COMS4995_009: Applied Deep Learning

Course Project Presentation Slides

Jiliang Ni
Lishenzhen Deng

Topic: Medical Imaging

- Goal: Develop a tool to assist physicians with tedious tasks.

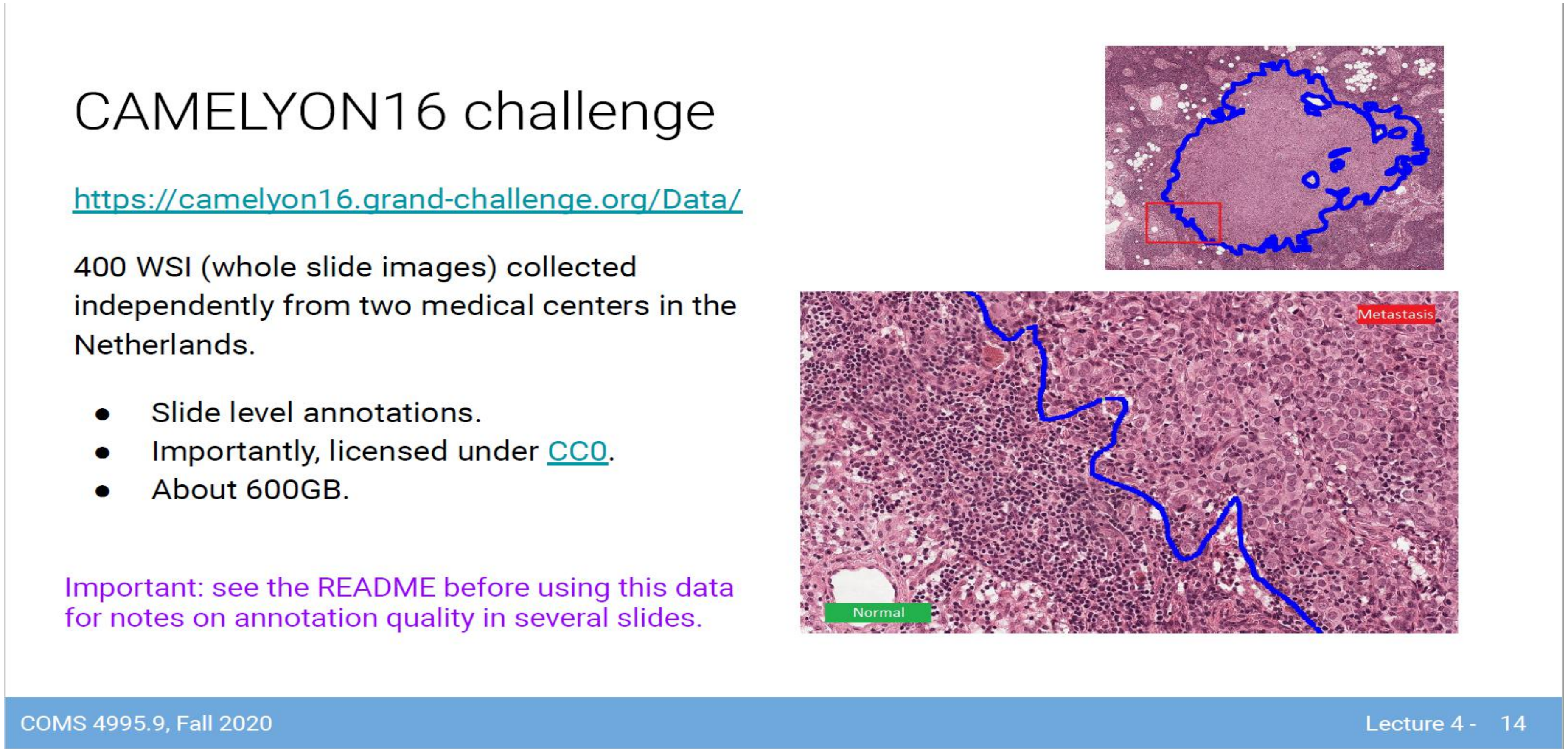
- Properties:
- Automate diagnosis process
- Reduce workload of physicians
- Improve efficiency and accuracy of tasks

Project Description:

- Goal: Detect cancer in gigapixel pathology images.

- Details:
- Given a collection of training data, develop a model that outputs a heatmap showing regions of a biopsy image likely to contain cancer.

Data: CAMELYON16 challenge



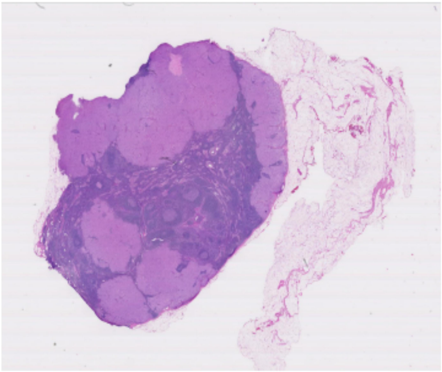
- The original slides and annotations are in xmls. But we got a bunch of converted data from TAs, which can be read with OpenSlide.

Project Details:

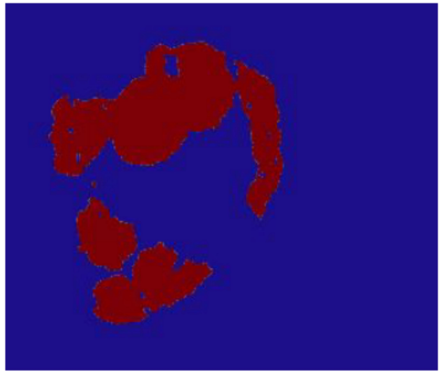
Project: Develop a tool to assist physicians

- Given a collection of training data, develop a model that outputs a heatmap showing regions of a biopsy image likely to contain cancer.
- Emphasis on **assist**. Not replace.

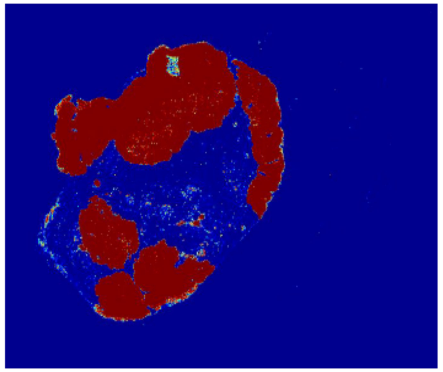
Of course, making this useful in a real-world clinical workflow is far more difficult than developing a model - this is just the first step.



Biopsy image

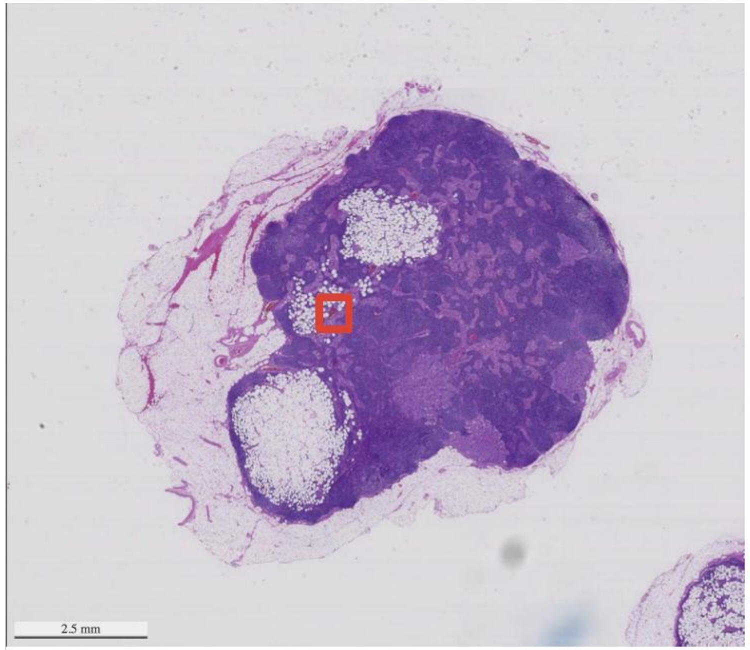


Ground truth (from pathologist)

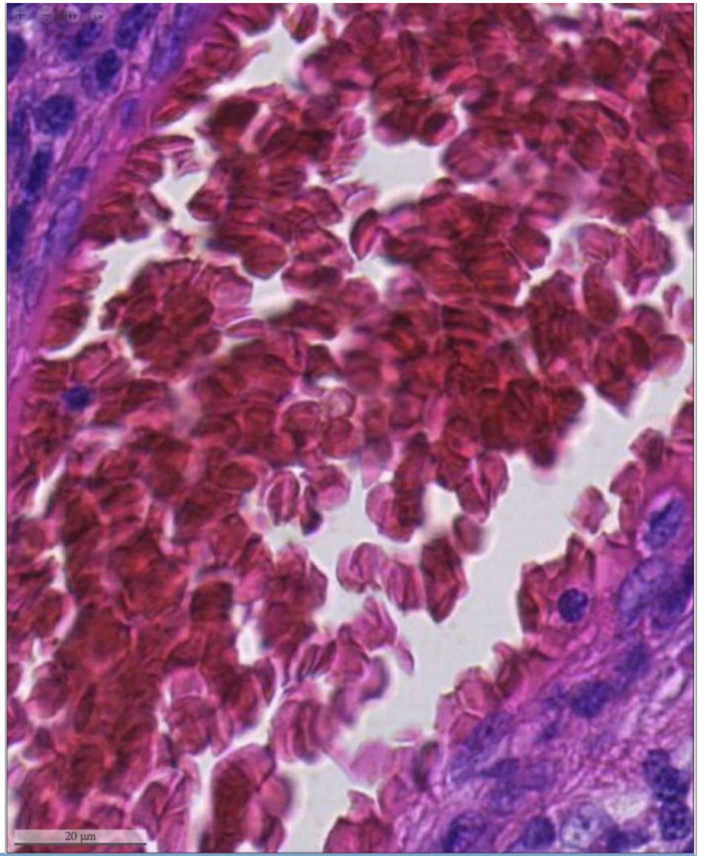


Model predictions

Project Details(continued):



7 magnification levels available per slide, up to 128x.



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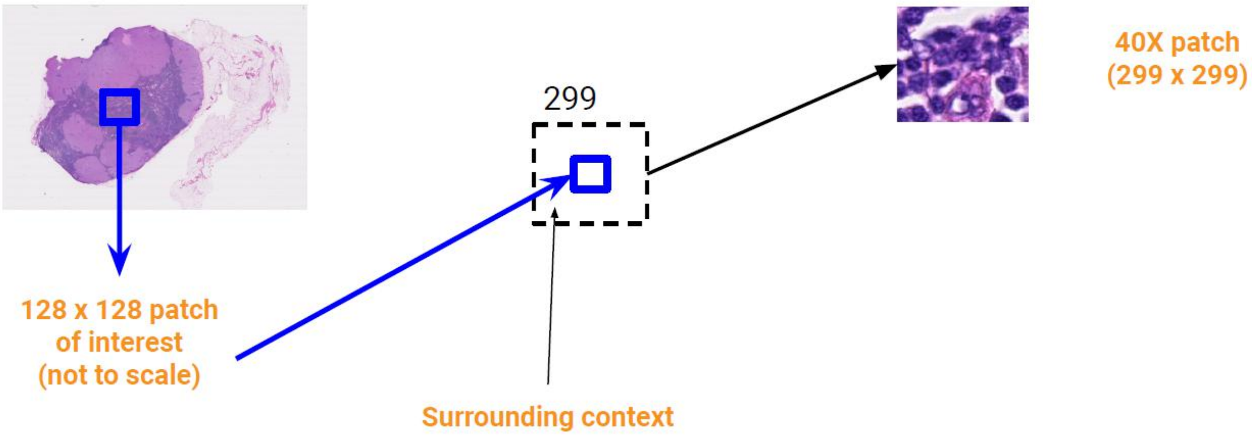
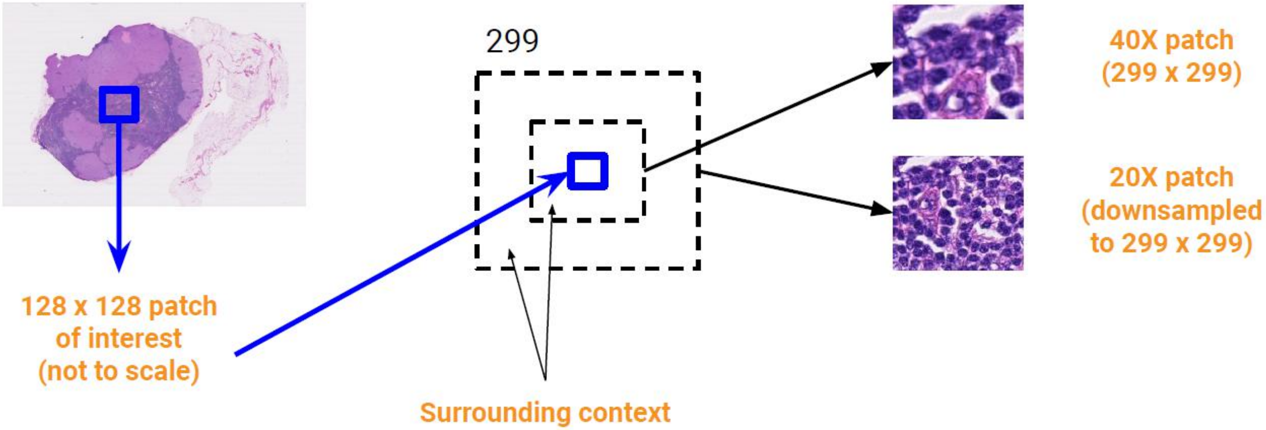
Project Details(continued):



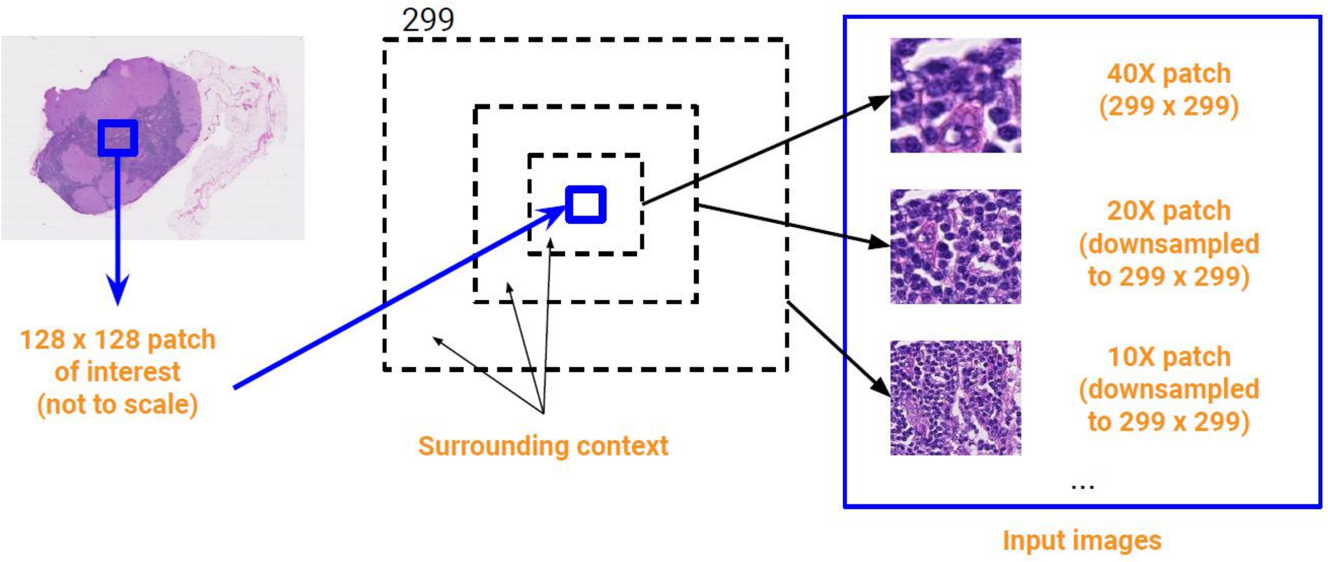
Detecting Cancer Metastases on Gigapixel Pathology Images, 2017

Project Details(continued):



Detecting Cancer Metastases on Gigapixel Pathology Images, 2017

Project Details(continued):



Detecting Cancer Metastases on Gigapixel Pathology Images, 2017

Approach:

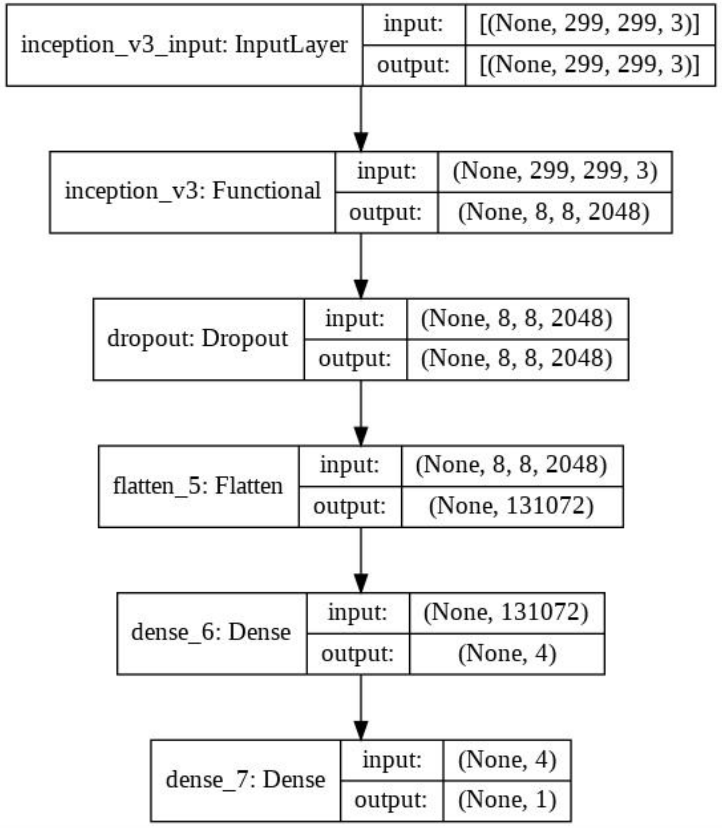
- Firstly, we focused on the middle zoom levels, which are level 5, 6, 7
- Pick three pictures as test data (“tumor_016.tif”, “tumor_031.tif”, “tumor_110.tif”)
- Then, we collected data by sliding the 100 * 100 filter window across each slide picture with stride 100, which makes patches not overlapping.
- To label the data, we follow the rule that if one 100 * 100 patch contains more than one tumor cell, it will be labeled as 1.
- We also ignored patches which have more than 60% non-tissue pixels to remove patches of background and corners
- The dataset consists of 80% training data, 20% validation data.

Approach(continued):

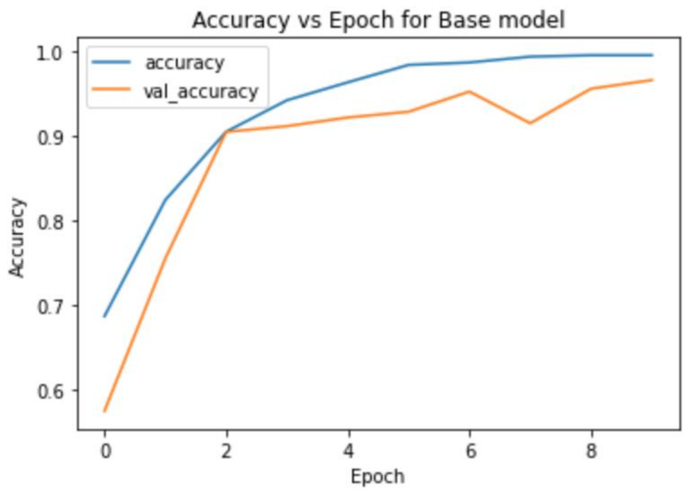
- In order to augment tumor training data, we applied vertical flip, rotation by 90 degrees and color inversion for every patch.
- After data augmentation, we transferred all training and validation data and labels tf.Data format, and contacted data and labels in different ways to fit the single-input model and multi-scale input model.

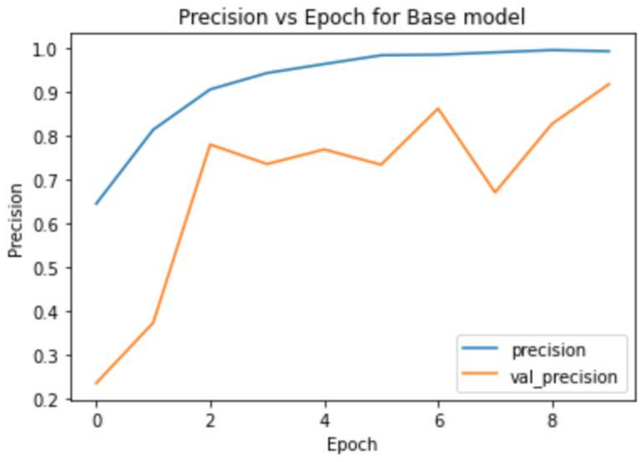
Model: Base model

- We trained the entire InceptionV3 model with additional Dropout, Flatten and Dense layers with relu and sigmoid activation functions, using RMSprop optimizer, binary_crossentropy loss function.
- The graph of the model:



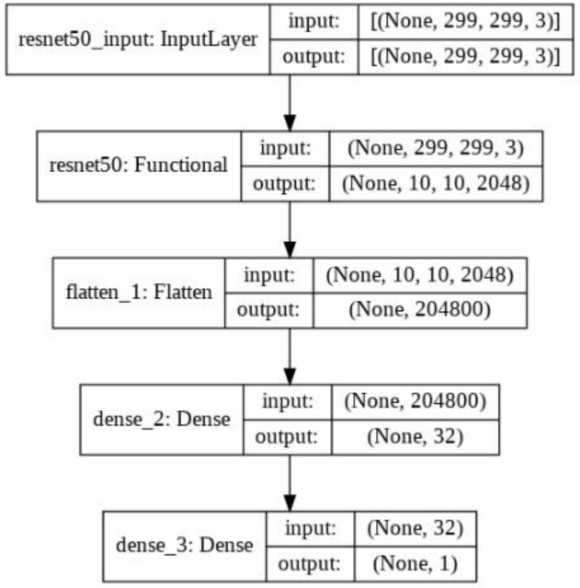
- Result: We achieved 95% best accuracy on validation data



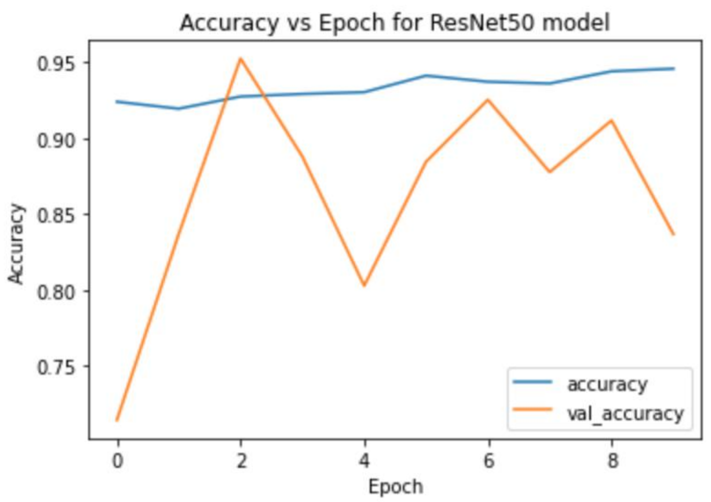


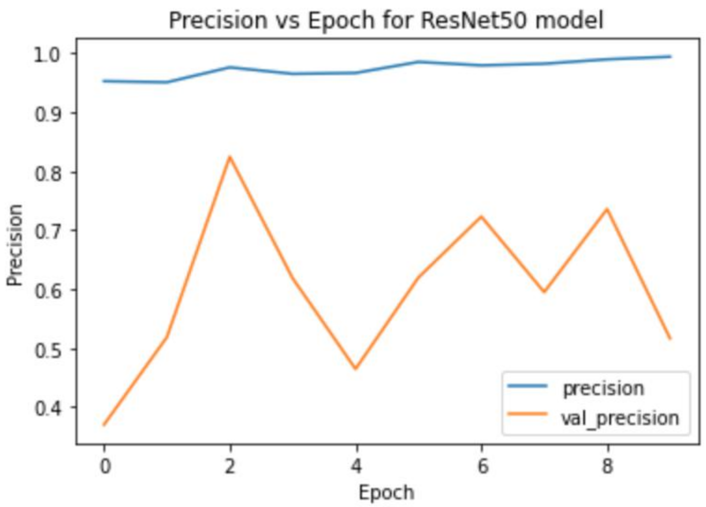
Model: ResNet50 model

- We trained the entire ResNet50 model with additional Flatten and Dense layers with relu and sigmoid activation functions, using RMSprop optimizer and binary_crossentropy loss function.
- The graph of the model:



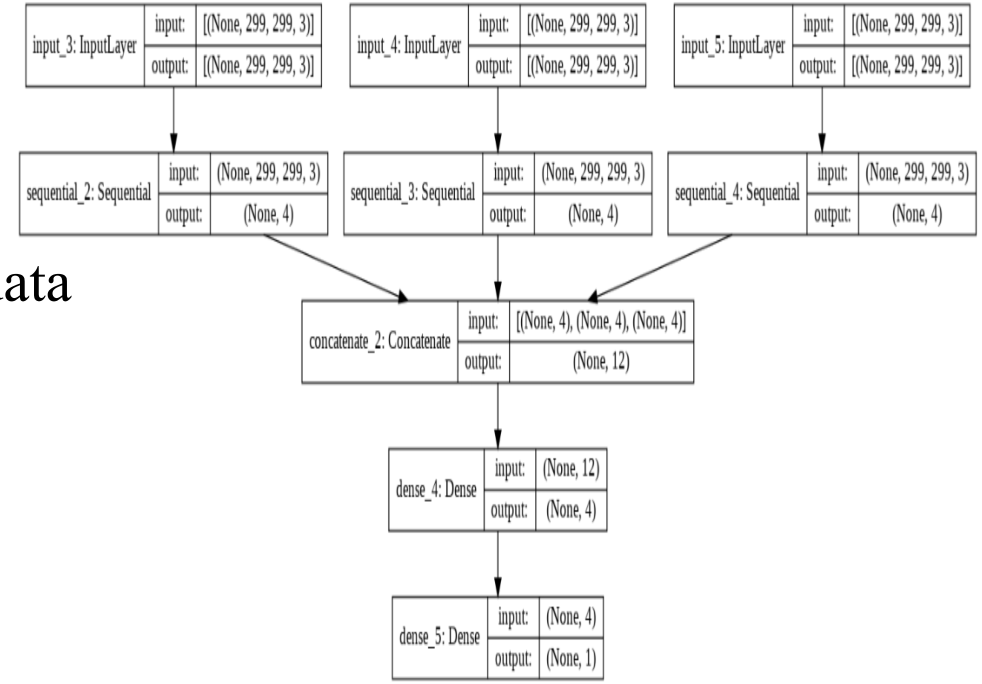
- Result: We achieved 95% best accuracy on validation data



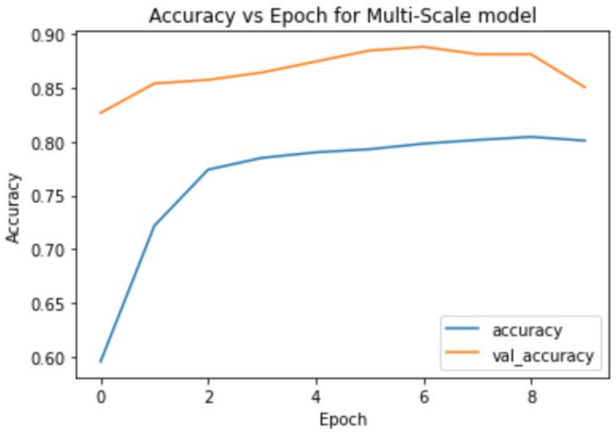


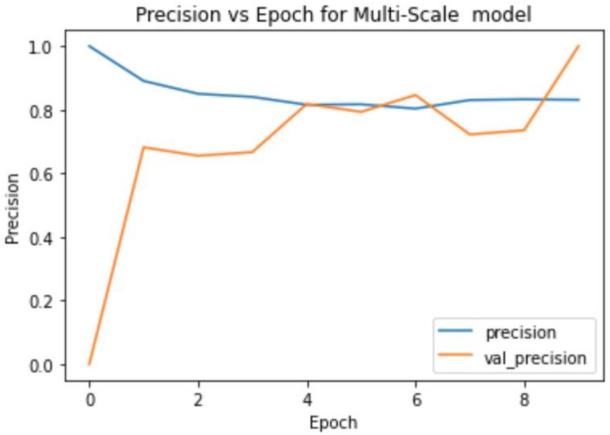
Model: Muti-scale model

- We trained a multi-scale model by firstly building three single-scale models with Conv2D, BatchNormalization, MaxPooling, GlobalAveragePooling, and Flatten layers. Then, we combined these three models into one multi-scale model which can process three different input, and concatenate the three output into same layer to generate prediction.
- The graph of the model:



- Result: We achieved 89% best accuracy on validation data



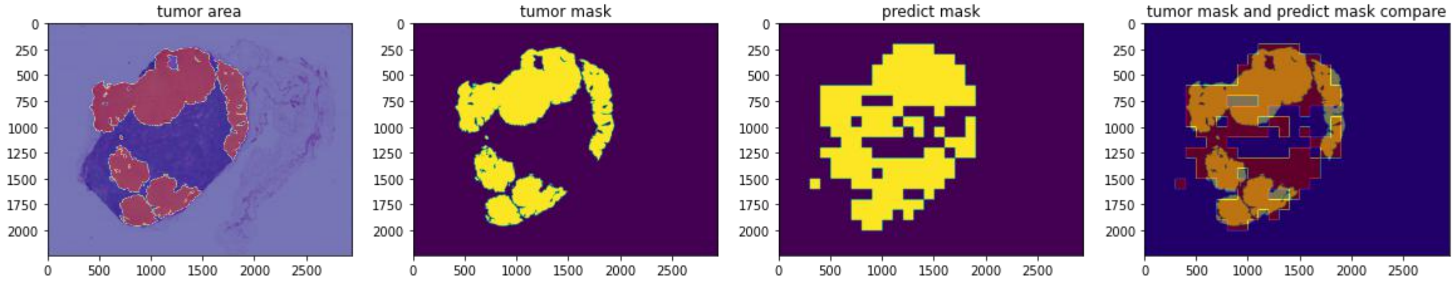


Visualizations of results:

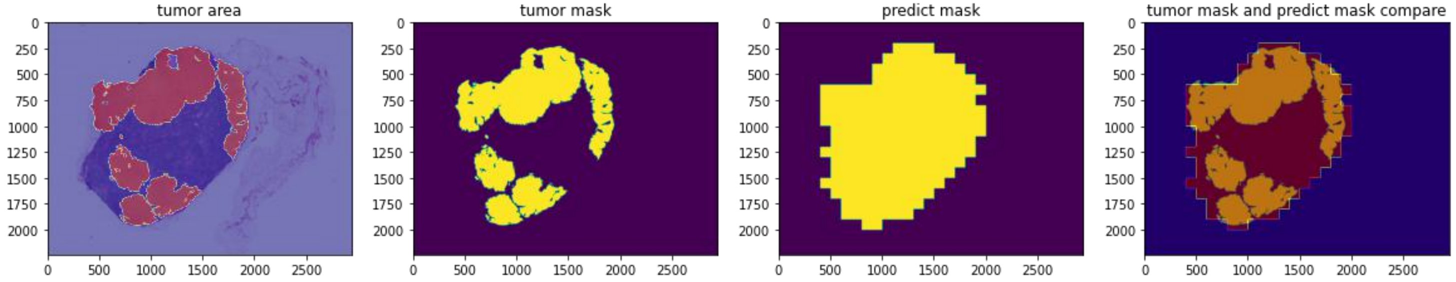
- After we trained the model on sets of 100 * 100 patches, we finally generated a heatmap, showing specific regions which represent tumor part.
- When the 100 * 100 filter window slides over the image, if a patch is predicted as tumor cell, the 100 * 100 patch will be marked as 1, otherwise 0.
- We filter out patches which have more than 60% non-tissue pixels from the model and they will be 0.

Visualizations of results(continue):

Base Model：



ResNet Model：



Multi—Scale Model：