Histopathologic Cancer Detection Using Deep Learning

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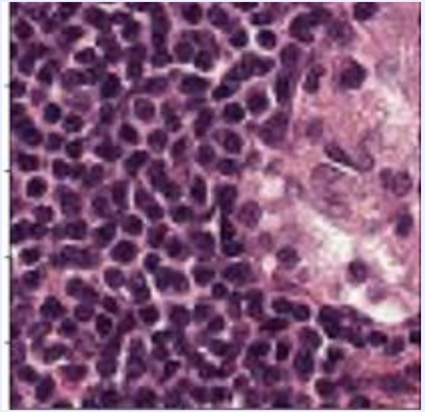
About Problem

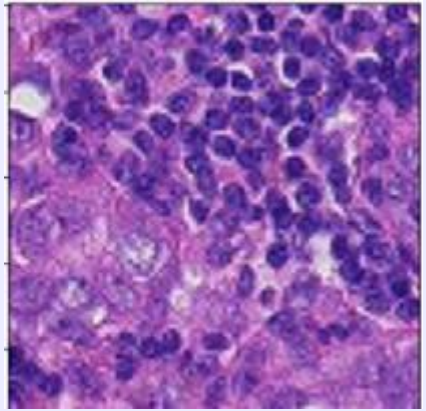
- A lot of people lost their live to cancer annually.Majority of deaths due to cancer could be prevented if it is detected in its early phases.

- In cancer diagnosis, radiologists must decide as to whether a possible abnormality in a given MRI/X-Ray image(s) is cancer and dismiss anything that may be mistaken for cancer cells. Moreover, there is always a chance of cancer passing unnoticed even through experienced eyes.

About Problem (continued)



Benign Cell



Malignant Cell

Objective and Motivation

- The ability of minimizing imperishable human error in detecting cancer cells is this primary motivation behind this project.

- The primary objective of this project is to prepare a Deep Learning model that analyses the small patches of pathology scans of metastatic cancer in early phases using Convolutional Neural Nets (CNN).

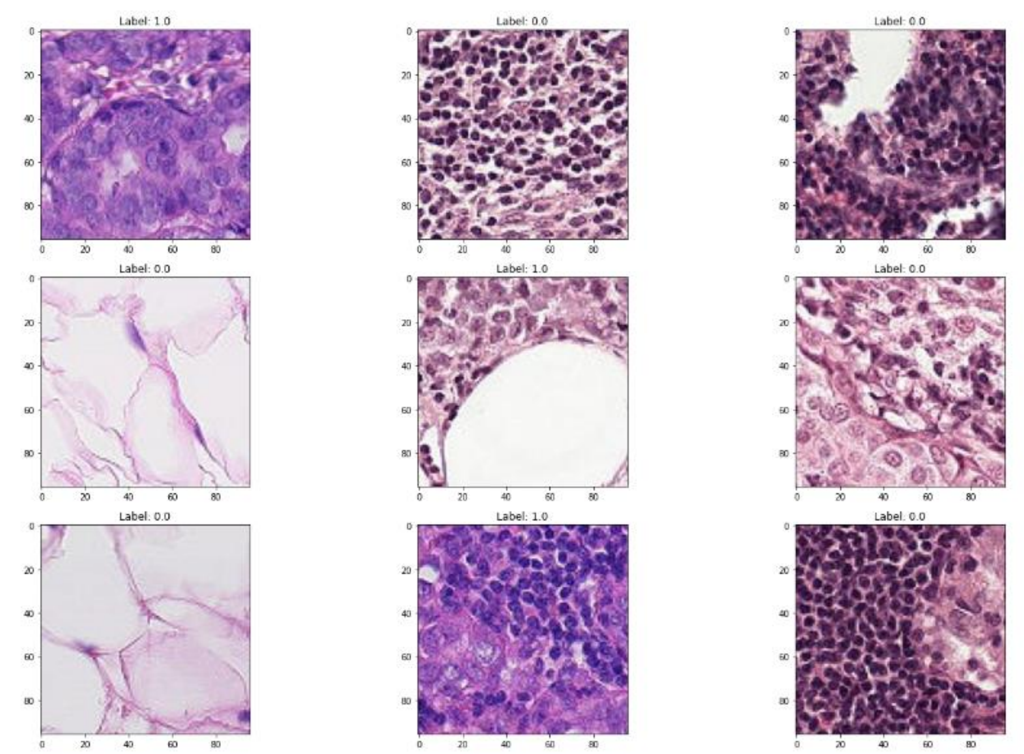
Dataset Description

- The dataset contains **96*96** (malignant/benign) images of pathology scans in '.tif' format. It contains **220K** labelled training images and **57.5K** unlabelled testing images. The images are taken from various sources, mostly cancer hospitals and labs across the United States.

- This dataset was originally hosted on Kaggle and it was provided by Bas Veeling , with additional inputs from Babak Etheshami Bejnordi, Geert Litjens, and Jeroen van der Laak.

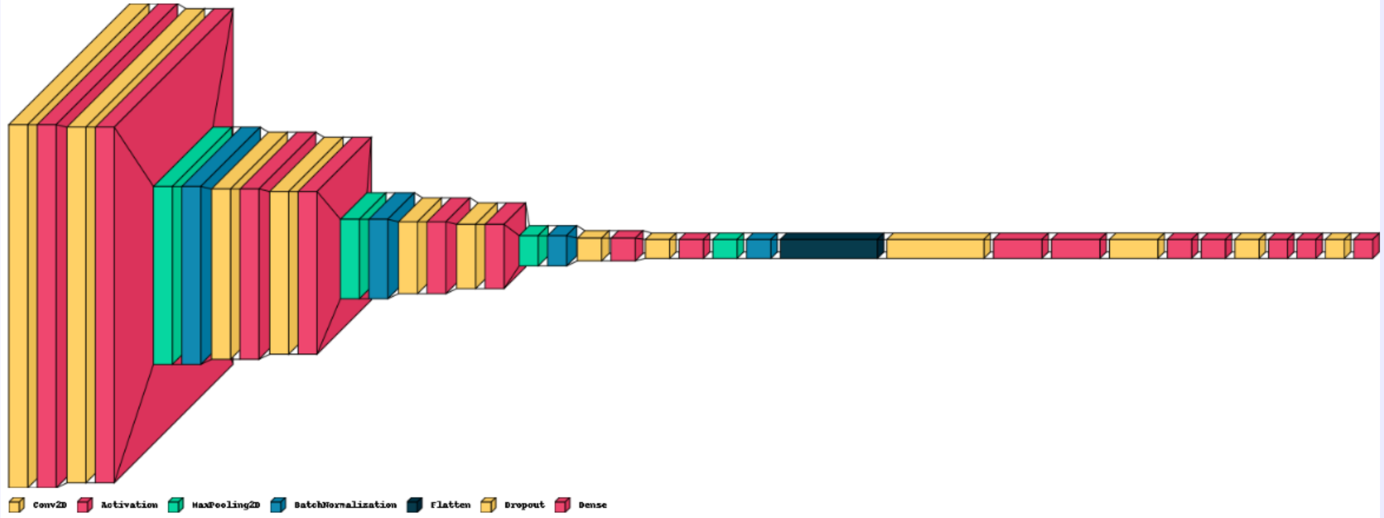
Dataset Description (continued)

Sample Images:



Architecture

The different CNN architectures are being used in this project, as described below:
Model 1:



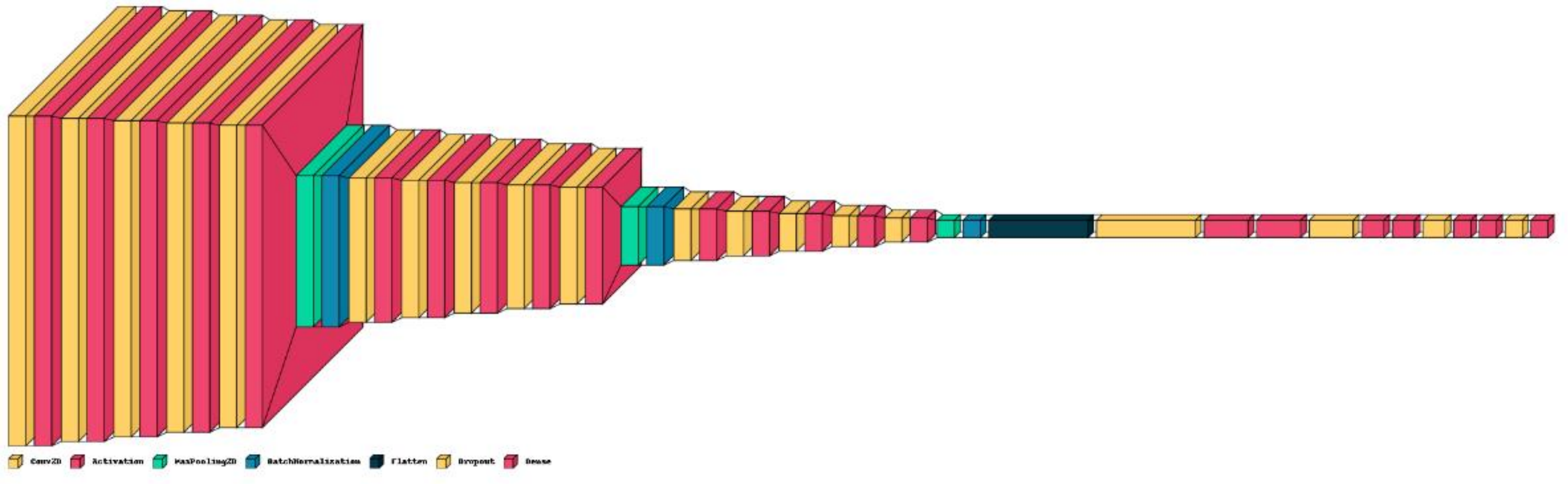
Filters: 32
Kernel Size: 3*3
Padding: “same”

Activation: “ReLu”
Max Pooling(Poolsize): 2*2
Dropout: 0.25

Optimizer: Adam(learning_rate=0.001)
Epochs: 30
Loss: Binary Crossentropy

Architecture (continued)

Model 2:



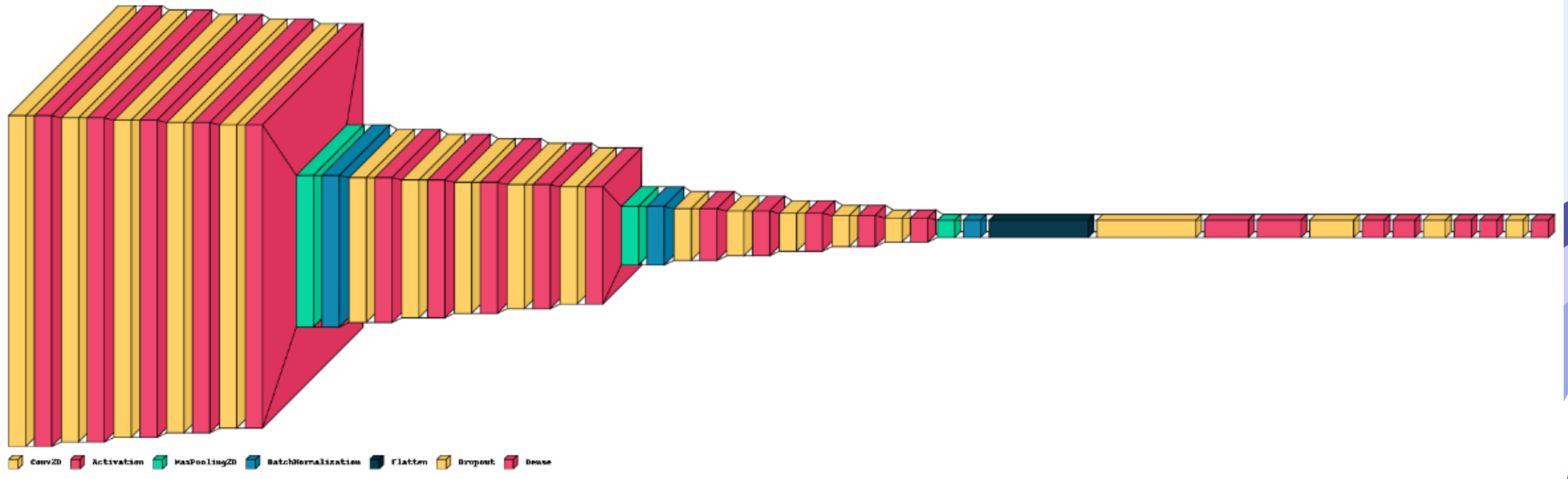
Filters: 32
Kernel Size: 3*3
Padding: “same”

Activation: “ReLu”
Max Pooling(Poolsize): 2*2
Dropout: 0.25

Optimizer: Adam(learning_rate=0.02)
Epochs: 30
Loss: Binary Crossentropy

Architecture (continued)

Model 3:



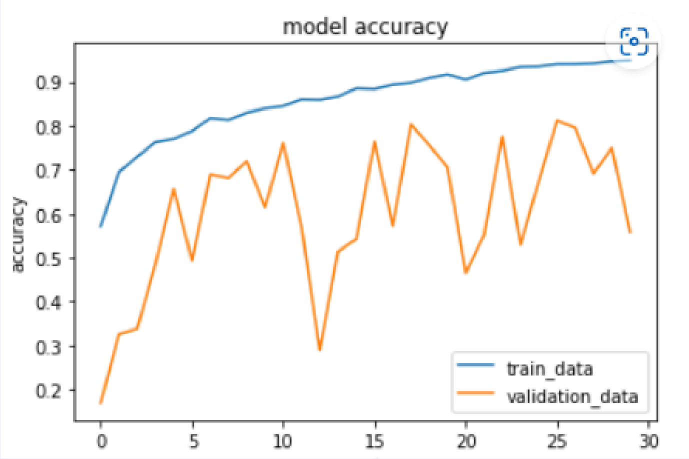
Filters: 32
Kernel Size: 3*3
Padding: “same”

Activation: “ReLu”
Max Pooling(Poolsize): 2*2
Dropout: 0.25

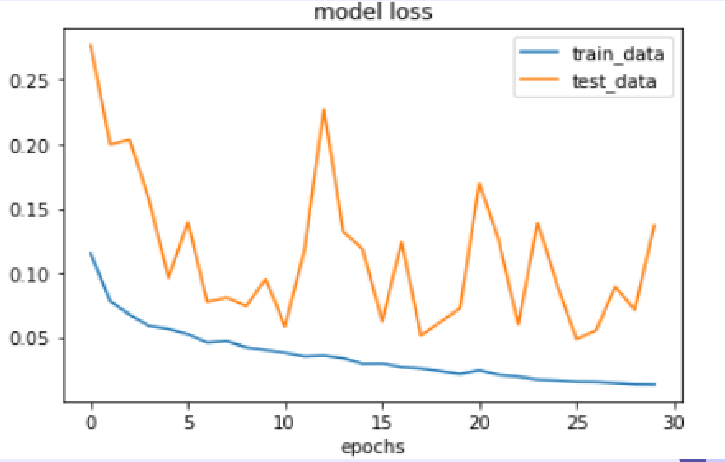
Optimizer: RMSprop(learning_rate=0.001)
Epochs: 30
Loss: Binary Crossentropy

Results

Model 1:



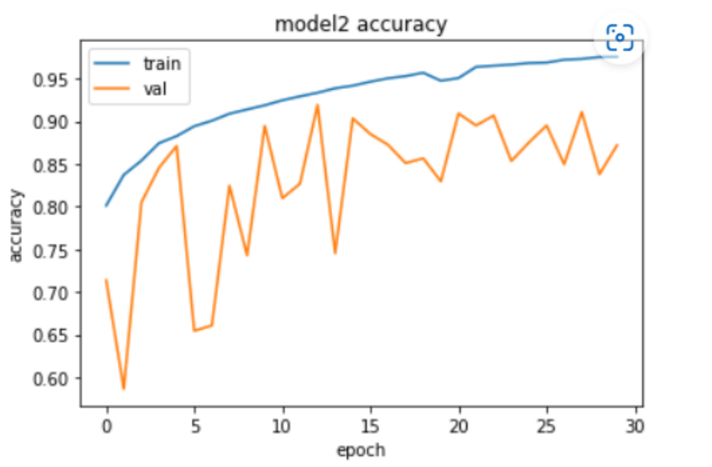
Model Accuracy



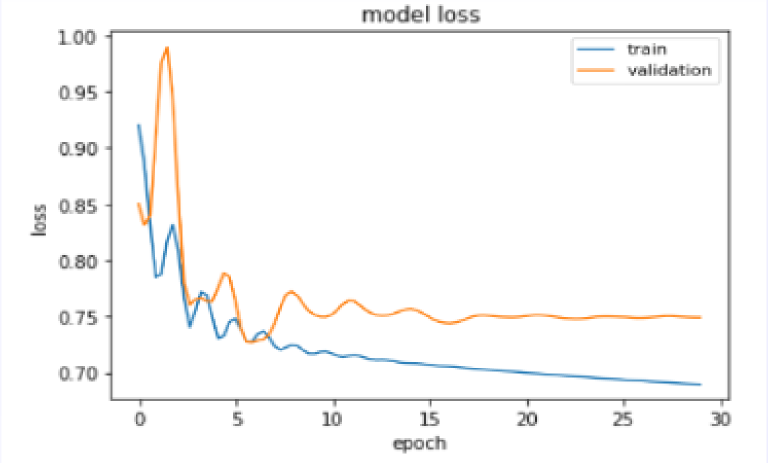
Model Loss

Results (continued)

Model 2:



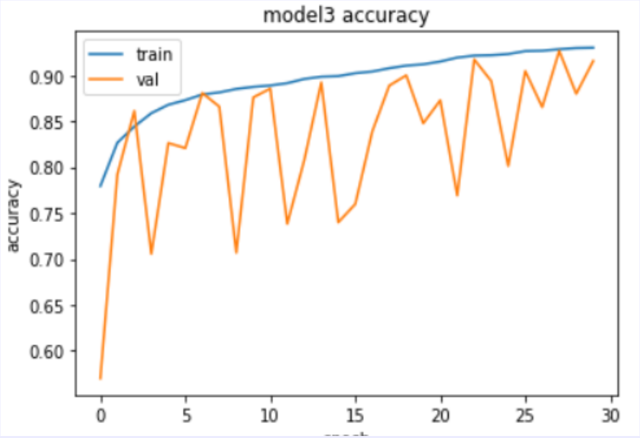
Model Accuracy



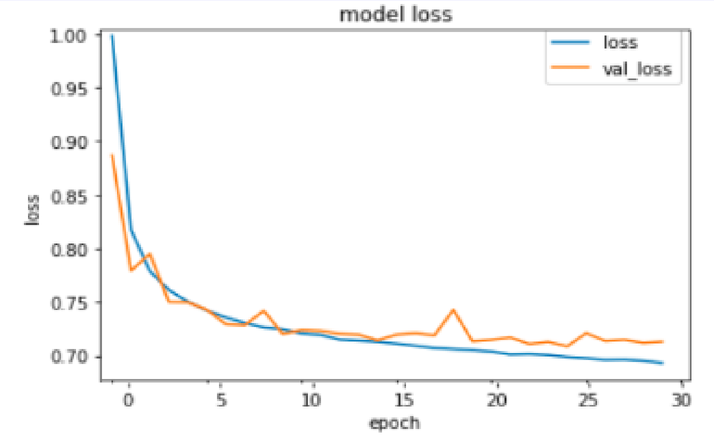
Model Loss

Results (continued)

Model 3:



Model Accuracy



Model Loss

Conclusions

- In this project, we were able to achieve high testing accuracy. However, this use case is highly critical and requires continuous improvements.
- **Model 3** has the highest testing accuracy (**approx. 90%**).
- **RMSprop(learning_rate=0.001)** seems to be the better optimizer for selected architectures.
- The use of some other CNN architectures and **transfer learning** could improve the performance at the expense of higher computational complexity and versatility.