# A Combined Radio-Histological Approach for Classification of Low Grade Gliomas

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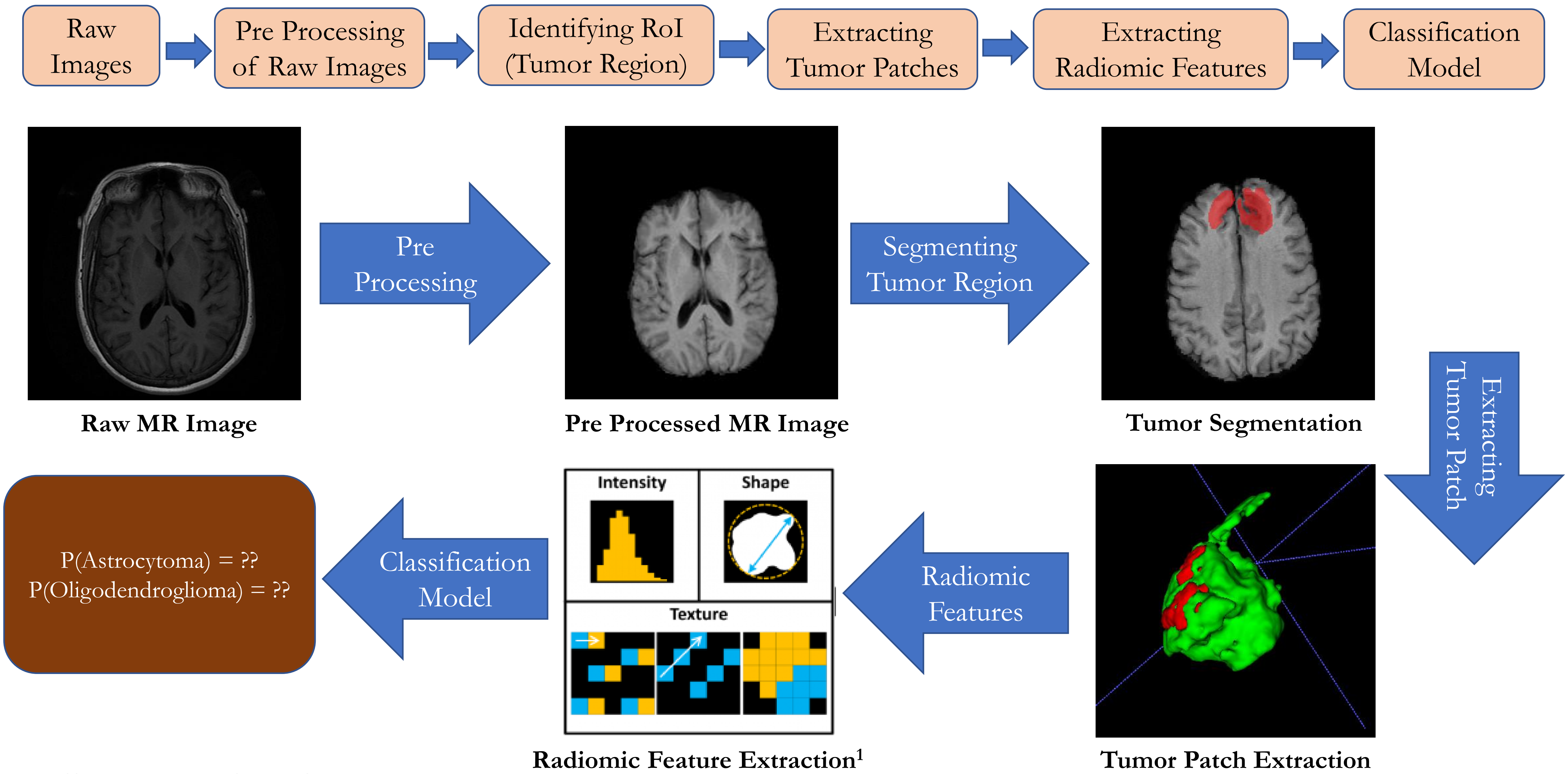
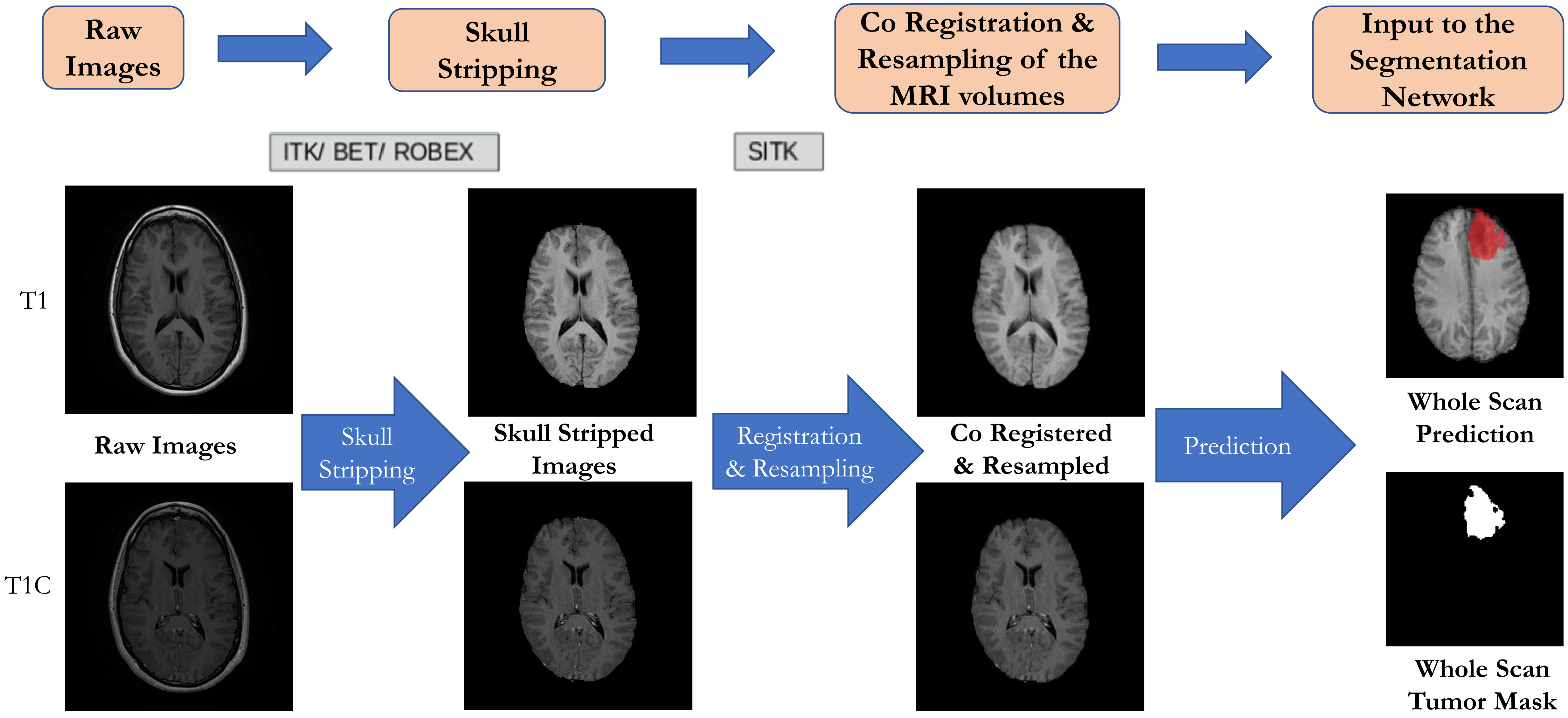
# Radiology Pipeline



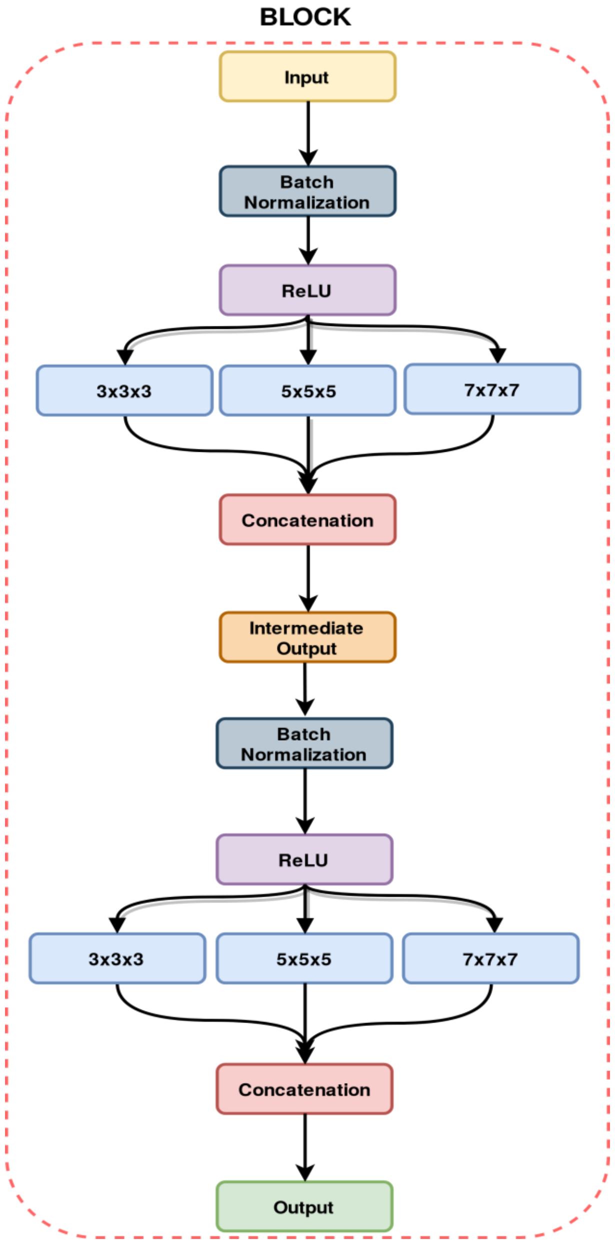

1.http://www.radiomics.world/?q=node/4

# Pre Processing of Magnetic Resonance Images

The MR dataset were fed into a pre-processing pipeline which involved skull-stripping (ROBEX), co-registration of MR sequences to T1c and re-sampling of MR volumes to isotropic voxels.

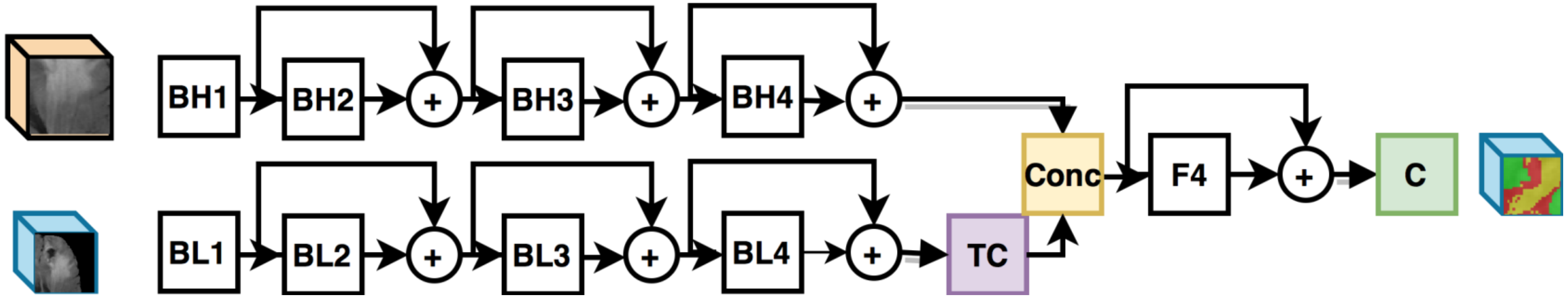


# Segmentation of Brain Tumor

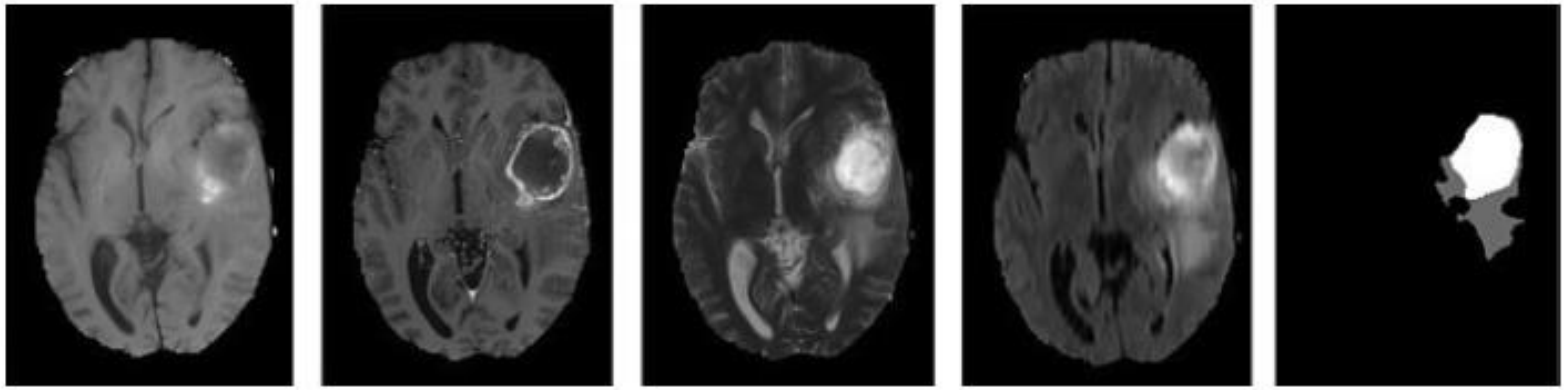



**Block in the 3-D Network**

- A Fully Convolutional 3-D Neural Network was used to segment the tumor
- The network architecture extracts both local and global features from 3-D patches
- Network trained on publicly available MICCAI BraTS 2018 dataset
- Architecture inspired by Deep Medic[1] and Havaei et al[2]




**3-D Neural Network Architecture**

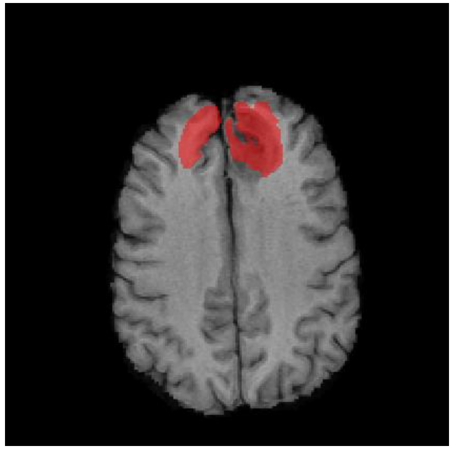


**From left to right: T1, T1C, T2, FLAIR, Segmented Tumor**


1. Kamnitsas K, Ledig C, Newcombe VF, Simpson JP, Kane AD, Menon DK, Rueckert D, Glocker B. Efficient multi-scale 3D CNN with fully connected CRF for accurate brain lesion segmentation. Medical image analysis. 2017 Feb 1;36:61-78.
2. Havaei M, Davy A, Warde-Farley D, Biard A, Courville A, Bengio Y, Pal C, Jodoin PM, Larochelle H. Brain tumor segmentation with deep neural networks. Medical image analysis. 2017 Jan 1;35:18-31.

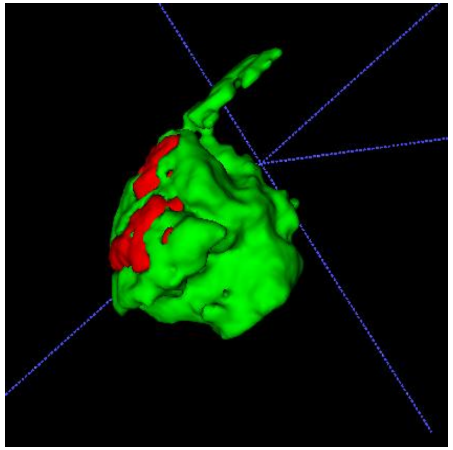
# Radiomics Feature Extraction

3D Medical Images Contain lots of Image Features → Linking Image Features to Clinical Features → Radiomics Data Set → Training a Radiomics Model based on these Features



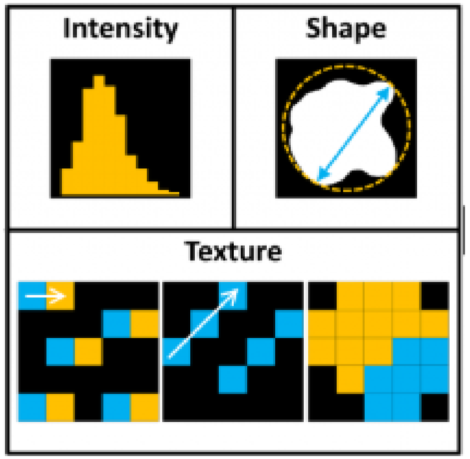
Segmented T1 Image

Extracting Tumor Patch



3D Tumor Patch

Radiomic Features




Radiomic Feature Extraction[1]

The features were extracted via the radiomics platform provided by pyradiomics[2]. These features describe, amongst others, tumor image intensity, texture and shape and size of the tumor.

| | |
|---|---|
| Shape Features (13) | First Order statistics (18) |
| GLCM Features (Gray Level Co-occurrence Matrix) (23) | GLRLM Features (Gray Level Run Length Matrix) (30) |
| GLSZM Features (Gray Level Size Zero Matrix) (16) | NGTDM Features (Neighbouring Gray Tone Difference Matrix) (5) |

1.http://www.radiomics.world/?q=node/4, 2. Joost JM van Griethuysen, Andriy Fedorov, Chintan Parmar, Ahmed Hosny, Nicole Aucoin, Vivek Narayan, Regina GH Beets-Tan, Jean-Christophe Fillion-Robin, Steve Pieper, and Hugo JWL Aerts. Computational radiomics system to decode the radiographic phenotype. Cancer research, 77(21):e104–e107, 2017.

# Two Class Classification

Each (16,1) length reduced radiomic features vector was used to train a Two Class Classification Model. Logistic Regression with LIBLINEAR as the optimization algorithm was used to train the model on a 5-fold cross validation basis.

| |
|---|
| Shape Features (13) |
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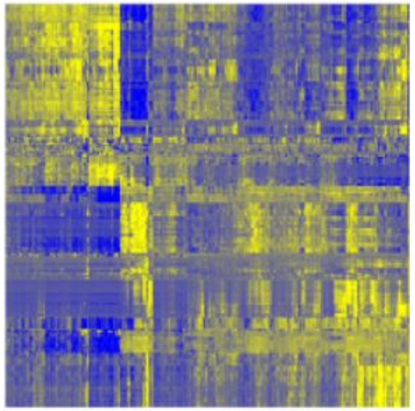
These 112 Features were reduced to 16 using Principal Component Analysis



Reduced Radiomic Features[1]

Two Class Classification Model

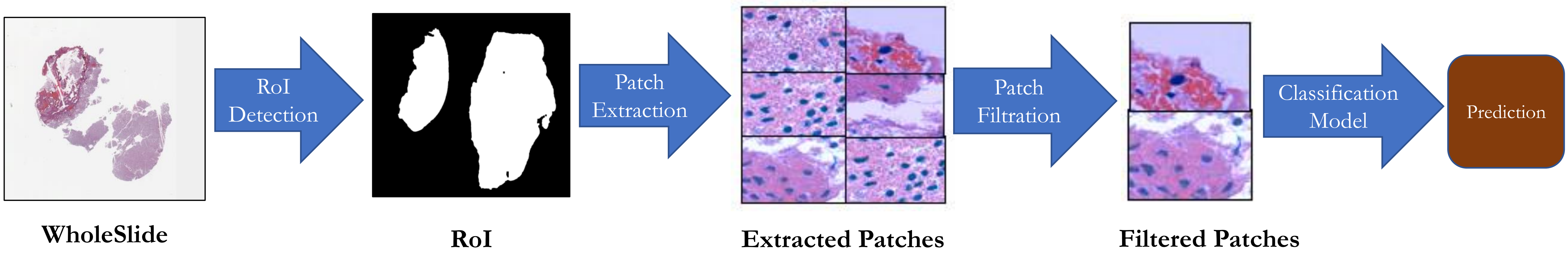
LOGISTIC REGRESSION MODEL
Optimization Algorithm: Liblinear
Basis: 5-Fold Cross Validation

**Test Phase**

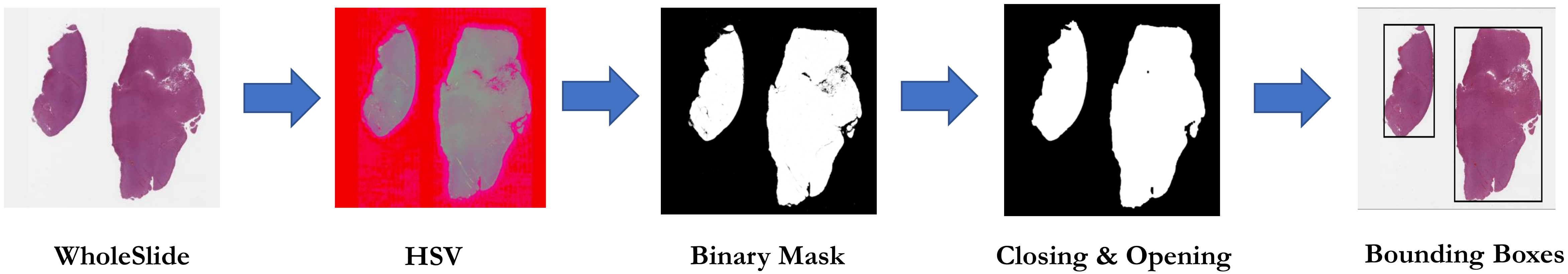
From each slide, patches are extracted exhaustively and stains are normalized. Trained autoencoder is used to extract features for each patch. Using these features outlier patches are filtered out using Isolation Forest. Voting based prediction on the set of filtered patches gives the class prediction

1.http://www.radiomics.world/?q=node/4

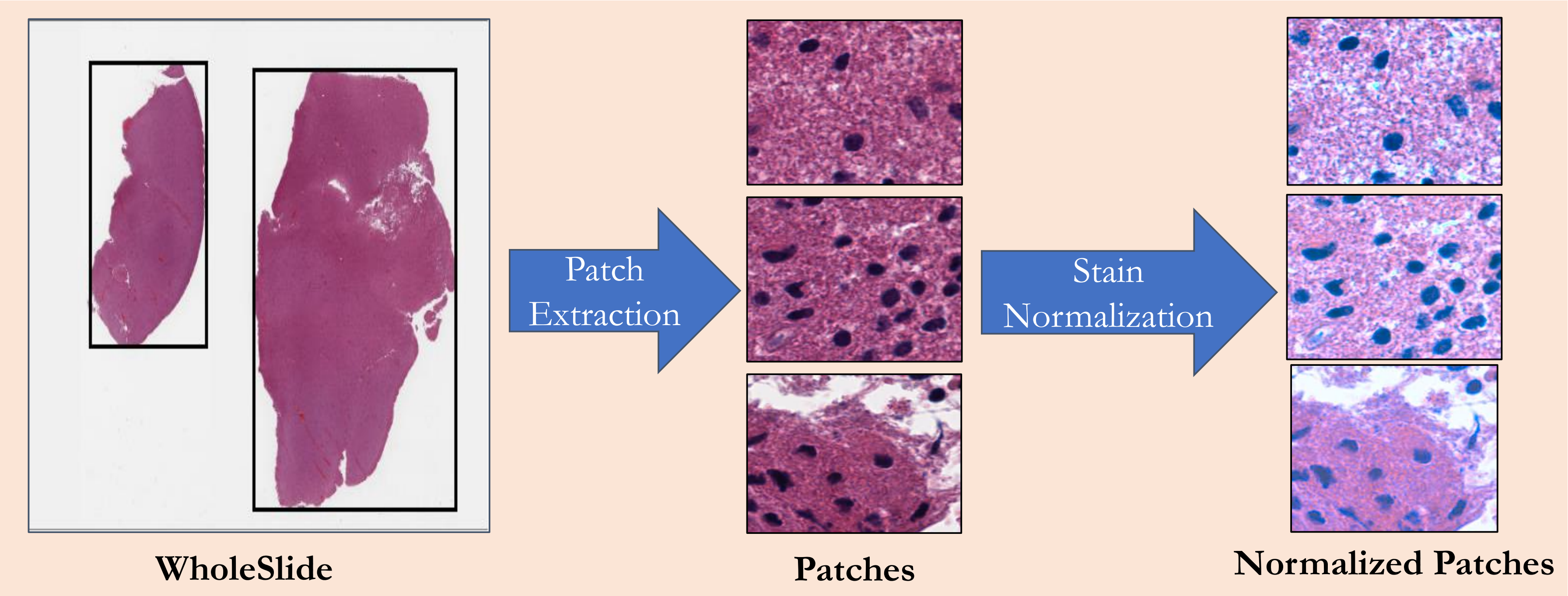
# Histopathology Pipeline



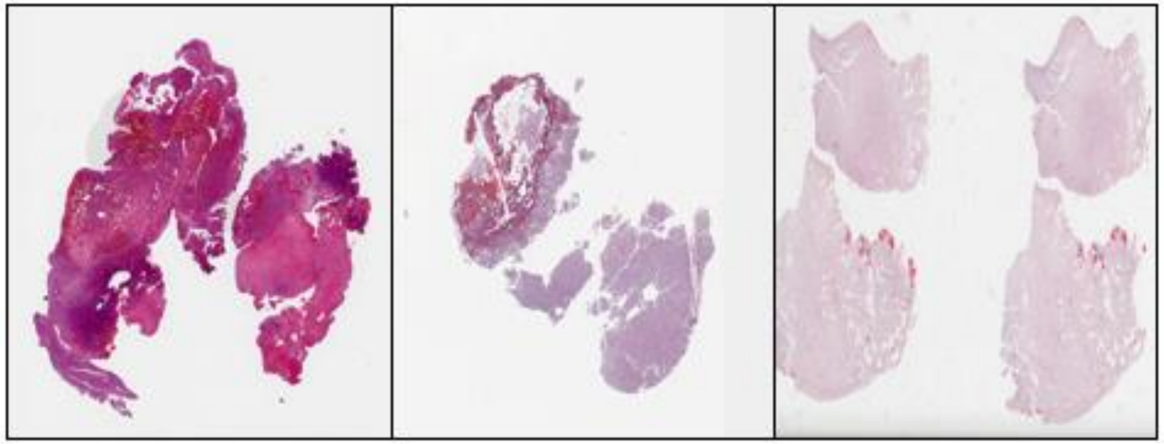

## - Region of Interest Detection



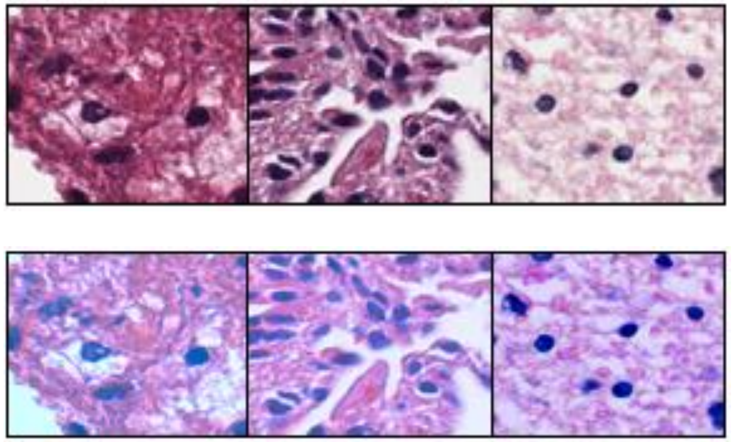
# Patch Extraction and Stain Normalization




- Patches of size 224 x 244 were extracted from each Slide
- Patches extracted from Level-0 ( highest resolution)
- Stain normalization[1] is used to normalize all the patches



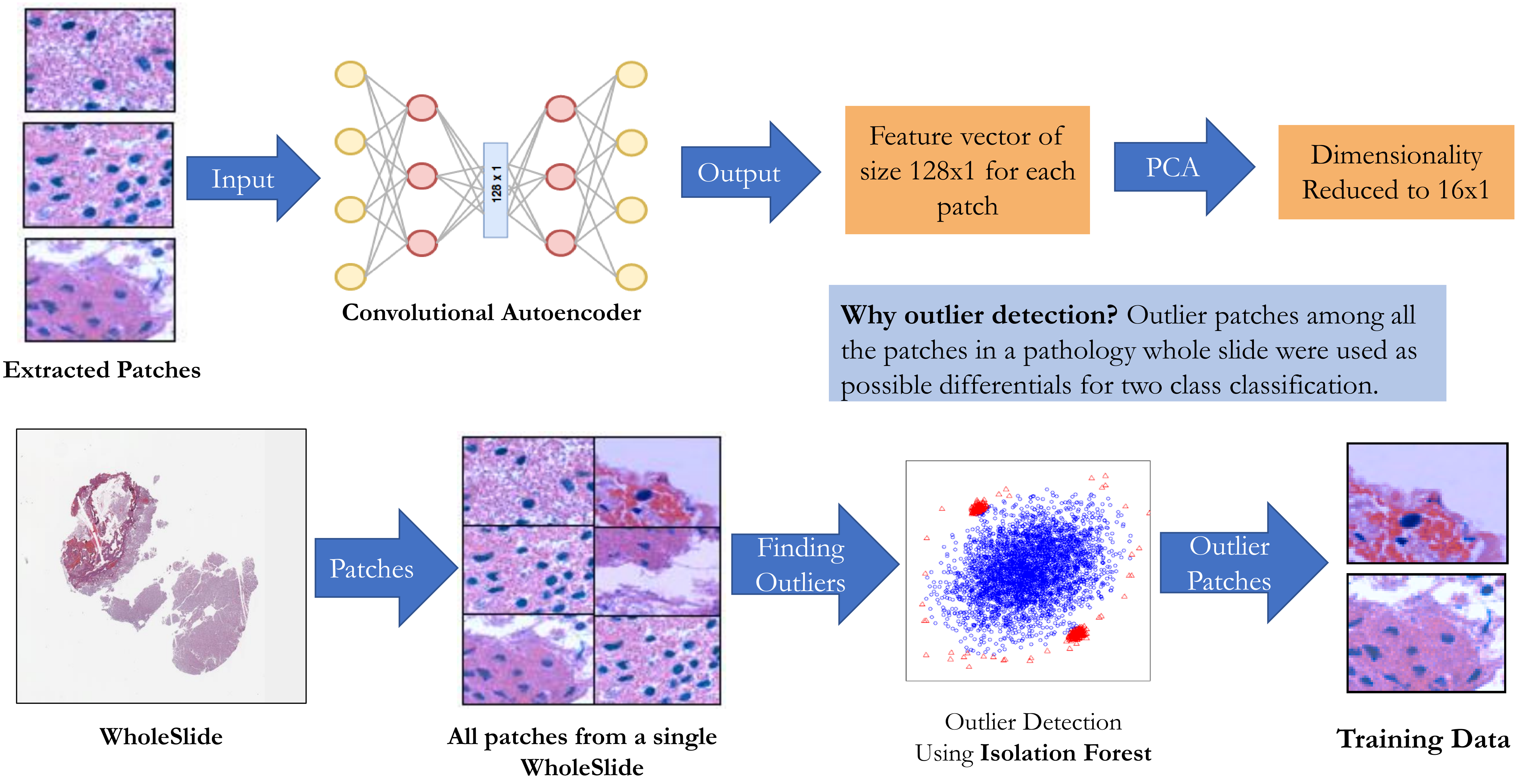
Variation in Stain Intensity



**Before Normalization**

**After Normalization**

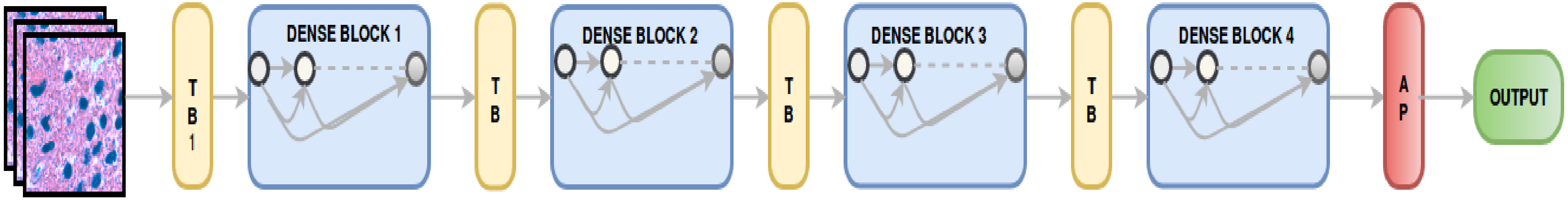
# Feature Extraction and Outlier Detection




**Why outlier detection?** Outlier patches among all the patches in a pathology whole slide were used as possible differentials for two class classification.

# Two Class Classification

- **Training Set:** 60k patches from 30 training slides used for training DenseNet Classifier
- Model trained using mini-batch Stochastic Gradient Descent

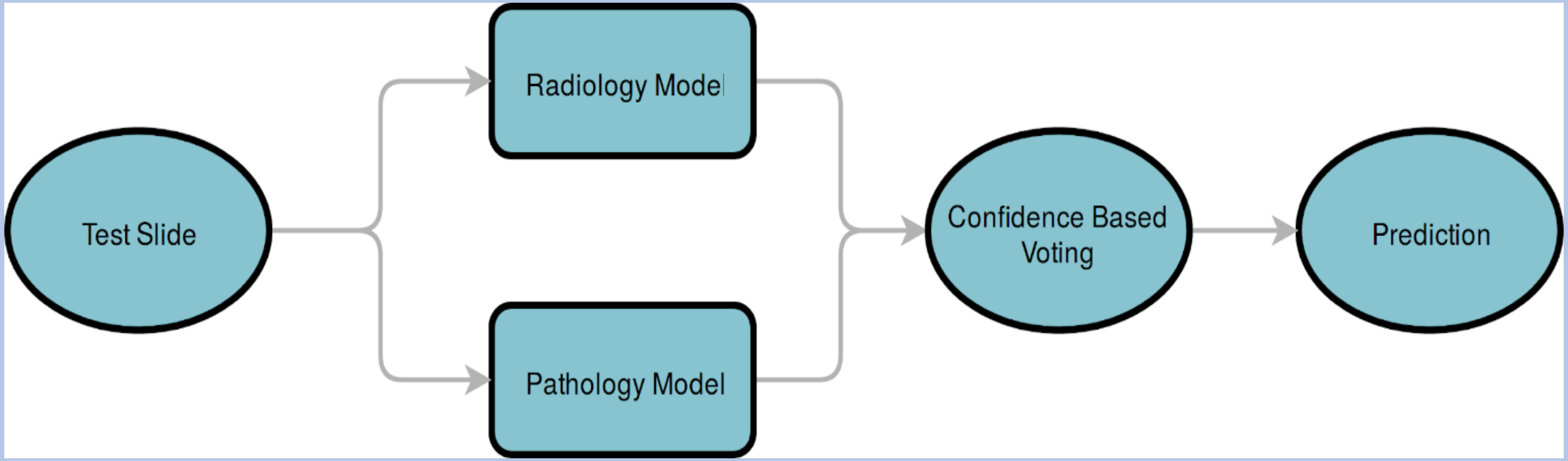



## Test Phase

- From each slide, patches are extracted exhaustively and stains are normalized
- Trained autoencoder is used to extract features for each patch
- Using these features outlier patches are filtered out using Isolation Forest
- Voting based prediction on the set of filtered patches gives the class prediction

# Combining Radiology with Pathology Results

- Both models achieve an accuracy of **80%** on the test set
- Confidence based voting was used to combine results from both the model
- Final accuracy with the combined results was **90%** on the test set




**Pipeline for Combining Results from Radiology and Pathology**