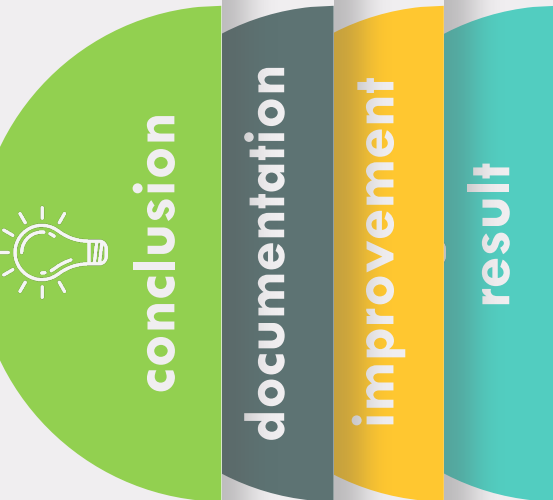


CNN Approach for Breast Cancer Diagnosis in Histopathological Dataset

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Highest Mortality

Breast cancer has the second highest mortality rate after Lung & Bronchial cancer, and about 30% of newly diagnosed cases are of breast cancer only.



Histopathology

Images are acquired by histopathology, which generally includes biopsy of the affected tissue.



Human Error

Manual detection is a tedious, tiring task and most likely to comprise human error, as most parts of the cell are frequently part of irregular random and arbitrary visual angles.



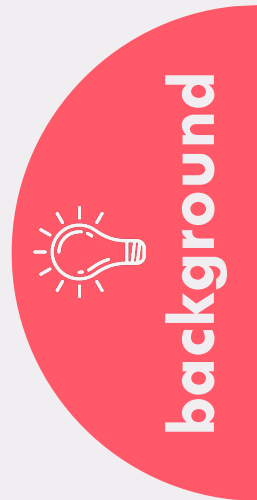
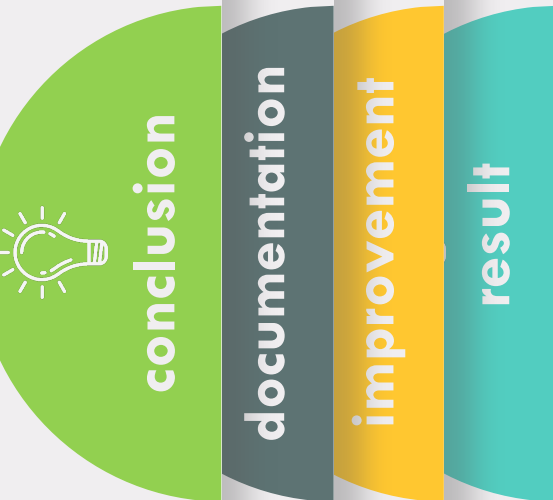
Benign/Malignant Classification

The goal is to identify whether a tumor is benign or of a malignant in nature, as malignant tumors are cancerous and should be treated as soon as possible to reduce and prevent further complications.

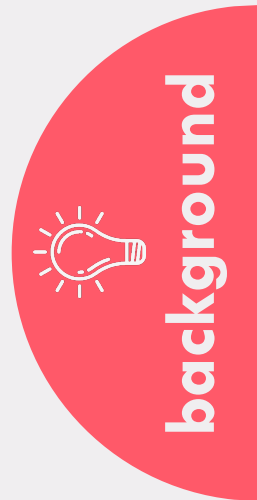
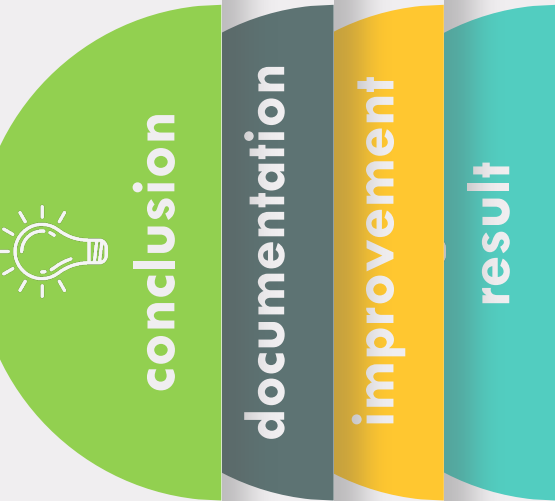


background

What is the potential of computational pathology?

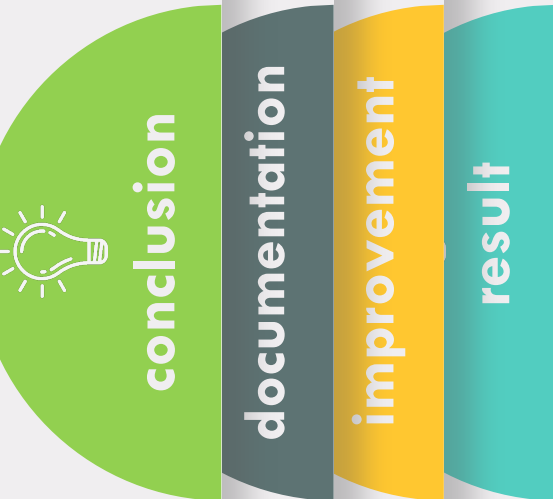
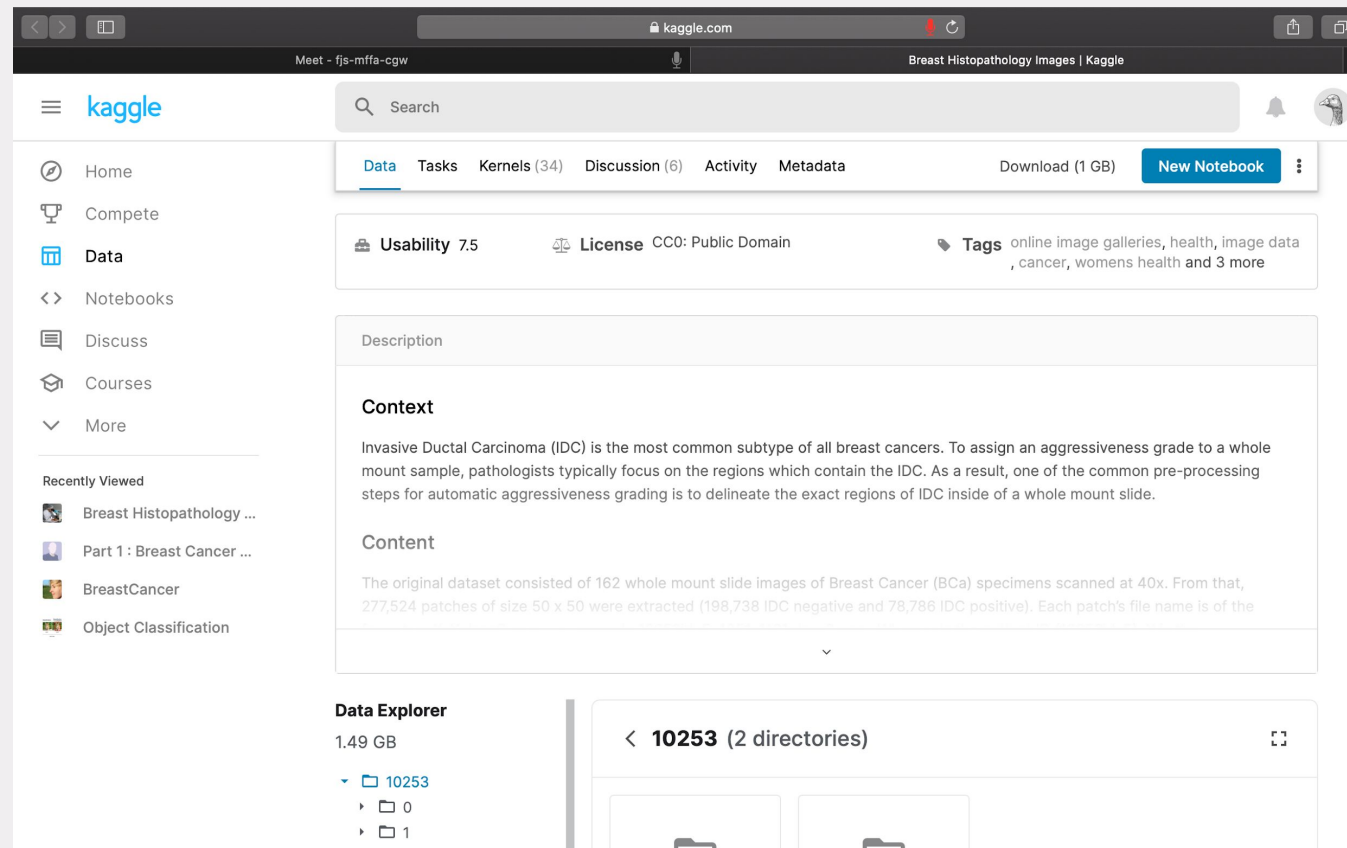


What is the potential of computational pathology?

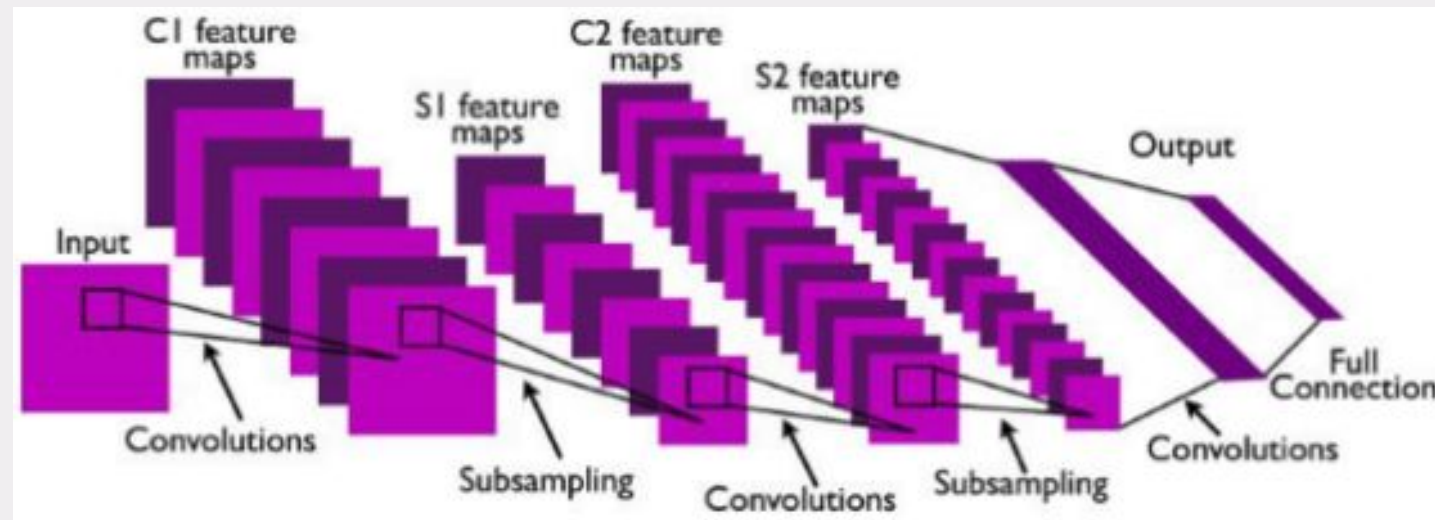


Why did we choose this dataset?

The original dataset consisted of 162 whole mount slide images of Breast Cancer (BCa) specimens scanned at 40x. From that, **277,524 patches of size 50 x 50** were extracted (198,738 IDC negative and 78,786 IDC positive). Each patch's file name is of the format: `uxXyYclassC.png` — > example `10253idx5x1351y1101class0.png`. Where `u` is the patient ID (10253idx5), `X` is the x-coordinate of where this patch was cropped from, `Y` is the y-coordinate of where this patch was cropped from, and `C` indicates the class where 0 is non-IDC and 1 is IDC.



CNN Implementation Baseline



- **Convolution Layer**
- **Pooling Layer (Subsampling)**
- **Full Connection Layer**



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Start Training

<<--TRAINING RESULTS:-->>

	precision	recall	f1-score	support
class 0(benign)	0.91	0.88	0.89	470
class 1(malignant)	0.95	0.96	0.95	1071
avg / total	0.93	0.93	0.93	1541

Confusion Matrix
[[412 58]
[43 1028]]

NETWORK is trained with Accuracy of 93.44581440622972%

Test an Image from Dataset

Select an Image for Testing

See Loss and Accuracy plots



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Output Class	Target Class	
	0	1
0	412 26.74%	43 2.79%
1	58 3.76%	1028 66.71%
	87.66% 12.34%	95.98% 4.02%
		93.44% 6.56%

Fig. 5. Confusion matrix.

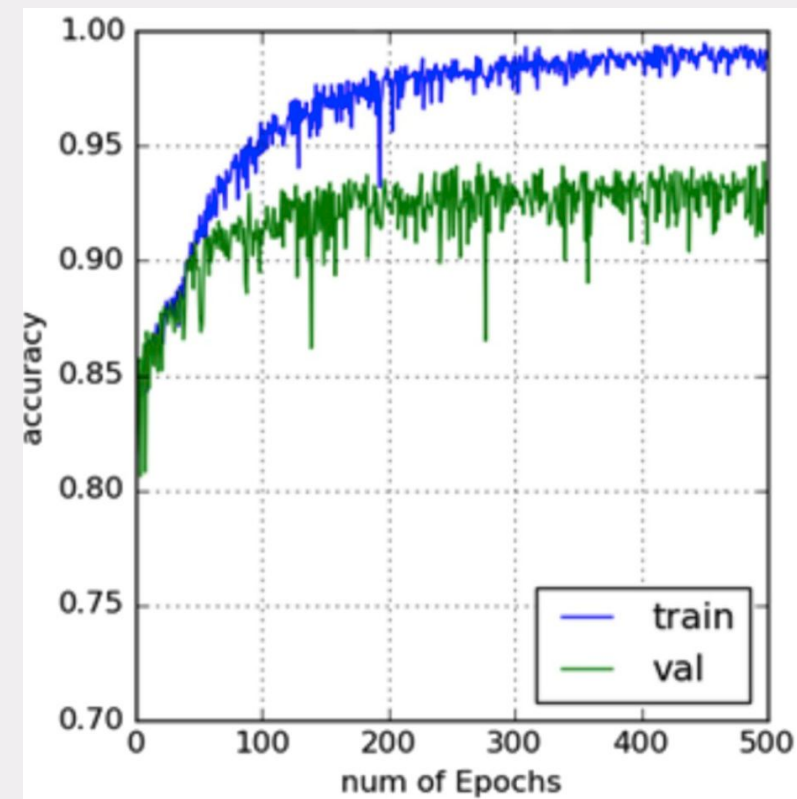


Fig. 9. Training accuracy and validation accuracy.



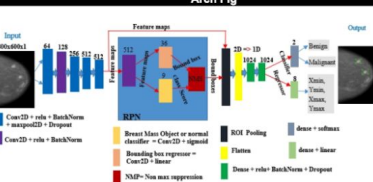
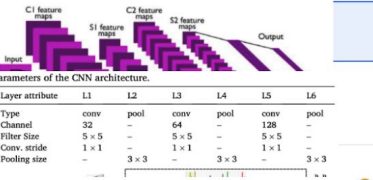
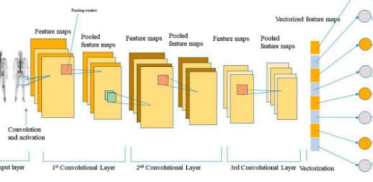


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S Researcher			Arch Fig		Preprocessing	Accuracy	Training model
1	Nrea et al., (2020)	Breast Cancer Detection Using Convolutional Neural Networks	<p>CNN architecture is designed for the feature extraction stage and adapted both Region of Interest (ROI) portion of the Region of Interest (ROI) portion of the faster R-CNN</p> <p>The proposed model architecture consists of 74 layers in total. It has 19 convolutional layers, with different filter sizes that have the function of extracting features such as edges, color and shape. The model starts with two traditional convolutional layers of 5 x 5 and 7 x 7 raw image database >> processed data (resized, reshaped) >> convolutional and pooling layers >> features >> fully connected layers >> malignant or benign class</p> 		<p>The images were passed through different preprocessing stages such as gaussian filter, median filter, bilateral filters and extracted the region of the</p> <p>This method enables the automated learning sets for different tasks instead of traditional machine learning techniques (17,18). It can achieve the of the feature sets for different tasks instead of</p> <p>Reducing redundant and unnecessary images (preprocessing) is begun with the implementation of our deep net by processing the images in the dataset.</p>	<p>The performance of the model on test data is found to be: detection accuracy 91.86%, sensitivity of 94.67% and</p> <p>Achieving a patch-wise classification accuracy of 90.5%, and an image-wise classification accuracy of 97.4% on the validation set. Moreover, we have achieved trained a convolutional neural network and obtained a prediction accuracy of up to 99.86%.</p>	<p>The feature extraction section has a series of five conv</p> <p>128, 256, 512, 512 number of filters for each convolution layer is followed by ReLU activation layer maxpooling layer and dropout layer the second layer w</p>
2	Alzubaidi et al., (2020)	Optimizing the Performance of Breast Cancer Classification by Employing the Same Domain Transfer Learning from Hybrid Deep Convolutional Neural	<p>CNN architecture is designed for the feature extraction stage and adapted both Region of Interest (ROI) portion of the Region of Interest (ROI) portion of the faster R-CNN</p> <p>The proposed model architecture consists of 74 layers in total. It has 19 convolutional layers, with different filter sizes that have the function of extracting features such as edges, color and shape. The model starts with two traditional convolutional layers of 5 x 5 and 7 x 7 raw image database >> processed data (resized, reshaped) >> convolutional and pooling layers >> features >> fully connected layers >> malignant or benign class</p> 		<p>The images were passed through different preprocessing stages such as gaussian filter, median filter, bilateral filters and extracted the region of the</p> <p>This method enables the automated learning sets for different tasks instead of traditional machine learning techniques (17,18). It can achieve the of the feature sets for different tasks instead of</p> <p>Reducing redundant and unnecessary images (preprocessing) is begun with the implementation of our deep net by processing the images in the dataset.</p>	<p>The performance of the model on test data is found to be: detection accuracy 91.86%, sensitivity of 94.67% and</p> <p>Achieving a patch-wise classification accuracy of 90.5%, and an image-wise classification accuracy of 97.4% on the validation set. Moreover, we have achieved trained a convolutional neural network and obtained a prediction accuracy of up to 99.86%.</p>	<p>The feature extraction section has a series of five conv</p> <p>128, 256, 512, 512 number of filters for each convolution layer is followed by ReLU activation layer maxpooling layer and dropout layer the second layer w</p>
3	Dabeer et al., (2020)	Cancer diagnosis in histopathological images: CNN based approach	<p>CNN architecture is designed for the feature extraction stage and adapted both Region of Interest (ROI) portion of the Region of Interest (ROI) portion of the faster R-CNN</p> <p>The proposed model architecture consists of 74 layers in total. It has 19 convolutional layers, with different filter sizes that have the function of extracting features such as edges, color and shape. The model starts with two traditional convolutional layers of 5 x 5 and 7 x 7 raw image database >> processed data (resized, reshaped) >> convolutional and pooling layers >> features >> fully connected layers >> malignant or benign class</p> 		<p>The images were passed through different preprocessing stages such as gaussian filter, median filter, bilateral filters and extracted the region of the</p> <p>This method enables the automated learning sets for different tasks instead of traditional machine learning techniques (17,18). It can achieve the of the feature sets for different tasks instead of</p> <p>Reducing redundant and unnecessary images (preprocessing) is begun with the implementation of our deep net by processing the images in the dataset.</p>	<p>The performance of the model on test data is found to be: detection accuracy 91.86%, sensitivity of 94.67% and</p> <p>Achieving a patch-wise classification accuracy of 90.5%, and an image-wise classification accuracy of 97.4% on the validation set. Moreover, we have achieved trained a convolutional neural network and obtained a prediction accuracy of up to 99.86%.</p>	<p>The feature extraction section has a series of five conv</p> <p>128, 256, 512, 512 number of filters for each convolution layer is followed by ReLU activation layer maxpooling layer and dropout layer the second layer w</p>
4	Araujo et al., (2017)	Classification of breast cancer histology images using Convolutional Neural Networks	<p>CNN architecture is designed for the feature extraction stage and adapted both Region of Interest (ROI) portion of the Region of Interest (ROI) portion of the faster R-CNN</p> <p>The proposed model architecture consists of 74 layers in total. It has 19 convolutional layers, with different filter sizes that have the function of extracting features such as edges, color and shape. The model starts with two traditional convolutional layers of 5 x 5 and 7 x 7 raw image database >> processed data (resized, reshaped) >> convolutional and pooling layers >> features >> fully connected layers >> malignant or benign class</p> 		<p>The images were passed through different preprocessing stages such as gaussian filter, median filter, bilateral filters and extracted the region of the</p> <p>This method enables the automated learning sets for different tasks instead of traditional machine learning techniques (17,18). It can achieve the of the feature sets for different tasks instead of</p> <p>Reducing redundant and unnecessary images (preprocessing) is begun with the implementation of our deep net by processing the images in the dataset.</p>	<p>The performance of the model on test data is found to be: detection accuracy 91.86%, sensitivity of 94.67% and</p> <p>Achieving a patch-wise classification accuracy of 90.5%, and an image-wise classification accuracy of 97.4% on the validation set. Moreover, we have achieved trained a convolutional neural network and obtained a prediction accuracy of up to 99.86%.</p>	<p>The feature extraction section has a series of five conv</p> <p>128, 256, 512, 512 number of filters for each convolution layer is followed by ReLU activation layer maxpooling layer and dropout layer the second layer w</p>
5	Zhu et al., (2019)	Breast cancer histopathology image classification through assembling multiple compact CNNs	<p>CNN architecture is designed for the feature extraction stage and adapted both Region of Interest (ROI) portion of the Region of Interest (ROI) portion of the faster R-CNN</p> <p>The proposed model architecture consists of 74 layers in total. It has 19 convolutional layers, with different filter sizes that have the function of extracting features such as edges, color and shape. The model starts with two traditional convolutional layers of 5 x 5 and 7 x 7 raw image database >> processed data (resized, reshaped) >> convolutional and pooling layers >> features >> fully connected layers >> malignant or benign class</p> 		<p>The images were passed through different preprocessing stages such as gaussian filter, median filter, bilateral filters and extracted the region of the</p> <p>This method enables the automated learning sets for different tasks instead of traditional machine learning techniques (17,18). It can achieve the of the feature sets for different tasks instead of</p> <p>Reducing redundant and unnecessary images (preprocessing) is begun with the implementation of our deep net by processing the images in the dataset.</p>	<p>The performance of the model on test data is found to be: detection accuracy 91.86%, sensitivity of 94.67% and</p> <p>Achieving a patch-wise classification accuracy of 90.5%, and an image-wise classification accuracy of 97.4% on the validation set. Moreover, we have achieved trained a convolutional neural network and obtained a prediction accuracy of up to 99.86%.</p>	<p>The feature extraction section has a series of five conv</p> <p>128, 256, 512, 512 number of filters for each convolution layer is followed by ReLU activation layer maxpooling layer and dropout layer the second layer w</p>
6	Papandriou et al., (2020)	A Deep-Learning Approach for Diagnosis of Metastatic Breast Cancer in Bones from Whole-Body Scans	<p>CNN architecture is designed for the feature extraction stage and adapted both Region of Interest (ROI) portion of the Region of Interest (ROI) portion of the faster R-CNN</p> <p>The proposed model architecture consists of 74 layers in total. It has 19 convolutional layers, with different filter sizes that have the function of extracting features such as edges, color and shape. The model starts with two traditional convolutional layers of 5 x 5 and 7 x 7 raw image database >> processed data (resized, reshaped) >> convolutional and pooling layers >> features >> fully connected layers >> malignant or benign class</p>		<p>The images were passed through different preprocessing stages such as gaussian filter, median filter, bilateral filters and extracted the region of the</p> <p>This method enables the automated learning sets for different tasks instead of traditional machine learning techniques (17,18). It can achieve the of the feature sets for different tasks instead of</p> <p>Reducing redundant and unnecessary images (preprocessing) is begun with the implementation of our deep net by processing the images in the dataset.</p>	<p>The performance of the model on test data is found to be: detection accuracy 91.86%, sensitivity of 94.67% and</p> <p>Achieving a patch-wise classification accuracy of 90.5%, and an image-wise classification accuracy of 97.4% on the validation set. Moreover, we have achieved trained a convolutional neural network and obtained a prediction accuracy of up to 99.86%.</p>	<p>The feature extraction section has a series of five conv</p> <p>128, 256, 512, 512 number of filters for each convolution layer is followed by ReLU activation layer maxpooling layer and dropout layer the second layer w</p>
7	Gao et al., (2020)	SD-CNN: a Shallow-Deep CNN for Improved Breast Cancer Diagnosis	<p>CNN architecture is designed for the feature extraction stage and adapted both Region of Interest (ROI) portion of the Region of Interest (ROI) portion of the faster R-CNN</p> <p>The proposed model architecture consists of 74 layers in total. It has 19 convolutional layers, with different filter sizes that have the function of extracting features such as edges, color and shape. The model starts with two traditional convolutional layers of 5 x 5 and 7 x 7 raw image database >> processed data (resized, reshaped) >> convolutional and pooling layers >> features >> fully connected layers >> malignant or benign class</p>		<p>The images were passed through different preprocessing stages such as gaussian filter, median filter, bilateral filters and extracted the region of the</p> <p>This method enables the automated learning sets for different tasks instead of traditional machine learning techniques (17,18). It can achieve the of the feature sets for different tasks instead of</p> <p>Reducing redundant and unnecessary images (preprocessing) is begun with the implementation of our deep net by processing the images in the dataset.</p>	<p>The performance of the model on test data is found to be: detection accuracy 91.86%, sensitivity of 94.67% and</p> <p>Achieving a patch-wise classification accuracy of 90.5%, and an image-wise classification accuracy of 97.4% on the validation set. Moreover, we have achieved trained a convolutional neural network and obtained a prediction accuracy of up to 99.86%.</p>	<p>The feature extraction section has a series of five conv</p> <p>128, 256, 512, 512 number of filters for each convolution layer is followed by ReLU activation layer maxpooling layer and dropout layer the second layer w</p>
8	Spanhol et al., (2016)	Breast Cancer Histopathological Image Classification using Convolutional Neural Networks	<p>CNN architecture is designed for</p>				

<https://bit.ly/bangkit-paper-review>

**Alzubaidi et al., (2020)**

Optimizing the Performance of Breast Cancer Classification by Employing the Same Domain Transfer Learning from Hybrid Deep Convolutional Neural Network Model

**Araujo et al., (2020)**

Classification of breast cancer histology images using Convolutional Neural Networks

**Dabeer et al., (2020)**

Cancer diagnosis in histopathological image: CNN based approach

**Gao et al., (2020)**

SD-CNN: a Shallow-Deep CNN for Improved Breast Cancer Diagnosis

**Papandrianos et al., (2020)**

A Deep-Learning Approach for Diagnosis of Metastatic Breast Cancer in Bones from Whole-Body Scans

**Zou et al., (2020)**

A Technical Review of Convolutional Neural Network-Based Mammographic Breast Cancer Diagnosis

**Zhu et al., (2019)**

Breast cancer histopathology image classification through assembling multiple compact CNNs

**Spanhol et al., (2016)**

Classification of breast cancer histology images using Convolutional Neural Networks

**Nrea et al., (2020)**

Breast Cancer Detection Using Convolutional Neural Networks



Adjusting learning rate

In order to enhance accuracy; 1×10^{-5} , 1×10^{-4} , 1×10^{-3} , 1×10^{-2} , 1×10^{-1}



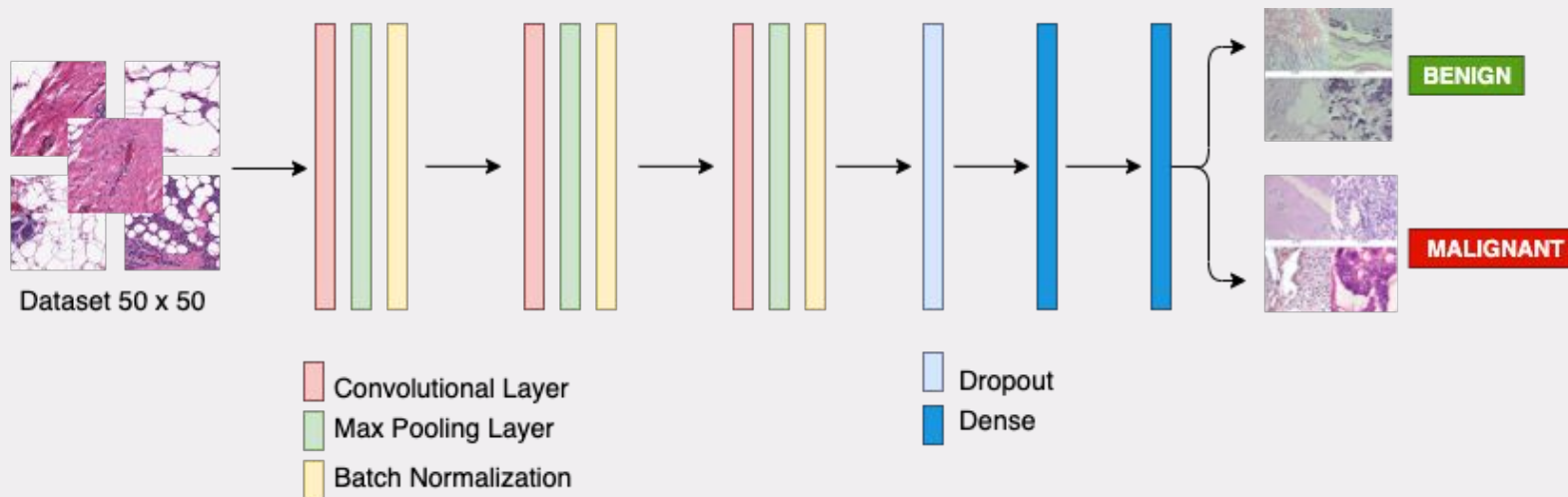
Change batch

By using Stochastic Gradient Descent



Adjusting epochs

Reduce epochs from 60 to 25



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We propose these neural networks;

```
jupyter Breast Cancer Attempt Last Checkpoint: Last Wednesday at 10:26 PM (autosaved)
```

```
File Edit View Insert Cell Kernel Widgets Help
```

```
model.summary()
```

```
Model: "sequential"
```

Layer (type)	Output Shape	Param #
conv2d (Conv2D)	(None, 50, 50, 32)	896
max_pooling2d (MaxPooling2D)	(None, 25, 25, 32)	0
batch_normalization_v2 (Batch Normalization)	(None, 25, 25, 32)	128
conv2d_1 (Conv2D)	(None, 25, 25, 128)	36992
max_pooling2d_1 (MaxPooling2D)	(None, 12, 12, 128)	0
batch_normalization_v2_1 (Batch Normalization)	(None, 12, 12, 128)	512
conv2d_2 (Conv2D)	(None, 12, 12, 128)	147584
max_pooling2d_2 (MaxPooling2D)	(None, 6, 6, 128)	0
flatten (Flatten)	(None, 4608)	0
dropout (Dropout)	(None, 4608)	0
dense (Dense)	(None, 128)	589952
dense_1 (Dense)	(None, 1)	129

```
Total params: 776,193  
Trainable params: 775,873  
Non-trainable params: 320
```

```
In [22]: model.compile(tf.keras.optimizers.SGD(1e-3), loss = 'binary_crossentropy', metrics = ['acc'])
```



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<https://github.com/BangkitProjectYOG4/Bangkit-Final-Project-IDC>

 **BangkitProjectYOG4** / **Bangkit-Final-Project-IDC**

Watch 0

Star 0

Fork 1

<> Code

Issues 0

Pull requests 1

Actions

Projects 0

Wiki

Security 0

Insights

No description, website, or topics provided.

6 commits

1 branch

0 packages

0 releases

2 contributors

Branch: master


New pull request

Create new file




Upload files


Find file

Clone or download

 **hansenidden18** Update README.md

Latest commit 8852ef6 3 hours ago

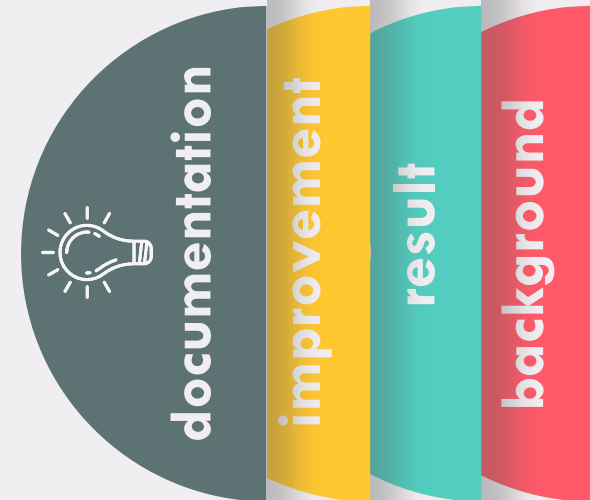
 README.md	Update README.md	3 hours ago
 dataframe.py	Add dataset image organizer and dataframe maker	5 days ago
 organize_data.py	Add dataset image organizer and dataframe maker	5 days ago

 README.md

Bangkit-Final-Project-IDC

Dataset source : ['Breast Histopathology Images'] (<https://www.kaggle.com/paultimothymooney/breast-histopathology-images>)

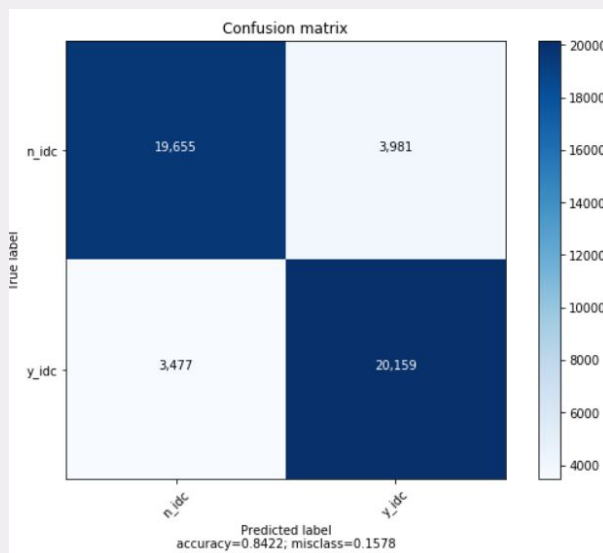
Dataset



From this project, we could achieve as 84% of validation accuracy. It can be improved by using more HD patches as the inputs, but it also has drawback as it is computationally expensive.

Breast cancer detection by using digital/digitized histopathology images is a milestone in the field of medical pathology. It has also opened a door to new opportunities for research as there are many undiscovered areas that can be revealed by techniques and tools of machine learning and deep learning. We may obtain improved results by altering the network design and parameters. As an improvement to the proposed method, one can implement an autoencoder instead of manually reducing image size. It can compress data without losing the prominent features, because autoencoders can re-generate up to 90% of the original image. From the point of method improvement, we can incorporate spectral imaging.

Our confusion matrix :



```
In [29]: acc = history.history['acc']
val_acc = history.history['val_acc']
loss = history.history['loss']
val_loss = history.history['val_loss']

epochs = range(len(acc))

plt.plot(epochs, acc, 'r', label='Training Accuracy')
plt.plot(epochs, val_acc, 'b', label='Validation Accuracy')
plt.title('Training And Validation Accuracy')
plt.legend(loc=0)
plt.figure()

plt.show()
```

