成都理工大學中英合作办学
CDUT Sino-British Collaborative Education

OXFORD BROOKES UNIVERSITY

UNDERGRADUATE PROJECT PROGESS REPORT

Project Title:	**Inception-Enhanced Depthwise CNN of Residual Learning for Breast Cancer Diagnosis**
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1 Introduction

1.1 Background

Breast cancer is one of the most fatal diseases so far in the world. It is said by American Cancer Society Surveillance that one out of eight women is affected by it [1]. According to statistics recorded by the World Health Organization (WHO) [2] among the 9.6 million cancer-related deaths, 627,000 females passed away due to breast cancer in 2018, in addition, WHO had also predicted that 43,600 women would die from breast cancer in 2021 [3], which indicates that breast cancer remains the leading cause of women death.

Breast cancer is similar to other types of cancer which can be early-stage (Benign) and later-stage (Malignant). Once the disease reaches the malignant stage, cancer might spread to other parts of the body which leads to catastrophic results, therefore, it is crucial to detect breast cancer at the early stage in order to provide appropriate treatment [4]. Mammography serves as a common approach for breast cancer detection in which the picture is normally taken through Magnetic Resonance Imaging (MRI), X-Ray, and Ultrasound, other methods rely on tissue samples from the affected area of the breasts and complete the diagnosis and classify by microscope [5].

It is unfortunate that the diagnosis still faces troubles. Manual diagnosis through medical images or microscope is time-intensive, expensive and prone to errors, as symptoms are likely to be overseen [6]. For example, ultrasound breast cancer image detection highly depends on the experience, capability and knowledge of radiologists and diagnosticians [7], which most small hospitals might not be equipped with.

Therefore, the development and deployment of a deep learning based system focused on the classification and diagnosis of breast cancer is the main goal of this project so as to avoid manpower waste, apply more targeted treatment to patients, lower death rate, and save more lives.

1.2 Aim

Various models in deep learning diagnosis utilize a specific single model, however, by doing so, there are chances that flaws of specific models could affect the performance in a negative way. To eliminate the drawbacks and maximize the performance, this project aims to develop and deploy a novel CNN model including Inception-ResNet model to classify the levels of breast cancer. Based on Wang et al. [8], Inception-ResNet possesses a remarkable balance between model accuracy and resource efficiency.

1.3 Objectives

The project will collect breast cancer symptom data from online sources, utilizing datasets like BreakHis, IDC, and mini-DDSM. BreakHis has benign and malignant categories with 9,109 microscope images from 82 patients. IDC contains 198,738 negative and 78,786 positive invasive carcinoma images. The data will be divided into training and testing sets for four different scaled images, with an 80% portion allocated for training and a 20% portion for testing. Within the training set, 10% of the images will be randomly selected as a validation set. It is essential to include both benign and malignant samples in both sets.

The project aims to build a Depthwise-Inception-ResNet-Attention model, with hyperparameter adjustments such as batch size, learning rate, dropout rate etc. Although primarily focused on binary classification, the project also approaches it as a multi-class problem to later identify more detailed symptoms and enhance generalizability.

In addition, the evaluation of the model will include metrics such as "Accuracy" and "Loss." Moreover, performance will be assessed using "Precision", "Recall", "F1-Score", "AUC-ROC", "AUC-PR", "Specificity", "Sensitivity", and the "Confusion Matrix”.

Lastly, the project will be deployed through a website which allows uploading medical pictures of breast cancer, and then give the classification results.

1.4 Project Overview

1.4.1 Scope

Convolutional Neural Networks (CNNs) were introduced to medical image processing in the 1980s and have become the dominant approach in this field [9]-[10]. While Inception-ResNet delivers impressive performance, models not tailored to specific scenarios often encounter issues like gradient vanishing, local minima, and overfitting. Therefore, enhancing Inception-ResNet through the incorporation of depthwise operations is imperative. By using depthwise operations, it will reduce the parameter count, thus, improving the network's efficiency and effectiveness, all the while conserving computational resources by eliminating unnecessary parameters [11].

The following are the significances of this project and potential contributions:

- Enhanced Breast Cancer Diagnosis Accessibility
- Improved Diagnosis Efficiency
- Reduced Misdiagnosis Rate
- Early detection and Prevention
- Conserved Medical Resources and Improved Allocation
- Increased Life Saving Rate
- Cost-Effective Healthcare Solutions
- Promotion of Public Health Awareness

1.4.2 Audience

The development of a specialized system for breast cancer diagnosis will bring about significant benefits to various stakeholders.

Medical Professionals: Radiologists and oncologists will benefit from the enhanced accuracy and efficiency of breast cancer diagnosis. The CNN can aid in early detection, reducing the chances of misdiagnosis and allowing for more timely interventions.

Hospitals and Clinics: Healthcare institutions will experience improved workflow and reduced diagnostic errors, which can lead to better patient care and outcomes. It can also streamline the diagnostic process, potentially reducing the burden on healthcare resources.

Breast Cancer Patients: Patients will benefit from faster and more accurate diagnosis, resulting in quicker treatment initiation and improved chances of survival. Additionally, reduced false positives and negatives can alleviate the emotional stress associated with diagnostic uncertainty.

Medical Researchers: Researchers can access a valuable tool for analyzing a vast amount of medical imaging data, facilitating advancements in breast cancer research and treatment methods.

In summary, the proposed depthwise-Inception-ResNet model promises benefits for medical professionals, healthcare institutions, breast cancer patients, and the broader research community by enhancing the accuracy, efficiency, and overall quality of breast cancer diagnosis and care.

2 Background Review

Various methods had enhanced breast cancer classification. This section will present works that had been done for breast cancer classification.

Hirra et al. [1] proposed Pa-DBN-BC, a patch-based deep learning method, achieving 86% accuracy in diagnosing cancer from histopathology images. Sahu et al. [6] introduced a model trained on mini-DDSM, yielding 99.17% and 97.75% accuracy for abnormalities and malignancy. Liang and Meng [9] achieved high accuracy in binary and eight-class classification with BreakHis datasets. Alkhaldi et al. [11] utilized ensemble optimization, attaining 92.874% accuracy in Invasive Ductal Carcinoma classification.

Xu et al. [13] introduced an attention mechanism network with 98% accuracy, albeit limited by the smaller BreakHis dataset. Wu et al. [14] trained on 224,426 mammography images, reaching an AUC of 0.895. Chougrad et al. [15] employed transfer learning, achieving 98.94% accuracy post-merging datasets. Yu et al. [16] used SCDA data augmentation with ResNet-50, obtaining 95.74% accuracy, 98.55% specificity, and 92.83% sensitivity. Arya and Saha [17] developed a stacked-based ensemble model with 90.2% accuracy for breast cancer prognosis. Whitney et al. [10] highlighted the efficacy of CNN transfer learning in diverse imaging modalities for accurate breast cancer diagnosis.

A summary of the different researchers and their findings and possible results can be found in Table 1.

Author	Datasets	Methods & Models	Results
Hirra et al. [1]	Histopathology images	Patch-based deep learning & Deep belief Network	86%
Sahu et al. [6]	Mini-DDSM & Ultrasound images(BUSI)	AlexNet+ResNet+MobileNeetV2	Abnormalities: 99.17% and 97.75% mini-DDSM and BUSI Malignancy: 96.92% and 94.62% mini-DDSM and ultrasound

Liang and Meng [9]	BreakHis	Convolutional Block Attention Module and Convolutional Multi-Layer Perceptron	95.5%
Alkhaldi et al. [12]	Invasive-Ductal-Carcinoma (IDC)	Multi-ResNet CNN	92.874%
Xu et al. [13]	BreakHis	DeNet	98%
Wu et al. [14]	224,426 mammography	Ensemble of Four ResNets	0.895 in AUC
Chougrad et al. [15]	INbreast, DDSM, BCDR	VGG16, ResNet50, IncetpionV3	DDSM: 97% accuracy, 0.98 on AUC; INbreast: 95.5% accuracy, 0.97 on AUC BCDR: 96.67% accuracy, 0.96 on AUC Independent database (MIAS): 98.23% accuracy, 0.99 on AUC
Yu et al. [16]	INbreast, mini-DDSM	SCDA augmentation & ResNet-50	95.74% accuracy, 98.55 specificity, 92.83% sensitivity
Arya and Saha [17]	1,980 patients ’ breast cancer data	stacked ensemble model	AUC of 0.93 and 90.2% accuracy

Table 1: Summary of Related Works

3 Technical Progress

3.1 Approach

The proposed CNN model comprises two individual models with two mechanisms. The basic idea is to combine Inception-V4 Model, Residual Network, and integrate attention mechanism and depthwise convolution which are respectively used to concentrate on relevant features and to reduce the computation resources.

3.1.1 Inception Network Version 4 (V4)

Inception V4, as shown in figure 1, introduced by Google researchers in 2016, is a deep learning architecture renowned for its advanced techniques, including inception modules that efficiently learn local and global features using filters of varying sizes. It excels in image recognition and offers scalability [18].

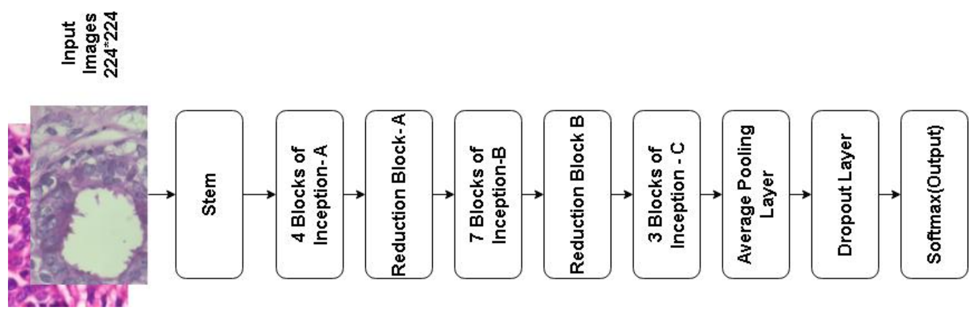


Figure 1: Inception V4 Architecture

3.1.2 Residual Network

ResNet blocks, as illustrated in Figure 2, were introduced to incorporate residual connections, effectively mitigating gradient-related challenges in deep networks and leading to enhanced training efficiency [19].

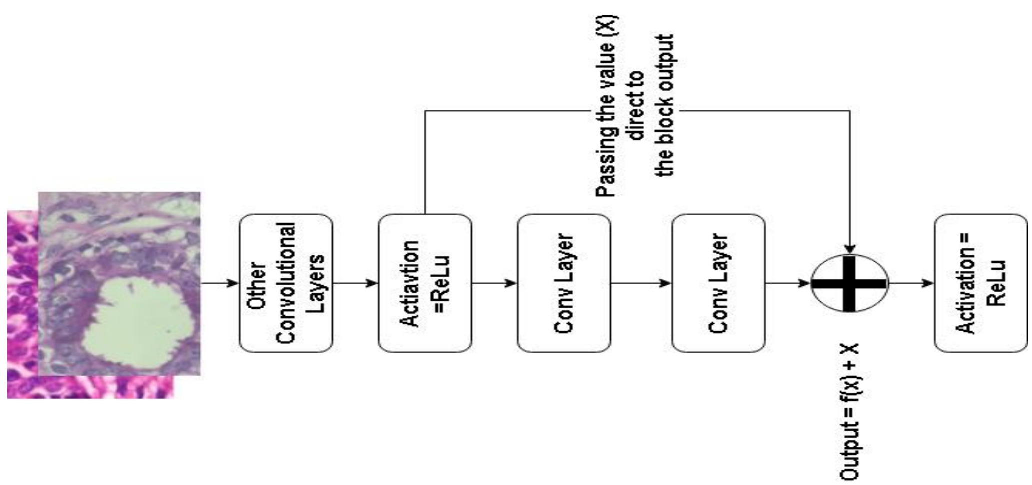


Figure 2: Basic ResNet Block

3.1.3 Inception-ResNet Block

Figure 3 illustrates the fusion of Inception V4 with ResNet Blocks, creating the Inception-ResNet Blocks structure. This hybrid design incorporates the multi-path feature extraction of Inception with the gradient-enhancing properties of ResNet. By combining these elements, Inception-ResNet Blocks enable efficient learning of intricate features, leading to more accurate and effective deep learning models [19]. The diagram visually showcases the amalgamation of these techniques, highlighting their collaborative strength in enhancing the network's capabilities.

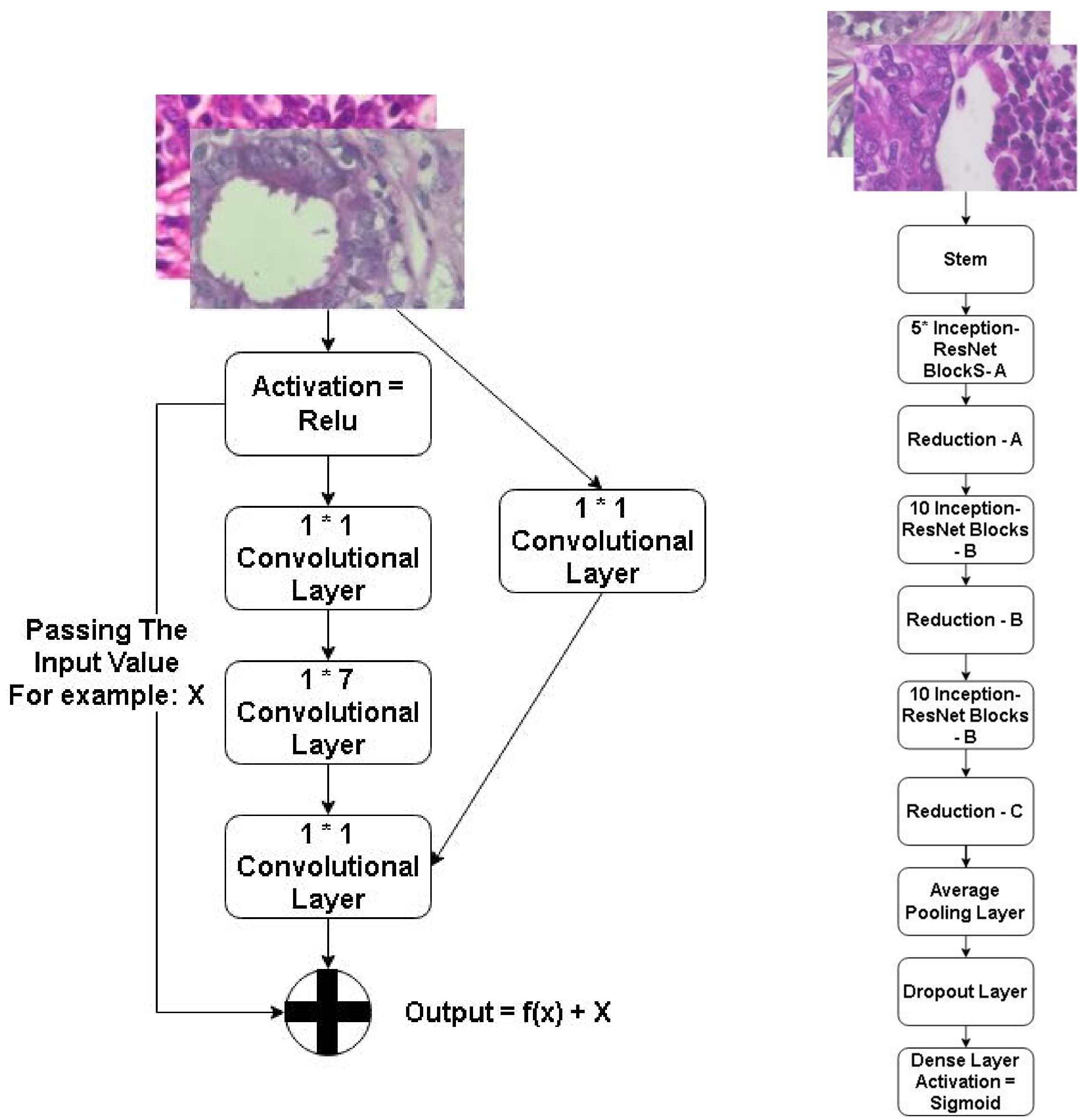


Figure 3: Inception-ResNet Block & Inception-ResNet Architecture

3.1.4 Depthwise Convolution Model

As for depthwise convolution model, it is shown in figure 4 that instead of being an individual model, it is a convolution methodology which reduces the parameters by bypassing unnecessary parameters to deplete the model size and resource being taken [12].

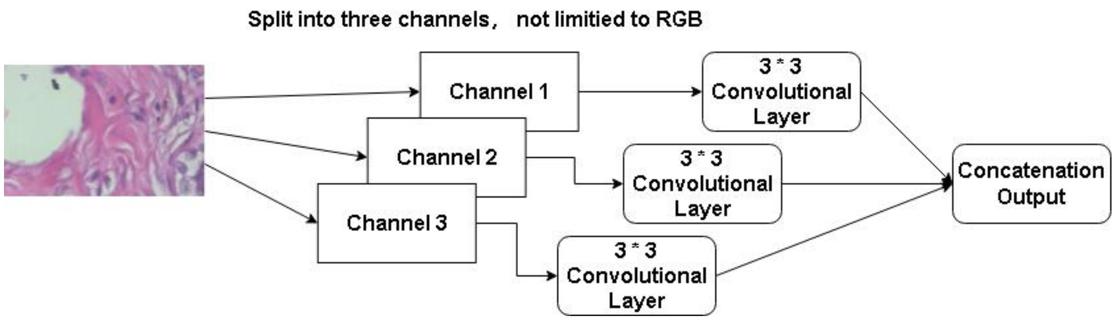


Figure 4: Depthwise Convolution

3.1.5 Depthwise-Inception-ResNet Model

Therefore, Depthwise-Inception-ResNet model is constructed by combining all above which shown in figure 5.

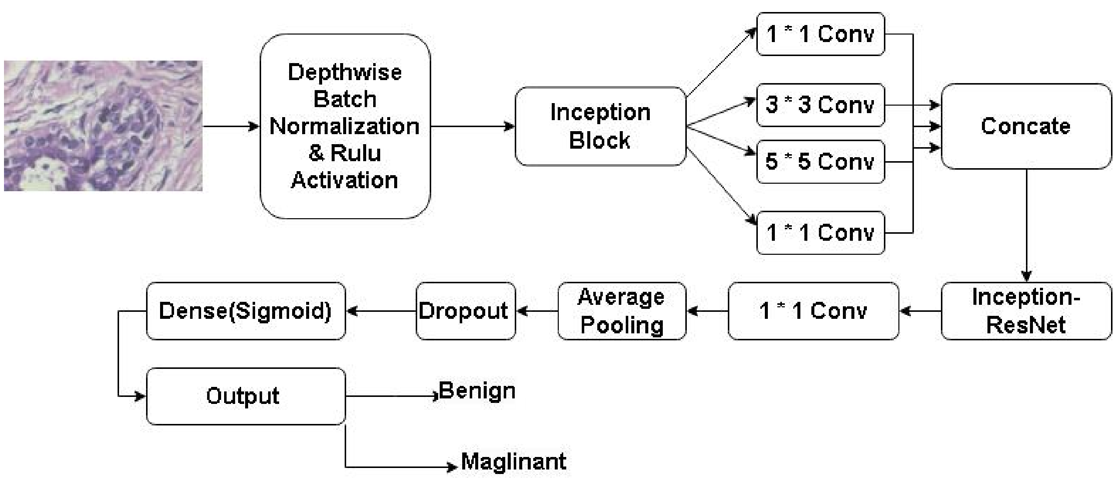


Figure 5: Depthwise-Inception-ResNet Network

Networks with attention mechanisms focus on specific areas for more relevant task-related features [20]. Attention combines a reference with keys to calculate scores, which are then used to determine importance, allowing concentration on specific information. The equations are as follows (equations 1-3).

$$\text{Attention Score}(Q, K) = Q * K^T \quad (1)$$

$$\text{Attention Weights } (Q, K) = \text{softmax}(\text{Attention Score } (Q, K)) \tag{2}$$

$$\text{Attention Values } (Q, K, V) = \text{Attention Weights}(Q, K) * V \tag{3}$$

The final network will be integrated with attention, therefore, it is shown in figure 6.

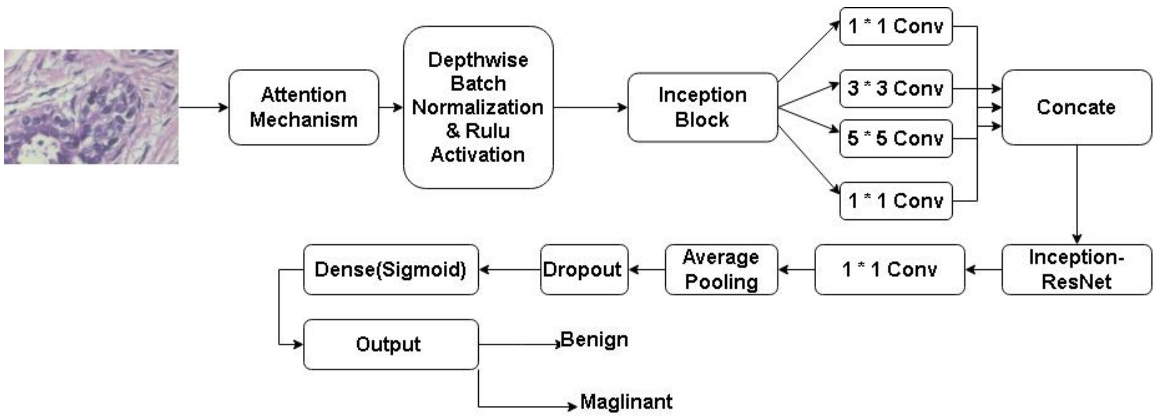


Figure 6: Depthwise-Inception-ResNet-Attention Network

3.2 Dataset

3.2.1 Dataset Introduction

During the training process, BreakHis will be the main dataset used for model training. The BreakHis dataset provides 9,109 histopathological images from 82 patients, categorized into 2,480 benign and 5,429 malignant samples at magnifications of 40X to 400X. Each RGB image has a resolution of 700 * 460 pixels. This dataset, created with the P&D Laboratory in Parana, Brazil, is instrumental for benchmarking in medical image analysis. It differentiates between non-invasive benign tumors and invasive malignant tumors capable of metastasis. Breast tumors are subtyped into adenosis, fibroadenoma, phyllodes tumor, and tubular adenoma for benign, and ductal carcinoma, lobular carcinoma, mucinous carcinoma, and papillary carcinoma for malignant, enabling detailed research studies. The nomenclature of each image provides insights into the biopsy type, tumor classification, patient ID, and magnification used.

3.2.2 Data Separation

The BreakHis file has four symptoms in each benign and malignant. And each symptom contains four different magnifications. In the case that binary classification is the main goal of the project, the data are separated based on the magnifications of images. Then, inside each magnification, there are “train” folder and “test” folder which all contain benign and malignant. The above maneuver were completed through Python codes which had imported PIL(Pillow library) specialized for file management.

After copying the file into corresponding directories, data are then split using a random file selecting Python code to randomly move a proportion of images into test folders so as to reach the ratio of 85% : 15% between train folder and test folder. Rest of the separation of validation and training data will be done within the model coding.

The structure of the data separation is provided in figure 7.

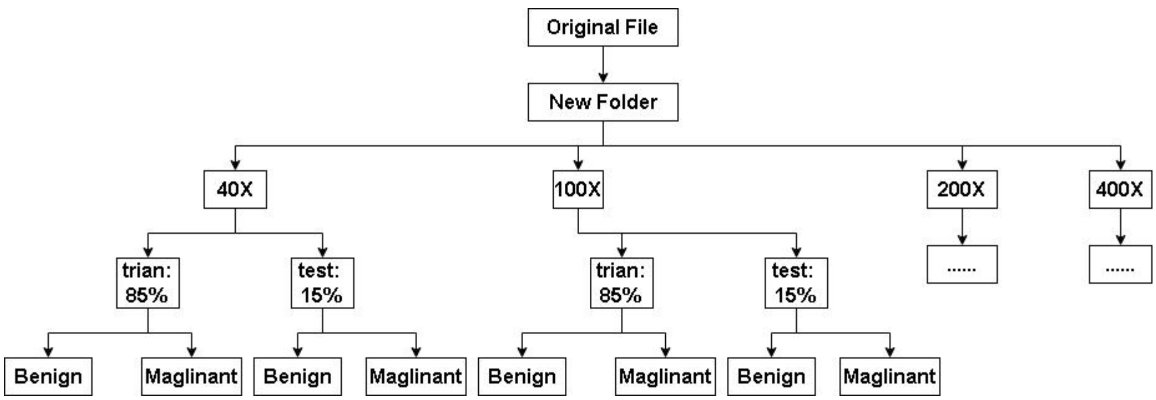


Figure 7: Dataset Structure

3.2.3 Data Balance

Firstly, based on the figure 8 provided below, it is noticeable that within each magnification folder, the benign images are far less than malignant images, which makes the data unbalanced. Therefore, this project had applied oversampling for balancing the dataset, which is shown in figure 9.

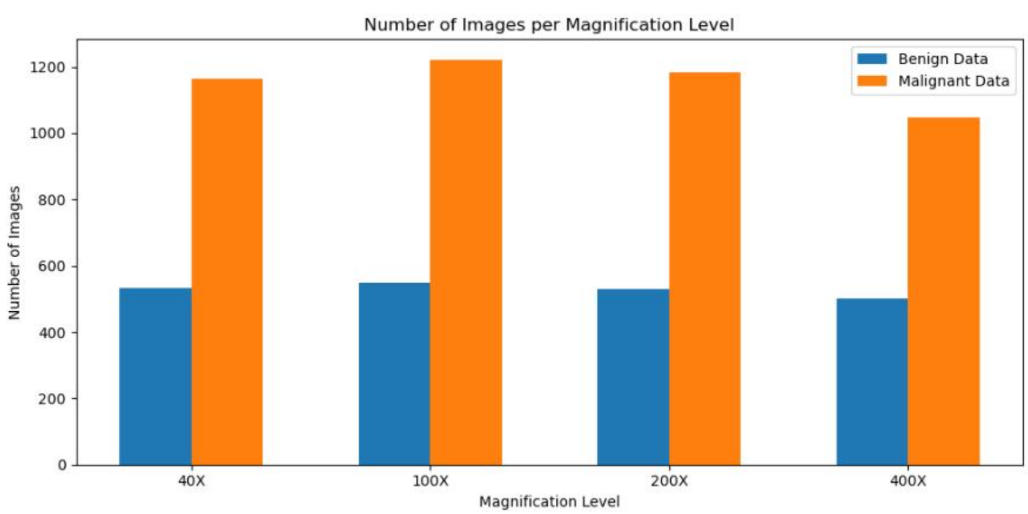


Figure 8: Number of images within Benign and Malignant Before Balancing

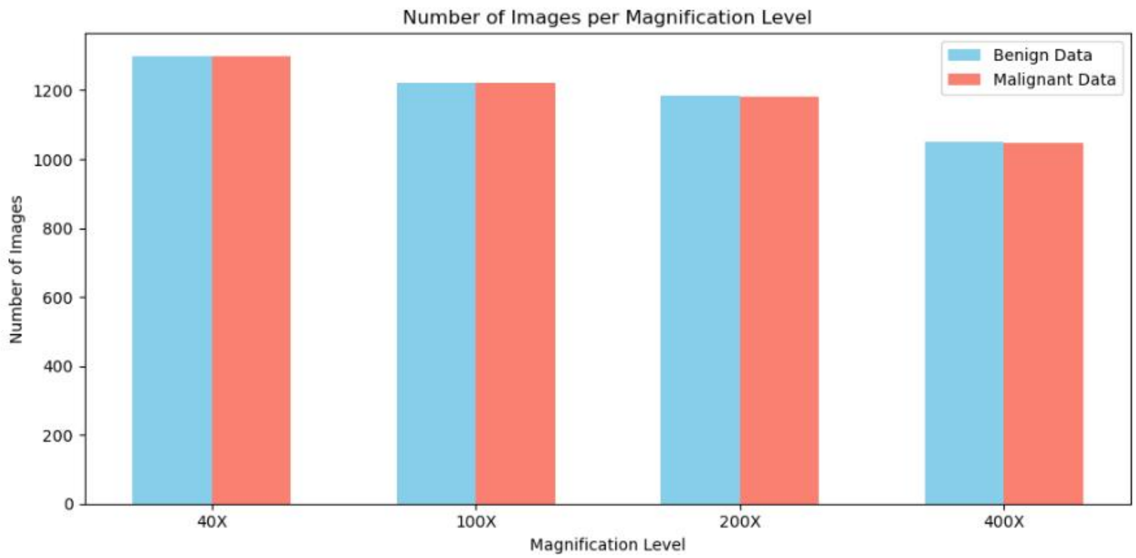


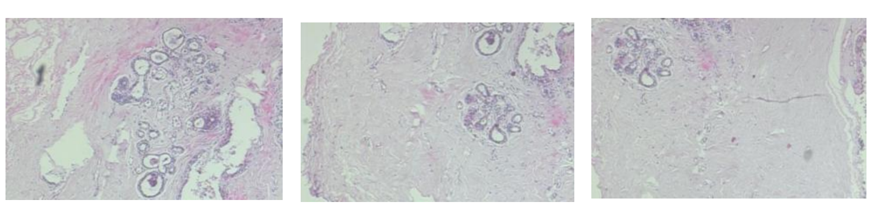
Figure 9: Images Number After Balancing

3.2.4 Data Resize

As the introduction mentioned, the image resolution is 700 * 460 pixels, which does not fit in the proposed model input. And therefore, this project had resize the images of all magnifications into 224 * 224.

3.2.5 Data Colour Channel Modification

This project had modified the images utilizing Contrast Limited Adaptive Histogram Equalization (CLAHE) which are then compared with the original image training results in order to select the better one. CLAHE operates by adaptively dividing the image into several small blocks, then performing histogram equalization on each of these blocks within certain contrast limits [21]. This approach improves the histogram distribution of the image, which is essential for enhancing detail and image quality. Images are displayed in the following figure 10.



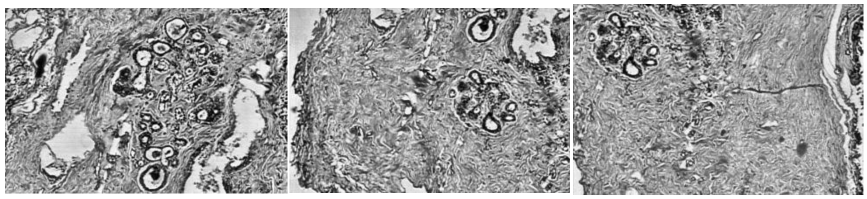


Figure 10: Images Transformation

3.2.6 Data Augmentation

The BreakHis dataset is augmented with rotations (20 degrees), shifts (20% width and height), shear (20%), zoom (20%), and horizontal flips, alongside rescaling the pixel values by 1/255.

3.3 Technology

The technology this project will be using is displayed in Table 2

Software	Framework	Tensorflow
	Language	Python
	Libraries and Application	Numpy, Keras, Matplolib, TensorFlow-Addons, Scikit-Learn
Hardware	Central processing unit(CPU)	Intel(R) Core(TM) i7-8750H CPU @ 2.2PGHz(12 CPUs), ~2.2GHz
	Graphic Processing Unit(GPU)	NVIDIA GeForce GTX 2060

Table 2: Summary of Relevant Technology involved in this project

3.4 Testing and Evaluation Plan

3.4.1 Data testing

By checking the BreakHis datasets downloaded from Kaggle, it is estimated that some techniques of data pre-processing will be implemented which will be displayed below.

1. This project is will re-divide the original BreakHis datasets for binary classification. Considering the fact that there are four groups of magnifications of the histogram, this project will create four magnifications which contains two categories of breast cancer level from the original datasets.

2. The project will check the image size inside each magnification category and ensure the size of images are consistent, otherwise, resize techniques will be applied.

3. The project must separate the data into specific ratio for the purpose of training, validation and testing.

4. This project must check the number of each set, aimed at balancing the two categories. It will affect the model learning and diagnosis accuracy otherwise.

5. This project will apply few methods of data pre-processing on the datasets and test on model training in case there are any factors such as colour or contrast that affects training results.

3.4.2 Model Performance Evaluation Criteria

This project will evaluate the performance of the model through following standards.

Accuracy: Accuracy is a quite intuitive metric and a criteria for evaluating model performances, which displays the overall correctness of a classification model. It calculates the ratio of the correctly predictions among the total predictions. The equation (4) is displayed below, where T, P, N, F represents, true, positive, negative and false. TP, TN, FP, and FN represent the counts of correctly identified positive cases, correctly identified negative cases, incorrectly identified positive cases, and incorrectly identified negative cases, respectively, in a classification model.

$$\text{Accuracy} = \frac{TP+TN}{TP+TN+FP+FN} \tag{4}$$

Loss: This criteria measures the cap between results of prediction labels and actual labels. Below shows the equation for classification.

$$\text{Loss} = -\sum_{c=1}^{M} y_{ic} \, log\,(\mathrm{P_{ic}}) \tag{5}$$

Precision: This is the criteria that shows the proportion of images that are positively classified as positive. Equation is shown below in (6).

$$\text{Micro Precision} = \frac{\sum_{i=1}^{n} TP_{\,i}}{\sum_{i=1}^{n} TP_{\,i} + \sum_{i=1}^{n} FP_{\,i}} \tag{6}$$

Recall: This is the criteria that displays the proportion positively identified as positive samples among the actual positive samples.

$$\text{Micro Recall} = \frac{\sum_{i=1}^{n} TP_{\,i}}{\sum_{i=1}^{n} TP_{\,i} + \sum_{i=1}^{n} FN_{\,i}} \tag{7}$$

F1-Score: F1-Score measures the performance of model by calculating the harmonic mean of Precision and Recall.

$$\text{F1 Score} = \frac{2 \times Micro\ Precision * Micro\ Recall}{Micro\ Precision + Micro\ Recall} \quad (8)$$

Confusion Matrix: It displays the accurate number of the True Positive, True Negative, False Positive and False Negative.

ROC: Receiver Operating Characteristic (ROC), which displays the trade-off relationships between the True Positive Rate(also known as sensitivity or recall) and the False Positive Rate of a model at different thresholds.

AUC: Area Under the ROC curve, which demonstrates the overall ability to distinguish between positive and negative samples. In the classification circumstance, AUC acts as metric to evaluate the performance of model for both classes. Generally speaking, a model is considered well performed when the curve rises towards the upper-left corner of the graph, and therefore, leaving more space to AUC. In a nut shell, the closer AUC gets to 1, the better the model is.

In summary, in order to evaluate the model performing on the binary classification of the level of breast cancer, this project will conduct a comprehensive evaluation, involving Accuracy, Loss, Precision, Recall, Precision-Recall Graph, F1-Score, Confusion Matrix, ROC graph, and AUC.

3.5 Experiment and Results

The project's experiment involves utilizing individual models based on InceptionNet, ResNet, and Depthwise CNN architectures. These models are then integrated to form composite structures, creating various combinations of the three foundational architectures. The objective is to analyze the performance of these hybrid models under different combinations and identify the magnification level that yields optimal training results.

3.5.1 InceptionNet Training on four Magnifications

The first two individual models provides not only the initial judgement of the performance on the BreakHis dataset, but also insights of which magnification works better for model training.

The pure InceptionNet is trained with original and resized version images which helps decide which scale of images should remained for further training. Results and Model details are provided below from figure11 to figure 22.

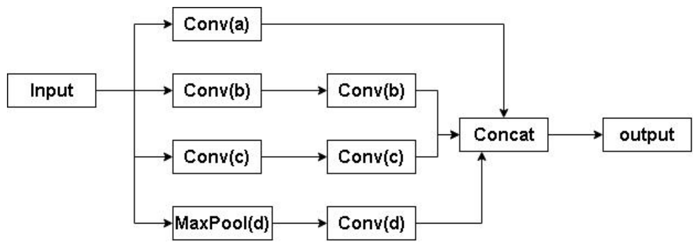


Figure 11: Initial Simple Inception Model

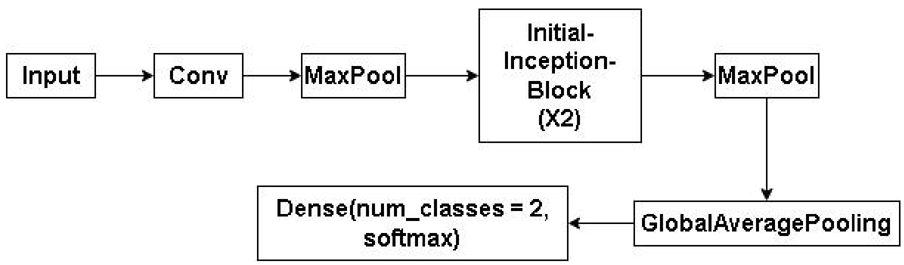
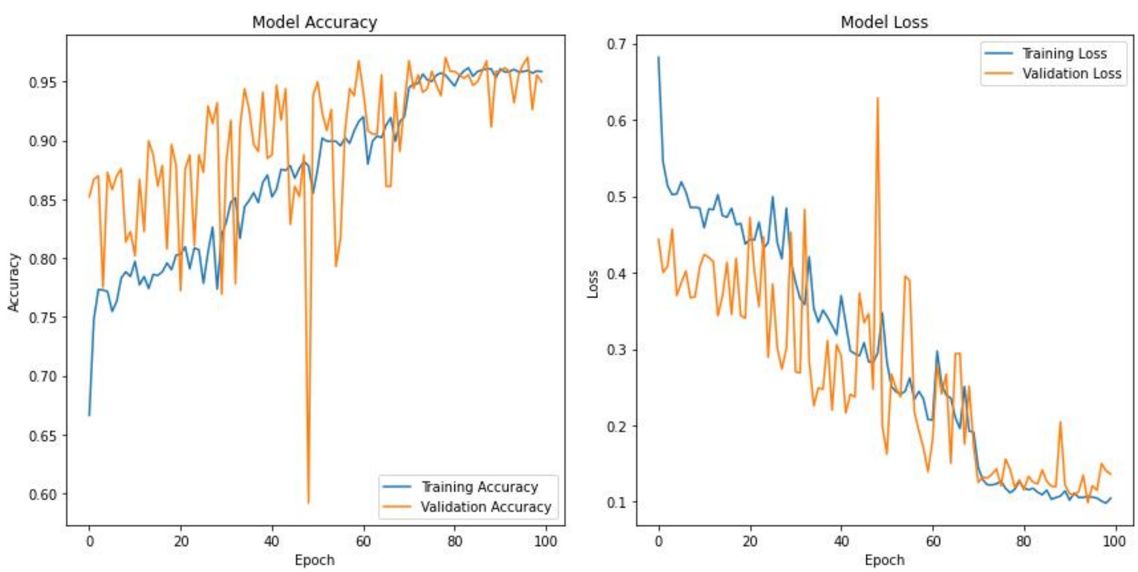
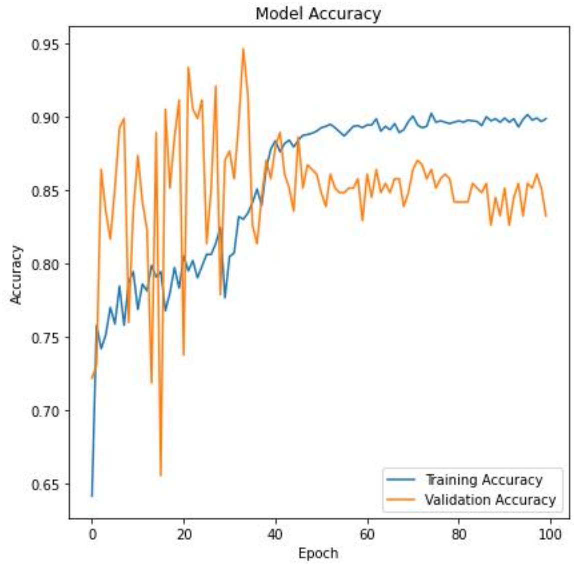


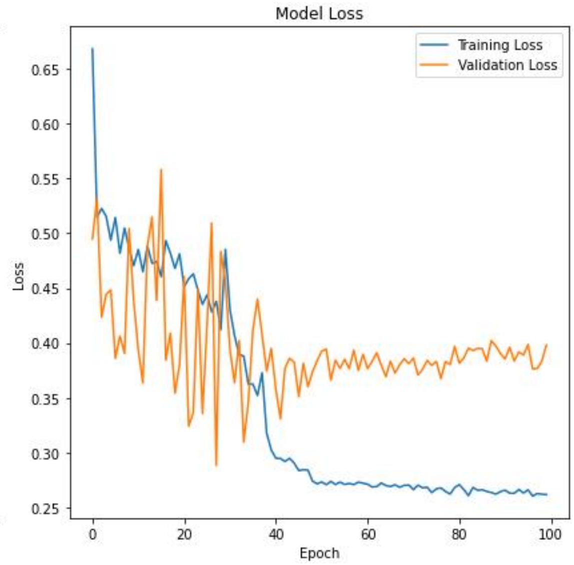
Figure 12: Initial InceptionNet



(a) Train Acc = 0.9584, Val Acc = 0.9497 (b) Train Loss = 0.1047, Val Loss = 0.1362

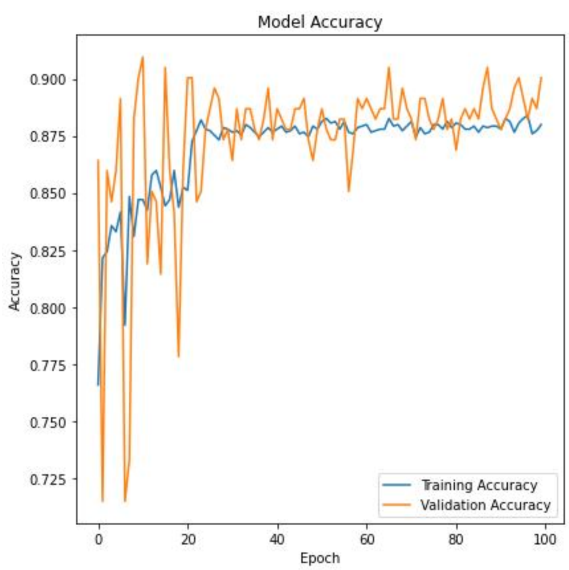
Figure 13 (a) and (b) present InceptionNet Accuracy and Loss of Train and Validation sets on 40X Raw Images

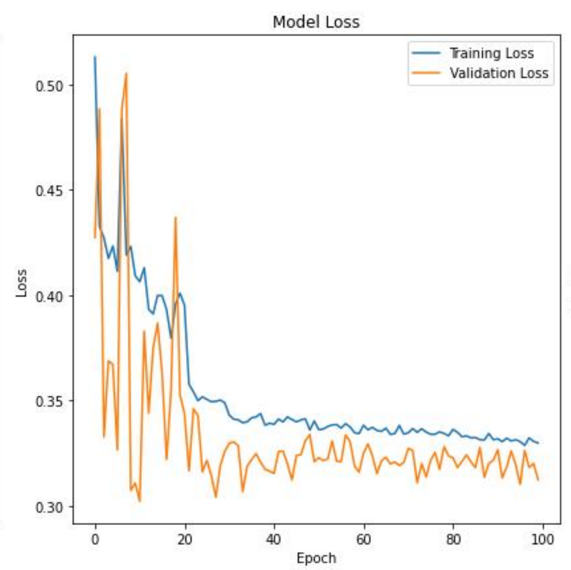




(c) Train Acc = 0.8985, Val Acc = 0.8323 (d) Train Loss = 0.2617, Val Loss = 0.3980

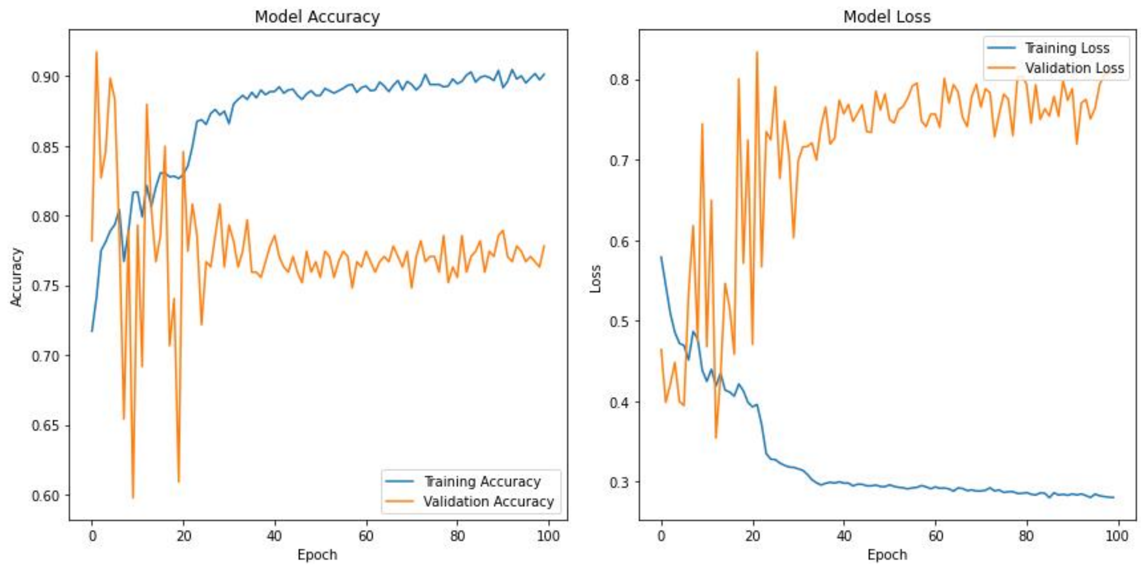
Figure 14 (c) and (d) display the InceptionNet Train and Validation Accuracy and Loss on 100X Raw Images





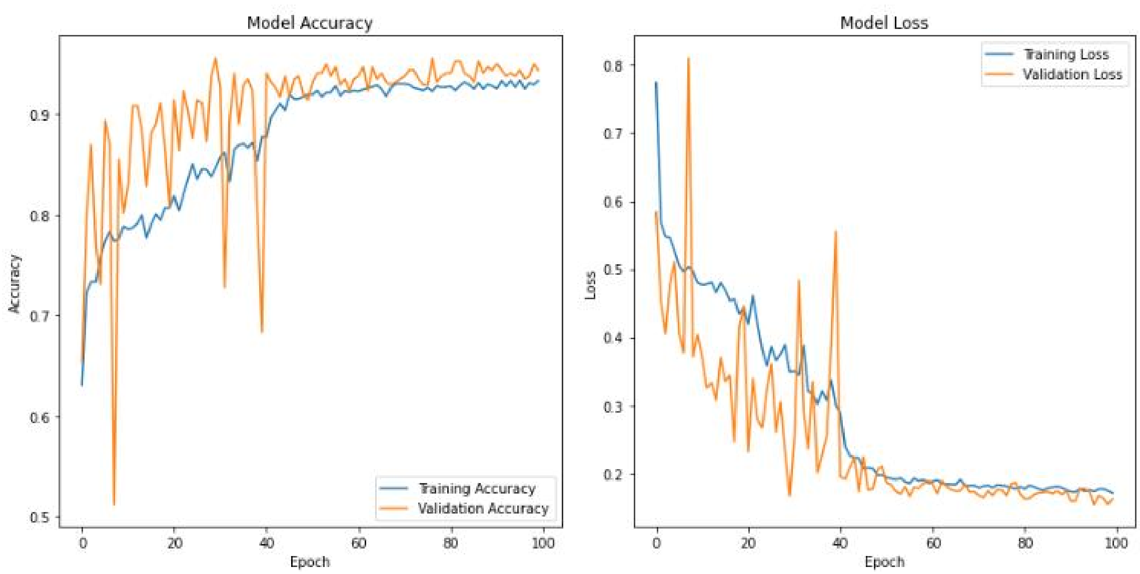
(e) Train Acc = 0.8799, Val Acc = 0.9005 (f) Train Loss = 0.3298, Val Loss = 0.3123

Figure15 (e) and (f) illustrate InceptionNet Train, Validation Accuracy and Loss on 200X Raw Images



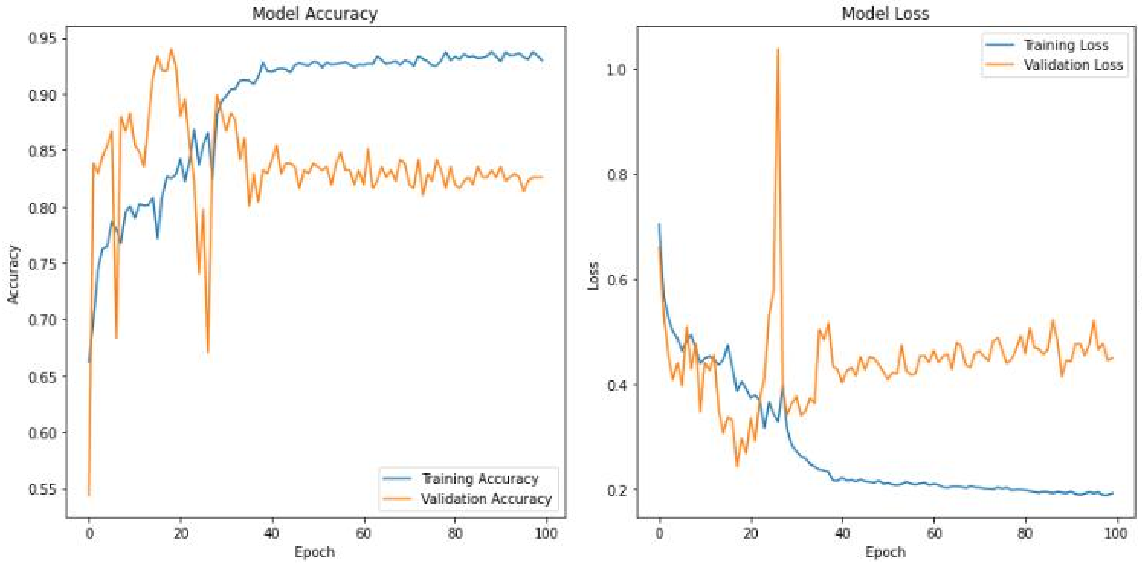
(g) Train Acc = 0.9012 , Val Acc = 0.7782 (h) Train Loss = 0.2804,Val Loss = 0.8079

Figure16 (g) and (h) demonstrate InceptionNet Train, Validation Accuracy and Loss on 400X Raw Images



(i) Train Acc = 0.9332, Val Acc = 0.9438 (j) Train Loss = 0.1709, Val Loss = 0.1617

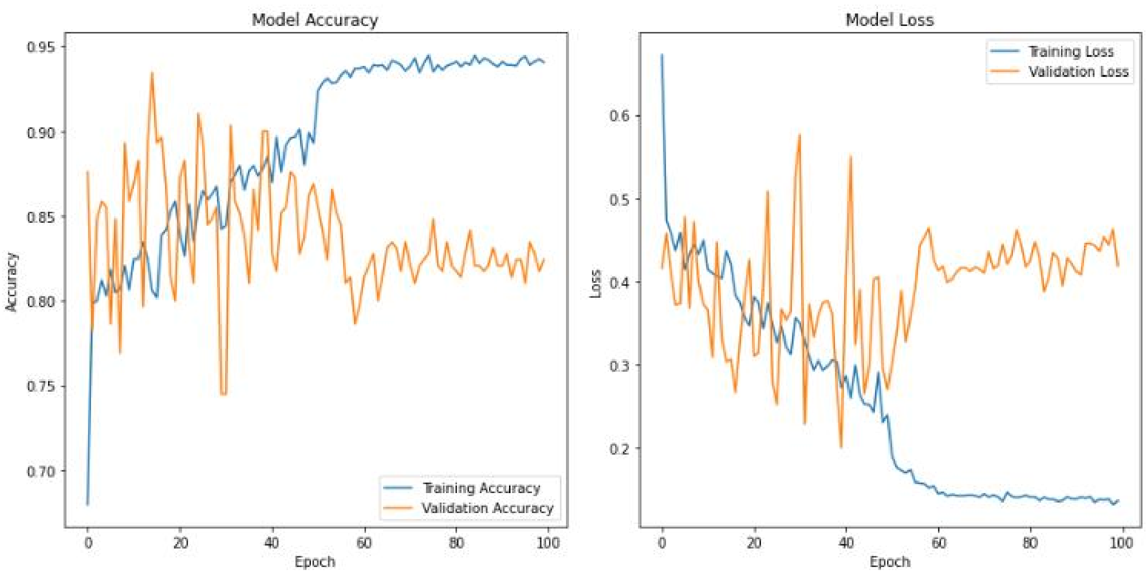
Figure17 (i) and (j) display InceptionNet Train, Validation Accuracy and Loss on 40X Resize Images



(k) Train Acc = 0.9295, Val Acc = 0.8259

(l) Train Loss = 0.1918, Val Loss = 0.4495

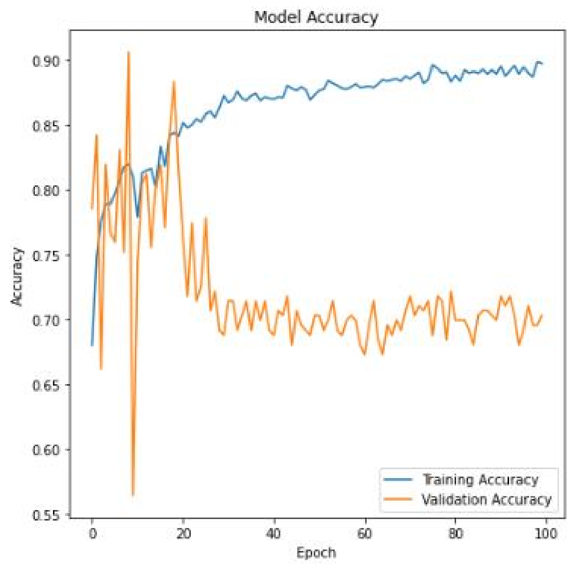
Figure 18 (k) and (l) display InceptionNet Train, Validation Accuracy and Loss on 100X Resize Images



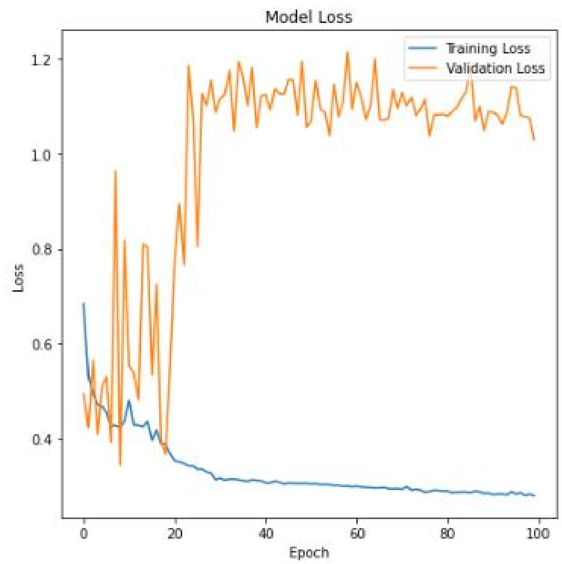
(m) Train Acc = 0.9406, Val Acc = 0.8241

(n) Train Loss = 0.1361, Val Loss = 0.4191

Figure 19 (m) and (n) present InceptionNet Train, Validation Accuracy and Loss on 200X Resize Images



(o) Train Acc = 0.8973, Val Acc = 0.7030



(p) Train Loss = 0.2782, Val Loss = 1.0301

Figure20 (o) and (p) demonstrate InceptionNet Train, Validation Accuracy and Loss on 400X Resize Images

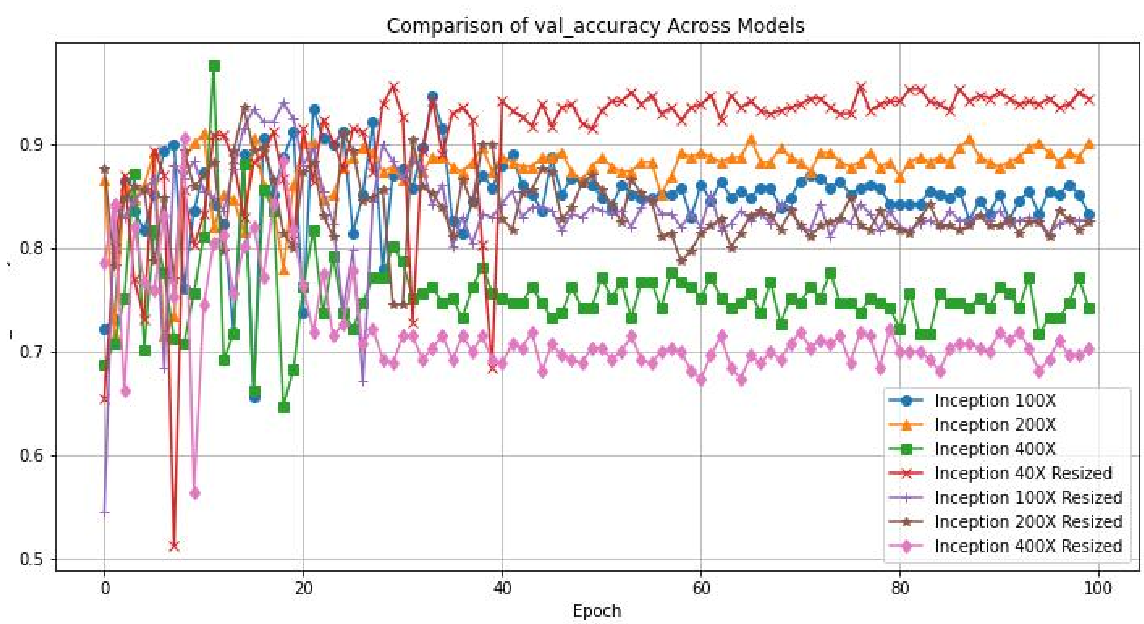


Figure 21: Comprehensive Comparison of Validation Accuracy Among Raw and Resized Images of Four Magnifications

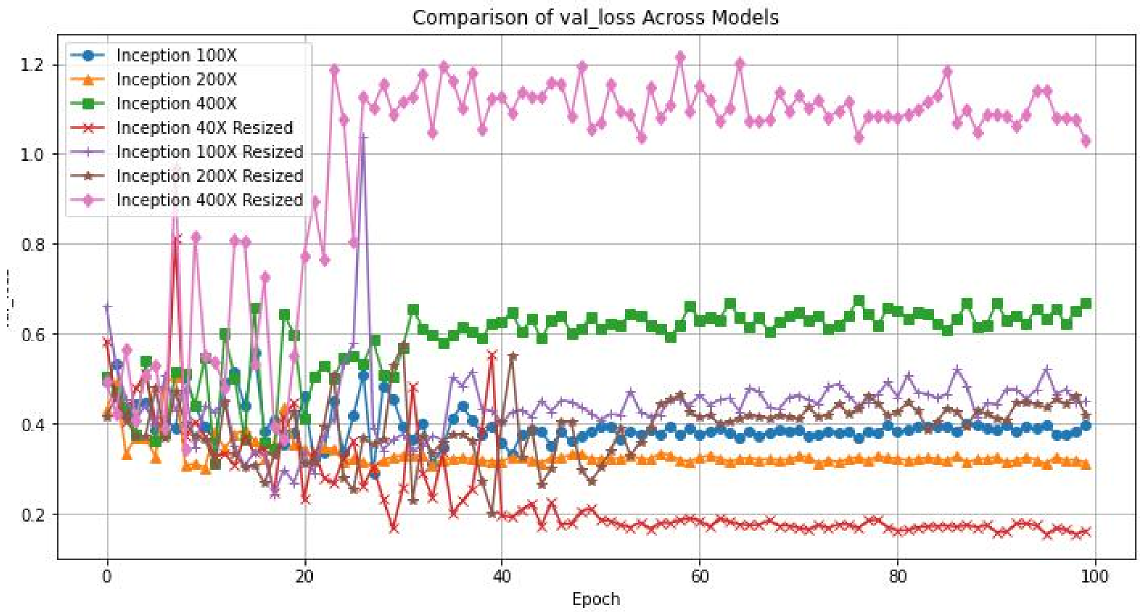


Figure 22: Comprehensive Comparison of Validation Loss Among Raw and Resized Images of Four Magnifications

Based on Figures 13 to 16, it is evident that without resizing the images, the model's performance during training varies among four magnification factors: 40X, 100X, 200X, and 400X. Notably, the model exhibits the best fitting performance when trained on images with a 40X magnification factor among these four options.

In Figures 17 to 20, after resizing the images to a size of 224 x 224 pixels to match the model input settings for this project, it is observed that, under the same four scenarios, the training performance of images with a 40X magnification factor continues to outperform the other three magnification factors.

Through the presentation of Figures 21 and 22, it becomes evident that most of the resized results surpass those without resizing. Furthermore, within this context, the training performance of images with a 40X magnification factor stands out as the most favorable. This phenomenon may be attributed to the fact that, at this magnification level, more details are captured, resulting in a richer set of features.

The upcoming experiment will further validate the suitability of magnification factors on resized images.

3.5.2 ResNet Training on Four Magnifications

The initial ResNet was trained on four magnifications with resized images based on the last part results. Model details and results are presented from figure 23 to 29.

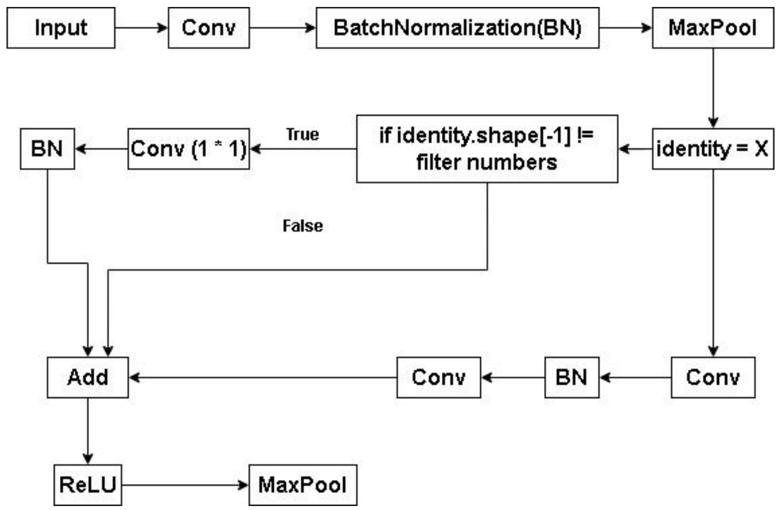
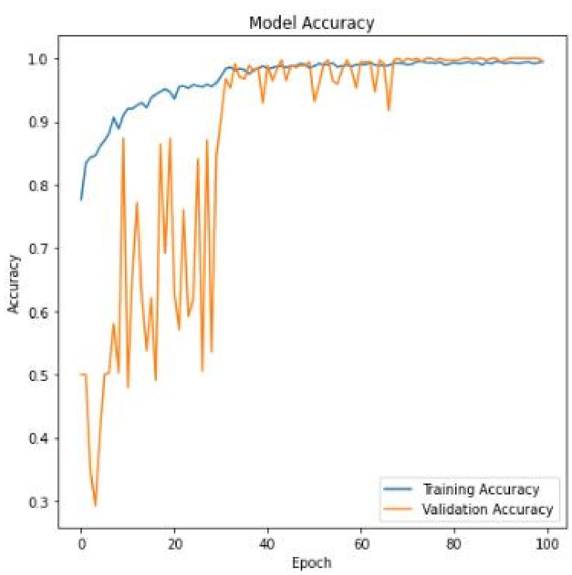
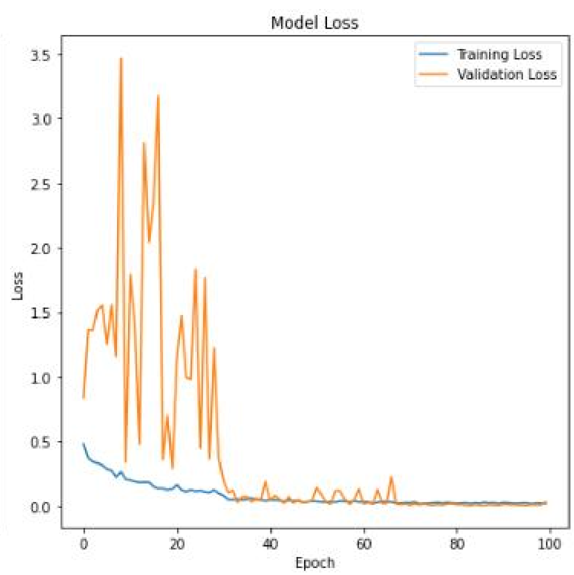


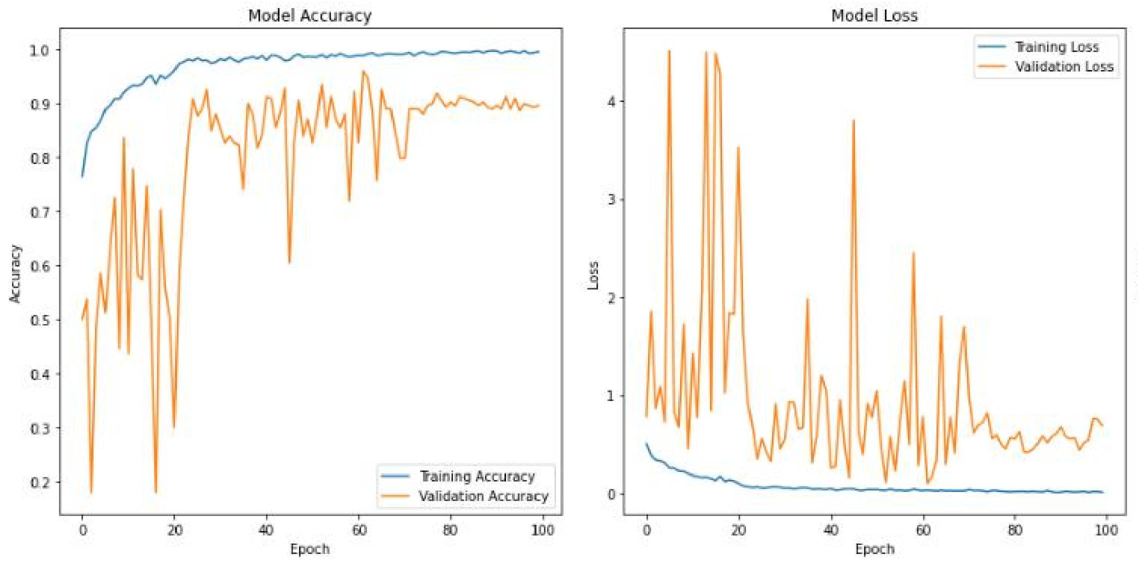
Figure 23: Initial Simple ResNet





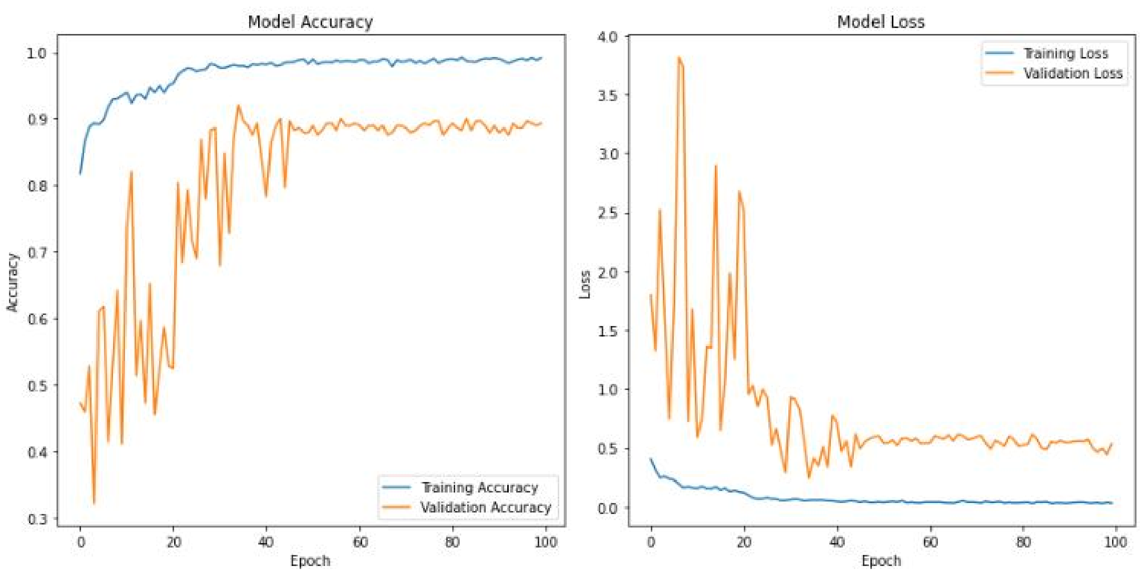
(q) Train Acc = 0.9947, Val Acc = 0.9941 (r) Train Loss = 0.0199, Val Loss = 0.0298

Figure 24 (q) and (r) illustrate ResNet Train, Validation Accuracy and Loss on 40X Resized Images



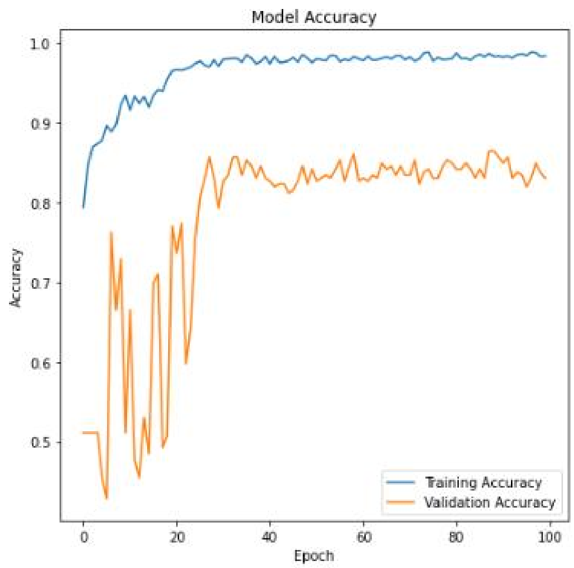
(s) Train Acc = 0.9948, Val Acc = 0.8956 (t) Train Loss = 0.0143, Val Loss = 0.6940

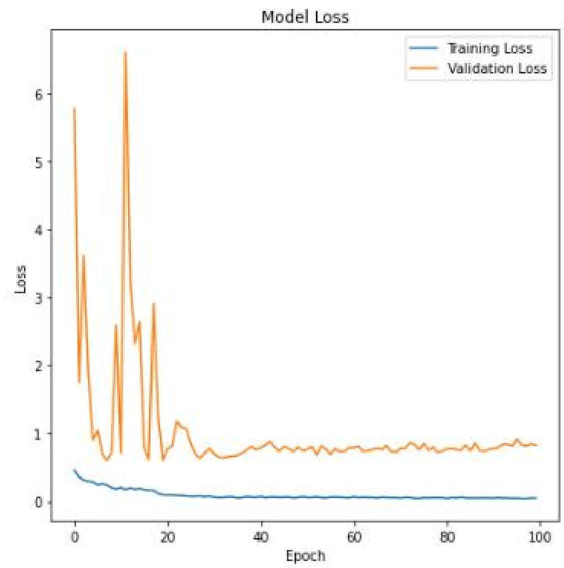
Figure 25 (s) and (t) display ResNet Train and Validation Accuracy and Loss on 100X Resized Images



(u) Train Acc = 0.9918, Val Acc = 0.8931 (v) Train Loss = 0.0293, Val Loss = 0.5330

Figure26 (u) and (v) display ResNet Train, Validation Accuracy and Loss on 200X Resized Images





(w) Train Acc = 0.9837 , Val Acc = 0.8308 (x) Train Loss = 0.0459, Val Loss = 0.8232

Figure27 (w) and (x) display ResNet Train, Validation Accuracy and Loss on 400X Resized Images

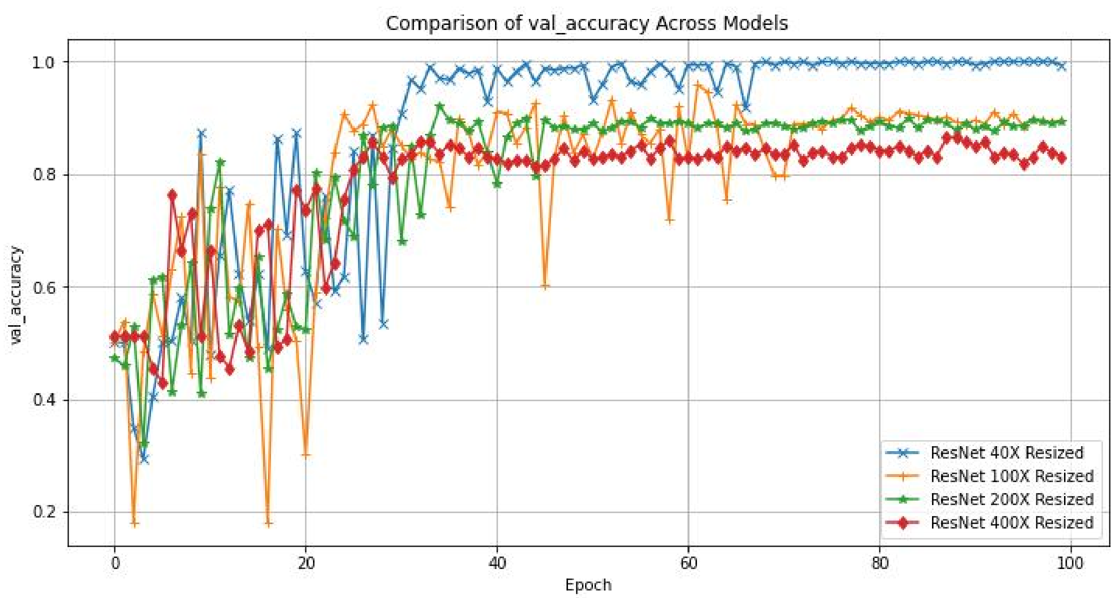


Figure 28: ResNet Validation Accuracy Comparison

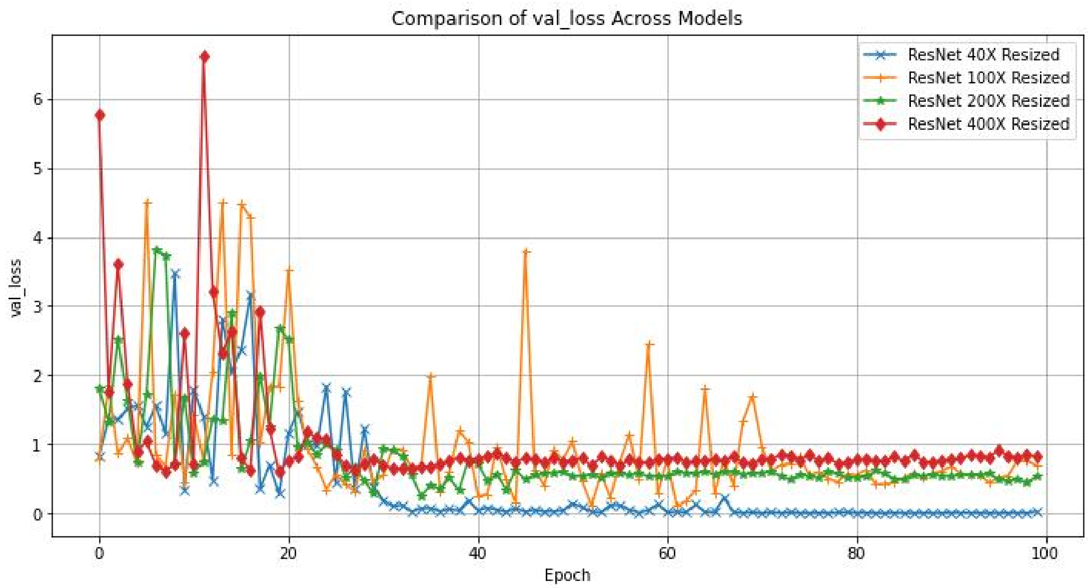
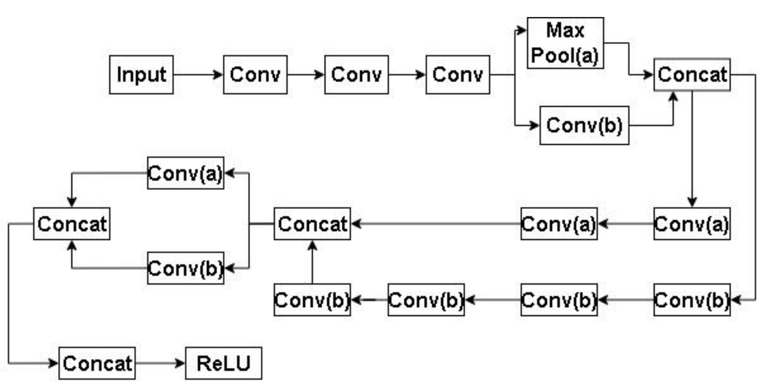


Figure 29: ResNet Validation Loss Comparison

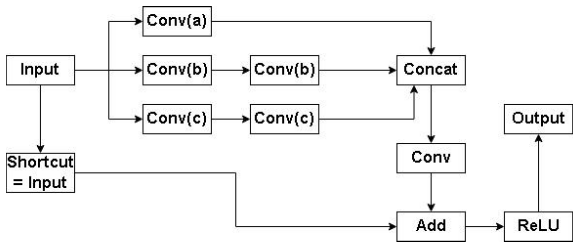
Based on the results shown in the figures, it's evident that ResNet demonstrates improved accuracy across all magnification factors (40X, 100X, 200X, and 400X) after resizing compared to before. Notably, while magnifications of 100X, 200X, and 400X show clear signs of insufficient fitting capabilities, the 40X magnification stands out with excellent fitting and high accuracy. This observation is further supported by a comparison of figures 28 and 29. Consequently, moving forward, this project has chosen to focus on the 40X magnification for subsequent experiments and model training.

3.5.3 Inception-ResNet Training on 40X magnifications

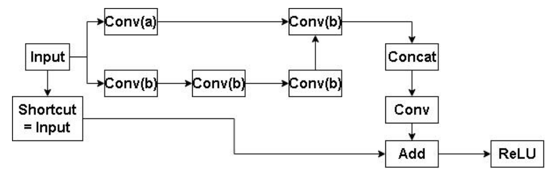
Figure 30 to 32 represent the structure of Inception-ResNet, and figure 33 illustrates the results training on the 40X magnified images.



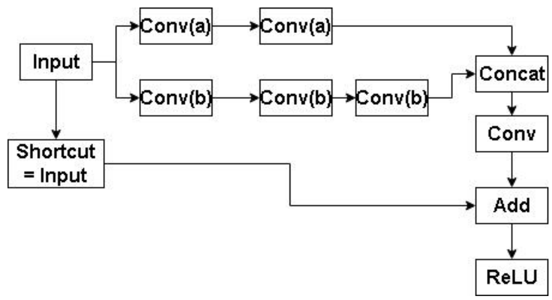
(1) Inception-ResNet-STEM Block



(2) Inception-ResNet-A Block

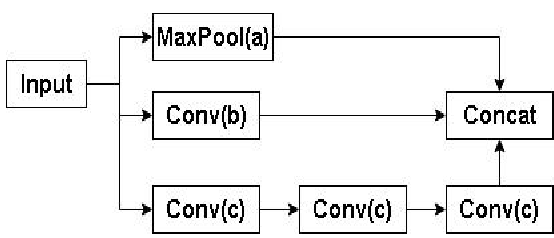


(3) Inception-ResNet-B Block

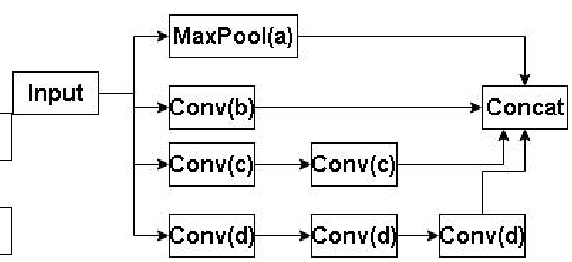


(4) Inception-ResNet-C block

Figure 30 (1), (2), (3), and (4) Present the Main Blocks of the Implemented Inception-ResNet Network



(5) Parameters Reduction-A Block



(6) Parameters Reduction-B Block

Figure 31(5) and (6) Demonstrate the Parameter Reduction Block within current Inception ResNet Block

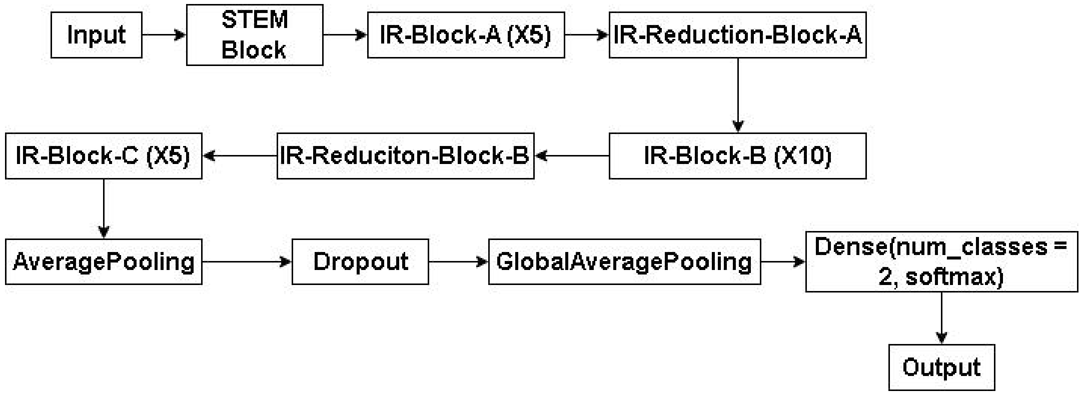
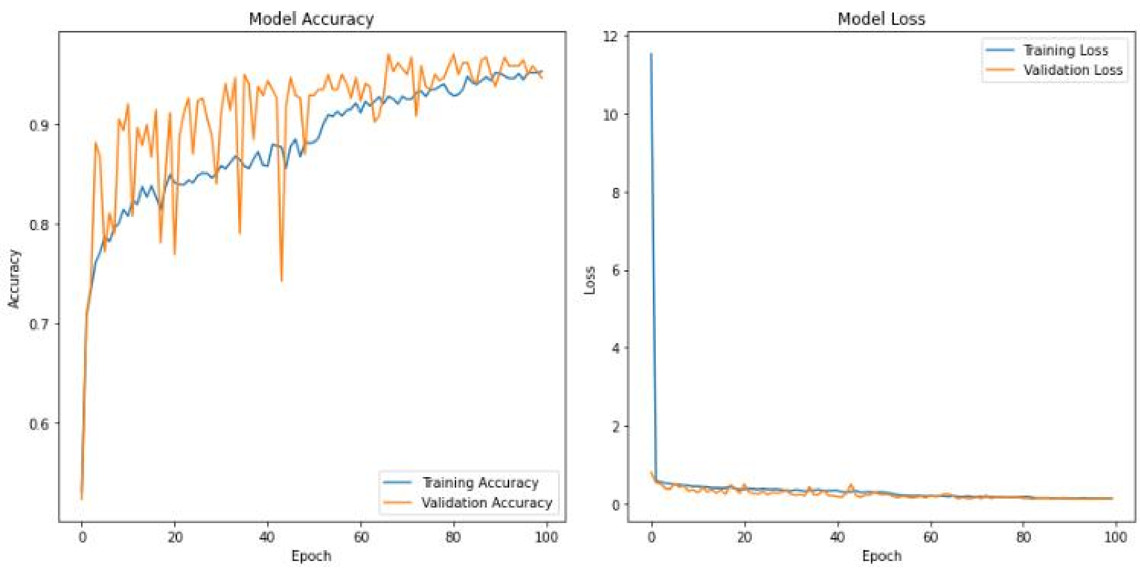


Figure32: Inception-ResNet Structure



(y) Train Acc = 0.9527, Val Acc = 0.9467 (z) Train Loss = 0.1302, Val Loss = 0.1354

Figure 33 (y) and (z) display Train, Validation Accuracy and Loss on 40X Magnified BreakHis Resized images

3.5.4 Depthwise CNN training on 40X magnifications

Before adding depthwise convolution, experiments of how individual depthwise convolutional network performs were applied as well. Figure 34 and 35 demonstrates the structure and results.

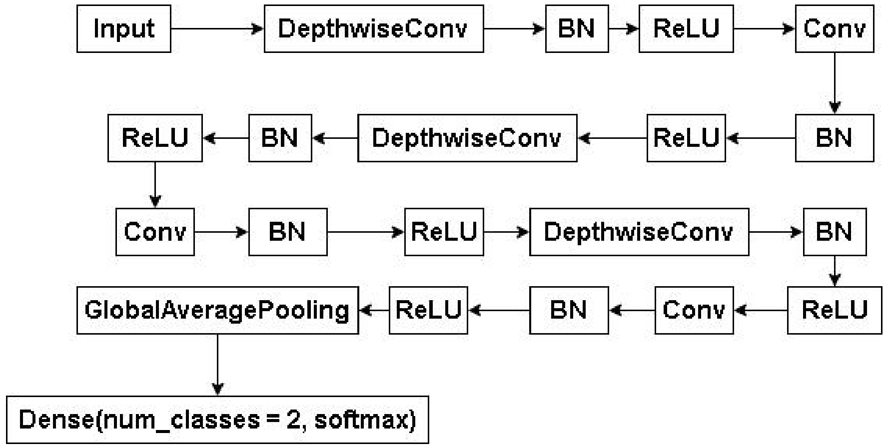
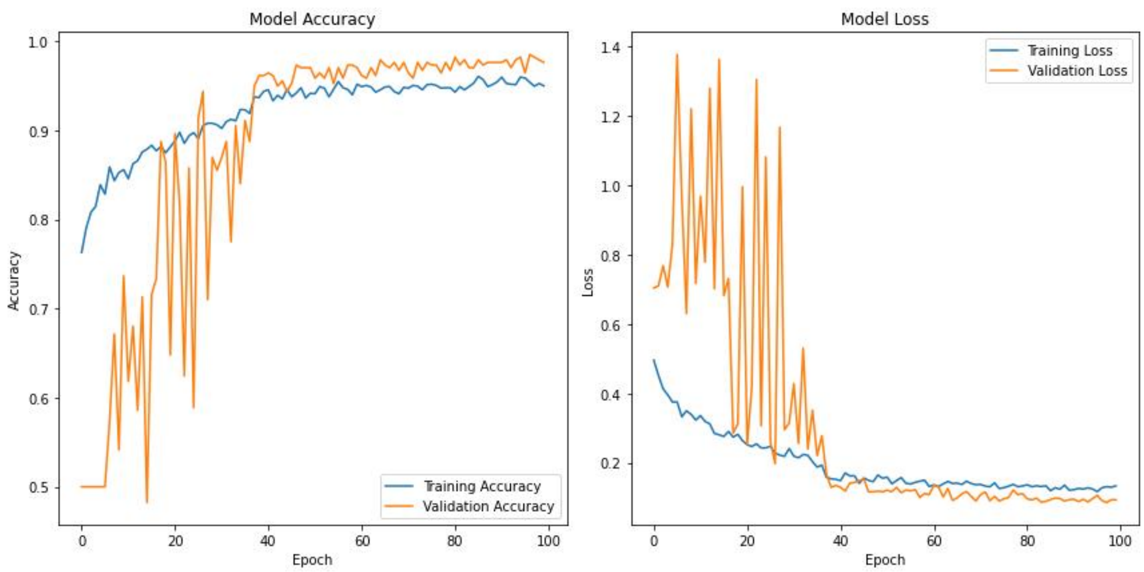


Figure 34: Basic Depthwise CNN Structure



(aa) Train Acc = 0.9500, Val Acc = 0.9763 (ab) Train Loss = 0.1334, Val Loss = 0.0929

Figure 35 (aa) and (ab) display Depthwise-CNN Train, Validation Accuracy and Loss on 40X Magnified Images

3.5.5 Inception-ResNet-Depthwise Training on 40X Magnifications

After getting the results of models above, these structures are integrated as a single model. By switching some of the convolutional layers within the Inception-ResNet to depthwise convolutional layers, it provides complexity and depth for the network. However, this project hopes to keep the model deep and complex while maintaining the efficiency of training, and thus, the only Inception-ResNet-A block is tweaked with a depthwise convolutional layer added.

The current structure is still an initial one which requires further modification. Model structures implementation and performance results are displayed below.

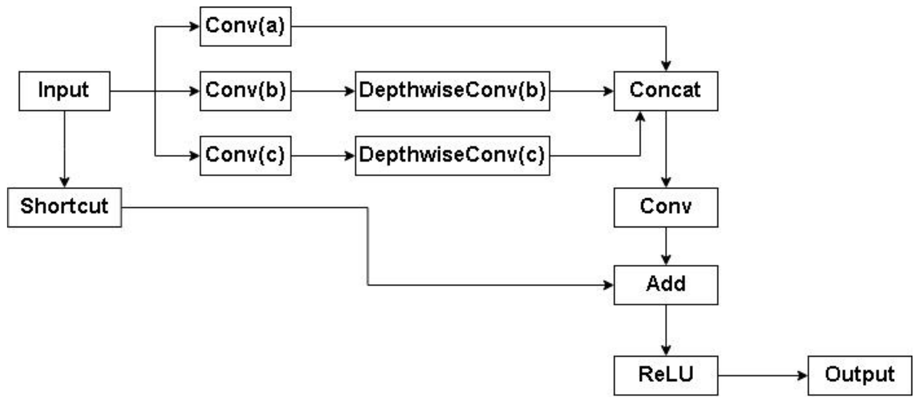


Figure 36: Depthwise-Inception-ResNet Block-A

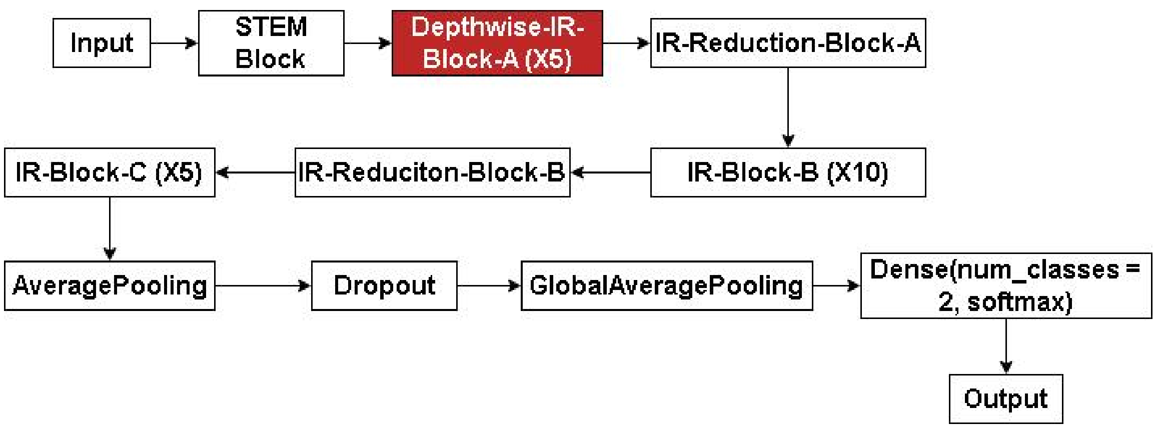
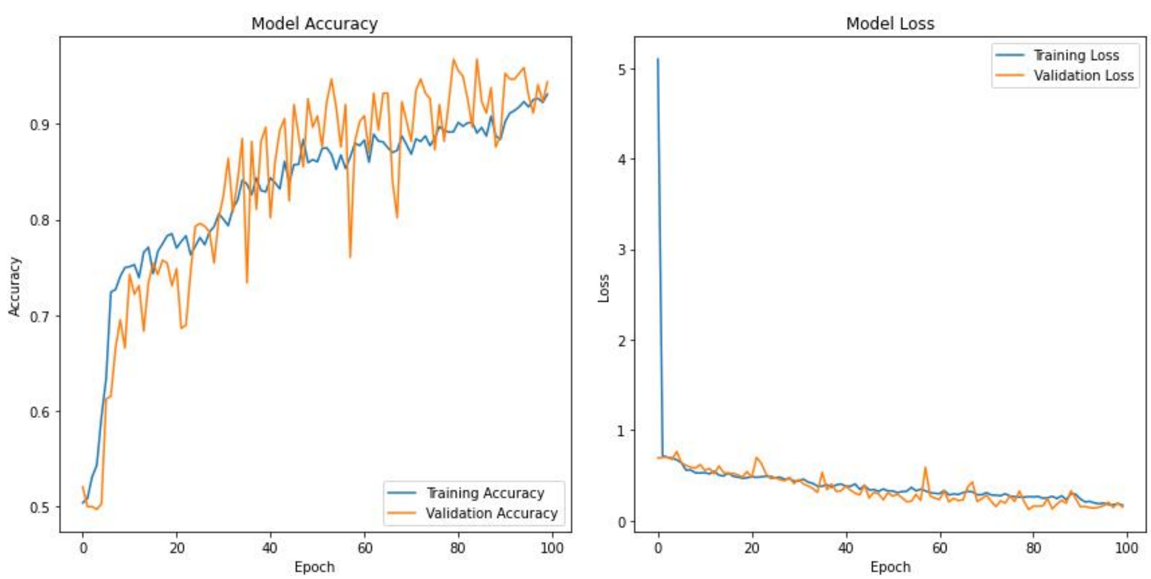


Figure 37: Depthwise-Inception-ResNet



(ac) Train Acc = 0.9310, Val Acc = 0.9438 (ad) Train Loss = 0.1699, Val Loss = 0.1496

Figure 38 (ac) and (ad) demonstrate Depthwise-Inception-ResNet Train, Validation Accuracy and Loss on 40X Magnified Images

3.5.6 Current Experiments Results Summary

This part will summarize the experiments taken during the progress of the project.

As mentioned above, individual models such as Depthwise Network, InceptionNet, and ResNet, combined models like Inception-ResNet and Depthwise--Inception-ResNet were applied to the dataset so as to provide insight about how networks with these structures are able to perform and whether they are wise selections. Training the individual models on different magnifications within the dataset optimized the structure of the training thereby selecting the best magnifications to train with.

The following table 3 portrays the summary results of each experiment the last experiment with the current Depthwise-Inception-ResNet presents a rather decent result.

Model Name	Magnification & Size	Validation Accuracy	Validation Loss
Individual InceptionNet	**Raw Images**		
	40X	0.9497	0.1362
	100X	0.8323	0.3980
	200X	0.9005	0.3123
	400X	0.7782	0.8079
	Resized: 224 * 224		
	40X	0.9438	0.1617
	100x	0.8259	0.4495
	200x	0.8241	0.4191
	400x	0.7030	1.0301
Individual ResNet	Resize: 224*224		

	40X	0.9941	0.0298
	100X	0.8956	0.6940
	200X	0.8931	0.5330
	400X	0.8308	0.8232
Inception-ResNet	Resize: 244* 244 40X	0.9467	0.1354
Depthwise-CNN	Resize: 244*244 40X	0.9763	0.0929
Depthwise- Inception-ResNet	Resize:244*244 40X	0.9438	0.1496

Table 3: Results Summary of Experiments

4 Project Management

4.1 Activities

Phase	**Objectives**
1. Preparation(Completed)	1. Review breast cancer deep learning. 2. Identify and narrow issues 3. Seek possible solutions. 4. Study classification methods.
2. Deep learning knowledge absorbing **(Completed)**	1. Research breast cancer symptom classification methods 2. Study at least six CNN models and relevant programming libraries. 3. Grasp loss functions, optimizers, model building, and optimization. 4. Investigate extra mechanism for suitability.
3. Data collection **(Completed)**	1. Gather 2 - 3 datasets from Kaggle 2. Split them into two classes: benign & malignant 3. Decide the training and test ratio
4. Development and Implementation **(Uncompleted)**	1. Build Inception-ResNet model. 2. Add depthwise into Inception-ResNet 3. Train, analyze, and compare models. 4. Optimize the chosen model and adjust hyperparameters if needed.
5.Testing and Finishing up **(Uncompleted)**	4. Change other similar datasets to check the generalization capability of the model 5. Analyze the results and summarize the work 3. Write Project Report and Prepare presentation

Table 4: Activities of the Project

4.2 Schedule

The schedule is shown as table 5 below

For instance: 1- 1 means Phase 1, Objective 1, and those finished activities are marked from purple to pink. The unfinished part is marked with green.

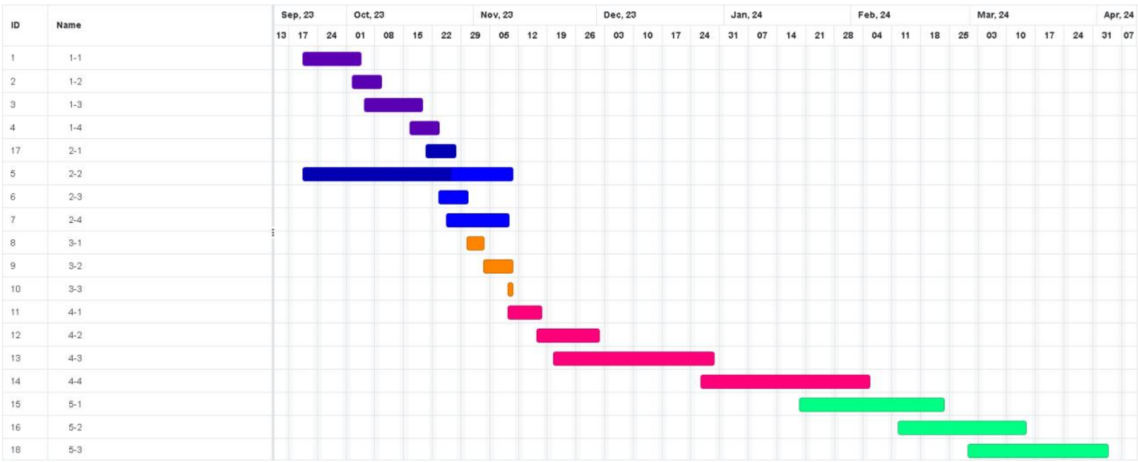


Table 5: Gantt Chart

4.3 Project Version Management

To manage the different versions of codes modification, I plan to use Github as the version management tools for keeping code updated and secure.

URL is as follow: https://github.com/Vio1etV/Final_Year_Project

Version Number	Code Name	Content	Results
1	Individual Model Codes for basic model testing	Individual model codes, design structure diagram, Pre-train model, h5 files etc Original Dataset, Modified Dataset, Datasets backups	The training results, csv file that contains the each epoch for later comparison
2	Few Combinations of models	The code for combination of the models Record of each combination	CSV of the each epoch for later comparison
3	A model which is similar to the final	The codes for different version of Depthwise-	CSV of each epoch for later comparison

	codes Reference code of different structure of CNN	Inception-ResNet Records of each run with different parameters	

Table 6: Version Control Progress

4.4 Project Data Management

A. All files including datasets, model codes, references, weekly reports and all sorts will be replicated into three copies for fail safe, one on local computer, one on hard drive, one on github

B. Upload the project to github for every modification, synchronize the project on three platforms

Following are documents of the Project for uploading and synchronization:

1. Reports (Weekly, Proposal, Progress, Final) & Presentation PPT
2. CNN model diagram
3. References
4. Datasets Link
5. Model evaluation documents
6. CNN model codes (Different versions)

4.5 Project Deliverables

A. The project proposal

B. Weekly report

C. Progress Report

D. Final Project Report

E. Project codes

F. Project presentation slides

G. Project presentation

5 Professional Issues and Risk:

5.1 Risk Analysis

Table 7 displays the analyzed risks during the project progress.

Risk ID	Potential Risk	Cause ID	Potential Causes	Severity	Likelihood	Risk	Mitigation ID	Mitigation
R1.1	Loss of Project data	C1.1.1	Poor version management	4	2	8	M1.1.1	Uploading to at least one cloud repository, add one git reporsitory to manange and update version of codes, datasets etc. Keep the key data on a mobile hard drive
		C1.1.2	Physical Hardware Destruction	4	1	4	M1.1.2	Protect the hardware such as computer. Keep important and relevant data on hard drive
R1.2	Memory Leakage	C.1.2.1	The model has huge numbers of parameters	4	3	12	M1.2.1	First check the code, whether it has large numbers of parameters. Second, before running the model, open the monitor of GPU performance to see if the training occupies more than the memory of GPU, if it is occupying, stop the training immediately and del the model before closing the window.
R1.3	Miss deadlinies	C1.3.1	Illness	3	1	3	M1.3.1	Keep healthy, take good care of myself while studying
		C1.3.2	Servere Injuries	4	1	4	M1.3.2	Stay safe when exercising
		C1.3.3	Poor time management	4	1	4	M1.3.3	Note down all deadlines on a place where I could see it from time to time. Balance study and relaxation reasonablly, and finish 5 days before deadline
R1.4	Software bugs	C1.4.1	Virtual Environment Error	1	1	1	M1.4.1	Keep the virtual environment clean and do not change any unfamiliar file of the tools

Table 7: Risk Analysis

5.2 Professional Issues

Identification and discussion of relevant legal, social, ethical and environmental issues in the context of the project. Refer to professional codes of conduct, e.g. BCS, ACM.

Legal: In the legal aspect, using deep learning models for breast cancer detection involves issues of data privacy and protection, liability and malpractice, and intellectual property. For instance, under regulations like GDPR and HIPAA, handling personal health data requires strict adherence to privacy and security standards. To address these issues, it's essential to anonymize patient data, establish clear liability protocols, and navigate intellectual property rights carefully, ensuring compliance with existing laws and ethical standards.

Social: In the social context, using deep learning for breast cancer detection involves ensuring equitable access and building public trust. It's important to make this technology widely accessible to avoid healthcare disparities and to communicate its benefits and limitations clearly to foster public acceptance.

Ethical: Ethically, using deep learning for breast cancer detection requires addressing biases for fair diagnosis across all demographics, ensuring the AI models are transparent and understandable, and maintaining informed consent from patients about the use of such technology in their healthcare.

Environment: From an environmental perspective, the use of deep learning models in breast cancer detection has implications such as a significant energy consumption and carbon footprint due to the computational intensity of training these models. It's important to consider and strive for energy-efficient computing practices to mitigate this impact.

Using deep learning for breast cancer detection raises complex legal, social, ethical, and environmental considerations, including data privacy, equitable access, algorithmic fairness, transparency, and energy efficiency. If handled and operated properly, the aforementioned issues associated with using deep learning for breast cancer detection can be effectively mitigated.

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