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LEVERAGING MATHEMATICAL AND COMPUTATIONAL ALGORITHMS IN DEVELOPING BINOMIAL NEURAL NETWORKS FOR X-RAY IMAGE CLASSIFICATION

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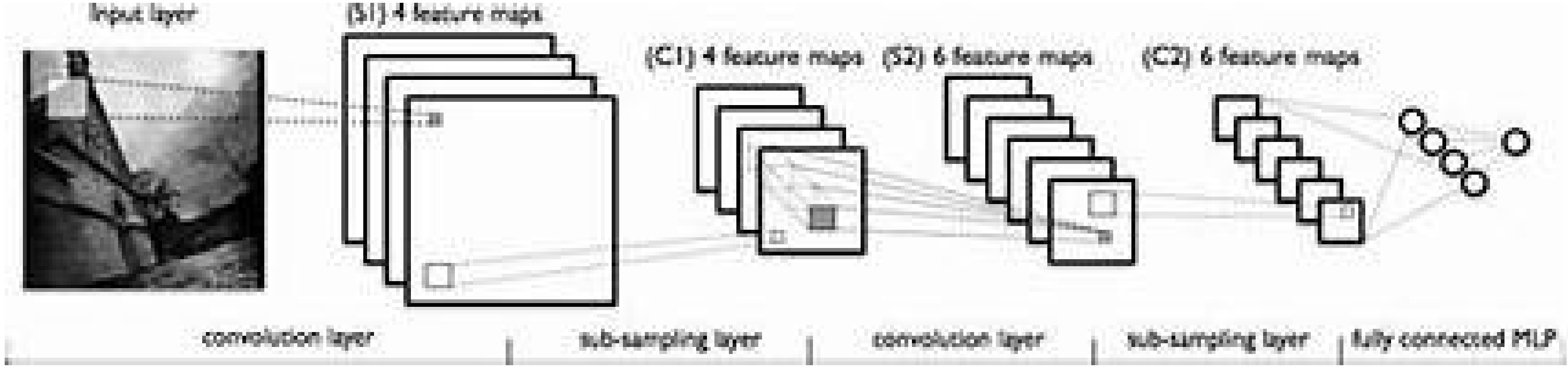
IMAGE CLASSIFIER

Image classification is a task where we train a model to identify if an image belongs to one or multiple classes.



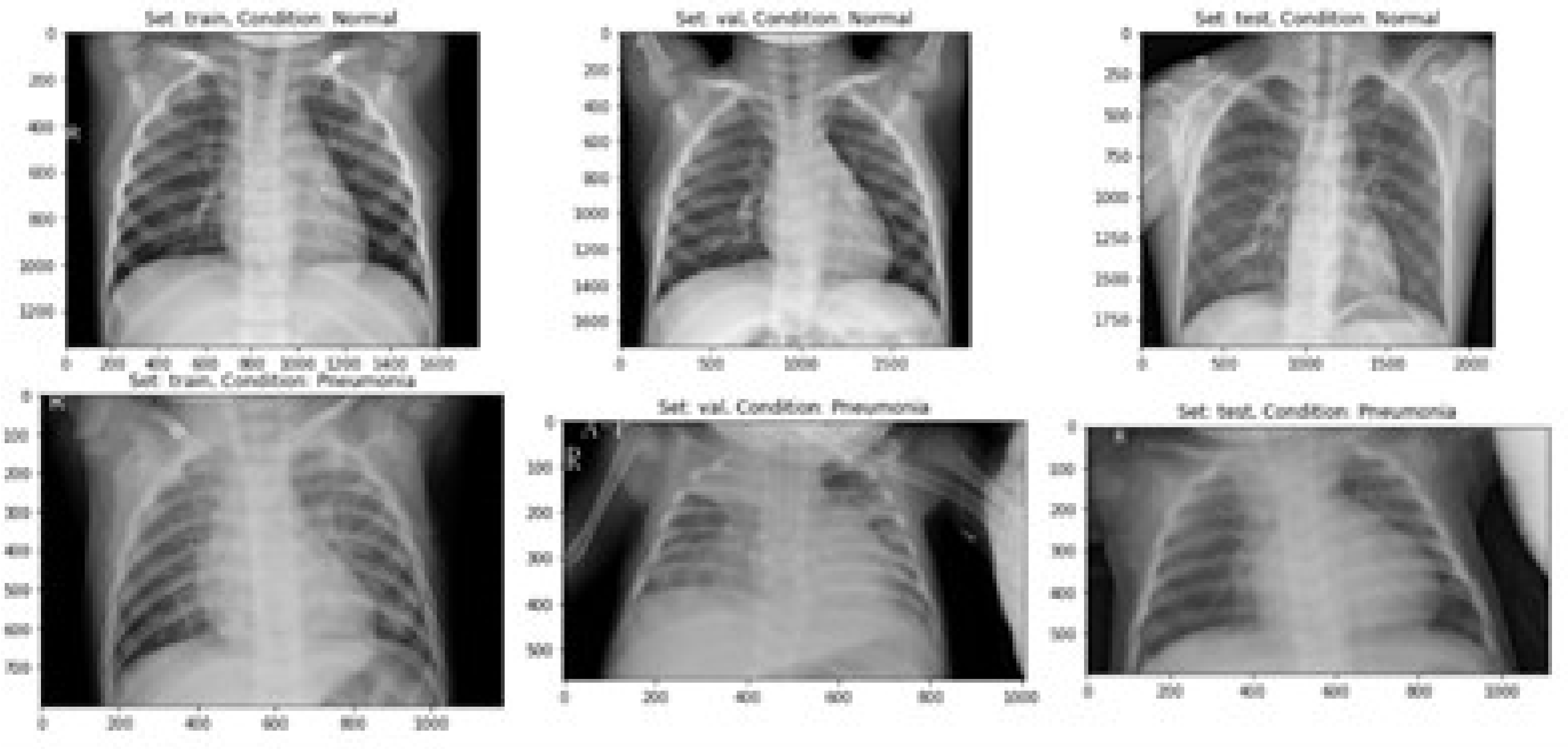
CREATION OF IMAGE CLASSIFIER

- STEP 1: DATA PROCESSING
- STEP 2: MODEL BUILDING
- STEP 3: TRAIN AND EVALUATE

DATA SOURCE

- provided by Dr Paul Mooney for Kaggle in 2017
- consists of 5836 X-Ray images
- divided into a training and testing
- contains two subset categories – normal and pneumonia
- covers both bacterial and viral pneumonia
- taken during routine clinical care and are diagnosed by a clinician.

EXAMPLES OF NORMAL AND PNEUMONIA CATEGORIES FROM THE TRAINING, TESTING AND VALIDATING DATA SETS



DATA DISTRIBUTION

	Training Set	Test Set	Validation Set
Normal	1082	234	267
Pneumonia	3110	390	773
Total	4192	624	1040
Percentage	71.5%	10.7%	10.8%

DATA AUGMENTATION

Techniques applied:

- rescaled,
- zoomed,
- vertically flipped

Results:

- increased number of the images
- Prevention of overfitting
- adding diversity to the image set

TRANSFER LEARNING

- Train with less or little data
- Faster Training
- Better Results

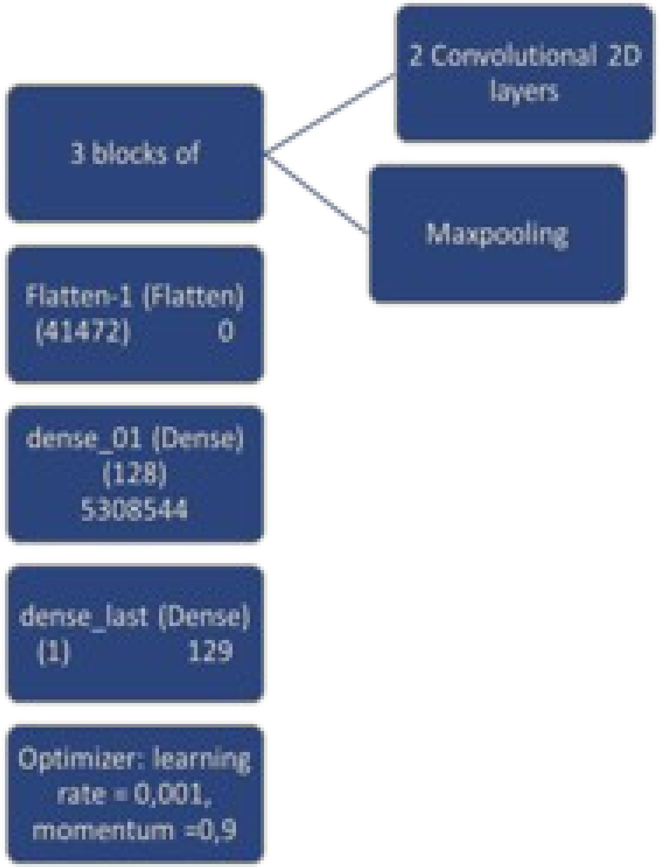
Pre-trained models and variations in tf.keras:

- DenseNet,
- Inception,
- MobileNet,
- NASNet,
- ResNet
- VGG

TRANSFER LEARNING: FEATURE EXTRACTOR OR FINE TUNING

- Base model with a Pretrained ConvNet minus the top (dense layer)
- Freeze all or some the layers of the base model
- Add a classifier on top of the base model
- Train with new datasets

CUSTOM CNN MODEL ARCHITECTURE



Layer (type) Output Shape Param #
conv_01 (Conv2D) (None, 224, 224, 32) 896

conv_02 (Conv2D) (None, 224, 224, 32)
9248
max_pooling2d_3 (MaxPooling2 (None, 112, 112, 32)
0
conv_03 (Conv2D) (None, 112, 112, 64)
18496
conv_04 (Conv2D) (None, 112, 112, 64)
36928
max_pooling2d_4 (MaxPooling2 (None, 56, 56, 64)
0
conv_05 (Conv2D) (None, 56, 56, 128)
73856
conv_06 (Conv2D) (None, 56, 56, 128)
147584
max_pooling2d_5 (MaxPooling2 (None, 28, 28, 128)

TRANSFER LEARNING WITH NASNETMOBILE

```
Layer (type)                 Output Shape              Param #
=================================================================
NASNet (Functional)          (None, 7, 7, 1056)        4269716
dropout (Dropout)            (None, 7, 7, 1056)        0
flatten (Flatten)            (None, 51744)             0
dense_01 (Dense)             (None, 128)               6623360
dense_last (Dense)           (None, 1)                 129
=================================================================
Total params: 10,893,205                  Trainable params: 6,623,489                  Non-trainable params: 4,269,716
```

MODEL EVALUATION

- accuracy,
- precision,
- recall,
- loss function
- AUC score
- F1 score

ACCURACY

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

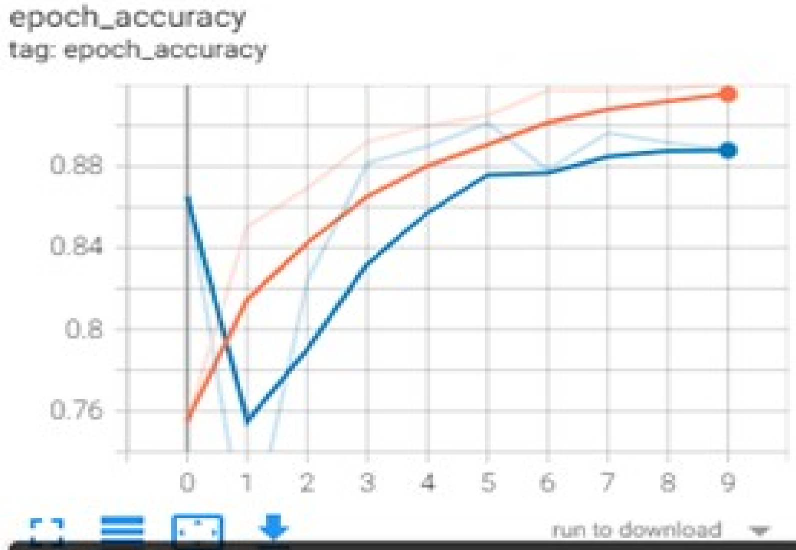
- intuitive performance measure
- the ratio of correctly predicted observation to the total observations.

ACCURACY COMPARISON

NASNetMobile

Name	Smoothed	Value	Step	Time	Relative
train	0.9581	0.9602	9	Sun Sep 12, 22:11:46	15m 39s
validation	0.9128	0.9161	9	Sun Sep 12, 22:11:46	15m 39s

CUSTOM CNN MODEL



Name	Smoothed	Value	Step	Time	Relative
train	0.9154	0.9206	9	Sun Sep 12, 21:27:53	16m 43s
validation	0.8877	0.8882	9	Sun Sep 12, 21:27:53	16m 43s

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

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

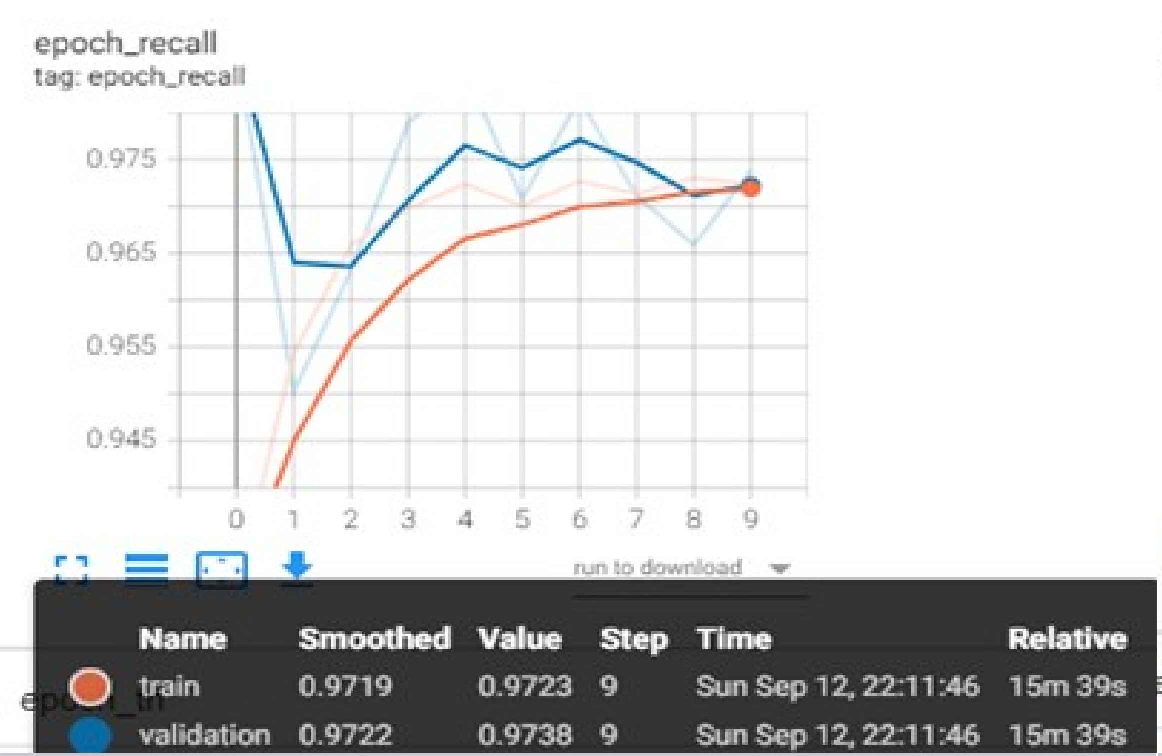
RECALL

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

The ratio of correctly predicted positive observations to the all observations in actual class with positive value

RECALL COMPARISON

NASNetMobile	CUSTOM CNN MODEL



PRECISION

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

- the ratio of correctly predicted positive observations to the total predicted positive observations

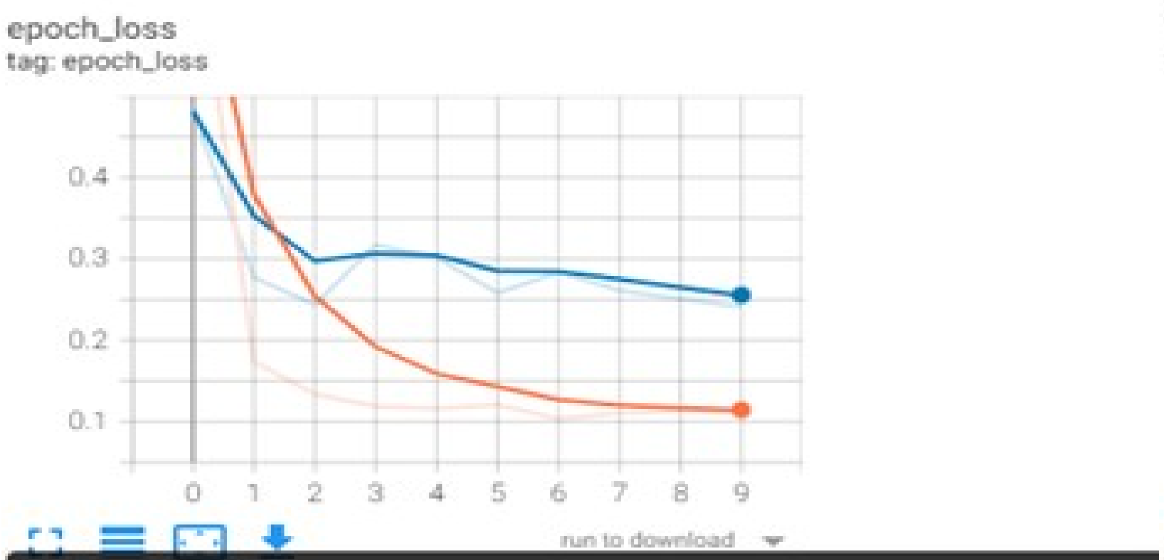
PRECISION COMPARISON

NASNetMobile

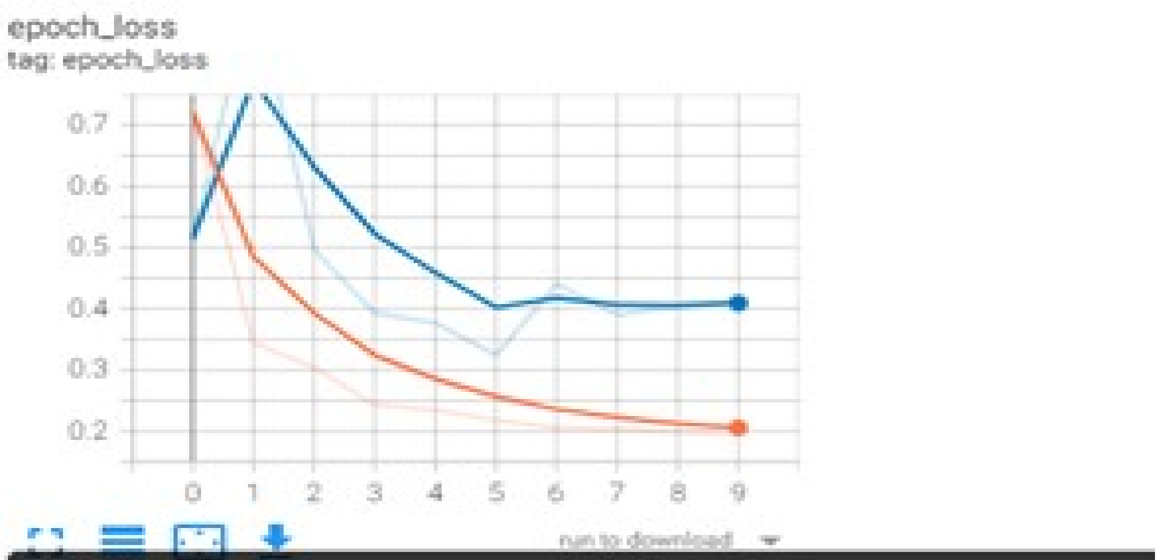
CUSTOM CNN MODEL

LOSS COMPARISON

NASNetMobile	CUSTOM CNN MODEL



	Name	Smoothed	Value	Step	Time	Relative
	train	0.1143	0.1103	9	Sun Sep 12, 22:11:46	15m 39s
	validation	0.2555	0.2413	9	Sun Sep 12, 22:11:46	15m 39s



	Name	Smoothed	Value	Step	Time	Relative
	train	0.2061	0.1963	9	Sun Sep 12, 21:27:53	16m 43s
	validation	0.4092	0.4143	9	Sun Sep 12, 21:27:53	16m 43s

F1 SCORE

$$F_1 = 2 \cdot \frac{\text{precision} \cdot \text{recall}}{\text{precision} + \text{recall}} = \frac{\text{TP}}{\text{TP} + \frac{1}{2}(\text{FP} + \text{FN})}$$

F1 COMPARISON

NASNetMobile

	Name	Smoothed	Value	Step	Time	Relative
	train	0.971	0.9724	9	Sun Sep 12, 22:11:46	15m 39s
	validation	0.9315	0.9329	9	Sun Sep 12, 22:11:46	15m 39s

CUSTOM CNN MODEL

	Name	Smoothed	Value	Step	Time	Relative
	train	0.9419	0.9453	9	Sun Sep 12, 21:27:53	16m 43s
	validation	0.9158	0.9178	9	Sun Sep 12, 21:27:53	16m 43s

MODEL EVOLUTION

CNN

TRANSFER LEARNING

PERFORMANCE BOOST

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THANK YOU

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