Breast Cancer Detection and Classification using EfficientNet_B0 and EfficientNet_B0-HSV

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Data Analytics

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Breast Cancer Detection and Classification using EfficientNet_B0 and EfficientNet_B0-HSV

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Abstract

Breast cancer is a critical health issue, and it is the leading cause of cancer deaths in women worldwide. Early detection can considerably improve the chances of survival. To establish the tumor's malignancy at the cellular level, a histological imaging evaluation is required. Manual examination of these slides takes time and is difficult and susceptible to human error. Due to the diversity in its properties in heterogeneity large size automated classification of histopathological images has been a serious issue. In this research work, histopathological images are gathered from Kaggle. This project implementation is based on transfer learning classification using EfficientNet_B0 and EfficientNet_B0 with HSV in pre-processing step. Transfer learning uses a feature vectors model trained on ImageNet .This experiment compares EfficientNet_B0 and EfficientNet_B0-HSV on various magnification levels. From the experiment, it was observed that using EfficientNet_B0-HSV at 100X and 200X magnification levels gave a better result in terms of precision. However, EfficientNet_B0-HSV failed to minimise false negative values compared to EfficientNet_B0.

1 Introduction

Breast cancer is a rapidly spreading disease in the world and it is the most common cancer in women worldwide and it has a high fatality rate. Breast cancer is medically analyzed and screened by a variety of techniques including mammography, ultrasonography, and biopsy. Mammography and ultrasonography are two techniques that help to detect tumors. A biopsy involves removing a sample of cells or tissues from the contaminated area and staining them with Hematoxylin and Eosin (H&E) to highlight essential features such as nuclei and cytoplasm and this study of tissue under a microscope is known as histopathology (Gurina and Simms; 2020). The tissue structure on the stained-glass slides is then examined by a pathologist to determine if it is benign or malignant and this is a time-consuming process.

Over the last few years, there is a substantial amount of research work is done on automated cancer diagnosis using deep learning algorithms that support pathologists to make decisions. Particularly CNN (Convolution Neural Network) gained more popularity but this comes with a limitation that it uses a lot of computing resources. Recent work demonstrated by (Tan and Le; 2019) proposed a new model EfficientNet that comes with set of models ranging from EfficientNet-B0 to EfficientNet-B7 derieved and scaled up from baseline model EfficientNet-B0,these use effective compound coefficient method for balancing the network depth, width, and image size resolution that increases the performance of the model, this method outperformed previous CNN models such as InceptionNet, ResNet, and DenseNet while using fewer parameters and reducing FLOPS(Floating Point Operations Per Second) and when applied to the ImageNet dataset, it achieved top accuracy.

This study will use Hue Saturation Value (HSV) to segment nuclei from histopathological images. To improve accuracy, this study explored and employed baseline model EfficientNet-B0 with a parameter adjustment, and ImageNet pre-trained weight with sigmoid classification function is utilized as transfer learning. This method improves breast cancer detection and classification by increasing the precision value. Deep learning with the fine-tuning method will boost efficiency and give clinicians reliable cancer diagnosis results. By saving time, this experiment will bring good value to the medical domain.

1.1 Research Question

This research seeks to find best configuration for EfficientNet_B0 to classify breast cancer histopathological images as benign or malignant.

1.2 Research Objectives

To answer the research question following study goals were performed –

- Examine the histopathological images which are stained with Haematoxylin and Eosin(H&E) to segment the nuclei with HSV by giving color range values.
- Design transfer learning model EfficientNet_B0 and EfficientNet_B0 combining HSV to classify the histopathological images.
- Comparison of efficiency between EfficientNet_B0 and EfficientNet_B0-HSV.

The structure of the paper is as follows. Section 2 focus on the literature review on HSV and EfficientNet and this is followed by Section 3 Methodology of the research while Section 4 and Section 5 gives deeper understanding of Implementation and Result analysis of the research work.

2 Related Work

In a recent years, a number of research work have been done on image segmentation and classification. Section 2.1 addresses the literature review on current works of HSV involved in segmentation and Section 2.2 provides details of existing research work on EfficientNet.

2.1 Related work on HSV

Image segmentation is critical in spotting malignant cells or nuclei in images. In recent years several research work has on image segmentation to improve the extraction of features from images. Below are some of previous research efforts made on image segmentation.

In the work proposed by (Bora et al.; 2015) did a comparative analysis of HSV and L*A*B on color image segmentation. The mean square error(MSE) and peak signal-to-noise ratio (PSNR) metrics were used to evaluate the performance of the models. In this experiment, it was found that HSV performed better than L*A*B, and it was found that PSNR ratio of HSV was minimum compared to L*A*B .Hence the authors in this work suggested that HSV can be used for color image segmentation in noisy data. In the research work by (Singh; 2020) demonstrated the new method to segment brain MR images, it consists of two parts. The first part is to segment brain MR images using a neutrosophic clustering algorithm and the second part is to apply HSV for visualization of images in segmented regions. The proposed method was used on 30 different MR pictures of Parkinson's disease (PD). The evaluation of the neutrosophic clustering algorithm and HSV was done separately, and the evaluation metrics considered were PSNR, MSE, and Structural similarity Index(SSIM). The proposed method using neutrosophic clustering algorithm and HSV outperformed other state of art methods in image segmentation. In addition, the proposed method took less time than existing image segmentation algorithms. In another research, work was conducted on tongue image segmentation by (Li et al.; 2017) the authors proposed the Contrast Limited Adaptive histogram equalization (CLAHE) method on the HSV color model to enhance the detection of the edge of the tongue in an image. The dataset used for the experiment consists of 264 images. The mean error pixel rate was used as an evaluation metric in this experiment it was evaluated against another model known as the snake model. The enhanced HSV model secured a low error pixel rate value of 5.3% whereas snake model secured a pixel rate value of 8.7%. By this experiment, it can be analyzed that enhanced HSV performed better than the snake model, and the authors of the work state that the enhanced HSV took less time per image to compute with a score of 0.0275 times per image than the snake model score of 3.1355 times per image. (Kartika and Herumurti; 2016) focused on research work for segmenting the body of koi fish. The proposed method used K-means as preprocessing step to separate objects and the HSV method was applied to extract color features. This experiment was conducted using Naïve Bayes without K-Fold cross-validation and SVM using K-Fold cross-validation. This segmentation method approach using K-Means and HSV together has achieved 97% accuracy. (Hema and Kannan; 2020) developed GUI tool to extract foreground value. This experiment demonstrated the use of HSV for image segmentation to extract the required foreground value. This experiment was conducted in two steps the first step is to select the ROI (Region of Interest) and the second step is to extract the foreground image in the selected ROI by applying HSV. In this work, multiple objects from different datasets are been used to extract foreground images and HSV segmented images were evaluated by (SSIM) .

2.2 Related work on EfficientNet

In the recent study, EfficientNet surpassed past state-of-the-art designs like as DenseNet and ResNet on the ImageNet classification problem while requiring fewer parameters and epochs to converge faster. Following are the related work on EfficientNet models.

The working principle of the model EfficientNets was established by (Tan and Le; 2019), this model uniformly scales network depth, width, and image size resolution using an effective compound coefficient method that outperformed previous CNN models. These EffcientNets models have fewer parameters, are faster, and are generalized effectively to achieve accurate results on the ImageNet dataset commonly used for transfer learning. In research work by (Miglani and Bhatia; 2020) compared two deep learning models ResNet-50 and EfficientNet-B0. These two models were applied to skin lesions for classification on the HAM10000 dataset. In this research work, it was found that Efficient-B0 used fewer parameters than ResNet-50 and in this work, ROC AUC values were used for evaluating the classification model, EfficientNet-B0 demonstrated a micro ROC value of 0.97 and macro AUC value of 0.93 and ResNet-50 demonstrated micro ROC value of 0.96 and macro AUC value of 0.91. In this comparison, EfficientNet-B0 produced good ROC AUC value than ResNet-50.The future of this work is to increase the performance of the model, it is advised to add more metadata information about patients.In another work of skin disorder detection by (Hridoy et al.; 2021), eight models between EfficientNet-B0 to EfficientNet-B7 were used using the transfer learning model. In this research, a new activation function known as Swish was applied and EfficientNet models achieved high accuracy and good efficiency over other state of art models of CNN. In this work, Although EfficientNet-B7 achieved the highest accuracy of 97.10% EfficientNet-B0 took the lowest training time and achieved 93.35% accuracy. This research work applied to recognize only 20 different types of skin disorders therefore the future of this work is to extend it to other types of skin disorders. In the research work conducted by (Chetoui and Akhloufi; 2020) applied EfficientNet-B7 to detected referable diabetic retinopathy (RDR) and vision threatning (VR). This test was conducted on two data sets namely EyePACS and APTOS 2019. For the classification rate the Area Under Curve (AUC) results acheived by this experiment surpassed other state of arts performance. For EyePACS dataset the AUC result of RDR was 0.984 and 0.990 for VR .Similary for APTOS 2019 AUC for RDR achieved 0.966 and AUC for VR 0.998.This signifies EfficinetNet-B7 has the higher ability of classifying images.In a research work of Brain tumor classification the authors (Nayak et al.; 2022) used EfficienNett-B0 with min-max normalization technique to enhance the image contrast and applied data augmentation technique on 3260 datasets of images.The authors compared the results of the experiment with other research work done on different models with same dataset and observed that the EfficientNet-B0 with min-max transformation performed better than other models. The accuracy result achieved with train data was 99.97% and on test data was 98.78%.

The COVID-19 diagnosis research work by (Marques et al.; 2020) was conducted in two parts. A binary classification involves images of COVID-19 and normal patients and in multiclass classification, which involves images of COVID-19, normal patients, and pneumonia. The dataset used in this research work is the X-ray image dataset consisting of 404 samples. The authors of this work have applied the EfficientNet − B4 model for transfer learning as it contains 19M parameters as it is feasible for their setup and average pooling 2d layer to reduce over-fitting and the total number of parameters. 10-fold Stratified cross-validation was used to evaluate the suggested model. The results of the experiment of binary classification were accuracy of 99.62%, recall of 99.63%, the precision of 99.64%, and f1 score is 99.62% and results for multiclass classification were accuracy of 96.70%, recall of 96.69%, precision of 97.54%, and f1 score is 97.11%. Although this research work shows good performance in all evaluation metrics author failed to compare the results with other state of art models. . In another research work on the detection of COVID-19 by (Diallo and Ju; 2020) used K-EfficientNet which is an extension of EfficientNet and during the training phase involved in resizing the images from 112*112 to 224*224, this research uses six independent datasets and named K-COVID, the data augmentation and transfer learning technique was applied this allowed to achieve 97.3% accuracy, 100% sensitivity, and 100% specificity. In another research work conducted by (Müftüoğlu et al.; 2020) for the diagnosis of COVID-19 on radiology images using EfficientNet-B0 total 137 images collected from 373 data sources were used for analysis and these are trained with EfficientNet-B0 along with this authors applied data differential privacy (DP) as a novelty in experiment to increase accuracy. The accuracy achieved by this model was 94.7% . In future the authors wants to extend the work for CT images with DP metrics.

In the research work by (Duong et al.; 2020) the classification of fruits was done by EfficienNet and MixNet the performance was validated on dataset 48905 images. Although this experiment claims that it improves the accuracy of classification of fruit using EfficinetNet and MixNet but there was no mention of evaluation metric values and in future authors of the work want to extend it to additional fruit datasets. In the work proposed by (Keh; 2020) for the detection of diseases in apple leaves using histopathological images in this work they used EfficientNet and compared it with other state of art methods such as VGG16, ResNet101, and DensNet161and further to improve the robustness of the models they used noisy student training which is the latest state of the art in ImageNet classification. The results of the experiment using the ensemble noisy student model achieved a good score of 0.982 in a classification task, using the ensemble noisy student model converged faster and was less prone to oscillation. As this experiment's accuracy is high, the authors suggested improving the speed of detection and classification, and the authors want to extend the work to various types of fruits and plants.

3 Methodology

As discussed in the Section2.1 applying HSV to segment the images increased the performance of the models by maintaining minimum PSNR,MSE values.In addition to that, applying HSV computation time was less compared to any other methods and from the Section2.2 study EfficientNet outperformed with other state of art models while using less parameter values.

In this research work, compares the performance of models to classify histopathological images as benign and malignant was done using EfficientNet and EfficientNet with HSV. This research work uses the open-source dataset from Kaggle[1].The research methodology followed as described in Figure 1.

Table 1: Total Image counts in BreakHis dataset

Magnification	Benign	Malignant	Total Count
40X	625	1370	1995
100X	644	1437	2081
200X	623	1390	2013
400X	588	1232	1820
Total Count	2480	5429	7909

Histopathological examination is critical in the discovery and classification of cancer cells, but it is time consuming and it depends on the pathologist's skills and broad know-

[1]https://www.kaggle.com/datasets/ambarish/breakhis

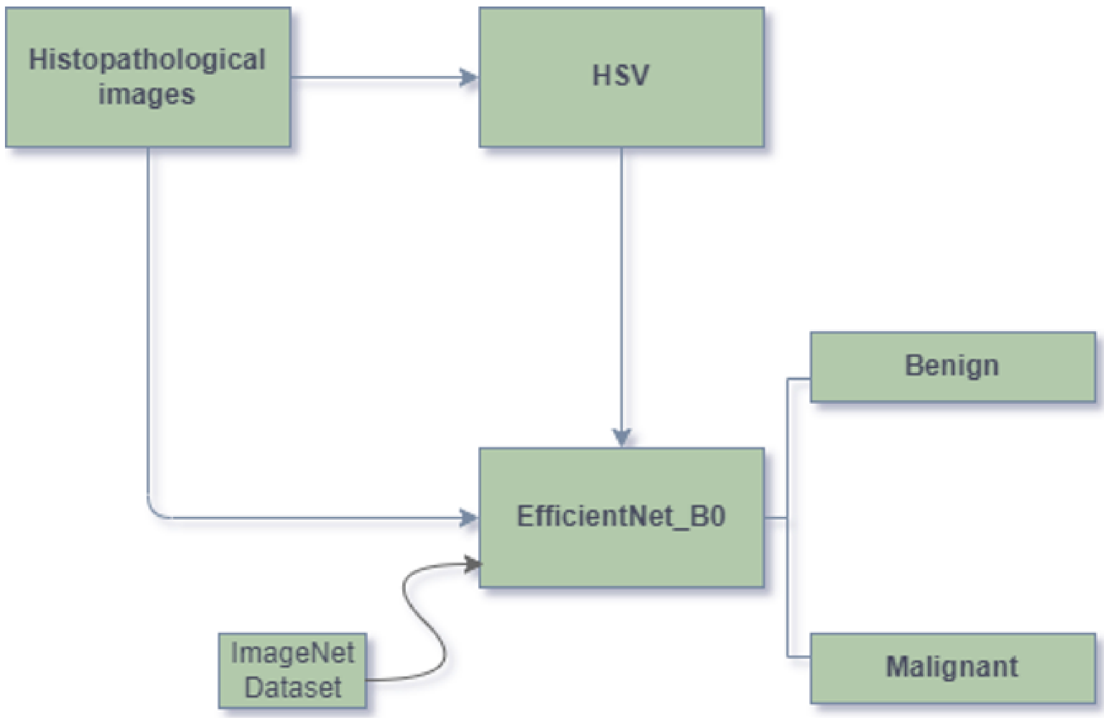
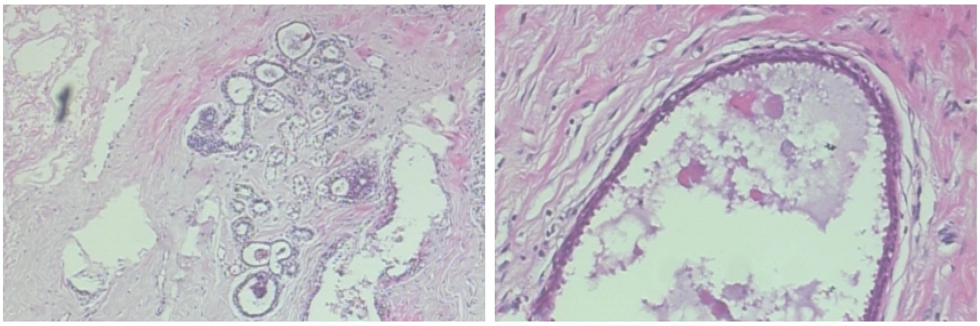


Figure 1: Research Methodology

ledge.As a result, the decision system, in conjunction with the computer-aided device, is particularly effective in recognizing and assessing abnormalities early on. In recent years, due to the developments in image scanning technologies pathologist, 's can investigate the structure of tissues and cells at different magnification levels more efficiently.

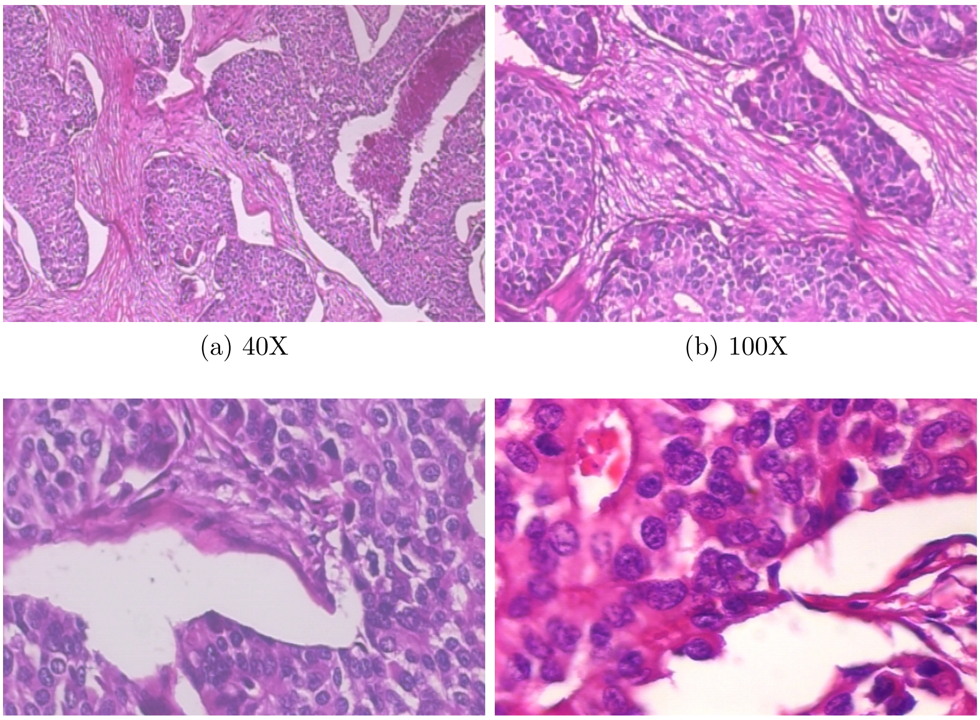
Over time, many fully automated systems for identifying and categorizing breast cancer were being developed. Histopathological images contain Hematoxylin and Eosin stains to mark nuclei purplish blue and HSV(Hue Saturation Value) a method help to segment the images to fetch nuclei.In this research work, an attempt made to develop automated breast cancer classification using EfficientNet with HSV as a novelty. One aspect of the research work involved identifying whether EfficientNet with HSV improved classifying images as benign or malignant and another aspect to identify whether applying HSV to images can isolate overlapped or clustered nuclei to get the required ROI(Region of Interest). Breast Cancer Histopathological images are obtained from the Kaggle BreakHis dataset.The collection contains photos of 7909 patients with magnifications of 40X, 100X, 200X, and 400X, and the image size at all magnification levels is 400×700. The dataset is divided into two categories: benign and malignant. The benign category includes four distinct varieties: adenosis, fibroadenoma, phyllodes tumor, and tubular adenoma. The malignant group includes four separate types of carcinoma: lobular, mucinous, and papillary. In Table 1 describes the count of images at each magnification level. Figure 2 shows samples of benign images at different magnification levels and Figure 3 shows samples of malignant images at different magnification levels.



(a) 40X (b) 100X

(c) 200X (d) 400X

Figure 2: Benign images at different magnification levels



(a) 40X (b) 100X

(c) 200X (d) 400X

Figure 3: Malignant images at different magnification levels

4 Implementation

4.1 Data Preparation

The experiment was conducted in two parts using EfficientNet_B0 and EfficientNet_B0-HSV and the dataset is divided into the train, test, and valid with a 70:20:10 ratio for each magnification level.

For the first part vanilla EfficientNet_B0 model was also applied to each of the magnification images separately. The second part EfficientNet with HSV, the RGB images were coverted to HSV. Hue(H) represents color in HSV, Saturation(S) indicates greyness in HSV, and Value(V) represents brightness in HSV.The Hue range is from [0,179] , Saturation and Value range is from [0,255]. The optimal value of Hue, Saturation and Value was obtained by setting minimum threshold value of (80,20,20) and maximum threshold value of (150,190,190) to segment the nuclei which is purplish blue color in histopathological images. The nuclei segmented images was saved in a different folder before applying EfficientNet_B0 and evaluation values were noted after applying EfficientNet_B0. The flow diagram Figure 4 shows the color segmentation step followed by applying HSV.

Below images from Figure 5 to Figure 12 shows the samples of images extracted nuclei using HSV at different magnification levels.

4.2 Model Architecture

As the dataset consists of four magnification sets of images, the two classification problems with eight models were constructed to correlate to these tasks and architectures. All the histopathological images are read from the folder and loaded into different data frames. These images placed in the data frame are checked for data imbalance bias problems and to improve performance benign images are upsampled by doubling the images. Images are being resized using resize_rescale() as EfficientNet_B0 accepts (224,224,3) image resolution. Tensorflow was used to load the pre-trained models with weights initialized to the ImageNet into the environment. The initial learning rate was set to 2e-05 and a dense layer of 512 neurons with ReLU activation was added, and then batch normalization, dropout layer of 0.5 probability to keep, and this were followed by adding a dense layer of 128 neurons with ReLU activation. These model's output layers were chosen based on the classification task Sigmoid activation function was used.

4.3 Loss Function and Optimizer

Binary cross entropy or Log loss was applied as a loss function in a binary classification problem which evaluates every predicted probability to the actual class outcome, which can be 0 or 1. The score is then computed, and the probabilities are penalized based on their distance from the expected value. That is, how near the value is to the true value.

SGD optimizer was used as it is computationally less expensive it uses a batch size of one to reach minima and performs at each iteration, the batch sizes are randomly shuffled and chosen for each iteration. All eight models were trained for 12 epochs with a batch size of 64 images, and the weights of the model with the best validation accuracy were kept for use on the test set

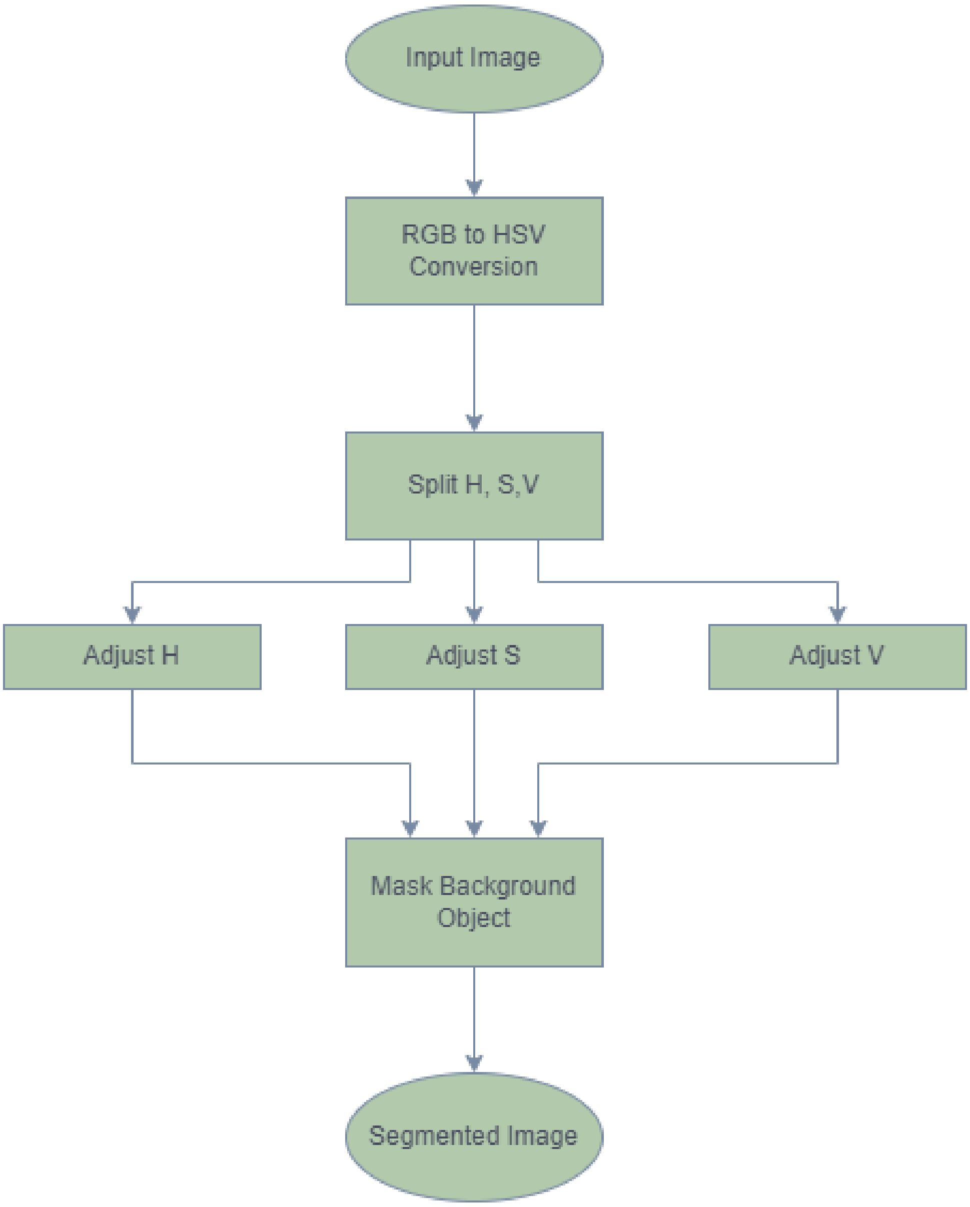


Figure 4: HSV diagram

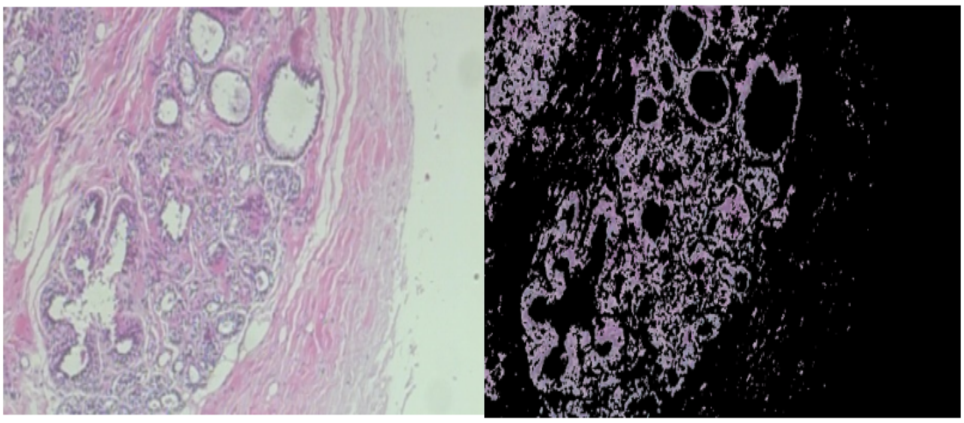


Figure 5: 40X magnification benign image before and after applying HSV

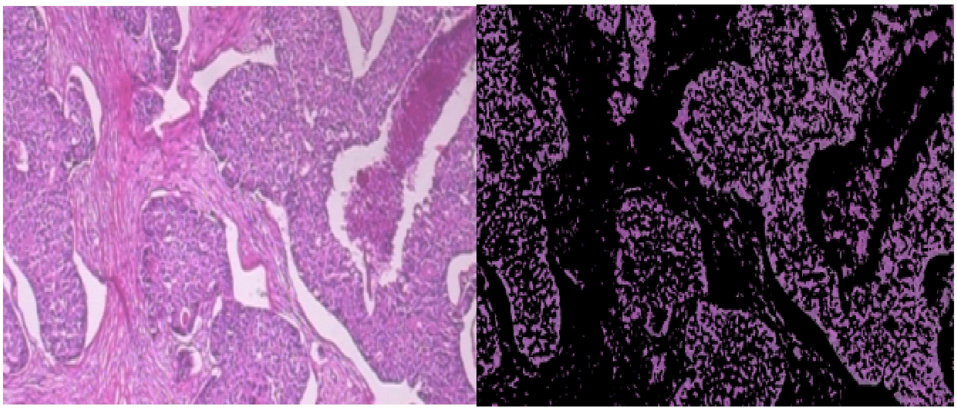


Figure 6: 40X magnification malignant image before and after applying HSV

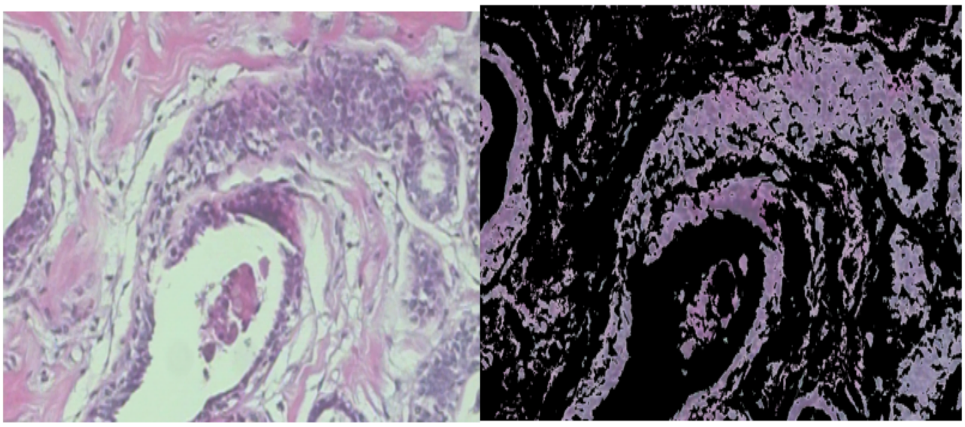


Figure 7: 100X magnification benign image before and after applying HSV

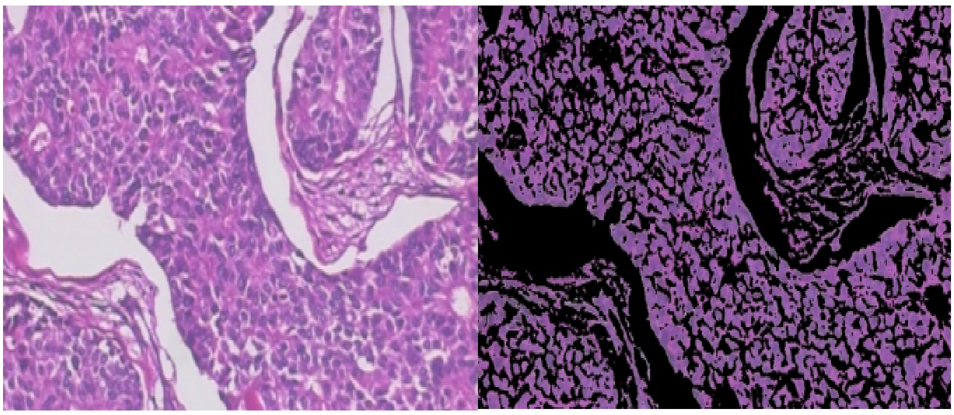


Figure 8: 100X magnification malignant image before and after applying HSV

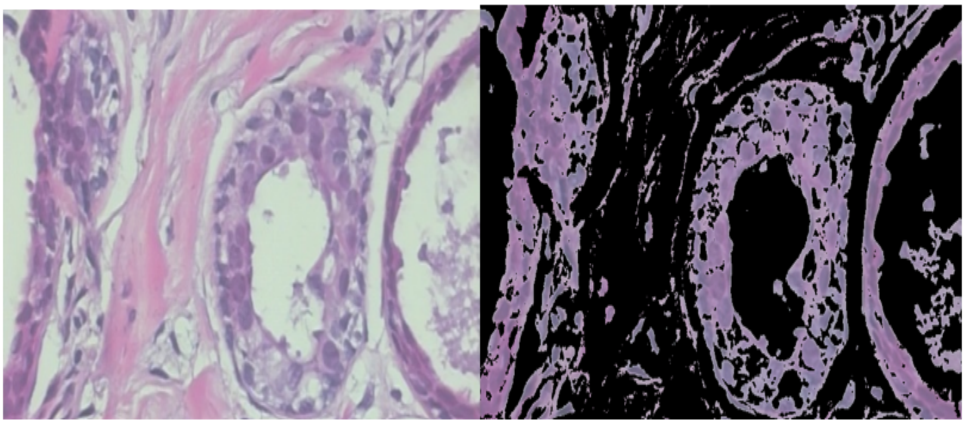


Figure 9: 200X magnification benign image before and after applying HSV

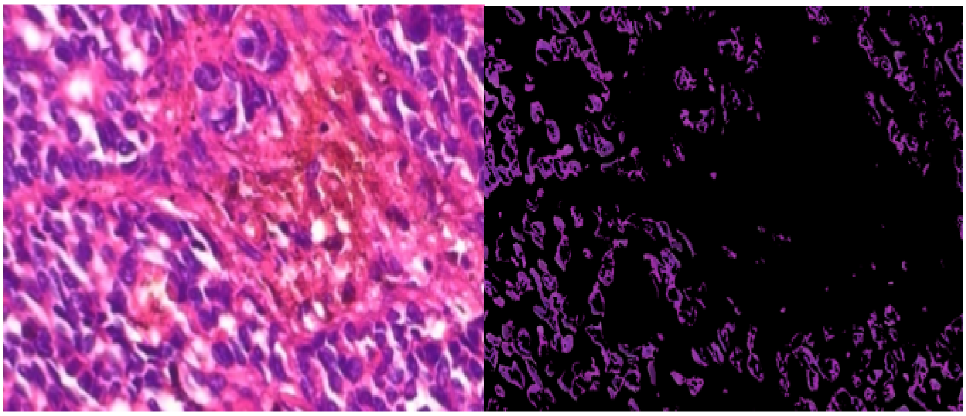


Figure 10: 200X magnification malignant image before and after applying HSV

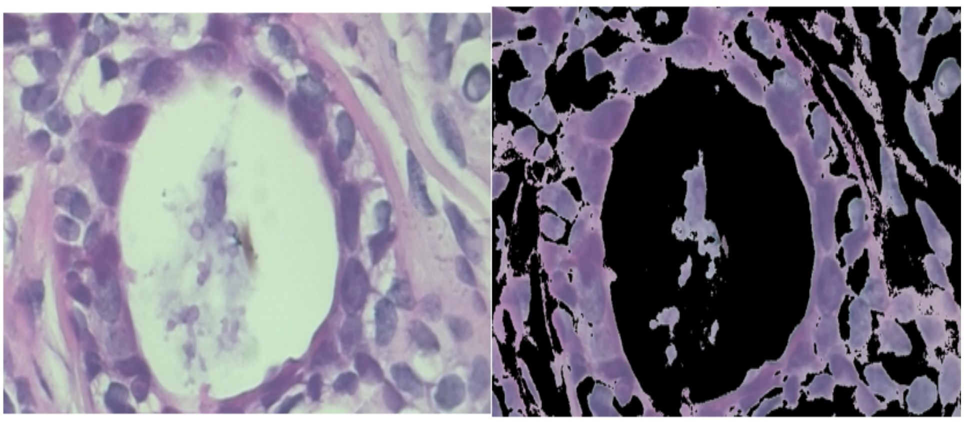


Figure 11: 400X magnification benign image before and after applying HSV

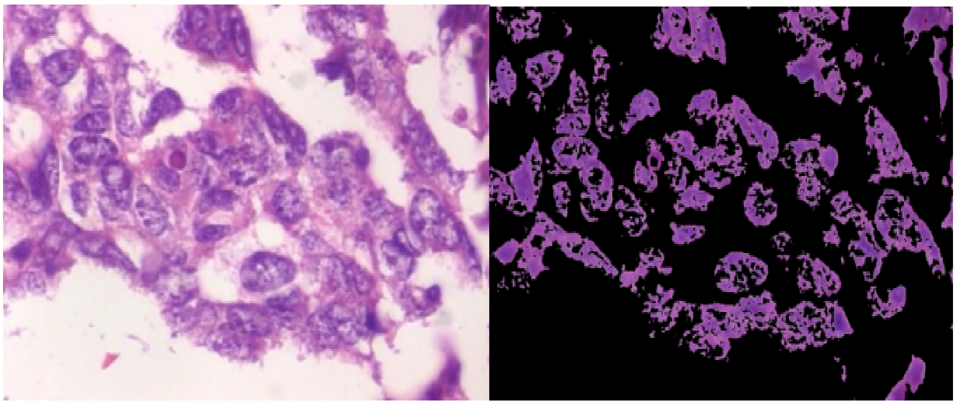


Figure 12: 400X magnification malignant image before and after applying HSV

5 Results Analysis and Discussion

This section represents the results of the experiment with pre-trained Transfer learning EfficientNet_B0 and EfficientNet_B0 with HSV(EfficientNet_B0-HSV) applied to a breast cancer classification dataset containing histopathological images. This is trained from the publicly available dataset BreakHis contains photos of 7,909 of 82 patients in two subsets of Benign containing 2480 and Malignant containing 5429 samples.In this work to evaluate the binary classification model, the evaluation matrix such as accuracy, precision, recall, specificity and false negative rate are considered and calculated using a confusion matrix. The formulas for calculating accuracy, precision, recall, specificity and false negative rate are as below-

$$Accuracy = \frac{True\ Positive + True\ Negative}{True\ Positive + True\ Negative + False\ Positive + False\ Negative} \quad (1)$$

$$Precision = \frac{True\ Positive}{True\ Positive + False\ Positive} \quad (2)$$

$$Recall = \frac{True\ Positive}{True\ Positive + False\ Negative} \quad (3)$$

$$Specificity = \frac{True\ Negative}{True\ Negative + False\ Positive} \quad (4)$$

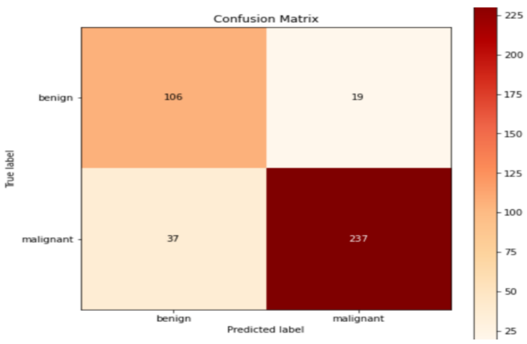
$$False\ Negative\ Rate(FNR) = \frac{False\ Negative}{False\ Negative + True\ Positive} \quad (5)$$

5.1 Experiment 1:Performance of EfficientNet_B0 without HSV at different Magnification levels

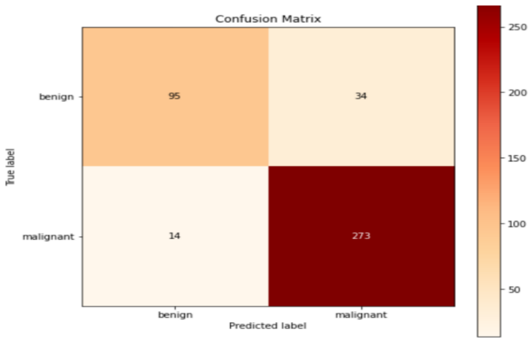
In this experiment, the EfficientNet_B0 is not applied using HSV as a segmentation step. The performance metrics are as Table 2 and confusion matrix achieved as shown in Figure 13- From the Table 2 it is observed that the magnification images at 100X and 200X maintains a least FNR values.

Table 2: EfficientNet_B0 Evaluation Metrics

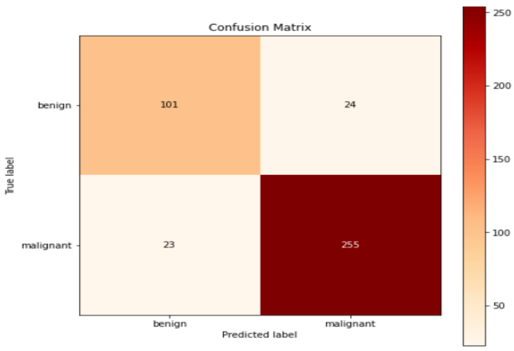
Magnification	Accuracy	Precision	Recall	Specificity	FNR
40X	86%	93%	86%	84%	14%
100X	88%	89%	95%	74%	5%
200X	88%	91%	91%	81%	8%
400X	83%	87%	89%	72%	11%



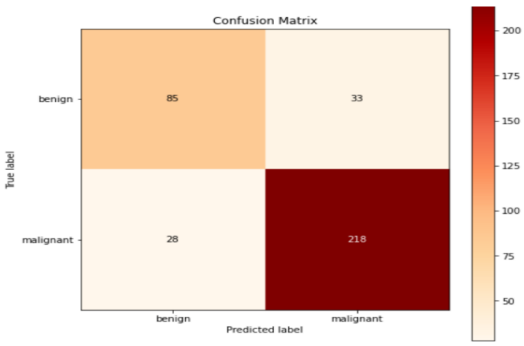
(a) 40X



(b) 100X



(c) 200X



(d) 400X

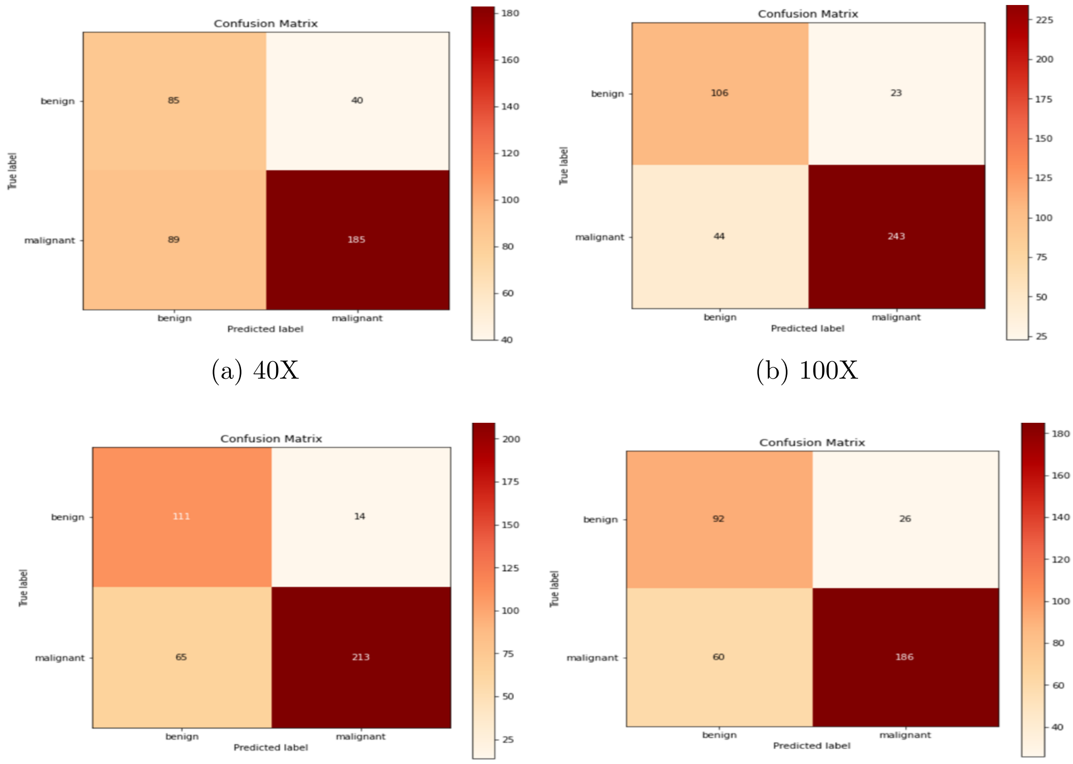
Figure 13: Confusion matrix of EfficientNet-B0 at different magnification levels

5.2 Experiment 2: Performance of EfficientNet_B0 with HSV at different Magnification levels

In this experiment, the EfficientNet_B0 is applied using HSV as a segmentation step. The performance metrics are as Table 3 and confusion matrix achieved Figure 14. From the table Table 3 it is observed that at 100X and 200X magnification level of images the model is maintains a high precision value.

Table 3: EfficientNet_B0-HSV Evaluation Metrics

Magnification	Accuracy	Precision	Recall	Specificity	FNR
40X	68%	82%	68%	68%	32%
100X	84%	91%	85%	82%	15%
200X	80%	94%	77%	87%	23%
400X	76%	88%	75%	78%	24%



(a) 40X (b) 100X

(c) 200X (d) 400X

Figure 14: Confusion matrix of EfficientNet_B0-HSV at different magnification levels

5.3 Discussion

The evaluation metrics accuracy, precision, recall, and specificity are all important in the performance of the model. In addition to this it is always advised to minimise false negative values. This is very crucial in a health care domain (Carter et al.; 2020).In this work negative class of breast cancer is considered as benign and positive class is breast cancer is considered as malignant.Assume, if a patient has the disease but the model predicts that the patient does not have it then this leads to Type-II categorisation error, which is critical and can cause a delay in the patient's treatment.Similarly if the model accurately predict the positive classes of breast cancer, but it will fail to correctly predict the negative classes of breast cancer then it leads to Type-I error, this error is not as critical as a Type-II error but still, it should be minimized as possible.In general, the model which maintains high precision, recall, specificity and has low FNR can predict accurately all the time.

From the experiment analysis by Table 2 and by graph plot Figure 15, Figure 16 the EfficientNet_B0 achieved the best performance in 100X magnification images with

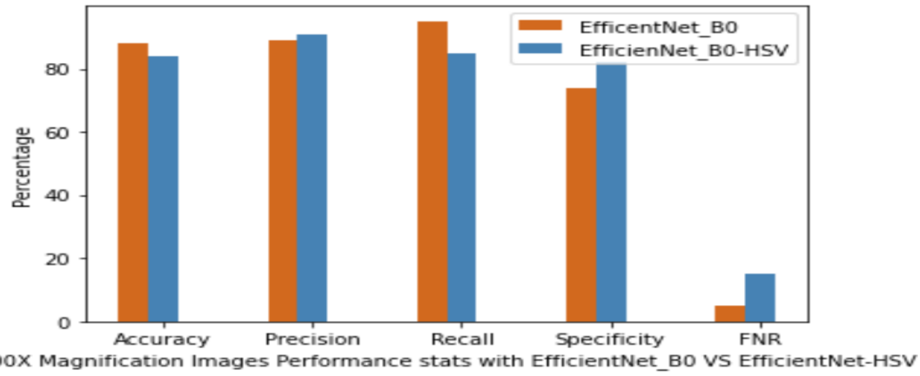


Figure 15: Performance of EfficientNet_B0 VS EfficientNet_B0-HSV at 100X

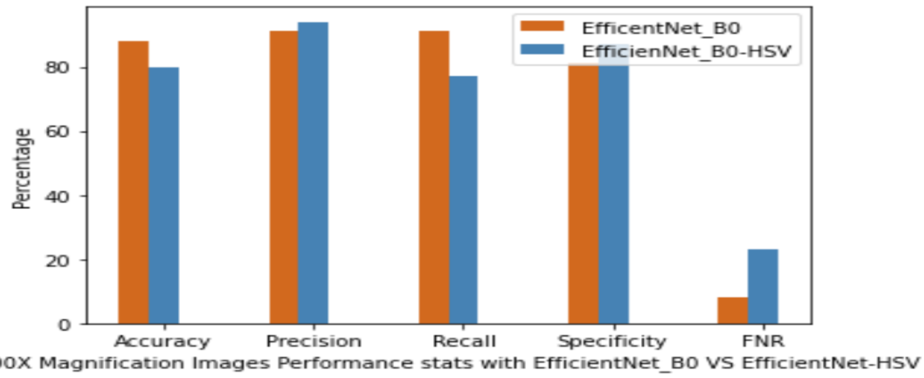


Figure 16: Performance of EfficientNet_B0 VS EfficientNet_B0-HSV at 200X

an accuracy of 88%, precision of 89%, recall of 95%, specificity of 74% FNR of 5%, and at 200X magnification images with an accuracy of 88%, precision of 91%, recall 91% ,specificity of 81% and FNR of 8%.

From the experiment analysis by Table 3 and by graph plot Figure 15, Figure 16 it can be observed that EfficientNet_B0-HSV achieved good performance results in magnification levels 100X with an accuracy of 84%, precision of 91%, recall 85%, specificity of 82% FNR 15%, and magnification level 200X with an accuracy of 80%, precision of 94%, recall 77%, specificity of 87% and FNR of 23%.

The main research work was involved in reducing FNR value .The EfficientNet_B0-HSV failed to achieve good results across all the magnification level images compared to EfficientNet_B0.

However, the EfficientNet_B0-HSV achieved good results in terms of precision value at 100X image magnification of 91% and at 200X image magnification precision value of 94% compared to vanilla EfficientNet_B0. This increase in precision helps to identify the patient with cancer early.Figure 17 shows the accuracy and loss plot of EfficientNet_B0-HSV at 100X magnification images and Figure 18 shows the accuracy and loss plot of EfficientNet_B0-HSV at 200X magnification images.

As shown in Figure 17 and Figure 18, as loss decreases by training data, validation loss also decreases. Similarly, as training data accuracy improves, validation data accuracy improves as well. From these graphs, it can also be seen that as the number of epochs increases, accuracy increases and loss decreases. If the model is trained over a large

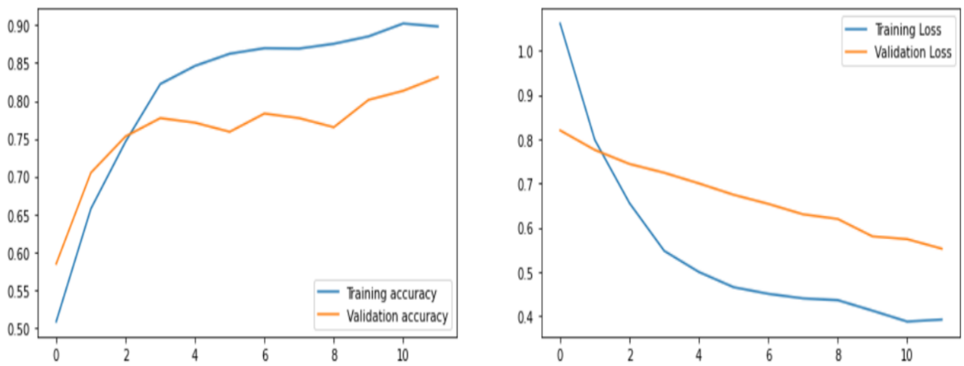


Figure 17: Accuracy and Loss of EfficientNet_B0-HSV at 100X model training at 100X

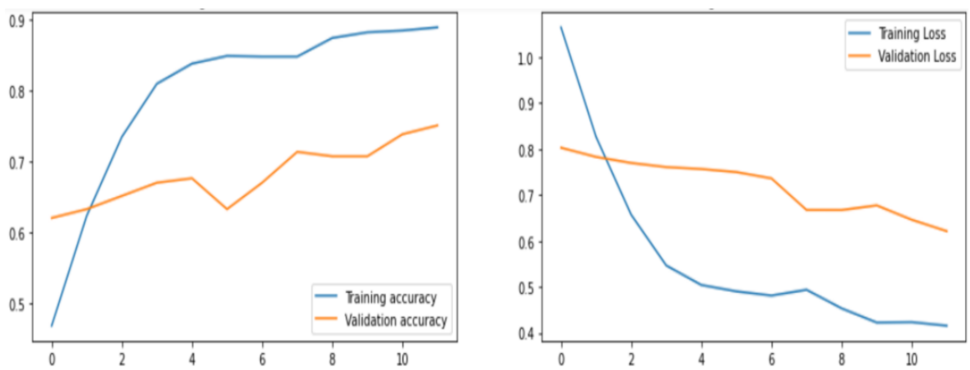


Figure 18: Accuracy and Loss of EfficientNet_B0-HSV at 200X model training at 200X

number of epochs, it will train more precisely and may improve accuracy. Due to the limited hardware resource, this work is run on a smaller number of epochs.

6 Conclusion and Future Work

This research is implemented to find best configurations of image magnification level to binary classify breast cancer as benign or malignant using EfficientNet_B0 and EfficientNet-HSV.

Applying HSV to histopathological images and then using the transfer learning model EfficientNet shows improvement in precision value of 91% at 100X and value of 94% at 200X magnification levels.However it failed to maintain low false negative values at all magnification levels compared to EfficientNet alone. The EfficientNet without applying HSV as color segmentation shows good performance by maintaining low FNR value at all magnification levels but the best configuration of magnification image was found on 100X with FNR 5% and on 200X with FNR 8%. This experiment concludes that as the model novelty with HSV applied as a image color segmentation step is efficient in detecting true positive value (Precision) cancerous cases at 100X and 200X magnification levels. Although this improvement in precision value helps to identify the patient with the disease more accurately but it is failed to achieve low false negative values this is known as Type-II error and is fatal

In the future, more parameters can be tuned with increase in number of epochs to increase the accuracy of the model,different ranges of HSV values of purplish blue can be tried to minimise the FNR.This work can also be extended to combine HSV with other transfer learning models.

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