DAYANANDA SAGAR UNIVERSITY

KUDLU GATE, BANGALORE – 560068

Bachelor of Technology in
COMPUTER SCIENCE AND ENGINEERING

Major Project Phase-II Report

(Breast Cancer Detection And Classification Using CNN)

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(2021-2022)

DAYANANDA SAGAR UNIVERSITY

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CERTIFICATE

This is to certify that the Phase-2 project work titled **"BREAST CANCER DETECTION AND CLASSIFICATION USING CNN"** is carried out by **Chetan SA (ENG18CS0073), Chaitanya Srikar (ENG18CS0078), Dharanisree PS (ENG18CS0088), Dhruv Budhiraja (ENG18CS0092), Hanumesh M (ENG18CS112),** a bonafide students of Bachelor of Technology in Computer Science and Engineering at the School of Engineering, Dayananda Sagar University, Bangalore in partial fulfillment for the award of degree in Bachelor of Technology in Computer Science and Engineering, during the year **2021-2022**.

Prof Ranjini.K	**Dr.Girisha S**	**Dr. A Srinivas**
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Dept. of CS&E,	School of Engineering	School of Engineering
School of Engineering	Dayananda Sagar University	Dayananda Sagar University
Dayananda Sagar University		
Date:	Date:	Date:

Name of the Examiner	**Signature of Examiner**
1.	
2.	

DECLARATION

We, **Chetan SA (ENG18CS0073), Chaitanya Srikar (ENG18CS0078), Dharanisree PS (ENG18CS0088), Dhruv Budhiraja (ENG18CS0092), Hanumesh M (ENG18CS112),** are students of seventh semester B.Tech in **Computer Science and Engineering**, at School of Engineering, **Dayananda Sagar University**, hereby declare that the phase-II project titled **"Breast Cancer Detection And Classification Using CNN"** has been carried out by us and submitted in partial fulfilment for the award of degree in **Bachelor of Technology in Computer Science and Engineering** during the academic year **2021-2022**.

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Signature of Students

TABLE OF CONTENTS

ABSTRACT

Changes in lifestyle and food habits have led to many chronic diseases such as high blood pressure, diabetes, and tumors. These diseases, especially tumors, are spreading very rapidly. The tumors are mainly of two types: benign tumors and malignant tumors. In the case of benign tumors, the disease is localized and does not spread in other parts of the body, and hence, this type of tumor is not that harmful to life. The malignant tumor, which is also known as a cancerous tumor, spreads to other parts of the body and affects them; hence, this type of tumor is very harmful. Several works on different machine learning methods such as logistic regression, random forest, support vector classifier (SVC), AdaBoost classifier, bagging classifier, voting classifier, and Xception model are carried out to classify the breast cancer tumor and evaluate their performances.The logistic regression classifier provides the scores of each precision, recall, and F1 measure as 0.72. The random forest method provides the score of each precision, recall, and F1 score as 0.80. The bagging and voting classifiers both have the values of each precision, recalls, and F1 scores as 0.81. In this case, both SVC and AdaBoost classifiers have the score of each precision, recall, and F1 score as 0.82. But, in the case of the deep learning method, Xception model is used to have the score of each precision, recall, and F1 measure as 0.90. Hence, we build a deep learning Convolutional Neural Network (CNN) model to efficiently classify the tumors at an early stage.

CHAPTER 1 INTRODUCTION

Breast cancer can be effectively treated through its early detection. , us, the availability of proper screening methods is important for detecting the initial symptom of breast cancer. Various imaging techniques are used for the screening to identify this disease; the popular approaches are mammography, ultrasound, and thermography. One of the most significant methods of early detection for breast cancer is mammography. Ultrasound or diagnostic sonography methods are popularly used as mammography is not effective for solid breasts. Considering these issues, small masses can be bypassed by radiations from radiography and thermography may be more effective than the ultrasound technique in diagnosing smaller cancerous masses. Due to the intrinsic difficulties associated with an image, with meager contrast, noise, and lack of appreciation by the eye, instruments have been prepared to make and improve image processing. Nowadays, artificial intelligence (AI), machine learning (ML), and convolutional neural networks (CNN) are the quickest rising areas of the healthcare industry. The main advantage of deep learning, especially CNN, is to have high-level features by using the top layer of the image automatically. These features improve classification accuracy as compared to hand-build features that are used in the classical methods. These top layered features are robust to the image transformation.

1.1. RELEVANT WORKS ON CNN:

The opportunity that CNN brings to research on medical imaging is not restricted to deep CNN for extraction of the imaging feature. Indeed, a second field that can support medical research is the use of CNN for synthetic image rendering.Wahab and Khan conducted a study by using MF-CNN (multifaceted fused-CNN) and a hybrid descriptor and revealed that, to assist with mitotic count-based selection of ROIs at lower resolution, acceptable was performed by Tsochatzidis et al to test the diagnosis of breast cancer with mammograms using CNN. They show that performance assessment in diagnosis is carried out on two datasets of mammographic mass such as DDSM-400 and CBIS-DDSM, with variations in the accuracy of the corresponding segmentation maps of ground truth.The study of Abdelhafiz et al. also discovered that augmentation approach was fruitful in the automatic identification of this cancer, when using the given dataset. Another researcher applied deep max pooling CNNs to identify images of mitosis in breast histology. The networks were competent to order the images based on pixel. A DL approach was used by Murtaza et al. for the automatic identification and investigation of IDC tissue zones. Context-aware stacked CNNs were presented by Hossain for the categorization of breast WSIs into simple DCIS (ductal carcinoma insitu), and IDC (invasive ductal carcinoma).

1.1.1. **AIM AND SCOPE:**

The main aim of this work is to build an algorithm to automatically identify whether a patient is suffering from breast cancer or not by looking at biopsy images. The algorithm had to be extremely accurate because the lives of people are at stake.This work aims to make use of Deep Convolutional Neural Networks(CNN) architecture to classify the given image as benign or malignant.

1.1.1.1. *Related Works on BCC using ML/AI:*

In 2019, Kadam et al., demonstrated a method for Breast Cancer Classification (BCC) using Feature Ensemble Learning. They developed Stacked Sparse Autoencoder and Softmax Regression for the detection of benign cells to malignant cells. They achieved 98.6% accuracy for the Wisconsin Breast Cancer Dataset (BCD) . Quite a lot of studies have been stated in the literature and are based on diverse approaches that could permit premature cancer investigation and prediction, which includes SVM, Decision Trees, Artificial Neural Network, Minimum Distance Classifier , Fuzzy Classifier, Fuzzy Rough Neural Network, Particle swarm optimization, microRNA and biomarkers, and others like Deep Learning approaches.. In 2018, Rankhlin et al., demonstrated a technique for the BCC from the Histology Image Analysis using deep convolutional neural networks. In 2016, Xu et al., proposed a method for the nuclei detection on breast cancer histopathology images using Stacked Sparse Autoencoder . In 2001, Baldi et al., demonstrated a detection method for breast cancer using mammography images. However, this method is not sufficient enough and misclassified almost 15% cases of breast cancer. M. Akayet al demonstrated a method for the diagnosis of breast cancer and they achieved an overall accuracy of 99.51%, sensitivity 100%, and specificity of 97.91%. They used 80-20% train + validate, and test ratio partitions.

1.2. FIGURES AND TABLES

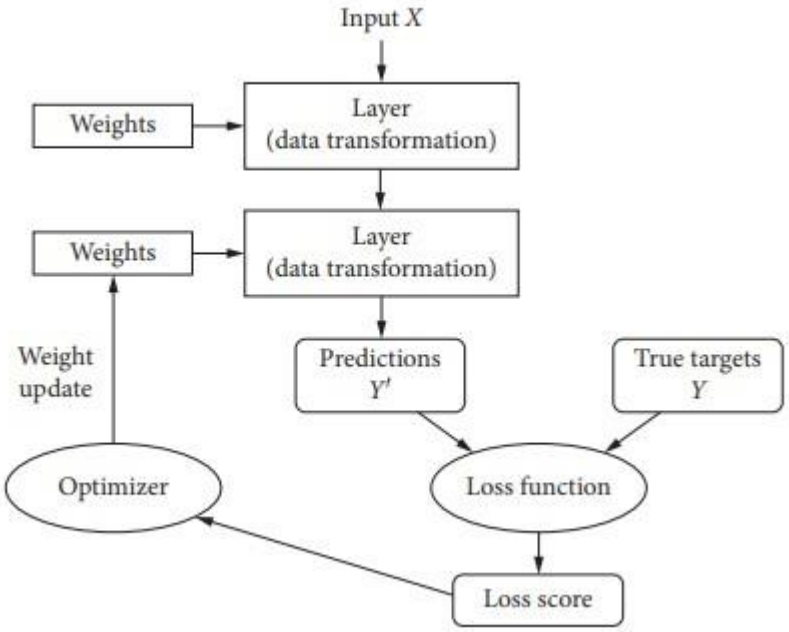

Figure 1.1 : Detailed process of a neural network (NN)

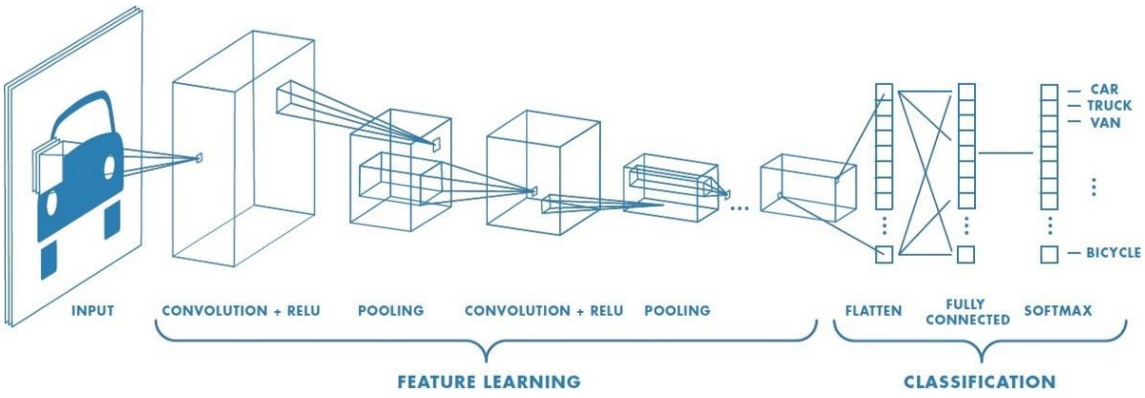

Figure 1.2 Typical CNN Architecture

```
Model: "sequential"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 vgg19 (Functional)          (None, 7, 7, 512)         20024384

 dropout (Dropout)           (None, 7, 7, 512)         0

 flatten (Flatten)           (None, 25088)             0

 batch_normalization (BatchN  (None, 25088)            100352
 ormalization)

 dense (Dense)               (None, 1024)              25691136

 batch_normalization_1 (Batc  (None, 1024)             4096
 hNormalization)

 activation (Activation)     (None, 1024)              0

 dropout_1 (Dropout)         (None, 1024)              0

 dense_1 (Dense)             (None, 1024)              1049600

 batch_normalization_2 (Batc  (None, 1024)             4096
 hNormalization)

 activation_1 (Activation)   (None, 1024)              0

 dropout_2 (Dropout)         (None, 1024)              0

 dense_2 (Dense)             (None, 1024)              1049600

 batch_normalization_3 (Batc  (None, 1024)             4096
 hNormalization)

 activation_2 (Activation)   (None, 1024)              0

 dropout_3 (Dropout)         (None, 1024)              0

 dense_3 (Dense)             (None, 2)                 2050

=================================================================
Total params: 47,929,410
Trainable params: 27,848,706
Non-trainable params: 20,080,704
```

Figure 2.1 CNN Architecture

1.3. SCOPE

Non-communicable diseases (NCD) such as breast cancer (BC) is one of the dominant factors of mortality around the globe. BC is the most common cancer among females. According to the report of the International Agency for Research on Cancer (IARC), 367, 900 new cases against BC were registered in China during 2018. Pathologists in routine examine visually and navigate the entire pathological images to analyze and identify the abnormalities inside the medical image. Moreover, the diagnosis based on the clinical diagnostic methods requires a significant amount of time to determine whether the medical image is cancerous or non-cancerous. This process is very tedious and prolonged. In addition, the human eye is less adept at subtle changes in the tissue and each medical professional has its own unique subjective mood of reading the pre-requisites as well as fatigue. This may result in different diagnostic conclusions by different doctors about the same medical image. Hence, the proposed work aims at classifying the image with high accuracy as human life is at peak risk. It reduces human interference unlike CAD related systems and provides the best accurate results.

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CHAPTER 2 PROBLEM DEFINITION

Build an algorithm in order to automatically identify whether a patient is suffering from breast cancer or not by looking at biopsy images. The algorithm has to be accurate because lives of people is at stake. The algorithm needs to be quick and as accurate as possible as People's lives are taken of at most importance and hence quick.. Hence , the main goal here is to minimize the human interference.

CHAPTER 3 LITERATURE REVIEW

The computer-aided diagnosis systems can be semiautomatic or automatic tools with which the radiologists find out the nature of the tumor. A paper [1] uses the K means clustering to classify a tumor. The deep learning methods based on convolution neural networks (CNN) [2] use high-level and robust features for different tasks such as in biomedical image analysis tasks like mitosis detection, semantic segmentation, classification, and blood cell counting. Nowadays deep learning-based method is getting popular due to the advancement of computing and computing technology. The main advantage of deep learning especially CNN is to have high-level features by using the top layer of the image automatically. These features improve classification accuracy as compared to hand-build features that are used in the classical methods. In case of not availability of a large amount of data, transfer learning can be used. Transfer learning fine-tunes the publicly available model for specific tasks and purposes. These publicly available models are pre-trained on a large amount of the data [3]. In the paper [4,5] set up their training procedure and CNN parameter on the pre-trained model to show their results suppressed the actual result by a large margin. In prior research, Wahab and Khan [6] used CNNs to investigate the automated detection of IDC-type breast cancer. Another researcher [7] applied deep max-pooling CNNs to identify images of mitosis in breast histology. The networks were competent to order the images based on the pixel. A DL approach was used by Murtaza et al. [8] for the automatic identification and investigation of IDC tissue zones. Context-aware stacked CNNs were presented by Hossain [9] for the categorization of breast WSIs into simple, DCIS (ductal carcinoma in situ), and IDC (invasive ductal carcinoma).

CHAPTER 4 PROJECT DESCRIPTION

Cancer is a disease that is really difficult to handle but, with timely investigations, a patient can be given extra years to survive or, in best-case scenarios, even walk out cancer-free after the right treatments. In order for all this to be even possible, we need to investigate first. Various imaging techniques are used for the screening to identify this disease; the popular approaches are mammography, ultrasound, and thermography. One of the most significant methods of early detection for breast cancer is mammography. Ultrasound or diagnostic sonography methods are popularly used as mammography is not effective for solid breasts. Considering these issues, small masses can be bypassed by radiations from radiography and thermography may be more effective than the ultrasound technique in diagnosing smaller cancerous masses. Nowadays, artificial intelligence (AI), machine learning (ML), and convolutional neural networks (CNN) are the quickest rising areas of the healthcare industry. The main advantage of deep learning, especially CNN, is to have high-level features by using the top layer of the image automatically. These features improve classification accuracy as compared to hand-build features that are used in the classical methods. These top layered features are robust to the image transformation. Our project's aim is to use these top layered features to help and detect cancers early which might be a difficult job for a human being as our eyes can't detect minute patterns and changes in reports.

4.1 PROPOSED DESIGN

4.1.1. DATASET DESCRIPTION:

We have obtained the mammograms images from Kaggle MIAS dataset. The size of all the images is 1024 pixels x 1024 pixels. When calcifications are present, centre locations and radii apply to clusters rather than individual calcifications. Coordinate system origin is the bottom-left corner, whose labels are as follows:

- 1st column:
  MIAS database reference number.
- 2nd column:
  Character of background tissue:
  F Fatty
  G Fatty-glandular
  D Dense-glandular
- 3rd column:
  Class of abnormality present:
  CALC Calcification
  CIRC Well-defined/circumscribed masses
  SPIC Spiculated masses
  MISC Other, ill-defined masses
  ARCH Architectural distortion
  ASYM Asymmetry
  NORM Normal

- 4th column:

  Severity of abnormality;

  B Benign

  M Malignant

- 5th, 6th columns:

  x,y image-coordinates of centre of abnormality.

- 7th column:

  Approximate radius (in pixels) of a circle enclosing the abnormality.

The original dimension of the dataset table is 322 rows*7 columns. But , we drop “nan” in severity column which indicates normal. Hence the size of the dataset is reduced to 115 rows*7 columns.

]:

	refnum	bg	ab_class	severity	x	y	radius
0	mdb001	G	CIRC	B	535.0	425.0	197.0
1	mdb002	G	CIRC	B	522.0	280.0	69.0
2	mdb005	F	CIRC	B	477.0	133.0	30.0
3	mdb010	F	CIRC	B	525.0	425.0	33.0
4	mdb012	F	CIRC	B	471.0	458.0	40.0
...	...	...	...	...	...	...	...
110	mdb274	F	MISC	M	127.0	505.0	123.0
111	mdb290	D	CIRC	B	337.0	353.0	45.0
112	mdb312	F	MISC	B	240.0	263.0	20.0
113	mdb314	F	MISC	B	518.0	191.0	39.0
114	mdb315	D	CIRC	B	516.0	447.0	93.0

115 rows × 7 columns

Table 1.1 Dataset description

4.1.2. CNN MODEL'S STRUCTURE:

We have built CNN architecture which consists of three convolution layers with dropout layer of value 0.2 as shown in figure 2.1 . A slight modification has been done to the images by cropping them , thus getting the Region Of Interest (ROI) using the radius parameter. The same above mentioned CNN architecture has been used for the cropped images as well and finally the results are compared for both with respect to training accuracy , test accuracy, F1 score, recall, precision and total parameters.

CHAPTER 5 REQUIREMENTS

5.1 FUNCTIONAL REQUIREMENTS :

Properties	**Functional Requirements**
Objective	Detects breast cancer
End Result	Output in the form of benign or real tumor
Focus	Quick Testing, Accuracy
Essentiality	Correct Results/ Investigation
Origin Type	Machine Learning/ AI
Testing	Component, API, UI testing, etc...
Types	Interface, prediction screen

5.2 NON-FUNCTIONAL REQUIREMENTS :

Properties	**Functional Requirements**
Objective	Prediction using CNN
End Result	Gives results after analysis & predicting
Focus	Final & accurate investigation
Essentiality	Good UI, Quick
Origin Type	Developers/Students
Testing	Performance, Accuracy, Usability, etc.

CHAPTER 6 METHODOLOGY

6.1. USE AND DESIGN OF CNN

As we have seen that there are numerous works done on Breast Cancer Classification using AI/ML methods, a significant amount of improvement can be seen when deep learning algorithms such as CNN are used. They not only help in code optimization, but also efficiently classifies the mammographic images into benign/malignant using minimum learning parameters. We have chosen CNN as it is excellent in image processing that makes use of filters or kernels in order to extract those features. As shown in figure 1.2, the CNN architecture is composed of three layers :

a. Convolution+Relu

b. Pooling

c. Fully Connected layers

The final step being the fully connected or deeply connected layer is where the actual classification takes place. In this case, it is a bi-classification problem. The previous layers such as convolutions and pooling are just pre-processing and extracting the features which help in final classification happening at fully connected layer .

We have used two forms of datasets where in first case , the entire image in the dataset is used to train the model. Whereas in second case, the images are cropped using radii values, hence creating the region of interest. The results are evaluated and compared for both the cases using f1 score, recall etc.

CHAPTER 7 EXPERIMENTATION

7.1. DROP NORMAL CASES FROM DATASET

In the original dataset, we drop those rows whose value for the column 'severity' is norm, which indicates that the particular mammogram is normal.

```
def create_mias_dataset(file_path: str) -> pd.DataFrame:
    ''' Creates a dataset with the data about the scans '''
    # create a dataset
    mammo = pd.read_table(file_path, delimiter='\s', engine='python')
    # rename the class column to avoid conflicts with the class keyword in python
    mammo.columns = ['refnum', 'bg', 'ab_class', 'severity', 'x', 'y', 'radius']
    # fill null severity with A for NORM class
    # mammo.severity = mammo.severity.fillna('A')
    # drop duplicates
    mammo.drop_duplicates(subset='refnum', keep='first', inplace=True)
    # set refnum as index
    # mammo.set_index(keys='refnum', drop=True, inplace=True)

    return mammo
```

```
# drop nan in severity which indicate norm
mias.dropna(subset=['severity'], inplace=True)
mias.reset_index(inplace=True)
mias.drop(['index'],axis=1,inplace=True)
mias
```

7.2. SPLITTING THE DATASET

```
x_train, x_test, y_train, y_test = train_test_split(X, Y,
test_size=0.15, random_state=2021,shuffle=True)
```

7.3. BUILDING THE CNN MODEL

```
base_model = VGG19(input_shape=(224,224,3), weights='imagenet', include_top=False)
model=Sequential()
model.add(base_model)
model.add(Dropout(0.2))
model.add(Flatten())
model.add(BatchNormalization())
model.add(Dense(1024,kernel_initializer='he_uniform'))
model.add(BatchNormalization())
model.add(Activation('relu'))
model.add(Dropout(0.2))
model.add(Dense(1024,kernel_initializer='he_uniform'))
model.add(BatchNormalization())
model.add(Activation('relu'))
model.add(Dropout(0.2))
model.add(Dense(1024,kernel_initializer='he_uniform'))
model.add(BatchNormalization())
model.add(Activation('relu'))
model.add(Dropout(0.2))
model.add(Dense(2,activation='softmax'))

for layer in base_model.layers:
    layer.trainable = False

model.summary()
```

7.4. PLOTTING THE RESULTS (TRAIN VS VALIDATE)

```
import matplotlib.pyplot as plt
def Train_Val_Plot(acc,val_acc,loss,val_loss):

    fig, (ax1, ax2) = plt.subplots(1,2, figsize= (15,10))
    fig.suptitle(" MODEL'S METRICS VISUALIZATION ")

    ax1.plot(range(1, len(acc) + 1), acc)
    ax1.plot(range(1, len(val_acc) + 1), val_acc)
    ax1.set_title('History of Accuracy')
    ax1.set_xlabel('Epochs')
    ax1.set_ylabel('Accuracy')
    ax1.legend(['training', 'validation'])


    ax2.plot(range(1, len(loss) + 1), loss)
    ax2.plot(range(1, len(val_loss) + 1), val_loss)
    ax2.set_title('History of Loss')
    ax2.set_xlabel('Epochs')
    ax2.set_ylabel('Loss')
    ax2.legend(['training', 'validation'])
    plt.show()
```

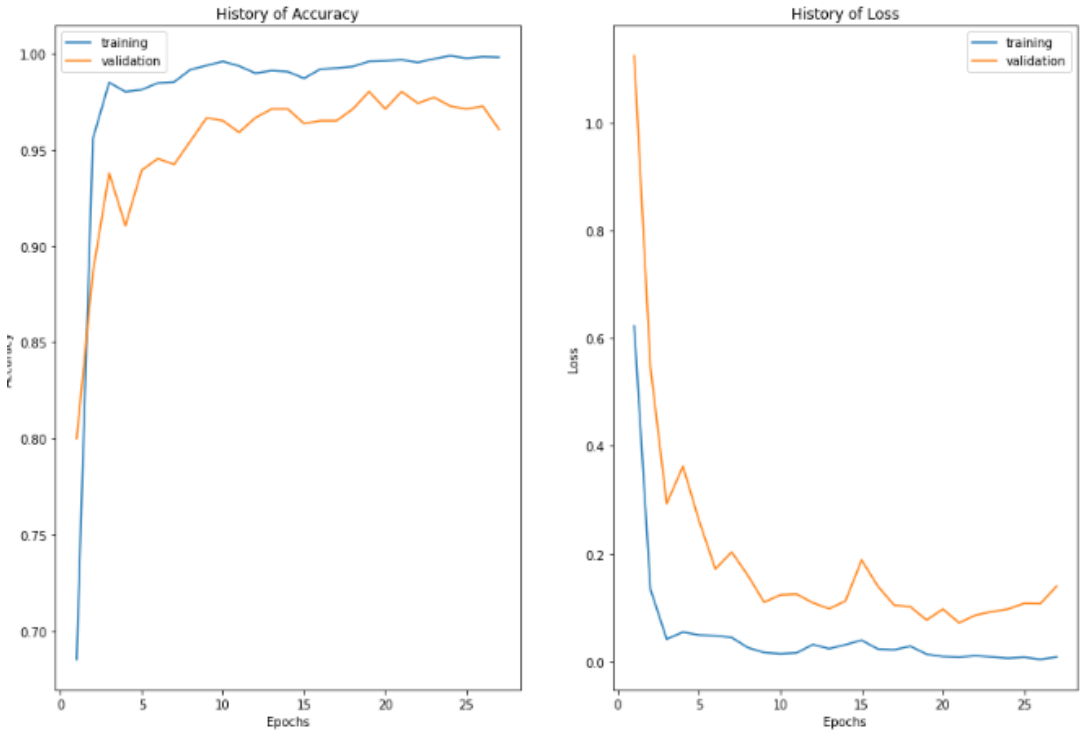
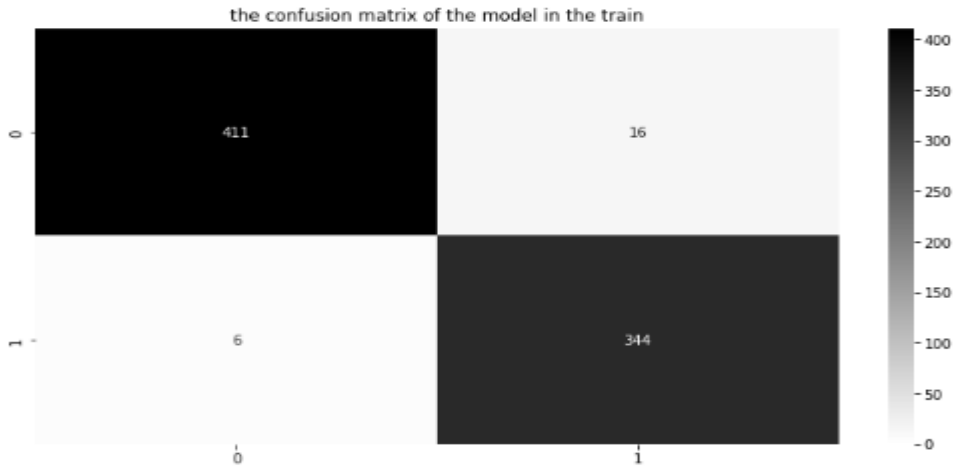


Figure 3: Model's Metrics Visualization

7.5. BUILD THE CONFUSION MATRIX

```
cm1 = confusion_matrix(y_test, y_pred)
plt.figure(figsize=(12, 6))
plt.title('the confusion matrix of the model in the train')
sns.heatmap(cm1, annot = True, fmt = 'g' ,vmin = 0, cmap = 'binary')
```



CHAPTER 8 TESTING AND RESULTS

8.1. THE INITIAL GUI

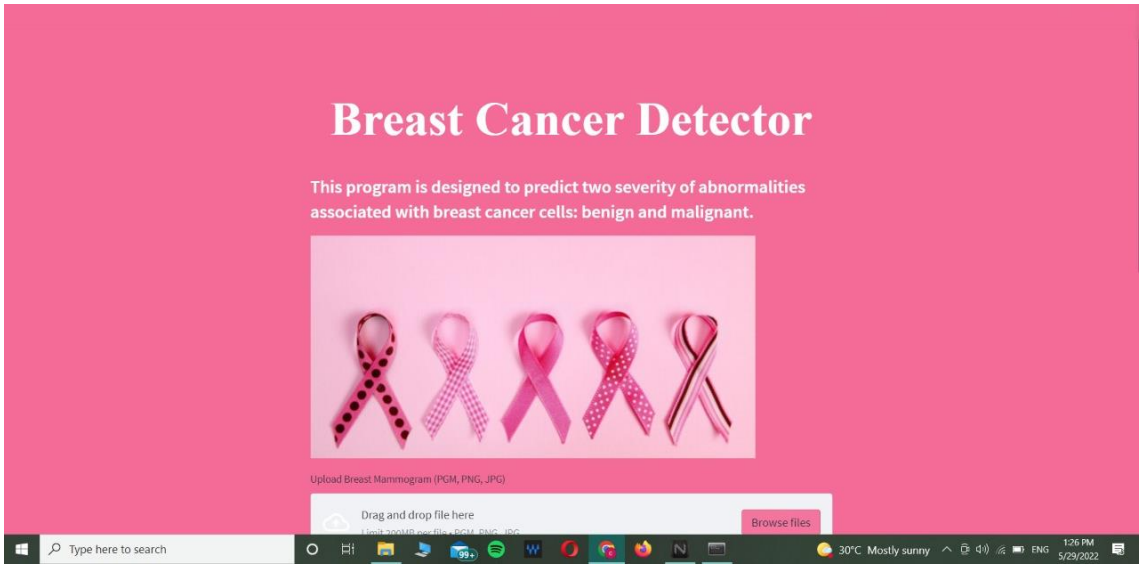


Figure 4.1: The initial GUI

8.2. TEST CASE FOR BENIGN TUMOR

8.2.1. BENIGN TUMOR WITH ACCURACY OF 100%

The following case has mammogram image of breast which is benign in nature. The accuracy in case if this image is found to be 100%.

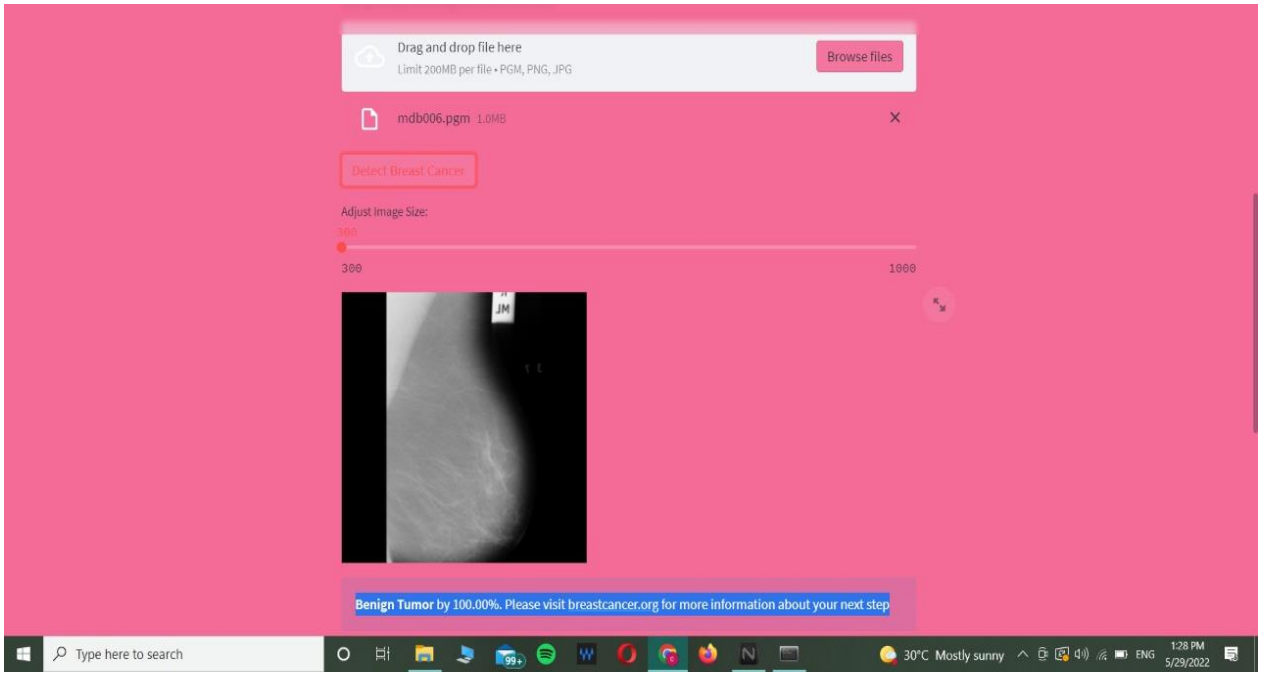


Figure 4.2: Test case for Benign with 100% accuracy

8.2.2. BENIGN TUMOR WITH ACCURACY OF 91%

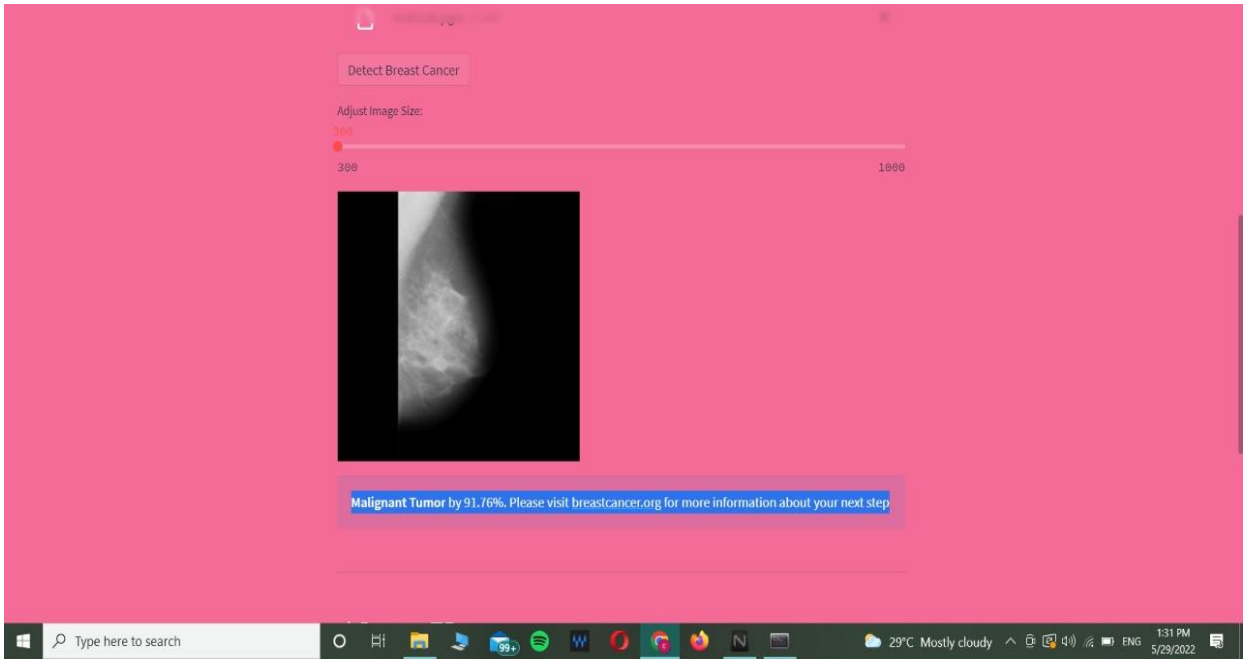


Figure 4.3: Test case for Benign with 91% accuracy

8.3. TEST CASE FOR MALIGNANT TUMOR

8.2.1.MALIGNANT TUMOR WITH ACCURACY 100%

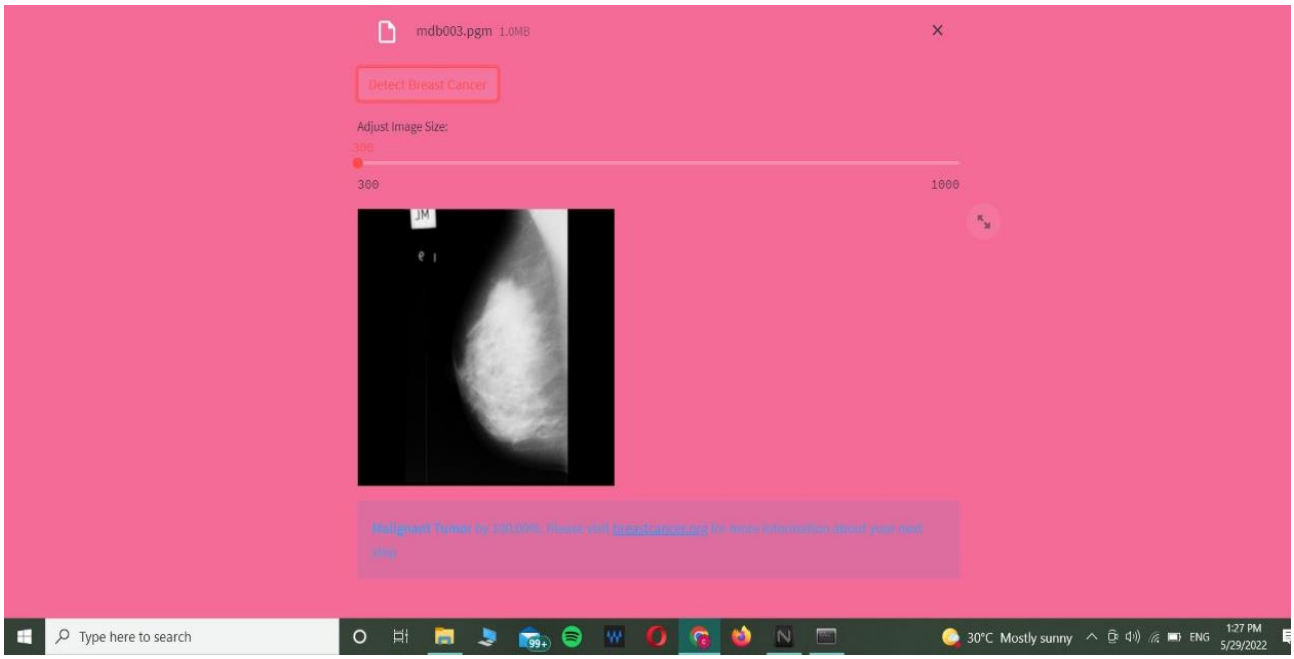
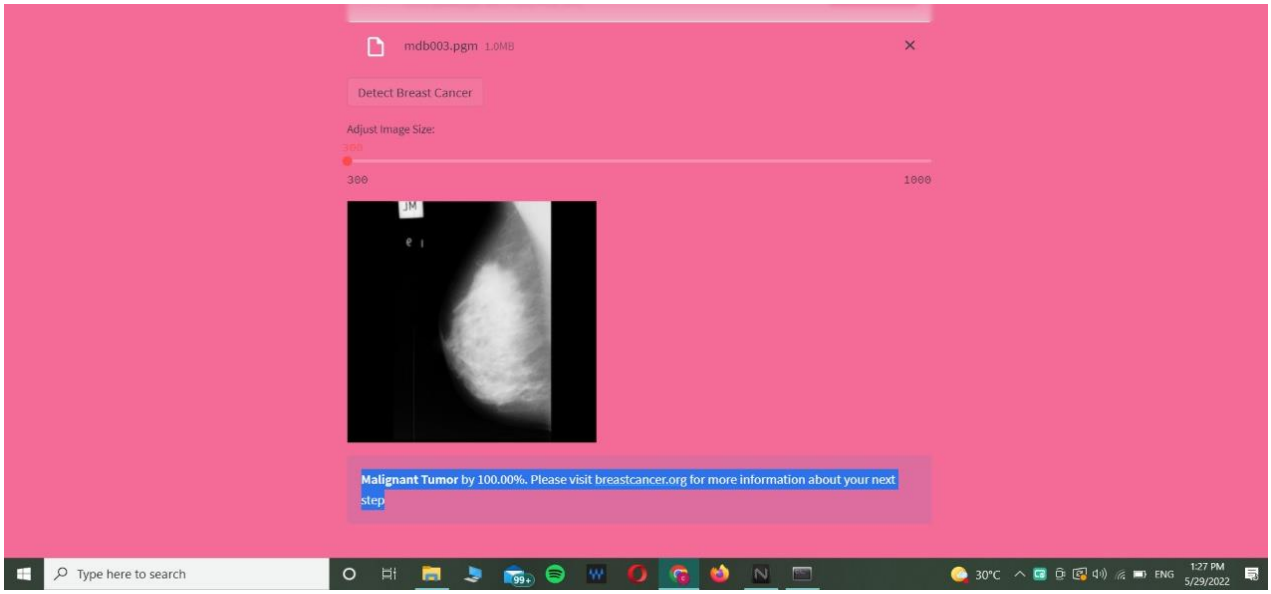


Figure 4.4: Test case for Malignant with 100% accuracy

8.2.2.MALIGNANT TUMOR WITH ACCURACY 100%



8.4. THE END SECTION OF WEB PAGE

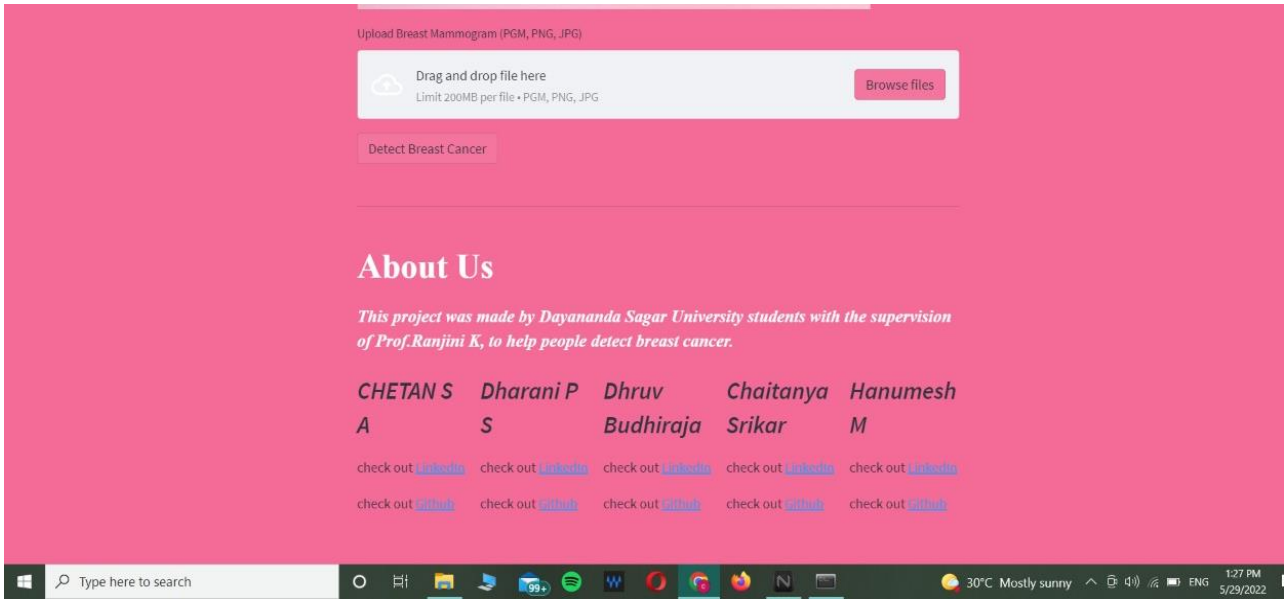


Figure 4.5: The End Section

CHAPTER 9 CONCLUSION

This work not only performs better than the traditional Machine Learning methods but also compared the results with two different forms of datasets. We can see that the accuracy obtained by cropping the image and getting the ROI leads to quite lesser accuracy compared to that of taking the whole image. We are also getting different values of accuracy for different image samples of benign and malignant which can be seen in the UI prompt after detecting the image. Hence, this work can be considered as an up thrust over previous underlying works on BCC (Breast Cancer Classification).

CHAPTER 10 FUTURE WORK

As mentioned earlier**,** the accuracy obtained by cropping the dataset images into ROI(region of interest) is quite less compared to that of the whole image . This is mainly because of the loss of information happening during the process of cropping around radius column of the image. This can be reduced or completely overridden by using SPP (Spatial Pooling Layer) and NiN(Network inNetwork). Therefore the above proposed work can be improvised further by building this new architecture called Deep SPP-NiN. The fundamental CNN architecture however remains the same -VGG16.

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