Breast Cancer Diagnosis in Histopathological Image using Machine Learning Approach

03CS7914 Project (Phase II)

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student, for the course work in **03CS7914 Project (Phase II)**, under our guidance and supervision, in partial fulfillment of the requirements for the award of the degree, M. Tech. Computer Science & Engineering (Image Processing) of **APJ Abdul Kalam Technological University**.

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Gowri B Nair

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Abstract

One form of cancer that begins in the breast is breast cancer. When cells start to multiply uncontrollably, cancer develops. Men are much less likely than women to develop breast cancer. One in eight females globally is impacted by it. Breast cancer cells often develop a tumor, which is frequently detectable on an x-ray or as a lump. The malignancy of the breast tissue cells is used to diagnose it. Histopathology pictures acquired by a microscope are used by modern medical image processing tools, which subsequently analyze the images using various algorithms and procedures. Medical imaging and pathology tools are being processed using machine learning techniques. Because manually identifying a cancer cell is laborious and prone to human mistakes, computer-aided processes are used to detect cancer cells and produce results that are superior to those of manual pathological detection systems. This is often accomplished in deep learning by first extracting features using a convolutional neural network (CNN), and then categorizing them using a transfer based on Resnet50.

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Chapter 1

Introduction

Finding uncommon occurrences, observations, or bodily components that deviate significantly from the norm is known as medical anomaly detection. The abnormality, in this case, was discovered after breast cancer was detected. Breast cancer is a tumor that starts in the cells of the breast. Women of all sorts are most likely to get breast cancer. In women than in males, breast cancer is more prevalent. Breast cancer symptoms include a tumor in the breast, bleeding nipple, and changes to the nipple's or breast's shape or texture. The two forms of breast cancer are benign and malignant. Non-cancerous benign tumors are life-threatening, but they do not spread outside of the breast and have aberrant growths. The two most frequent reasons for lumps are cysts and fibrosis. These alterations could cause breast enlargement and pain. A cancerous tumor that starts in the breast cells is called a malignant tumor.

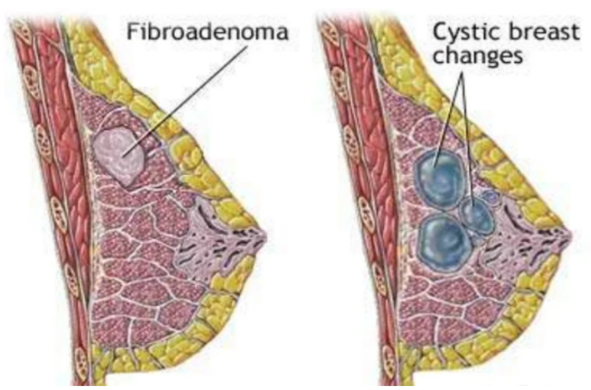

Figure 1.1: Common benign causes of breast lumps

Early detection is necessary to advance the cancer battle. Breast cancer detection methods have been developed, including digital pathology and medical image processing. Every eighth woman on the planet receives a breast cancer diagnosis. Typically, breast cancer cells develop a tumor, which may be felt as a lump or seen on x-rays. It is identified by checking for cancer in the cells of the breast tissue. The stage of cancer determines the course of treatment. By far, mammography is the most widely used imaging method.

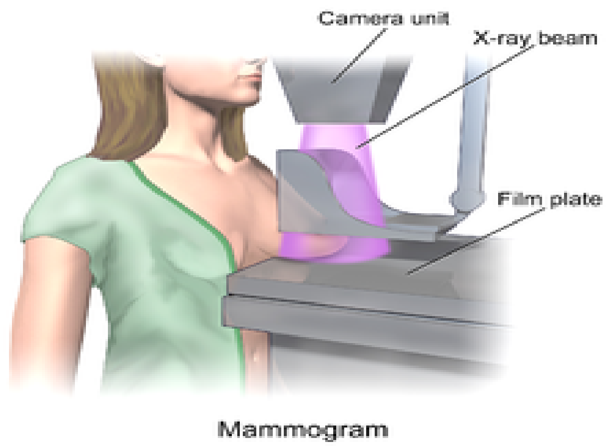

Figure 1.2: Mammogram

For the cancer fight to succeed, early detection is crucial. Medical image processing and digital pathology are two examples of breast cancer detection methods that have been developed. It is now quite easy to store tiny glass slides as digital slides on a computer for processing because of the arrival of technical equipment such as specialized scanning machines and improvements in storage/cloud capabilities. It has enabled speedier analysis, systematic and safe pathology data preservation, and remote diagnosis. Histopathological pictures are captured using a microscope in modern medical image processing techniques, and these images are then analyzed utilizing a variety of algorithms and methodologies. Machine learning techniques are increasingly being used to analyze medical pictures and pathology tools. Medical image processing based on machine learning produces more precise results as compared to objective diagnosis.

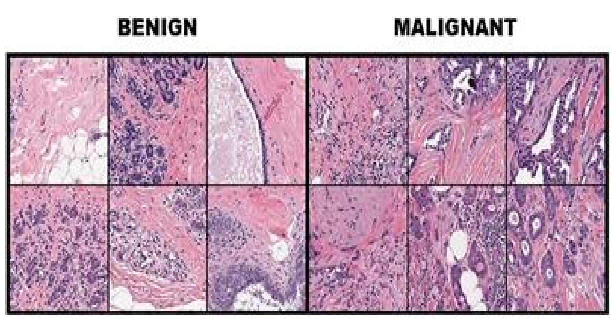

Figure 1.3: Histopathological image of Benign and Malignant tumor

Since malignant tumors are harmful and need to be treated right away to lessen and avoid subsequent issues, the objective is to determine if a tumor is benign or malignant in nature. It is, in essence, a binary classification issue that may be handled using a variety of machine learning techniques.

1.1 Proposed Project

As machine learning algorithms are already being utilized for analyzing medical images and pathology tools, the project's goal is to identify and categorize breast cancer using machine learning. The manual identification of cancer cells is a laborious job that is subject to human mistakes.

1.1.1 Problem Statement

Develop an effective method for medical imaging that requires the detection of breast cancer.

1.1.2 Proposed Solution

The proposed solution is using convolutional neural network that uses the histopathological input image to classify whether the tumor is benign or malignant.

Chapter 2

Report of Preparatory Work

2.1 Literature Survey Report

Cancer diagnosis in histopathological image: CNN based approach

In [1], they presents and evaluates a deep learning architecture for automatic breast cancer diagnosis that includes machine learning and image categorization ideas. Different Deep Neural Network topologies have been described, particularly ones geared to image data, such as Convolutional Neural Networks. This took the raw pixels from the labelled (benign/malignant) input image and highlighted the visual patterns, which were then utilised to discern between non-cancerous and cancer-containing tissue, similar to how digital staining uses a classifier network to highlight image segments important for diagnostic judgments. The RGB colour model was used to train the CNN, which included 2480 benign and 5429 malignant samples.

Breast cancer detection by leveraging Machine Learning

In [2] they present the innovative DNNS approach for detecting breast cancer. The proposed method, unlike others BC detection methods namely; Na¨ıve Bayes Classifier, Support Vector Machine (SVM) Classifier, Bi-clustering and Ada boost Techniques, R-CNN (Convolutional Neural Networks) Classifier, Bidirectional Recurrent Neural Networks (HA-BiRNN), is based on the Support value of a deep neural network. A normalising method has been used to improve image performance, efficiency, and quality. Experiments have shown that the suggested DNNS is far superior to existing approaches. The proposed method is proven to be favourable in terms of performance, efficiency, and image quality, all of which are critical in today's medical systems. There are three stages to the proposed DNNS approach. The input cytology pictures are pre-processed for noise removal in the Pre-processing phase. This was accomplished by the use of an effective filtering mechanism. The entropy, geometrical, and textural elements are retrieved from the pre-processed images in the second phase. The final phase uses the retrieved images to segment the breast tumour. This was accomplished through the use of Histo-sigmoid based fuzzy clustering.

Breast Cancer Detection using Machine Learning Techniques

The proposed methodology in [3] will help us discriminate between malignant and benign tumours more quickly. CNN, despite being a sophisticated and difficult classifier, may extract critical characteristics without the need for preprocessing. It is more capable since it filters the relevant factors and is also more adaptable because it can work with picture data very well.Breast cancer is the most common reason for deaths due to cancer. Detecting cancer at an early stage is critical. For the goal of diagnosing breast cancer data, a variety of Machine Learning approaches are accessible. This research proposes a Machine Learning model for doing automated breast cancer diagnosis. CNN was used as a classifier model, and Recursive Feature Elimination (RFE) was used to choose features. The research also compares five algorithms: SVM, Random Forest, KNN, Logistic Regression, and Nave Bayes classifier. On the BreaKHis 400X Dataset, the system was tested. The system's accuracy and precision are used to evaluate its performance. To anticipate the outcomes in terms of probability, activation functions such as ReLu have been utilised.

Cancer Cells Detection Using Digital Image Pro- cessing Methods

In [4] the purpose is to find the cancerous cells present in the CT images of lung and give more accurate result by using various enhancement and segmentation techniques such as thresholding and watershed transform. Due to the normal path of lymph from the lungs, which travels toward the middle of the chest, lung cancer frequently spreads in this manner. When a cancerous cell spreads from the location of its origin to a lymph node or to another area of the body through the path of blood flow, this is known as metastasis. Thresholding helps distinguish between the foreground and background. The grey level image can be transformed to a binary image by selecting an appropriate threshold value T. The position and shape of the objects of interest should be completely disclosed in the binary image (foreground). Markers are employed in the watershed segmentation process. A connected element that is a part of an image is a marker. Both internal and exterior markers—associated with the backdrop and points of interest, respectively—are included in the markers. A watershed segmentation method using markers can extract distinct boundaries from an image. The benefit of watershed segmentation is that it generates a special answer for a certain image. Marker watershed segmentation also solves the over-segmentation issue.

Deep Features for Breast Cancer Histopathological Image Classification

In [5] they used the BreaKHis dataset to look into the usage of DeCAF characteristics for breast cancer detection. Because of the vast scale of the BreaKHis dataset, they were able to compare CNNs trained from scratch with (DeCAF) features repurposed from another CNN trained on natural images on the same dataset, which is frequently not achievable with medical imaging datasets due to their small size. The results show that these features are a feasible alternative for quickly developing picture recognition systems based on deep learning, and that this system outperforms systems based on visual feature descriptors.Recent BC recognition results reveal that Convolution Neural Networks (CNN) can achieve higher recognition rates than hand-crafted feature descriptors, but at the cost of increased system complexity, which necessitates more training time and specific knowledge to fine-tune the CNN architecture. DeCAF (or deep) features are an in-between solution based on reusing previously taught CNNs as feature vectors, which are subsequently utilised as input for a classifier trained specifically for the new classification problem. They compare DeCaf features to other techniques in order to better understand how they compare. The experimental results demonstrate that these features can be a feasible option to fast creation of high-accuracy BC recognition systems, surpassing task-specific CNNs in some situations and generally outperforming standard hand-crafted textural descriptors.

Deep Learning in Breast Cancer Detection and Classification,

In [6], they examine and contrast the most recent proposed models for breast cancer detection and classification in order to lower the breast cancer-related death rate. A Convolutional Neural Network (CNN) is a set of convolutional layers that can extract features from images without the need for feature engineering. As a result, CNN has become the most extensively utilised method for image interpretation tasks in a variety of disciplines, including the identification and classification of breast cancer. Following CNN's success in standard object detection tasks, various studies have used deep CNNs to overcome the limitations of traditional mass detection methods. In this research, we analyse the most recent machine learning-based breast cancer detection and classification models and offer them in the form of a comparative study. In addition, the datasets that are free to use and popular are listed in this document to make any new experiments and comparisons easier. The recent top accuracy models based on simple detection and classification architectures are You Only Look Once (YOLO) and RetinaNet, according to the comparison analysis.

Boosting Breast Cancer Detection Using Convolutional Neural Network

The [7] paper proposes a convolutional neural network (CNN) method for improving the automatic detection of breast cancer by detecting hostile ductal carcinoma tissue zones in whole-slide images (WSIs). The research explores a suggested system for automatically detecting breast cancer that uses several convolutional neural network (CNN) designs, comparing the results to those obtained using machine learning (ML) algorithms. The proposed approach is shown to be successful, yielding results with an accuracy of 87 percent, potentially reducing human errors in the diagnosing process. Furthermore, our suggested approach outperforms the 78% accuracy of machine learning (ML) techniques. As a result, the suggested method enhances accuracy by 9% over the results of machine learning (ML) algorithms. For image recognition and healthcare monitoring, several earlier research have advocated using AI and CNN. However, the accuracy percentage for a medical side answer is too low, at roughly 60% for all classes, 75% for only bulk class, and 100% for only calcification. Except for the only calcification argument, the accuracy of all arguments and the mass alone argument can be improved to produce a better outcome. As a result, the goal of this study is to use CNN to improve the precision of breast cancer diagnosis. The current research provides a breast cancer diagnosis system based on multiple regression and DL approaches. The suggested approach analyses a number of CNN architectures for the diagnosis of this sort of cancer automatically.

Breast Cancer Diagnosis Using Deep Learning Algorithm

The [8] research demonstrates how the UCI Dataset may be used to diagnose breast cancer using deep learning technologies. Because deep learning techniques are almost exclusively employed for tasks with high task objectives, such as computer vision, image processing, medical diagnosis, and neural language processing. However, in this paper, we use deep learning technology to analyse the Wisconsin Breast Cancer Database, and we've discovered that it's quite useful for diagnosing breast cancer with a 99.67 percent accuracy. This work is organised into three sections. First, we gathered data and used a pre-processing algorithm to scale and filter it. Next, we separated the dataset into training and testing groups and generated graphs to visualise the data. The dataset in this database contains 569 rows and 30 features. In this research, we employed 11 features obtained after pre-processing to diagnose breast cancer. However, before training the model, we used several pre-processing algorithms for the scaled dataset, such as Label Encoder, Normalizer, and StandardScaler, and then applied the model and attained accuracy. In this research, we compare deep learning algorithms to various machine learning algorithms and show that our suggested system outperforms the competition.

2.2 System Study Report

Since manually detecting a cancer cell is a difficult process that is prone to human error, computer-aided approaches are utilized to provide better results than manual pathological detection systems. This is commonly done in deep learning by first extracting features using a convolutional neural network (CNN), and then categorizing them using a Transfer Network constructed using the Resnet50 architecture.

Chapter 3

Project Design

3.1 Resource Requirements

3.1.1 Hardware & Software Requirements

Processor : Intel Core i5 7th Gen 3.2GHz
Supporting Software and Libraries : Python, Tensorflow, Keras, OpenCv
RAM : 8GB
Graphics Card : 6GB NVIDIA GeForce GTX 1060 GPU
Operating System : Any Operating System
Supporting Environment : Google Colab
and PC available in Computer Lab-4 CEC

3.1.2 Data Requirements

The Wisconsin Original Data Set (UC Irvine Machine Learning Repository), MITOS- ATYPIA-14, and BreakHis are only a few of the datasets that are accessible for histopathological stained photos (Kaggle). We used the BreakHis database, which was built from data from a survey conducted by PD Lab, Brazil, between January 2014 and December 2014[1]. Due to the scarcity of samples and the need to maintain patient anonymity about their demographic data, gathering a dataset of MRI images of breast cancer is extremely challenging.

3.2 Method

The suggested approach is divided into two phases. Histogram equalisation is used in the preprocessing stage to improve the input image. The improved picture is forwarded to the trained network in the second phase of CNN, where it will be classified as benign or malignant depending on its characteristics.

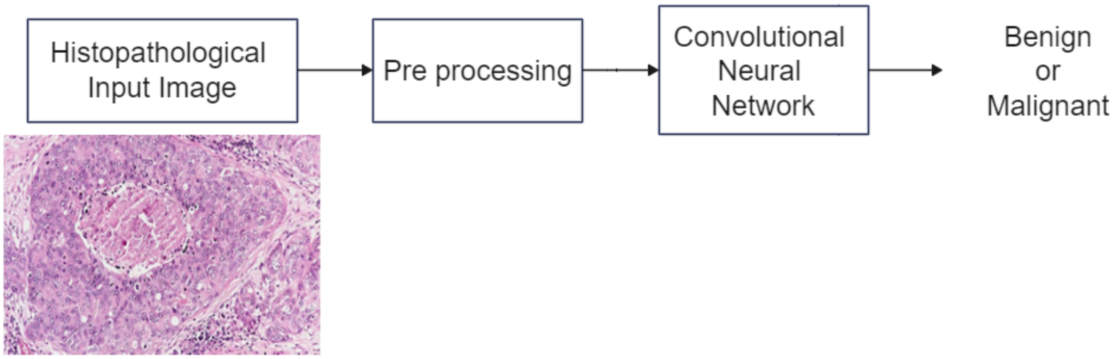

Figure 3.1: Design Block Diagram

3.2.1 Histopathological Image

Histopathology, which is the study of tissue disorders and entails looking at microscopic slides with tissues, cells, and other components, has been widely utilized to diagnose many cancers. Histopathologists are medical professionals who use a microscopic examination of cells or tissues to produce diagnoses in order to reach agreements on the type, severity, and course of treatment for various illnesses.

It is now quite simple to keep microscopic glass slides in the form of digital slides on a computer for processing thanks to the development of cutting-edge technology, such as specialised scanning devices and advancements in storage/cloud capabilities. It has made it possible to diagnose patients remotely, conduct analyses more quickly, and store pathology data in a secure manner.

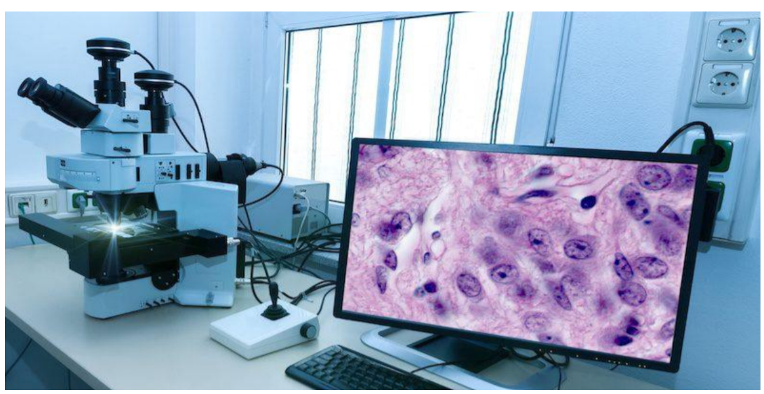

Figure 3.2: Device used to digitize histopathological image

3.2.2 Preprocessing

Contrast enhancement can be used to improve the low contrast and low quality of the histopathology input picture. Contrast enhancement involves manipulating and redistributing the picture pixels in a linear or non-linear manner to enhance the separation of hidden structural changes in pixel intensity into a more visibly distinct structural distribution. For contrast enhancement, in this case, the Histogram Equalization approach is applied.

Histogram equalization

An image's histogram reveals how many pixels are present in each of the ranges of intensity. Histogram equalization is a type of contrast amplification that extends the histogram to make all values appear (more or less) equally often. The complete gamut of potential values is used to create the final image. This frequently yields positive results, particularly when it comes to highlighting features in areas of a grayscale image that are too bright or too dark. Simple histogram equalization of the red, green, and blue channels when applied to color photos improves contrast but may also alter the color balance.

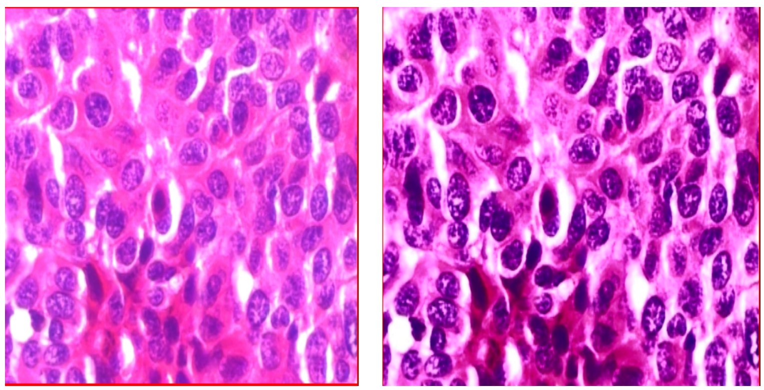

Figure 3.3: a) input image b) after histogram equalization

A method for changing picture intensities to improve contrast is histogram equalization. To achieve this, first, obtain the histogram for the input image. Additionally, determine the cumulative distribution function that corresponds to the normalized histogram as follows:

$$cdf(j) = \sum_{j=0}^{k} \frac{n_{j_r}}{n} \tag{3.1}$$

n being the total number of pixels in the image. Transform input image's intensity r_k into output image's intensity s_k

$$s_k = T(r_k) = round(cdf(r_k) * (L-1)) \tag{3.2}$$

where round() rounds down to the nearest integer. Store s_k into equalized array.

3.2.3 Convolutional Neural Network

A deep learning network design known as a convolutional neural network (CNN or ConvNet) learns directly from input, doing away with the requirement for human feature extraction. CNNs are very helpful for recognising objects, people, and scenes in photos by looking for patterns in the images. For categorising non-image data, such as audio, time series, and signal data, they can be highly useful. CNNs are a key component of many computer vision and object identification applications, including those used in self-driving cars and face recognition.

Residual Networks, or ResNets, instead of learning unreferenced functions, learn residual functions with reference to the layer inputs. Residual nets let these layers fit a residual mapping rather than expecting that every few stacked layers directly match a desired underlying mapping. To create a network, they stack residual blocks on top of one another; for example, a ResNet-50 uses these blocks in fifty layers.

A convolutional neural network with 50 layers is called ResNet-50. It loads a network that has already been trained using data from the ImageNet database and more than a million photos. The trained network is able to categorize photos into 1000 different item categories. The foundation is transfer learning.

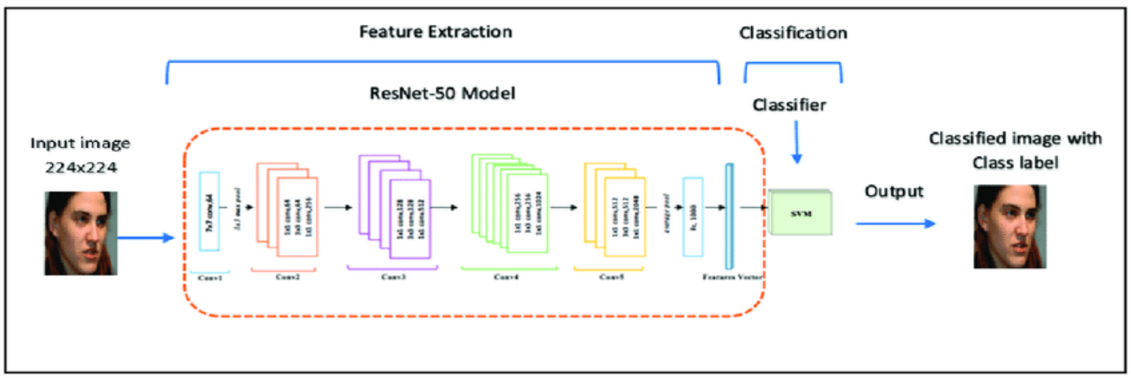

Figure 3.4: Resnet50 Architecture

ResNet50 is a variant of ResNet model which has 48 Convolution layers along with 1 MaxPool and 1 Average Pool layer. It has $3.8x10^9$ Floating points operations. It is a widely used ResNet model.

Transfer Learning

Transfer Learning is a machine learning research issue (ML). It focuses on retaining information obtained while resolving one issue and using it to address an unrelated but similar issue later on. To put it another way, TL is a machine learning approach where a model developed for one job is used for another similar task. Learning a new task depends on learning an earlier task.

Chapter 4

Implementation

The aim of the project is the detection and classification of breast cancer using machine learning. First of all, the input image is the histopathological image. Histopathology is the study of diseases of tissues that involves the examination of microscopic slides consisting of tissues, cells, etc, that has been extensively used for the diagnosis of various forms of cancer.

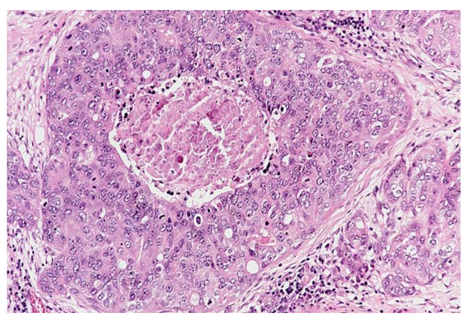

Figure 4.1: Histopathological image

The histopathological picture is then pre-processed using histogram equalization, which is used to equalize the image's intensity because the image might have fluctuations in intensity in various locations and certain sections of the image may not be clearly seen. Histogram equalization extends the histogram such that all values appear (more or less) equally often. It is a type of contrast enhancement. The whole range of potential values is utilized in the final picture. As a result, after performing histogram equalization, the image's contrast will be improved, bringing out any sections or details that were before hidden.

The picture may then be categorised as benign or malignant using the CNN model known as resnet50. A convolutional neural network with 50 layers is called ResNet-50. It loads a network that has already been trained using data from the ImageNet database and more than a million photos. The trained network is able to categorise photos into 1000 different item categories. There are 5 stages in the ResNet-50 model, each having a convolution and an identity block. Each identity block and each convolution block each have three convolution layers. Over 23 million parameters may be trained with the ResNet-50. Transfer learning serves as its foundation. The technique of employing a model that has already been trained on one dataset to train and predict on another is known as transfer learning. The primary objective of the resnet50 is to recognize the characteristics of the picture at each stage and then categorize it as malignant or non-cancerous.

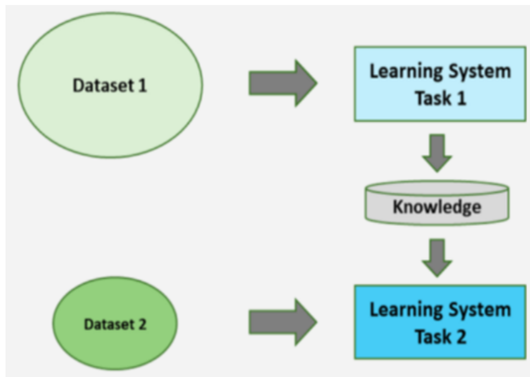

Figure 4.2: Transfer Learning

Utilizing the Google Colab platform, the proposed model is implemented in the TensorFlow framework. The model is trained with a Histopathology image dataset with a batch size of 64 and an image size of 224 × 224. The optimizer used is the Adam optimizer. Here the pre-processing strategy is used, which is implemented in the OpenCV framework. The model is trained using more than 8000 images and it is trained in 100 epochs.

Image Size	224x224
Batch Size	64
Epoch	100
Optimizer	Adam

Figure 4.3: Training Parameters

Chapter 5

Results & Conclusions

5.1 Performance Analysis of Model

Testing the model allows for model evaluation to determine its performance analysis using the BreakHis dataset. The accuracy of the model is 94%.
Some of the results of testing of the model with BreakHis dataset is shown below.

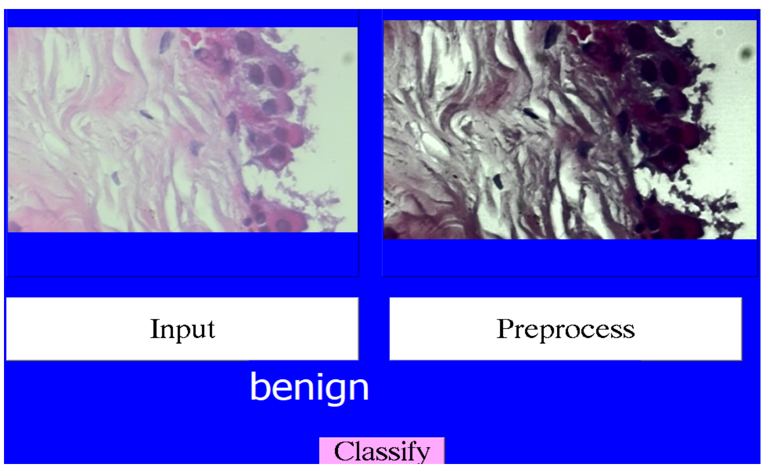

Figure 5.1: Test

5.2 Conclusion

I studied a lot of research papers and other resources based on cancer detection and it is found that most of the research relies on convolutional neural networks. I proposed a CNN model called Resnet50 for the classification of the tumor whether the tumor is benign or malignant. Resnet50 is not often used in the classification of tumors. I have trained the dataset BreakHis database, preprocessed the image using histogram equalization, and tested the model using images from the dataset and the images outside the dataset to classify whether it is benign or malignant.

5.3 Future Scopes

In this project detection of breast cancer is done with pre-processing using histogram equalization, in future the other pre-processing step can be done and here histopathological images are used for the detection, in future images such as MRI images, CT, ultrasound, mammogram images, X-ray, etc can be used for the detection of breast cancer.

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