

- Convolutional Neural Networks (CNNs) are optimal for image classification
- Feature extraction is automatically performed
- A CNN architecture can have multiple convolutional and pooling layer



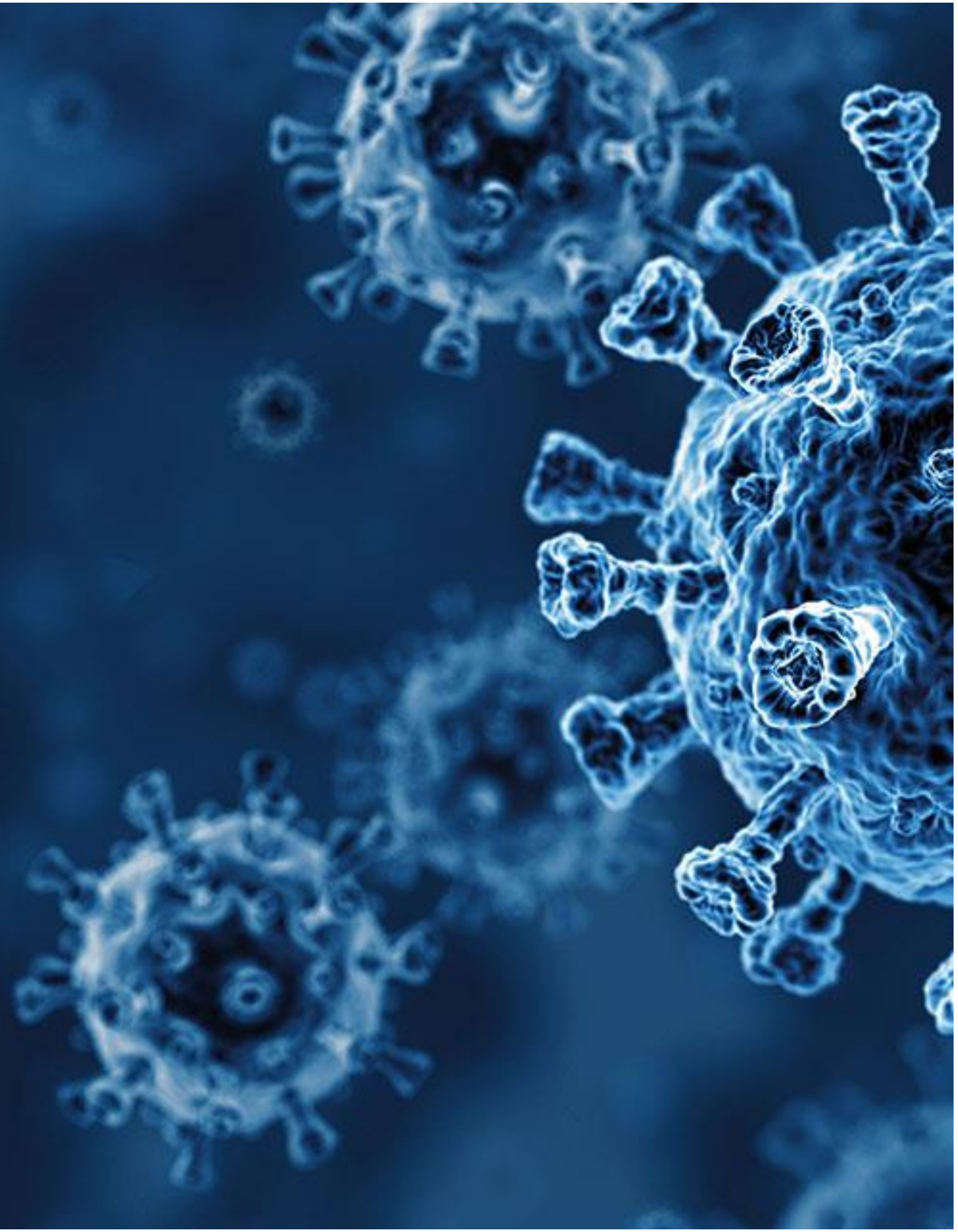
Transfer Learning

- Re-use of pre-trained model on a new problem
- Increase in model performance
- Decrease in training time and overfitting
- VGG-16, Inception-V3 and ResNet-50 models with pre-trained weights are used



Transfer Learning process [4]

Current Progress



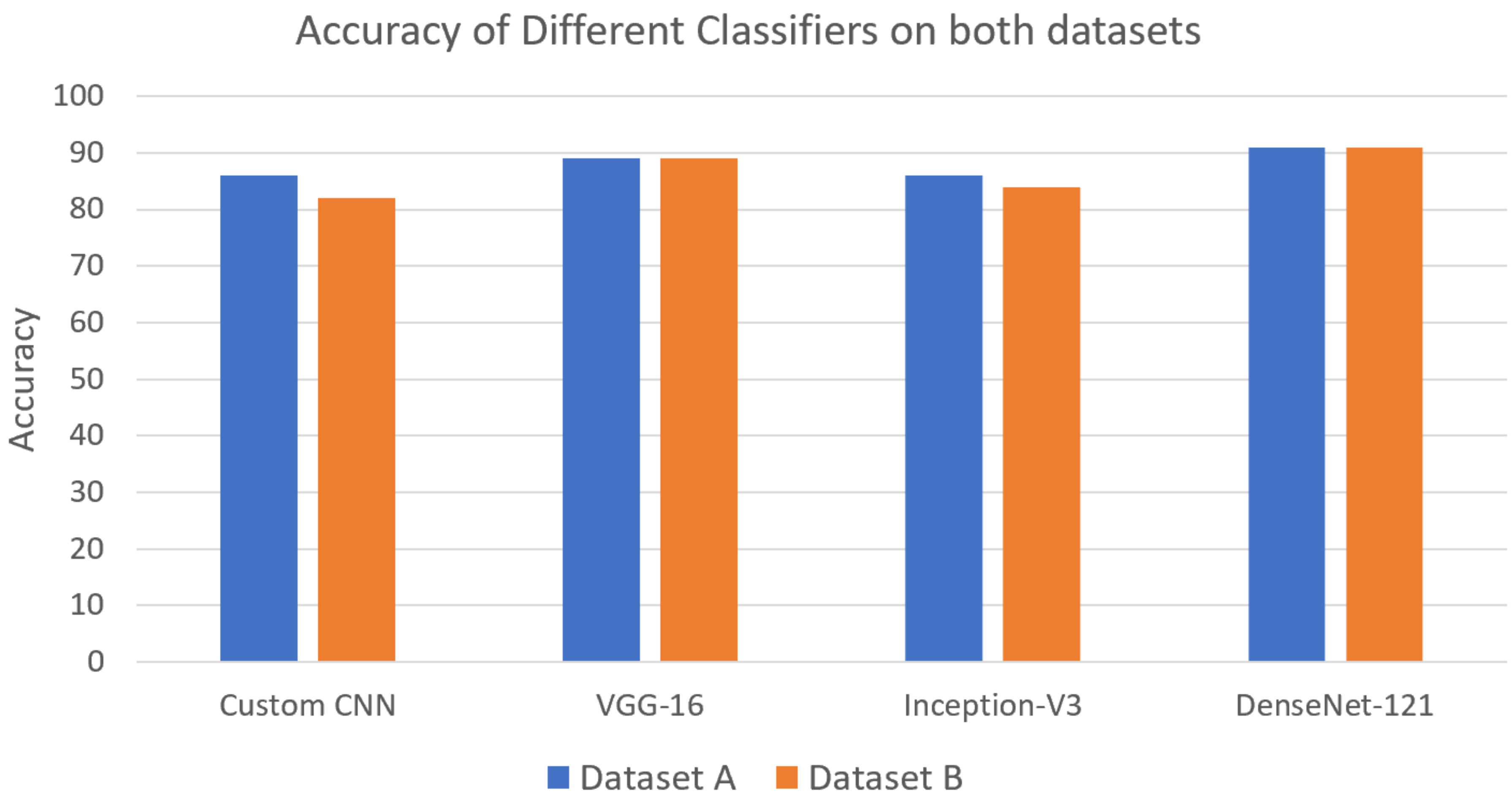
Evaluation Metrics

- Successful implementation of custom CNN, VGG-16, Inception-V3 and DenseNet-121 models
- Accuracy, Precision, Recall and F1-score were used as evaluation metrics
- Accuracy was used as the primary evaluation metric

Class	Precision	Recall	F1-Score	Accuracy
COVID-19	0.93	0.85	0.89	0.91
Normal	0.83	0.92	0.87	
Viral Pneumonia	0.98	0.96	0.97	

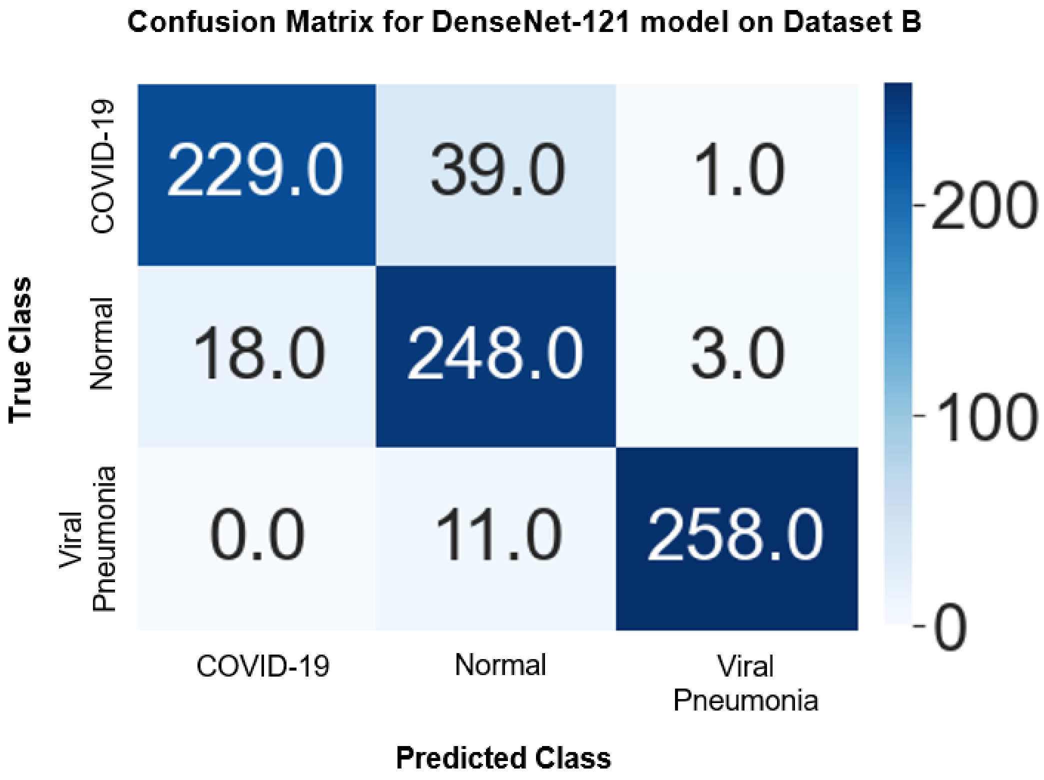
Classification Report for the DenseNet-121 model on Dataset B

Comparison of Methods



Classifier Performance

- Confusion matrices were used to visualize the model performances
- Testing set contained 269 images for each class.
- DenseNet-121 model did display good performances in identifying chest X-ray images of patients with Viral Pneumonia and patients that are normal
- Not so great at classifying chest X-ray images of COVID-19 patients
- Model does show struggle in differentiating chest X-ray images of COVID-19 and normal patients.



Key findings

258 correct predictions for Viral Pneumonia class
248 correct predictions for Normal class
40 incorrect predictions for COVID-19 class

Comparison to Literature

Study	Data Preparation Techniques	Machine Learning Model	Accuracy (%)
Our best performing model	**Data Augmentation**	**DenseNet-121**	**91.00**
Alam *et al.* [5]	Region of Interest Extraction	VGG-19	99.49
Reynaldi *et al.* [6]	CLAHE (1)	ResNet-101	99.61
Shorfuzzaman and Masud [7]	Data Augmentation & CLAHE (1)	ResNet-50V2	98.00
Sarki *et al.* [8]	Mathematical Morphology	VGG-16	87.50

(1) CLAHE - Contrast Limited Adaptative Histogram Equalisation

Completion Plan

- Continue developing Machine Learning models
  - CNN models (from literature) such as ResNet-50 and VGG-19 needs to be implemented.
- Pre-processing techniques such as Region of Interest extraction and image contrasting needs to be applied
- End goal: Develop the best performing Machine Learning model for chest X-ray image classification

Conclusion

- Machine Learning models can be used to detect COVID-19 in chest X-ray images and differentiate it from other respiratory diseases
- Results show that CNN models can successfully extract important features from the chest X-ray images to perform classification
- The DenseNet-121 model outperformed all the other models implemented on the testing set
- The DenseNet-121 model does show good capability in differentiating viral pneumonia and COVID-19 chest X-ray images. The model, however, did show struggle in differentiating COVID-19 and normal chest X-ray images.
- More advanced pre-processing techniques needs to be applied to achieve a higher performance accuracy

References

[1] Australian Government. “Coronavirus (COVID-19) case numbers and statistics.” Department of Health. https://www.health.gov.au/health-alerts/covid-19/case-numbers-and-statistics (accessed June 10, 2022).

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[3] Business Partner Magazine. “How Machine Learning is working step-by-step.” Business Magazine partner. https://businesspartnermagazine.com/how-machine-learning-working-step-by-step/ (accessed June 10, 2022).

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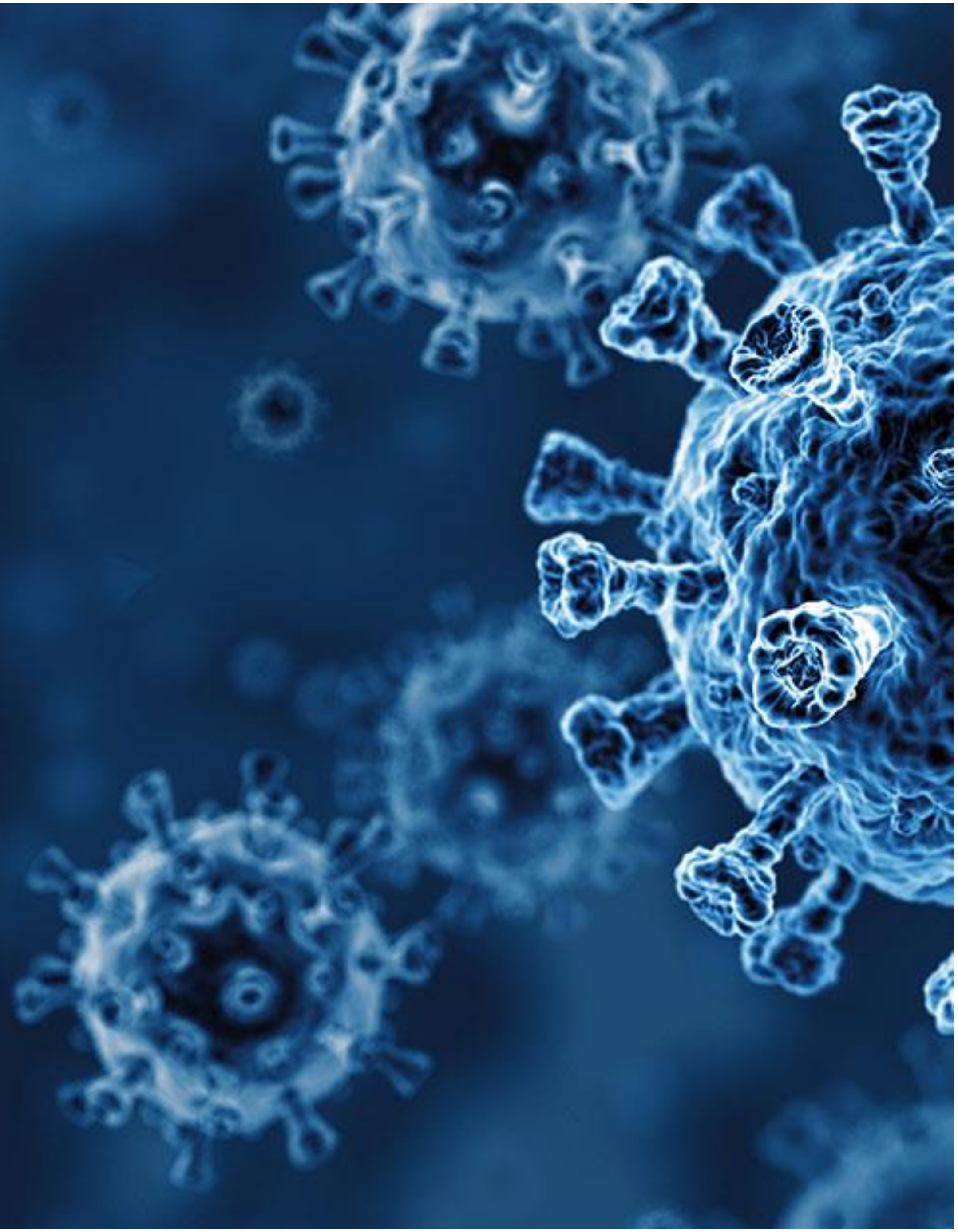
[8] R. Sarki, K. Ahmed, H. Wang, Y. Zhang and K. Wang, “Automated detection of COVID-19 through convolutional neural network using chest x-ray images,” *PloS one,* vol. 17, no. 1, p. 262052, 2022.

Thank you for Listening!



Evaluations Metrics

$$\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN}$$

Accuracy can be defined as the number of correct predictions over the total number of predictions.

$$\text{Recall} = \frac{TP}{TP + FN}$$

Recall can be defined as the number of positive class predictions over the total number of positives.

$$\text{Precision} = \frac{TP}{TP + FP}$$

Precision can be defined as the number of true positives over the total number of positive predictions.

$$\text{F1 score} = 2\ \frac{\text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}}$$

F1-score can be defined as the harmonic average of precision and recall.