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The Impact of Data processing and Ensemble on Breast Cancer Detection Using Deep Learning

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ABSTRACT

According to the World Health Organization, cancer is the second leading cause of mortality. Breast cancer is the most prevalent cancer diagnosed in women around the world. Breast cancer diagnostics range from mammograms to CT scans and ultrasounds, but a biopsy is the only way to know for sure if the suspicious cells detected in the breast are cancerous or not. This paper's main contribution is multi-fold. First, it proposes a deep learning approach to detect breast cancer from biopsy microscopy images. Deep convolution nets of various types are used. Second, the paper examines the effects of different data preprocessing techniques on the performance of deep learning models. Third, the paper introduces an ensemble method for aggregating the best models in order to improve performance. The experimental results revealed that Densenet169, Resnet50, and Resnet101 are the three best models achieving accuracy scores of 62%, 68%, and 85%, respectively. without data preprocessing. With the help of data augmentation and segmentation, the accuracy of these models increased by 20%, 17%, and 6%, respectively. Additionally, the ensemble learning technique improves the accuracy of the models even further. The results show that the best accuracy achieved is 92.5%.

1. Introduction

Cancer is a major public health concern in the world today and is responsible for one out of every six deaths worldwide, making it the second leading cause of death after cardiovascular disease [1]. Breast cancer is the most common type of cancer diagnosed in women around the world.

BreastCancerisadiseasethatisdefinedbythecreationofabnormalcellsinthebreastthatgrowatanuncontrollable rate and have the ability to invade and damage breast tissues [2]. bc can a ect both men and women, but it is more common in women, according to [3]. Cancer can be classified into two types: carcinomas and sarcomas.The former type is cancers that arises from the breast's epithelial component, which includes the cells that line the lobules and terminal ducts. The later type is a rare cancer that arises from the breast's stromal (connective tissue) segments, accounting for less than 1% of all predominant cancers. Carcinoma is classified further into several subtypes, including colloid, papillary, micropapillary, medullary, and tubular carcinoma. However, the most widespread subtypes are invasive and in situ carcinoma [4].Ductal Carcinoma In Situ is a type of non-invasive breast cancer that develops when abnormal cells are discovered in the membrane of the breast milk duct. Non-invasive refers to the fact that the malignant cells did not spread from their original location (breast milk duct) [5]. While Invasive Ductal Carcinoma is a type of breast cancer in which the malignant cells that form in the milk ducts have spread to other regions of the breast. 80% of all cancer cases are for Invasive Ductal Carcinoma[6]. Other types of Breast Cancer include metastatic breast cancer, acrfullibc, and triple-negative. Patients can choose from a variety of screenings and diagnostic tests. They are determined by their age as well as other factors such as medical and family history. Mammograms are commonly used for screening [7].some cases MRIs and ultrasounds [8].The result of screening using Mammogram , MRI and ultrasounds are classified into one of six categories including negative, benign findings, Probably Benign Findings, Abnormality, Highly Suggestive of Malignancy, and Known Biopsy-Proven Malignancy. The breast is in the negativecategoryifitisnormalandfreeofanymasses, architecturaldistortions, orsuspiciouslesions. BenignFindings indicates a negative outcome, but a benign finding may exist.The phrase "Probably Benign Findings" denotes that the scan results are usually benign. It is recommended that the discovery be closely monitored to ensure its stability. The risk of developing cancer is estimated to be less than 2%. Abnormality occurs when a suspicious lesion is discovered in tests that have a high probability of being malignant but are not malignant mammographically. Highly Suspicious of Malignancy denotes that the lesions have a greater than 95% chance of being cancer Known Biopsy-Proven Malignancy means that lesions found on scans and imaging have been confirmed to be malignant using a biopsy test. Breast test diagnosing is di erent type a breast screening because it is used to look at a current problems; e.g., discharge of the nipple dominant mass.Then, if a screening mammography or ultrasound reveals suspicious or strongly suggestive lesions of cancer, a biopsy should be undertaken. A biopsy is still the only way to find out exactly what happened if unusual lesions are found in scans and imaging are malicious or not, and it is the only way to find out for sure. [9] A breast biopsy is a procedure where a small piece of breast tissue is taken for pathologists to look at.There are numerous types of biopsy tests available, including Fine Needle Aspiration (FNA), Core Needle Aspiration (CNA), Surgical (open), and Lymph Node Biopsies [10]. The type of biopsy a person gets depends on what kind of lesion they have. Pathologists get the samples and perform histopathology procedures on them. Hematology is the microscopic study of diseases in tissues [11]. This is how they come up with the diagnosis: The pathologists who do histopathology are the only ones who can help patients choose the right treatment plans. Because of the variety and complexity of the tests, breast cancer types, and the di erences in pathologists' skills, the histopathology process could lead to a lot of wrong conclusions [12]. Automating this complicated and time-consuming process is very important because it reduces opportunities of misdiagnosing people, prevents Patients to wait for a long time for the test and helps the pathologists have a lot of work to get the results and start the right treatment plans.

The fundamental contribution of this research is to present a method that uses Deep Learning techniques to automate the histology procedure. The worrisome lesion observed on the microscope biopsy images is detected using this method.These lesions are to be classified into Benign, Breast Cancer Invasive Ductal Carcinoma, or Ductal Carcinoma In Situ. To automate a system like our suggested approach, there have been a number of attempts and trial [13]. The paper's most significant contribution is as follows. A deep learning algorithm is first used to identify breast cancer from biopsy microscope pictures. Vgg16, Resnet50, Inception, Alexnet, Resnet101, and Densenet169 are some of the deep Convolution Neural networks (CNNs) that we use to analyse the data. We test our hypothesis on the BACH dataset, which contains 400 histopathological pictures divided into four categories, Normal, Benign, Invasive Carcinoma, Carcinoma In-Situ [14].The images are first preprocessed using several approaches, such as data augmentation, segmentation, and Patching. We also present an ensemble strategy to improve the classifiers' accuracy.

This paper is organised as follows: Section 2 gives overview about CNN and classification evaluation metrics. Section 3 discusses related research e orts in breast cancer diagnosis. Section 4 discusses the research methodology. Section 5 discusses experimental results. Finally,section 6 concludes the paper.

2. Background

Machine and deep learning Convolution neural networks are a sub-type of artificial neural networks that are capable of performing a wide variety of tasks, including image categorization. [15, 16, 17, 18, 19].Convolution neural networks (CNNs) have been demonstrated in the literature to be one of the most e ective ways for increasing recognition rate and speed when compared to other detecting methods [20]. Typically, as seen in Fig. 1, the CNN architecture consists of many linked layers. Convolution layers, pooling layers, and fully connected layers . These levels are discussed in further detail below.

The convolution layer extracts the feature map from the input picture using filters as illustrated in Fig. 2.As seen in Fig. 3 Sliding the filter over the input picture performs the convolution procedure. A matrix multiplication process is done at each point, and the result is added to the feature map. A stride value specifies the filter's movement step on the input picture. The stride value determines how the filter wraps around the input volume. Typically, the filter slides over the input picture pixel by pixel.

The pooling layer is in charge of decreasing the network's parameter and computation count. As seen in Fig. 4 , the pooling operation is performed on the convolution layer's feature map. The goal of pooling is to save training time and to address training di culties such as overfitting. There are di erent types of pooling layers, including maxpooling and average-pooling. Pooling is most frequently used for max pooling, which selects the maximum value in each window.

The fully connected layers are neural networks that are responsible of classification function to provide the final result.

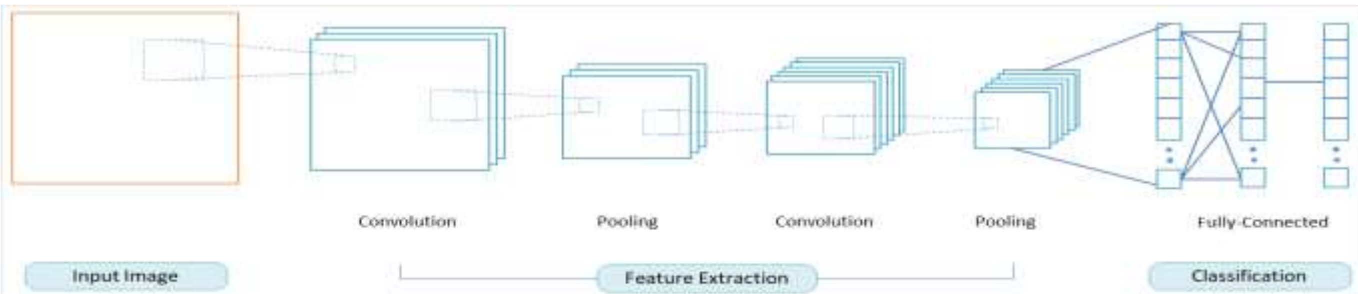

Figure 1: Generic architecture of the convolution neural network model

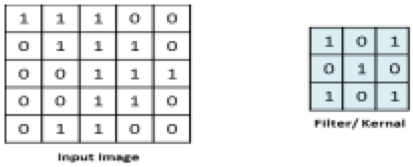

Figure 2: Convolution layer

Figure 3: Convolution process

Figure 4: Max pooling operation

2.1. Evaluation Metrics

Several evaluation metrics are used to evaluate the performance of the classification. The most common metrics include, accuracy (ACC), precision (PREC), sensitivity (recall) (REC), specificity, and f-score (F1). They are calculated as follows:

$$Acc = \frac{TP+TN}{TP+FP+TN+FN} \tag{1}$$

$$prec = \frac{TP}{TP+FP} \tag{2}$$

$$Rec = \frac{TP}{TP+FN} \tag{3}$$

$$prec = 2 * \frac{Prec*Rec}{PrecRec} \tag{4}$$

Where TP, TF, FP, and FN indicate the true positive, true negative, false positive, and false negative respective

3. Related Work

Deep learning methods [21, 22, 23, 24] have widely used in several type of application domains [25, 26, 27, 28, 29, 30, 31]. These techniques have a significant influence on the early diagnosis of a variety of diseases [32, 33]. Additionally, they havebeen usedtoaid inthe diagnosisandclassification ofmany formsofcancer. [34, 35]. Numerous authors advocated utilising deep learning approaches to diagnose breast cancer using MRIs, mammograms, ultrasound, or pathology examinations . In what follows, we categorize these research e orts based on the type of images used in diagnosis.

3.1. MRI Images

SeveralauthorsusesMRIimagesforcancerdetection. Forexample, theauthorsin[36]introducedatwo-dimensional median filter for the detection of breast cancer in MRI images. They extracted features using discrete wavelet transform (DWT) and subsequently reduced the number of features using principal component analysis (PCA). Finally SVM classifier is trained to determine the tumour existence. In their experimental test, 153 breast MRI pictures were used in the dataset that were splitted into 64 for training and 89 for testing. Their proposed approach obtained a final accuracy of 98.3 %, a specificity of 96.72%, and a sensitivity of 96.42%. Unlile the previous work, deep convolutional neural networks (CNNs) were used to classify breast cancer tumours in an e cient Adaboost Algorithm (DLA-EABA) [37]. Images from MRIs, ultrasounds, digital breast tomosynthesis, and mammograms were incorporated into the system for training and testing.The accuracy, sensitivity, and specificity of their findings were 97.2 5% , 98.3 5% t, and 96.5% respectively.

3.2. Ultrasound Images

Several research e orts applied deep learning methods on ultrasound images. For example, the authors in [38] presented a deep learning CNN approach to identify the ultrasound breast images into malignant or benign. The used dataset consists of 579 benign and 464 malignant lesion patients at Sichun Provincial People's Hospital and was annotated by expert physicians. They compared numerous models in their tests, including R-CNN, YOLO, Faster R-CNN, SSD, and CNN architectures such as ZFnet and BGG116 . SSD300 has shown to be more suited for tumour identification, whereas CNN-based models were found to be more suitable for classification. SSD300+ZFnet had the highest average accuracy rate in both benign and malignant with 96.89%, 67.23%, and 79.39 % F1 scores, respectively. Similar work is proposed in [39], where The authors presented a method for classifying breast cancer using ultrasound pictures and transfer learning. Ultrasound scans of normal and malignant patients were used to train a deep convolutional neural network. They build a CNN model and used VGG16 architecture in their experiments. Their results achieved accuracy of 0.97% accuracy and AUC of 0.98% AUC. Another work is proposed in [40]. In the later work, the authors presented a method for breast cancer diagnosis utilising breast ultrasound pictures. The trials employed a dataset of 219 patients includes 614 volumes of breast ultrasound, comprising 745 cancerous regions, and 144 normal cases with 900 volume, all of which were normal. The whole strategy attained a sensitivity of 95% with a false positive rate of 0.84% percent per volume.

3.3. Mammogram Images

Several authors uses Mammogram images for cancer detection. For example, the authors in [7] proposed deep learning method to detect breast-cancer from mammograms. In their experiments, they utilized the MammogramsMIAS dataset, which included 322 images classified into 189 normal and 133 abnormal breasts, respectively. The anomalous images exhibited asymmetry, with one of the breasts containing a major density bulk, and the images' original dimensions were 1024x1024. The training was conducted in a 70:30 ratio of training to testing. The approach utilised consisted of two steps. The first phase was training, during which pictures were subjected to certain preprocessing techniques such as noise reduction using morphological operations, and then passed through the CNN for features extraction. Following that comes the testing step, during which the input picture is preprocessed and then sent through the trained CNN to forecast and obtain the results. Matlab 2017 was chosen as the implementation platform. Finally, a precision of 65% was obtained. Similar work is proposed in [41]. The authors provided a fully automated system for detecting, analysing, and classifying microcalcification in a mammography dataset gathered at two medical institutions and included 990 images with lesion kinds. Additionally, performance di erences between handmade and deep learning extracted images were identified, and the two types of images were blended to increase classification performance. Throughout, the procedures employed consisted of three primary phases. To begin, the suspicious region of interest was extracted using an automatic picture preprocessing procedure. Second, the radionics feature are created by hand, which included statistical, morphological, and textural data, as well as a fine-tuned pre-trained CNN model. Finally, classifiers were trained and evaluated using the SVM model on deep, handmade, merged, and filtered features. To integrate mammography pictures and extract calcification, region of interest extraction points are used. To obtain all information about interesting locations, a coarse segmentation approach was applied. Morphological erosion was used to remove pixels from the breast border, followed by morphological top-hat filtering, which created a gray-scale picture that was subsequently transformed to a binary image . Finally, pictures were dilated and the calcification area was defined as the greatest connect region. Additionally, a deep CNN framework was developed for the extraction of deep features. The architecture comprised of five convolutional layers, each with its own set of convolutional filters, with ALexnet serving as the basis for feature representation. Along with overcoming overfitting, an Imagenet "o -theshelf" model was utilised. Additionally, we utilised a canonical correlation analysis to merge handcrafted and deep features. Finally, CNN with morphological feature filtering reached an accuracy score of 88.59%. Similarly, the author in [42] proposed a work in which They examined the performance of several networks in two distinct scenarios, the first of which involved training the network using previously taught weights and the second of which involved randomly initialising the network with weights. A deep convolutional neural network was utilised to evaluate mass lesions in mammograms using this dataset. The scientists employed two datasets: DDSM-400, which comprised 400 extracted mass areas of interest, and DDSM-upgraded, which contained 10,239 pictures. The training and testing datasets were separated, and only mass-concerned instances were recovered, comprising 1319 and 378 areas of interest, respectively. To extract ROIs, a kernel with a defined size was clipped for all lesions with the mass in the middle. Additionally, data augmentation was performed to improve the performance of the rotation and flipping operations. In terms of performance, a fine-tuning scenario using transfere learning of Resnet-50 and Resnet-101 on both datasets obtained an 85 percent performance, but a from-scratch training scenario achieved a lower performance. Finally, Alexnet's from-scratch training attained outstanding performance. Similar work is proposed in [43]. The authors employed an eight-layer CNN followed by the integration of two enhancement techniques: batch normalization (BN) and dropout (DT). Finally, they used rank-based stochastic pooling (RSP) in place of conventional maximum pooling. This led in the creation of BDR-CNN, a combination of CNN, BN, DO, and RSP. This BDR-CNN was then hybridised with a two-layer GCN to create our BDR-CNN-GCN model, which was subsequently used for breast mammography analysis. They repeated their BDR-CNN-GCN method ten times on the mini-MIAS dataset achieving accuracy score of 96.101.60%, a sensitivity score of 96%, and a specificity score of 96%. Other work was proposed in [44]. The authors classified mammograms in an enhanced dataset using the transfer learning approach and CNN. Alexnet was used to generate the feature maps. The obtained area under the receiver operating characteristic curve (AUC) is 0.73 with data augmentation and 0.62 without data augmentation.

3.4. Pathology Images

Several authors introduced deep learning methods for cancer detection based on pathology images. For example, the authors in [45] developed a system capable of classifying benign and malignant tumours using a collection of histological pictures. The maximum accuracy attained throughout the model's training phase was 0.99%. Similar work is proposed in [46], where The authors presented a method with the goal of lowering the death rate from breast cancer and saving women's lives. To help minimise the rate, eight breast cancer sub-types were classified into two groups: benign and malignant, with each subtype having four sub-classes. The authors of this article took photos with a magnification of 40x to cover the region of interest, and then amplified the image to focus only on the area of interest. The CNN model consisted of three layers: a convolutional layer that assisted in extracting image features and applying image processing filters, a pooling layer that performed computations to prevent over-fitting, and finally, fully-connected layers that contained the output. The dataset was divided into train and test segments with ratios of 90% and 10%, respectively. The accuracy attained with this model was 73.68% percent. Additional work was proposed in [13]. The authors presented a method with the goal of lowering the death rate from breast cancer and saving women's lives. To help minimise the rate, eight breast cancer subtypes were classified into two groups: benign and malignant, with each subtype having four sub-classes. The authors of this article took photos with a magnification of 40x to cover the region of interest, and then amplified the image to focus only on the area of interest. The CNN model consisted of three layers: a convolutional layer that assisted in extracting image features and applying image processing filters, a pooling layer that performed computations to prevent over-fitting, and finally, fully-connected layers that contained the output. The dataset was divided into train and test of ratio of 90% and 10% respectively. The accuracy attained with this model was 73.68%. Other work is proposed in [47].The authors utilized a CNN approach with three convolution layers activated using the ReLU method, a max-pooling layer, and a preprocessing input layer. The images were preprocessed to gray-scale and sliced using the bit-plane slicing method, which splits the image into eight bit-plane images, each of which contains information about the spatial distribution of texture and the intensity of thefrequency, withtheincreasebitplaneswillcontainmoreinformationthanthelowerbit-planes. Thedatasetincluded three types of tumours: benign, malignant, and fibrous. Bit-planes were found to improve both the recognition rate and classification performance in this recognition. In comparison to bit-planes and fused images, the fourth, fifth, sixth, and seventh bit-planes performed well and had a high classification accuracy in CNN. Similar work is presented in [48]. The authors showed that the manual diagnosis had no e ect in comparison to automatic diagnosis, and that the solution for determining the type of acrlongbc is to develop an cad using deep learning techniques. cad was passed through three ways. The first approach was cnn, which aids in feature extraction and image transfer from the input picture to a feature map via a convolutional layer. Global average pooling was utilised continually to combat overfitting, rather than the fully-connected layer, which contains massive hardware and is constrained in terms of size. In conclusion, this model correctly detected bc pictures and that global average pooling was the superior strategy in terms of parameter count, training time, and over-fitting control. Other work is proposed in [14], The authors automated the interpretation of breast cancer histology images using computer-aided design (CAD) technologies. Their solutions achieve better performance compared to human experts. The best algorithm classified high-resolution microscopy pictures of normal, benign, in situ, and invasive cancer with an accuracy of 0.87%. The information was created from patient records in three hospitals in Portugal. The dataset consists of 500 images splitted int 400 training and 100 testing images, respectively.

4. Research Methodology

In the proposed approach (see fig.5, we use CNN-based architectures with a variety of various pre-trained architectures and preprocessing approaches. Before training the model, several preprocessing approaches are used to the pictures to determine their e ect on the accuracy. Color deconvolution and colour normalisation were employed as preprocessing techniques prior to performing the segmentation procedure.

Following that, colour normalisation was used to homogenise the colour pattern across all photos, and finally, nuclei were segmented using the local maximum clustering approach. Additionally, data augmentation are adopted to increase the number of training image, as the data is insu cient to train the model accurately. [49]. There are variety of data augmentation methods to sub-sample images. We consider shear, flip horizontally, and rotation technique. Additional employed preprocessing approach in our proposed research methodology is patch extraction; the images are resized into 6 patches with a combined size of 299x299 and a stride of 99 pixels around the image size. The training images are created with a resolution of 2048x1536. The design includes Resnet50 which is a CNN with 50 layers. Resnet50 also assists in avoiding overfitting the training data by utilizing skip connection gates, which allows the model to omit a CNN weights if it is not required [50]. Another varient of Resnet is the Resnet101 architecture, which is a CNN with 101 layers allowing the model to retrain the last layer, hence reducing the model's training time. [51].

4.1. BACH challenge dataset

BACH challenge dataset is consider one of the challenging dataset in pathological cancer detection [52]. The authors initially contrasted preprocessing and postprocessing approaches. They emphasized that the frequently used preprocessing method in digital pathology is stain normalization, since it provides more steady performance on both training and testing data. In terms of postprocessing, they concentrated on three approaches often used in computer vision tasks: segmentation, classification and detection. Several authors were used the dataset in their proposed classification model. For example, Aditya et al. [53] made use of the BACH data collection for the task Three hundred images were utilized for training and one hundred for validation splitted into a random 75 for each category for training and the other 25 were for validations. They achieved overall accuracy score of 85%. Similar authors [54] classified breast cancer using the BACH dataset using a Separable Convolutional Neural Network (SCNN). Their dataset is partitioned into the ratios 80%, 10%, and 10% representing training, validation, and testing respectively. The authors claim to attain a level of accuracy of 100 percent, which is very dubious given their reference list of just 14, implying that little study was conducted to get such a high level of accuracy.. In another work [55], The authors suggested a context-based patch-based RNN model for breast tumour classification. They tested several datasets and found that those using the BACH dataset got the maximum accuracy of 90%. Similarly, in [56] the author suggested a strategy for breast cancer categorization based on CNN. The authors employed two benchmark datasets: the BACH dataset and BreakHis. They attained an accuracy of 83% with augmentation and 82% without augmentation using the BATCH dataset. While they reached 90% without applying the data augmentation technique, while reached 98% with the consideration of data augmentation using the BreakHis'. Other work in [57] in which the authors presented a CNN approach for detecting breast cancer's region of interest. For training, validating, and testing, they integrated four datasets. There are a total of 584 data images available; 425 are utilized for training and 59 as testing. Experiments were conducted on four Unet architectures including U-net in addition to Resnet152, their proposed network with Resnet152, and pruned Resnet network. Separate datasets were created. Three data cohorts were merged to train the model, which was then evaluated on a fourth.

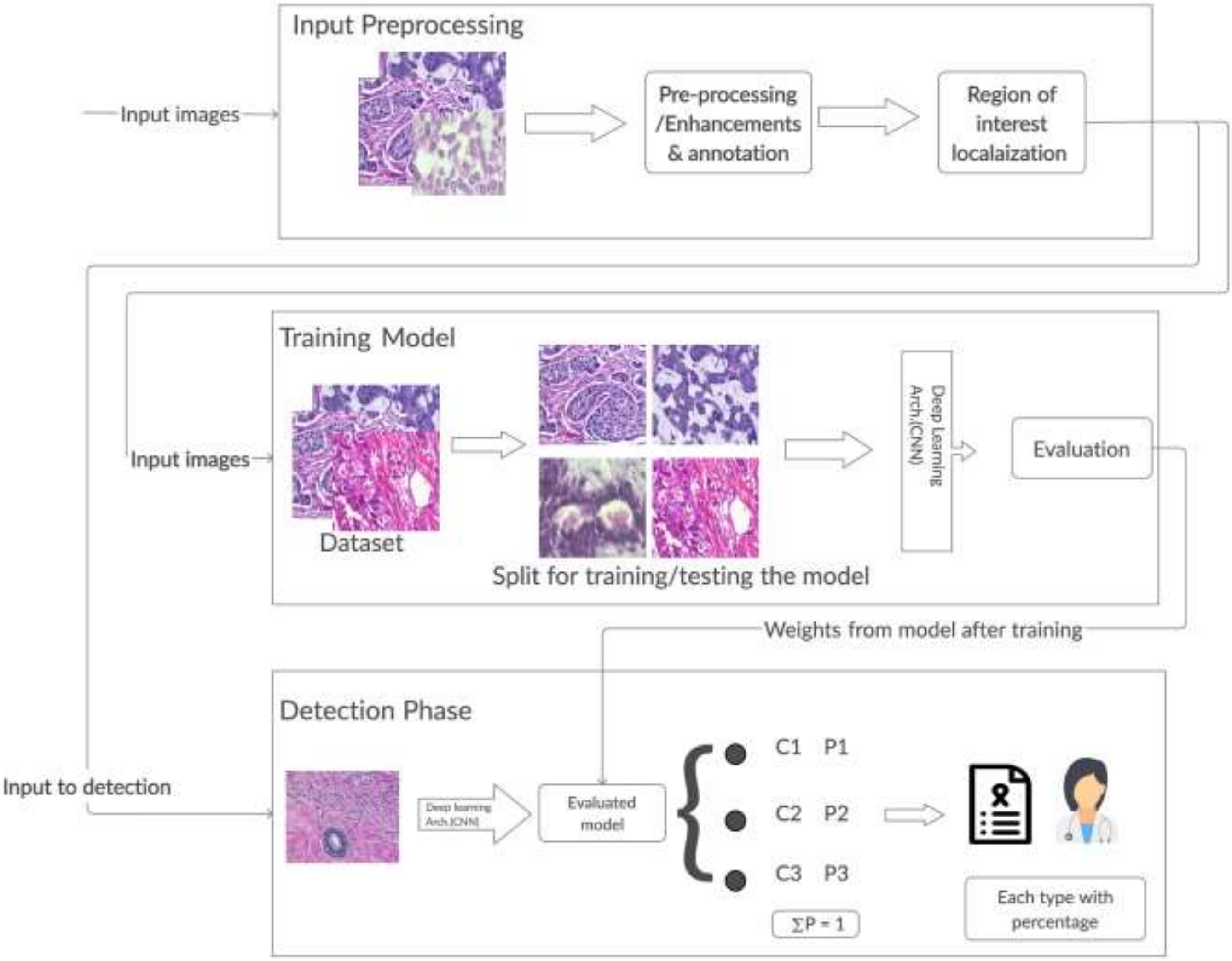

Figure 5: The proposed approach

5. Experimental Results

Generally, the adopted dataset is a di cult taken from the BACH challenge, which comprises images annotated by two very skilled pathologists. The data include 400 histological images of the breast divided into four categories namely: 100 normal image, 100 invasive carcinomas, 100 benign, and 100 in situ carcinomas. [14].These images are divided into training, validation, and testing parts with ratio split of 80%, 10%, and 10% respectively. Each split has an equal number of classes. The proposed technique balances data in such a way that the accuracy is su cient for performance measure.

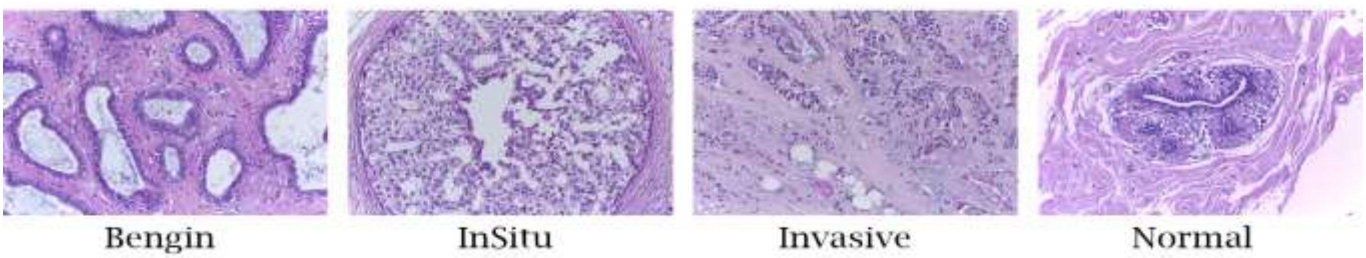

Figure 6: Samples of BACH dataset

Table 1
Summary Results of the Accuracy

Type of the Model	Accuracy
Alexnet	0.5
VGG16	0.25
Resnet101	0.82
Inception	0.25
Densenet169	0.62
Resnet50	0.68

Table 2
Summary of the results After Pre-Processing

Model/Pre-processing	Resnet50	Resnet101	Densenet169
Augmentation	0.75	0.85	0.77
Segmentation	0.73	0.60	0.68
Segmentation with Patches	0.73	0.75	0.78
Segmentation with Augmentation	0.85	0.88	0.82

Six CNN-based models are adopted in our proposed experiments, and the outcome of each model is summed up in TABLE 1. Resnet101 is the best outperformed model with accuracy score of 82% without any preprocessing technique. Thus, in order to investigate the e ect of preprocessing, we select the best outperformed models to test the preprocessing strategies. According to the results found in the TABLE 1, the best architectures achieving the best accuracy are Resnet50, Resnet101,and Densenet169.

We implemented our pre-processing techniques to the datasets, including nuclei segmentation, data augmentation to increase the dataset's distribution,. Also, we employed cropping patches, which is another technique for increasing the dataset's image count, in order to observe the e ect of each technique on each model and the e ect of combining these techniques. By using the Segmentation approach to the pictures, the accuracy of Densenet169 was increased by 5%, but the accuracy of Resnet50 and Resnet101 remained unchanged. On the other hand, The Data Augmentation experiment enhanced the accuracy of the three models, with Resnet101, Densenet169, and Resnet50 accuracy increasing by 3%, 15%, and 7%, respectively. This demonstrates that Data Augmentation has a significant influence on both enhancing accuracy and lowering overfitting.

The following experiment combined Segmentation with the Crop Patches approach, which did not outperform the e ect of Data Augmentation on the three models. However, it increased the accuracy of Resnet50 and Densenet169, as seen in TABLE 2. The last type of experiment combines segmentation and data augmentation. This combination produced the most accurate model of the three. It outperformed the other strategies and increased the accuracy of Resnet101, Resnet50, and Densenet169 by 6%, 17%, and 20%, respectively. .

Finally, We applied Ensemble using hard voting method [58] where we vote on categorization by combining Resnet101, Resnet50, and Densenet16. The ensemble approach produces the findings displayed in TABL 3. Combining the three models had no beneficial e ect on the accuracy of the "Segmentation" and "Segmentation and Patches" approaches. However, it improved the precision of techniques such as "Augmentation" and "Segmentation and Augmentation." The approach known as "Segmentation and Augmentation" attained the highest accuracy of 92.5%.

Table 3
Summary of the results using Ensemble

Model/Pre-processing	Resnet50	Resnet101	Densenet169
No Pre-Processing		0.775	
Augmentation		0.85	
Segmentation		0.70	
Segmentation with Patches		0.775	
Segmentation with Augmentation		0.925	

mentation." The approach known as "Segmentation and Augmentation" attained the highest accuracy of 92.5%.

6. Conclusion

Breast cancer is the most common type of cancer in women worldwide. Mammograms, CT scans, and ultrasounds are all used to diagnose breast cancer, but only a biopsy can definitively determine whether or not suspicious cells discovered in the breast are malignant. A biopsy remains the only way to determine whether unusual lesions discovered in scans and imaging are malicious. A breast biopsy is a procedure in which a small piece of breast tissue is removed and examined by pathologists. This study introduced a deep learning approach to biopsy diagnosis in order to save time for both patients and pathologists while also lowering the risk of misdiagnosis, which could lead to other complex and decline in health. The paper presented several types of deep learning models that were tested on histopathological dataset taken from the bach-challenge. Furthermore, the paper demonstrated the e ect of data preprocessing on trained models. The findings revealed that data augmentation and image segmentation improved predictive accuracy. Finally, using the ensemble method with the most performed 3 models improved accuracy even more, yielding a score of 92.5%.

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