Cancer classification using Deep Learning from Medical Image Data

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A thesis submitted to the Department of Computer Science and Engineering
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Declaration

It is hereby declared that

1. The thesis submitted is my/our own original work while completing degree at Brac University.
2. The thesis does not contain material previously published or written by a third party, except where this is appropriately cited through full and accurate referencing.
3. The thesis does not contain material which has been accepted, or submitted, for any other degree or diploma at a university or other institution.
4. We have acknowledged all main sources of help.

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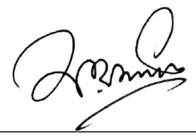

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Ethics Statement

In every level of research, this research paper is free of any plagiarism. Total security of the informants or any relevant people have been ensured.

Abstract

Cancer is a disease in which some of the body's cells grow uncontrollably and spread to other parts of the body. Cancer can start almost anywhere in the human body, which is made up of trillions of cells. There is usually no cure for this disease and it is often believed to be untreatable. Breast cancer ranks second among the most fatal cancers, especially in women. Every year many women suffer and die because of breast cancer. Early detection of the disease can save many lives. Breast cancer screening with mammography is essential because it can detect any breast masses or calcifications early on. Because breast tissue is dense, detecting cancer mass is difficult, leading radiologists to use machine learning (ML) techniques and artificial neural networks (ANN) to speed up the detection of cancer. This paper explores the Mini DDSM dataset, containing 9698 digital mammogram images, which were augmented and preprocessed, and fed into CNN and MobileNet Architecture with the aim of detecting normal, benign and cancerous tissues with high accuracy. Therefore, our aim is to apply the deep neural network based algorithm on a cancer image dataset to classify cancer and take advantage of image analysis, pattern recognition, and classification processes, and then validating the image classification outcome against medical specialist expertise. The main objective of this research is to acquire a higher accurate outcome on detecting cancer from medical mammography.

Index Terms— Breast cancer detection, neural network, Deep learning, Digital image processing.

Dedication

This research is dedicated to the individuals specially women who want to know if they are safe from breast cancer or not. The authors, the teachers and the supporters all have been dedicated to improve the quality of this paper throughout the journey.

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We want to thank our beloved Almighty Allah, our honorable Supervisor Faisal Bin Ashraf for his valuable time, guidelines, feedback and immense support. Moreover, our parents, friends and faculty members supported us whenever we needed any help.

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Chapter 1

Introduction

1.1 Overview

Breast cancer has become one of the most major life taking diseases among women in all over the world. To form a breast cancer it takes time. It doesn't happen overnight. At first the cancer begins from a cancerous tumor which starts to form into breast tissue. Consequently, it doesn't stop by forming only a tumor. It keeps spreading among its nearby cells by the time. However, breast cancer is not only common in women but also in males. WHO estimated that there would be approximately 2,650 cases of breast cancer in 2021. They further estimated 43,600 women would die from breast cancer in the same year. Taking these statistics into account, it is clear that breast cancer is highly prevalent in women today. It is estimated that 1 out of 8 women will develop breast cancer in their lifetime, making it among the leading causes of death in women. Breast cancer is affecting millions of women worldwide at an alarming rate. Many factors are working towards this problem. An important factor is a misdiagnosis. Consequently, we can only save lives through research. It is an early diagnosis that can save the most lives from breast cancer. In order to detect breast cancer early when it is best to handle it and before it has grown large enough to cause symptoms, mammography, X-rays, and biopsies are the most effective methods. It goes without saying that doctors are the best in terms of examining diagnostic reports, but they are also human, and human beings are prone to making mistakes. However, machines never make mistakes unless or until we give them the wrong commands. Therefore, we came up with this idea to detect cancer cells using deep learning. Using deep learning, we can improve the detection rate of cancer cells by up to 100%. Sometimes the result is so accurate that it can defeat the human eye. Since manual image processing is very slow and time-consuming. And, sometimes it becomes impractical for large amounts of data, which is why an automatic processing system is needed. In breast cancer detection mammograms show a better result because their image is processed in such a way that the pectoral muscle regions are already removed as it causes the detection procedure to be skewed. In the past few years, we can see that in spite of having so many diagnosis methods, doctors are not able to identify early-stage breast cancer with higher accuracy. As a result, the initial stage of treatment can not be provided and cancer becomes life-threatening. However, it is the image data from the mammogram which is still examined by the doctors. Since doctors are also human and human error can occur. Hence, the purpose of this research study is to diagnose breast cancer by using mammography image data processing with a higher accuracy rate. In our system, CNN architecture is being used and we are implementing a modified model of MobileNet. MobileNets are small deep neural networks that are well-suited to mobile and embedded vision applications. It performs better and is more suitable for mobile apps. Convolutional neural network with a small size and low latency. Furthermore, we can use this system to detect breast cancer and treat it at an early stage. In this way, the rate of cancer patients can be reduced. Based on our research, we have adapted our proposed model in a way that will ensure higher accuracy.

1.2 Motivation

The most frequent malignancy among women is breast cancer. Majority of the women in the world are being affected by breast cancer at an alarming rate. However, there are many factors that are working behind this reason. Misdiagnosis is one of the major reasons. Mammography, X-rays, and biopsies are the most effective ways to detect breast cancer early, when it is better to handle and before it has grown large enough to produce symptoms. Undoubtedly, doctors are the best in terms of examining diagnosis reports but they are also human and human beings are prone to making blunders. On the other hand machines are machines they never make mistakes unless or until we give them wrong commands. Therefore, we came up with this idea to detect cancer cells using deep learning. By using deep learning we can bring up the cancer cell detection rate upto 90% . Sometimes the result is so accurate that it can defeat the human eye. In our system CNN architecture is being used. And we are implementing a modified model of Mobilenet. MobileNets are small deep neural networks that are well-suited to mobile and embedded vision applications. It performs better and is more suitable for mobile apps. Convolutional neural network with a small size and low latency. Furthermore, we can use this system to detect breast cancer and treat it at an early stage. In this way the rate of cancer patients can be reduced.

1.3 Problem Statement

Nowadays breast cancer has been increasing at an alarming rate among women as well as men of all ages. There are many diagnostic methods to diagnose breast cancer. Mammograms, ultrasounds, MRIs, PET scans, thermography, and CT scans are just a few examples. Since manual image processing is very slow and time consuming. And, sometimes it becomes impractical for large amounts of data, which is why an automatic processing system is needed. In breast cancer detection mammograms show a better result because its image is processed in such a way that the pectoral muscle regions are already removed as it causes detection procedure to be skewed. In the past few years , we can see that in spite of having so many diagnosis methods, doctors are not able to identify early stage breast cancer with higher accuracy. As a result the initial stage of treatment can not be provided and the cancer becomes life threatening. However,it is the image data from the mammogram which is still examined by the doctors. Since doctors are also human and human error can occur. Mammograms show a better result for those whose breast tissue is non

dense . But when it comes to highly dense tissue it shows poor results in diagnosing cancer.
Finally, the purpose of this research study is to diagnose breast cancer by using image data processing with a higher accuracy rate. In this procedure neural networks along with deep learning are being used.By the help of deep learning model it can attain extremely higher accuracy in image classification, comparable to that of humans. Deep learning is a new subfield of artificial intelligence and machine learning that uses numerous nonlinear processing layers to learn features directly from data.

1.4 Research Objectives

Main objective of this research is to use the power of Artificial intelligence in the medical field with more reliability. AI is something of a blessing for mankind. It's a tremendously powerful tool to use and solve problems. Here we are using deep learning technology to detect cancer cells from diagnosed image data. Our proposed model is so efficient that it can run on any device with minimum system power. Since it's a very efficient model it has so many advantages. Our agenda is to get a higher accuracy rate by establishing this proposed model which can even run on smartphone GPUs.

1.5 Thesis Structure

This thesis work is organized as following structure:

Chapter 1 shows the introduction which consists thesis overview, our motivation behind this work, problem statement, and research objectives.

Chapter 2 presents the related works which includes the background study we did for this paper.

Chapter 3 presents our overall dataset analysis which includes collection of data, extracting their feature and processing them and then the system work flow.

Chapter 4 presents the implementation of algorithms.

Chapter 5 shows the analysis of our result and interpretation of that result.

Chapter 6 concludes the paper with summary and future possibilities.

Chapter 2

Related Work

Cancer develops when the body's normal control mechanisms fail. It is not possible for old cells to die, and they continue to grow, resulting in new, abnormal cells. Tumors can form from these extra cells. Since ancient times, humans have been aware of breast cancer. Ancient Egyptians were the first to note the disease more than 3,500 years ago. The condition was described fairly accurately in both Edwin Smith and George Ebers papyri. History has recorded its occurrence in nearly every period. As the lumps in the body that develop into tumors have visible symptoms, physicians have recorded them from early times. As a result, breast cancer usually manifests itself as a visible lump, unlike other internal cancers.

According to paper[5], the earliest signs of Breast cancer are microcalcification and masses which can be detected with the help of modern technologies. Calcium deposits which are very small in size, make clusters inside the soft breast tissues that refer to microcalcification. Since size and shape varies from person to person and in mammography masses show poor image contrast this combinedly makes detection of masses in breast tissues more challenging than the detection of microcalcification. As the texture, color, shape, and spatial relations reflect the subtle variance in many degrees, using these aspects, features of the image can be distinguished. Generally, these types of classifications can be done by different approaches such as using Support Vector Machine (SVM), decision tree, rough sets, and last but not the least using Artificial Neural Network (ANN). To detect breast cancer at an early stage here in this paper, the author proposed the applications of ANN in mammography, ultrasound, MRI, and IR imaging. Sometimes, it is difficult to differentiate between the abnormalities and normal breast tissues, because of their subtle appearance and ambiguous margins though masses and microcalcifier are the early signs of breast cancer. The required information revealed that it is only 3% during a mammogram where vessels and normal tissues cover a part of the suspicious region. So, it is very difficult for radiologists to identify a cancerous tumor in this situation. To overcome the limitations of mammograms and assist the radiologists in reading the mammogram much better, computer-aided diagnosis(CAD) has been developed. In CAD, the ANN model is most commonly used for interpretation and biopsy decision-making. Here, to assist in mammography interpretation the author mentioned two ways in ANN; which are, applying classifiers on image data (ROI). After that, from the signal of a pretrained image it extracts the feature to understand the conditions. Lastly, for detecting breast cancer malignancies, the author states that their latest research suggests some hybrid method which improves CNN.

The author also added that the algorithm that is the combination of some k-means clusters along with the (BPNN) ensures that it provides a satisfactory performance for detecting breast cancer malignancies.

According to this paper[8], Breast cancer cases have increased worldwide. The paper discusses how to detect breast cancer and then treat it. Mammography and MRI, two of the most important imaging modalities, are used here to identify the tumorous portion more accurately. Breast cancer can be detected early by using image analysis and treated more effectively, saving lives and making treatment less complicated for medical professionals.

Image processing is a widely used method in a wide range of medical fields. Image processing uses some techniques to gather information for detecting cancer. It is very helpful in the early detection of various cancers. Image processing is a technique for extracting important information from images by performing relevant operations on them. This process is basically a signal exchange where the input data is a picture, and the result can be another picture or characteristic of that picture. Medical imaging serves a number of purposes, including revealing internal structures and diagnosing and treating diseases. In terms of how the segments are detected, two approaches can be distinguished: 1) Detection Based on Discontinuity 2) Detection-Based on Similarity Detection Based on Discontinuity: Based on discontinuity here images get partitioned into parts. Detection-Based on Similarity: The concept of separating an image's pixels based on some degree of resemblance. This article discusses some of the symptoms of breast cancer. Women die quite frequently from breast cancer. In 2016, 14,5 lakh new cases of cancer were reported in India, a number that is expected to reach 17.3 lakh by 2020, according to the Indian Council of Medical Research. Understanding the signs and symptoms of a problem is crucial for any research. Although the existence of these signs and symptoms does not necessarily indicate the existence of breast cancer, they should not be disregarded and should be addressed as soon as possible if they are identified. The symptoms include swelling or shrinking of the breast that is unexplained, a lump in the breast, inverted breast, swollen or ridged breast skin, A milky discharge and thickening of the chest or underarm region. Breast pain is not that much serious but if it includes the symptoms then a physician should be consulted. The presence of a lump in any body part is a symptom of breast cancer. Mammogram: A mammogram detects breast cancer by means of X-rays and ionizing radiation. Often, breast lumps can be detected by mammography before they can be felt. Mammograms that reveal an abnormal area of the breast may be followed up by a further test that provides an even clearer and more precise image. Ultrasound and MRI tests may be performed. When the mass is found solid, they recommend a biopsy. Biopsy: The diagnosis method of taking cells from suspicious areas in order to determine if cancer is present. A biopsy is the only test that can determine for sure whether someone has cancer. If the test results reveal that the tumor is cancerous, additional testing is recommended (hormone receptor and HER2/neu tests). In this paper, there are some methods used to determine cancer more efficiently. Such as Image Conversion, Image Filtering, Histogram Analysis, Edge Detection Based Segmentation, Thresholding-Based Segmentation. Image Conversion: The grayscale conversion process is another crucial step in image processing. Signal processing for colored images is difficult due to the three-dimensionality of the information (RGB data). Grayscale conversion is therefore necessary. Due to this conversion, there

is no color information in grayscale pictures.. Image Filtering: In image filtering, noise is removed from an image, and its visual properties are enhanced. Filtering results in a higher quality image, which can be used for many useful tasks. There are many filtering techniques available. Here Gaussian smoothing filters have been used. Histogram Analysis: Histograms can be thought of as graphical representations of tonal distribution within an image. Plotting pixel values for tonal values is done here. The x-axis is the gray level (intensity, brightness) of the image. The y-axis is the count of how many pixels in the image have the gray level. Edge Detection Based Segmentation: Detecting edge involves detecting abrupt changes in intensity or changes in intensity function, as outlined in edge detection methodology. Edge detection is done by using a variety of approaches and operators. Thresholding-Based Segmentation: Thresholding is a simple method of segmenting images. Based on the intensity values of the pixels in the image, thresholding produces clusters of those pixels. Here images of mammograms and MRIs have been filtered using a Gaussian filter to reduce the level of noise. The tumorous portion of mammograms and MRI images are then extracted using thresholding and edge detection. Using entropy measurements, a comparative analysis was performed on the thresholding and edge detection methods to obtain the best results. Also, the experiment found out the best edge detection method among Sobel, Canny, and Prewitt on MRI and mammogram images. This research aims to enhance image quality and improve the visibility of tumorous portions. Edge detection algorithms have shown superior results for mammograms and MRIs compared to thresholding, which is compared using so-called entropy. Both mammograms and MRI are being evaluated for edge detection operators. The Canny operator outperforms Sobel and Prewitt. In both major types of breast cancer, Canny Edge detection may be able to segment the tumors.
According to the research[3], the leading cause of death among women is breast cancer. A variety of image processing and classification techniques have been used to diagnose and detect breast cancer. However, the disease is still one of the most deadly diseases. Breast cancer cannot be prevented as long as the cause remains unknown. Breast cancer can only be cured by early detection of tumors. The most efficient and easiest way to diagnose breast cancer is to use CAD (Computer-Assisted Diagnosis) on the mammographic image. By discovering accurate data, mamma cancer deaths can be reduced. Early signs of breast cancer include masses and microcalcification clusters. Breast cancer can be predicted at an early stage with their help. DDSM (Digital Database for Screening Mammography) is a database containing approximately 3000 cases used by researchers throughout the world for cancer research. The image for this research is taken from the DDSM database. For the detection of cancer, this paper describes how texture features are analyzed quantitatively. From a mammogram ROI, texture measures are used to distinguish benign, ordinary, and threatening microcalcifications. The principles of component analysis (PCA) are further used to reduce these features as well as to identify the mass of a system. To further understand the cancer pattern in the mammography image, the images are compared and passed through a Back Propagation algorithm (Neural Network). It says breast cancer diagnosis and treatment remain expensive and time-consuming. This may be because every cancer is different from its host, and each requires customized treatment. Some of the difficulties in automated detection can be related to the fact that it is probable to misjudge an object of interest when it is large in

size. It seems impossible to match samples because mammograms show unique sizes, different shapes, and varying appositions of microcalcifications. There may be low contrast in the Region of Interest (ROI). In some instances, the enveloping tissues can be completely distinct from suspicious reaches. As a consequence of thickening skin and tissues, particularly among young women, suspicious locations are virtually undetectable. This leads to a high rate of false-positive cases due to dense tissues being confused with calcifications. From the paper, we get to know that various classification problems are applied to digital mammography images in order to diagnose breast cancer. Digital mammography has become the standard method for diagnosing breast cancer. It discusses the use of multiple image processing algorithms to detect cancer. The techniques in computer-aided mammography include image pre-processing, image segmentation, feature extraction, feature selection, and classification. Researchers have carried out many studies on image processing in an attempt to find cancer. However, the accuracy rate is between 75Since cancer is one of the oldest diseases, a great deal of research has been conducted. It is impossible to cure cancer with a single medicine as it is a collection of multiple diseases. It is crucial to determine the type of cancer to customize the medication, so cancer can be treated if it is found early.

This paper[1] said that in terms of danger, breast cancer is second only to lung cancer. Detecting a tumor early can save lives because it is easier to treat and prevent the tumor from spreading. Cells that grow abnormally are tumors. Breast cancer was only detected with an X-ray for many years. It has been demonstrated that there are many different methods that can be used as an alternative to x-ray analysis, such as neural networks, artificial intelligence, and data mining. This study examined a disease that is very dangerous. The number of deaths among women worldwide due to this alarming disease. In addition to describing the patient's state, they proposed an efficient method to diagnose and treat this disease. In their proposed model, they used image processing techniques for feature extraction, while machine learning algorithms were applied in two types of supervised learning algorithms, LR and BPNN. According to the results, the LR model employed more features than the BPNN model. BPNN, on the other hand, contributed a regression value of more than 93

From paper[10], By comparison of genes expressed in normal tissues with diseased tissues, gene expression profiles can be obtained from multiple tissue samples.Since, there is insufficient sample data for a given tumor and generally gene expression data are high in dimension, these data need a number of specific ways to deal. For performing accurate classification still resulting features space contains sufficient reports for reducing the dimensionality of gene expression is the first challenge here.In this paper, they propose a more general way of learning features by applying unsupervised feature learning and deep learning methods, for facilitating and developing more generalized versions of cancer classifiers.They used a sparse automatic encoder method from unlabeled data to learn a concise feature representation. Author said that, in their proposed method, in the area of gene expression data, they addressed dimensionality problems. At first, from features space, they tried to reduce the dimensionality using PCA. Secondly, after getting the PCA results they applied it like the representations of compressed features that encode available information in testing sets. After that, for the classification to find a sparse representation for data either one or a multi-layered sparse auto-encoder are being used along with some

original gene expressions. Their proposed method's main strength is the combination of dimensionality reduction through PCA and for general classification tasks, the unsupervised non-linear sparse feature learning for the construction of effective features. For improving and assisting the accuracy of classifications, their methodology allowed the use of unlabeled data effectively and also various types of microarray data that are not related to specific tasks of classifications. Author claims that along with improving the accuracy their proposed model gives a more generalized and scalable approach in gene expression data to enhance cancer diagnosis and classification in comparison with the baseline algorithm.
Retrieving from paper[7], from samples of mammogram classifying the lesions of malignant masses and benign here, authors proposed a new CAD system which is basically a deep learning approach based on a support vector machine.Here, they used two segmentation approaches: one is segmenting the ROI manually and secondly they used techniques based on threshold and region. Their feature extraction tool was DCNN on the other hand, to obtain better classification results, the DCNN last layer that is connected fully is connected with SVM. Author states that they tested their experiments in 2 data sets, one is DDSM and another one is (CBIS-DDSM). Here, a CAD system has various kinds of steps like segmentation and enhancement of images, classification, extraction of features and finally there is a classifier evaluation system. The uniqueness of this work is, first of all,using two different types of techniques extracting ROI and then with SVM replacing the DCNN architecture's last layer that is connected fully. In transfer learning, for using the ImageNet dataset, the DCNN is pre-trained firstly containing natural images around 1.2 million which classify around 1000 classes. After that a new layer replaced the last fully connected layer for classifying malignant masses and benign. In terms of classification, here, ROI is classified according to their features as either benign or malignant. They used different types of techniques for classifiers such as ANN, binary decision tree, SVM and LDA. The SVM architecture which is based on DCNN consists of convolutional layers having 5 stages. Those are activations of RELU and polling layers followed by the 3 layers that are fully connected. Lastly, to obtain better accuracy, the SVM classifier is connected with the last layers that are connected fully. On account of training and testing phases the mentioned image data set is divided into a 70:30 ratio. In order to apply it on proposed methods a subset from the data set was extracted where the sample was augmented to 4 images. Based on the two methods mentioned earlier in the methodology segmentation and enhancement of samples were done. After that, they extracted their features with the help of CNN. Then, for classification, the samples went through the Support Vector Machines. Lastly, their reports found out that 94% of AUC was identified using the CAD that was mentioned using deep CNN and it was highest for CBIS-DDSM dataset. Whereas, the former approach achieved AUC 81% while the latter achieved 83% by Huynh and Giger published in 2016 where they collected 219 numbers of their experimental breast lesions from Chicago medical center University and applied those on their experiment.
So far we have seen many feature-based approaches on the contrast here in paper[2], the author mentioned an alternative solution based on deep learning approach. In order to achieve this goal with the help of CNN the author suggested this model for classifying hematoxylin and eosin stained biopsy images of breast. A classification system is used here, in order to categorize images in 4 categories, they are normal

tissue, benign lesions, in situ carcinomas and invasive carcinomas. Furthermore, it is classified in two classes named carcinoma and non-carcinoma. Including nuclei and overall tissue organization the architecture of the network is designed in order to retrieve information in different scales.This proposed mode allows the suggested system to be extended to whole-slide histology pictures. A CNN is also used to extract features for training a Support Vector Machine classifier. A 77.8% accuracy rate is claimed for four classes and an 83.3% accuracy rate is claimed for carcinoma and non-cancer. Furthermore, their method is 95.6% sensitive to cancer cases. Authors here used a set of 249 training images, and a separate set of 20 test images. In the given data set, there is a balance among the four classes. In order to objectively determine the pathology classification we choose the images in this way. An extra test set of 16 photos with higher uncertainty is included with the "extended" dataset. Next, for the detection method, the images are split into twelve contiguous patches that are non-overlapping. After that, likelihood matches are computed according to patch-wise classifiers trained with CNN and CNN+SVM. Patch probability fusion methods are utilized to create the image-wise classification. In order to classify the 512*512 histology image patches into tissue classes, CNNs are being used. A feed-forward neural network is used here to recognize visual patterns. The model is divided into two segments for training and testing: 75% of the training set and 20% of the testing set. Lastly, the author states that due to the extended dataset the performance of their model is lower as the extension makes the system more complex. Last but not the least, their proposed model shows improved accuracy only when two classes (non-carcinoma and carcinoma) are considered. Accuracy for the CNN model is 77.6% and for the CNN+SVM model they achieved 76.9% accuracy. From the study[6] we get to know that 2.8 million women worldwide have already been diagnosed with breast cancer, according to a recent study from 2016. Medical care for a breast cancer patient is expensive, but in order to prevent breast cancer and maintain one's health, the prevention of breast cancer is essential. Various techniques have been developed over the past two decades. The most common of them are mammography and ultrasound. Even so, mammograms can occasionally produce false positives when another test is used to diagnose the patient. Furthermore, patients and physicians may benefit from exploring alternative methods of diagnostic imaging due to the potential side effects of mammography. The literature review started with a formal comparison of infrared digital imaging in which cases of precancerous tissue and areas surrounding breast cancer are assumed to have an increased thermal activity between a healthy breast and one with cancer. This research revealed that a Computer-Aided Diagnostic (CAD) using infrared image processing cannot be accomplished without some sort of model, such as the well-established hemispheric model. The novel contribution of this paper is the development of advanced computer vision techniques with deep learning models for comparing several breast cancer detection techniques. Based on the literature review, it was apparent that computer scientists could make significant contributions to the field by working in the area of breast cancer detection. Therefore, It went over the most frequent methods for detecting breast cancer. along with their strengths and weaknesses. The non-immersive nature of one technique and the need to process significant amounts of data with more efficient techniques gave that technique a promising future. With the help of infrared imaging and the use of a medical agent, tumors can be detected very accurately. In the future study, they will employ a thermal sensitivity camera of 0.5 in order to build a breast model that will enable a more precise diagnosis.

Chapter 3

Dataset and Preliminary Analysis

3.1 Data acquisition :

There are so many public datasets available on the internet like Digital Database for Screening Mammography (DDSM). An updated version is known as CBIS-DDSM. But this dataset has some drawbacks. The DDSM dataset is currently obsolete. It was maintained at the University of South Florida for the purpose of keeping it accessible on the web. CBIS-DDSM provides an alternative host of the original DDSM, but unfortunately, images are stripped from their original identification filename and from the age attribute. Therefore, we are using the light-wet version of the DDSM dataset known as MIni-DDSM

3.2 Data preparation :

After obtaining the mammogram images, the images will be resized to 224*224, based on the CNN and MobileNet model that will then be used in the next phase. The ground truth images are then transformed into one-hot labels using categorical encoding, in which the pixels of the background, benign, and cancer tumor masses are coded.

3.3 Datasets :

We have already mentioned that we have used a public dataset of digital mammograms to train the proposed CNN and Mobilenet model. This is the lighter version of Digital Database for Screening Mammography (Mini-DDSM). This dataset contains the age attribute (figure 3.1).

Total images	Benign	Normal	Cancer
9698	3374	2728	3596

Table 3.1: Mini DDSM Data Set

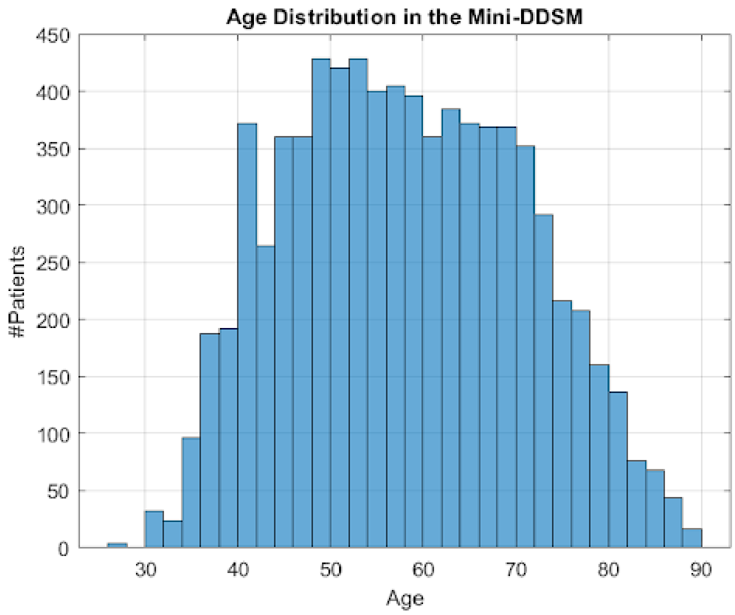


Figure 3.1: Age Distribution In Mini-DDSM

Along with 3 cases of the folder. First Benign condition, secondly cancer, and the normal condition of the patient. The number of images for each class is shown in a pie chart 3.2 below.

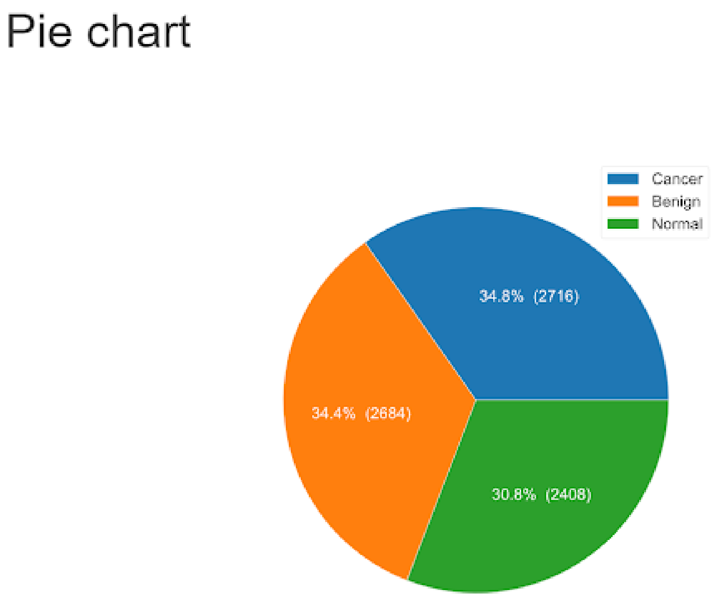


Figure 3.2: Image Classifications

Here are some images from every class:

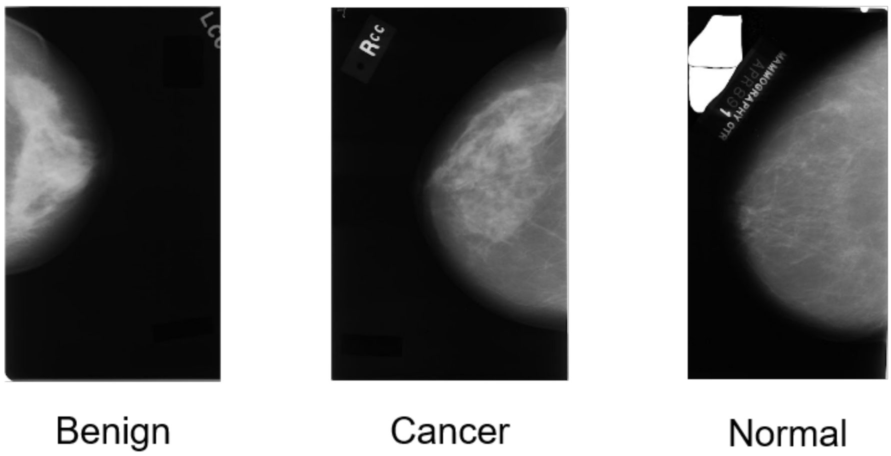


Figure 3.3: Picture From Every Class

It has also provided the left and right side view of every case images Since the lesion binary mask is based on the original freeman chain-coding, this data set provides the benefit. The images and count are shown in figure 3.4 and 3.5 below:

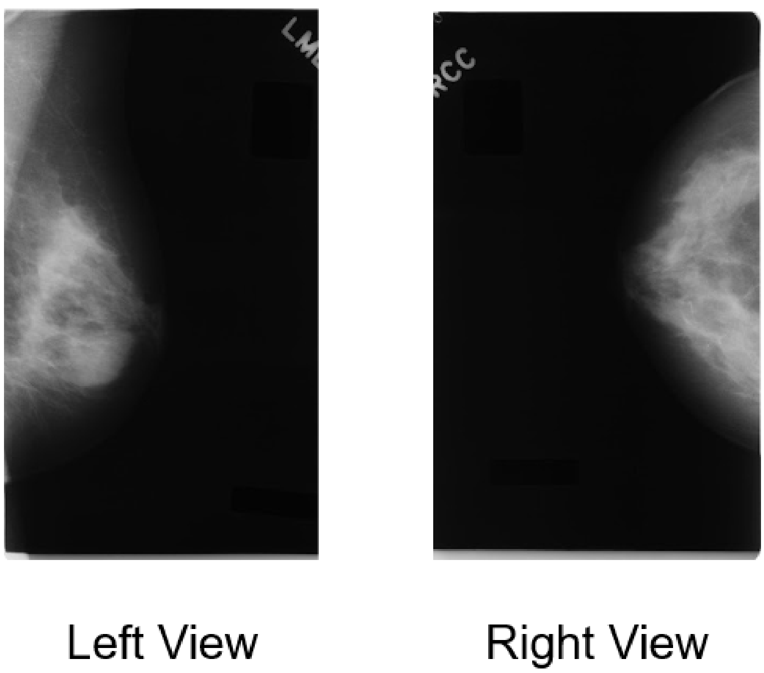


Figure 3.4: Left-Right View

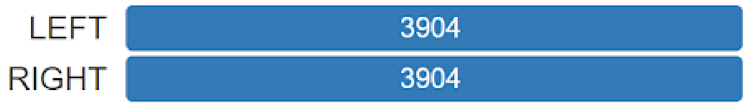
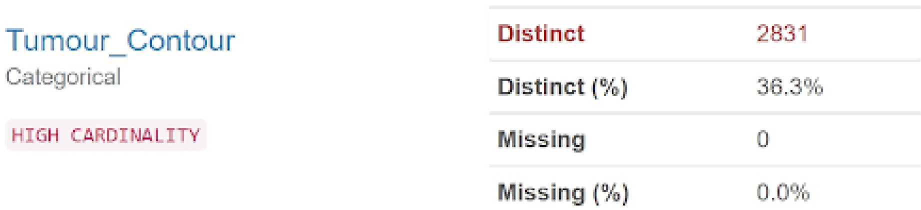


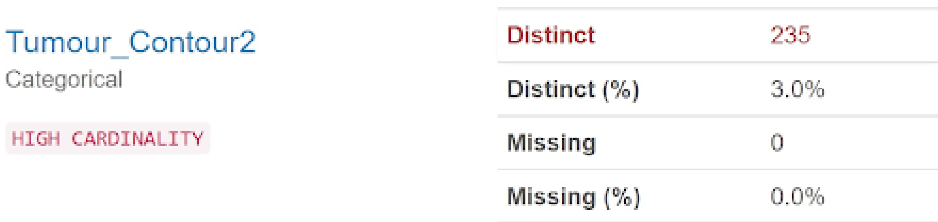
Figure 3.5: Image count

Moreover, It also has a suspicious/tumor contour binary mask. Image contouring is the process of identifying structural outlines of objects in an image which helps to identify the shape of the object. Our data set provides contour in both cancer and benign cases (figure 3.6 and 3.7).



Distinct	2831
Distinct (%)	36.3%
Missing	0
Missing (%)	0.0%

Figure 3.6: Benign Case



Distinct	235
Distinct (%)	3.0%
Missing	0
Missing (%)	0.0%

Figure 3.7: Cancer Case

3.4 Evaluation metrics

The problem of class imbalance affects mammography segmentation and classification. The normal class is made up of normal tissue that corresponds to background pixels, thus it takes precedence over the benign and cancer classes, which represent tiny regions in the pictures. The issue of class imbalance is widespread in many real-world databases and must be addressed.

Chapter 4

Methodology

4.1 Working Overview

The main phases of our proposed method are as follows: In the image classification techniques the first step is image pre processing . In this process the mammogram image emphasizes the anomalies which improves the low contrast into higher higher contrast. To attain detailed information the enhancement operation is performed. Enhancement tool is a very supportive diagnosis tool and it helps to get better visual quality of the image. Thirdly, the segmentation stage comes. Segmentation is the process of extracting the malignancy from the original picture so that the accuracy improves and diagnosis becomes better. There Are many types of algorithms which are used for the segmentation such as Edge-based, Clustering, Region-based, Thresholding. Now the feature extraction and selection stage comes. Specific properties of the mammography pictures, such as density, size, form, and structure, are retrieved and chosen at these stages. Finally the classification of images is performed. In this stage all the images are categorized as normal and abnormal. This classifier improves performance of classification and it helps to detect the abnormality in tissue.

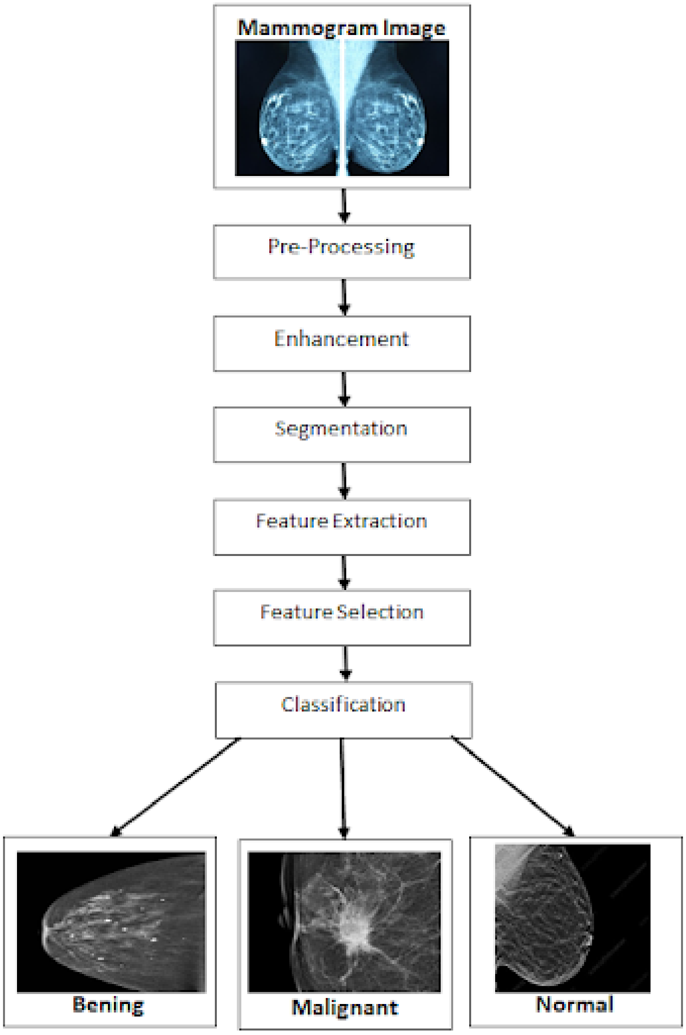


Figure 4.1: Data Extraction Diagram

4.2 Implementation Overview

The diagram 4.2 shows the workflow of our proposed model. There are few steps. Firstly dataset is uploaded. In our model we used image data set which contains cancer benign and normal images. Secondly the data is pre-processed. This step is very important as it cleans the data-set. After pre-processed the data is being splitted into train image and labels. Then the comes the proposed model. Our model is CNN based model. The data is feed to the model. Model loading process is finished. Now it will show the predicted output. Our proposed model will predict cancer/benign or normal accurately and will also highlight affected area. By using the grad cam feature affected area is clearly marked. Now we can evaluate the model and compare the proposed model with other deep learning models.

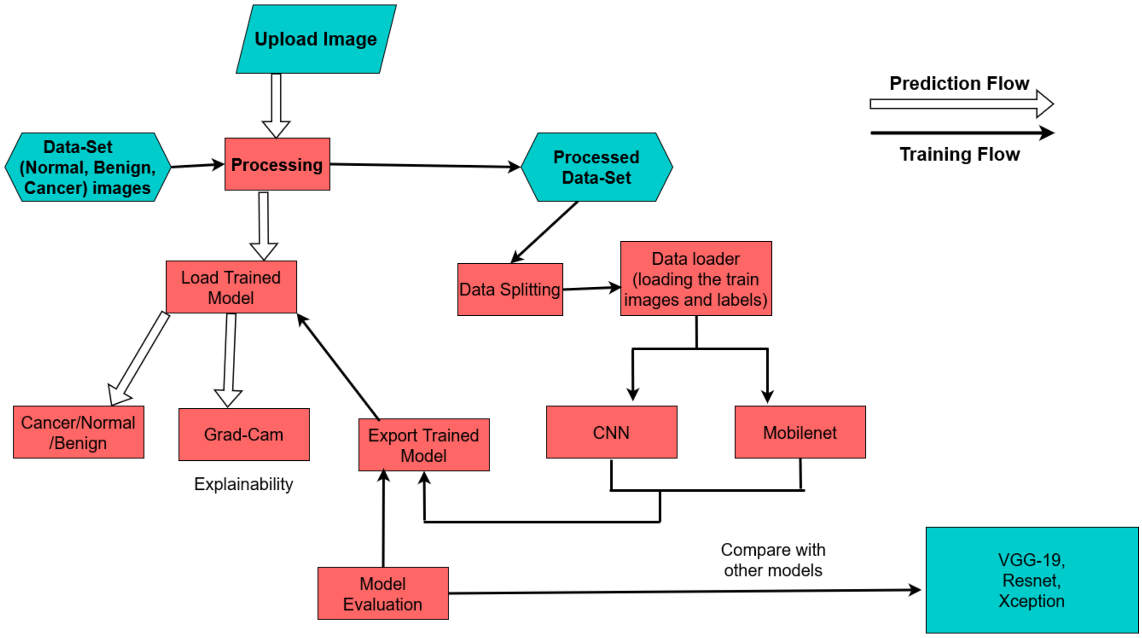


Figure 4.2: WorkFlow Diagram

4.3 Convolutional Neural Network (CNN)

In recent years, neural networks have made significant strides toward closing the gap between human and machine abilities. A convolutional neural network (figure 4.3), often known as CNN or ConvNet, is a type of artificial neural network that has been widely utilized for image analysis and classification challenges. CNN differs from traditional multi-layer perceptrons in that it incorporates hidden layers known as convolutional layers. They function similarly to any other layer in that they accept input, change it in some way, and then send the modified input to the following layer. These modifications are known as convolution operations in the hidden convolution layer. These convolutional layers can recognize patterns more precisely. In our scenario, whether or not a particular mammogram has malignant tissue. Finally, patterns from these hidden layers are detected and sent to the output layer.

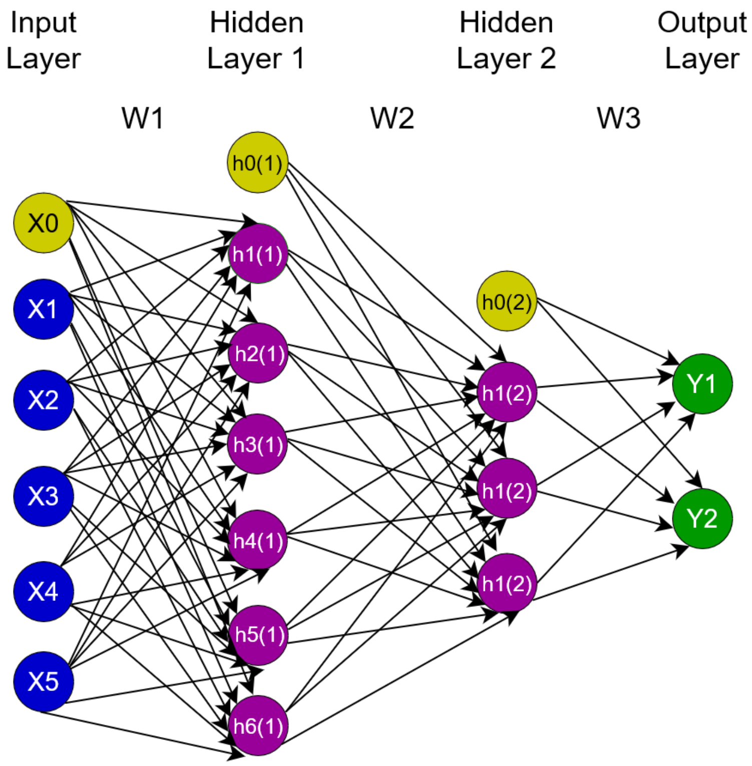


Figure 4.3: Architectural Description of CNN

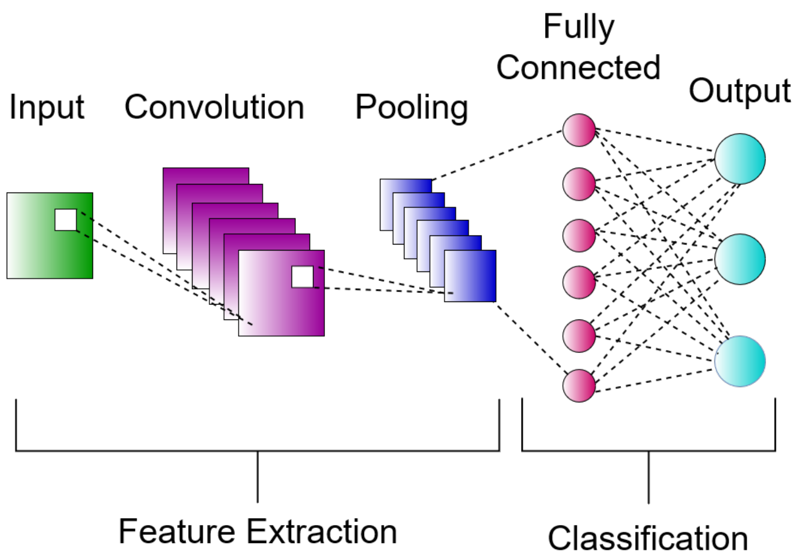


Figure 4.4: Fully Connected CNN

4.4 MobileNet

The MobileNet model in figure 4.5, as its name implies, is intended for usage in mobile applications and is TensorFlow's first mobile computer vision model. It is a CNN architecture model which stands out since it requires extremely little computing power to run or perform transfer learning.As a result, it's a suitable fit for mobile devices, embedded systems, or PCs with low computational efficiency or no GPU that don't require a lot of precision. Due to its compute, graphic processing, and storage limitations, it is also perfect for web browsers. It's a reduced-parameter deep neural network that improves classification accuracy. Depth-wise separable convolutions are used by MobileNet. When compared to a network with conventional convolutions of the same depth in the networks, it greatly reduces the number of parameters. As a result, light-weight deep neural networks are created. Surprisingly, in the case of picture classification or pattern recognition, this design produces quite promising results. Starting with the input layer, mobileNet's input size is 224*224. MobileNet employs depth-wise separable convolutions. Two procedures are used to create a depthwise separable convolution. There are two types of convolution: depthwise and pointwise, as seen in the diagram below.

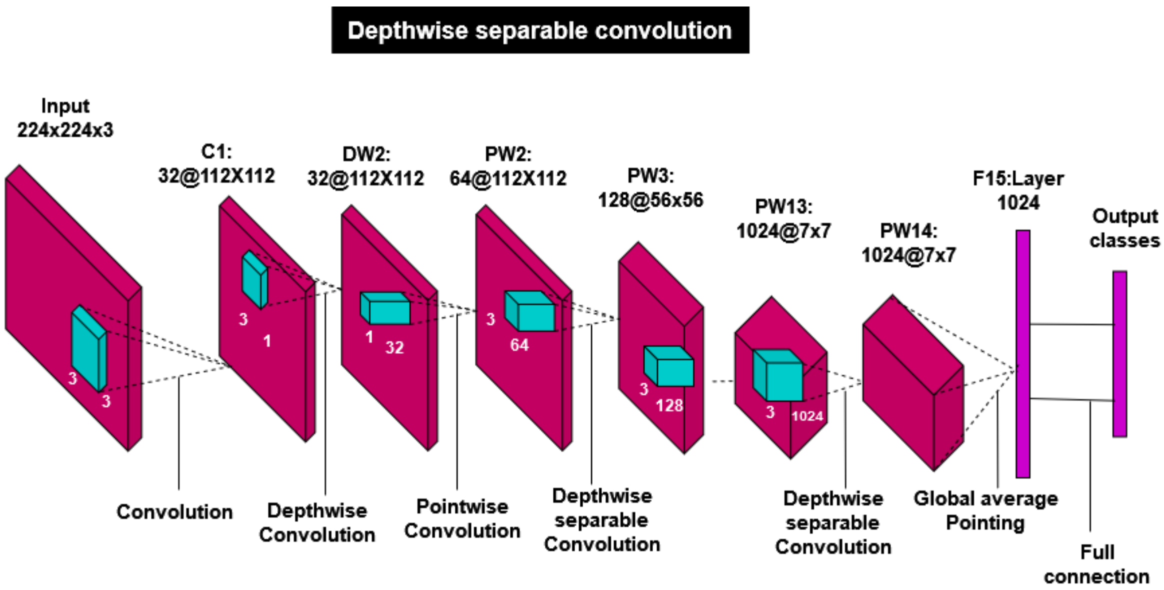


Figure 4.5: Mobilenet Model

Depthwise convolution filters and points convolution filters make up a depthwise separable convolution filter. According to Figure 2, the depthwise convolution filter performs one convolution on each input channel, but the point convolution filter creates a point convolution by combining the output of depthwise convolution with 1 * 1 convolutions.

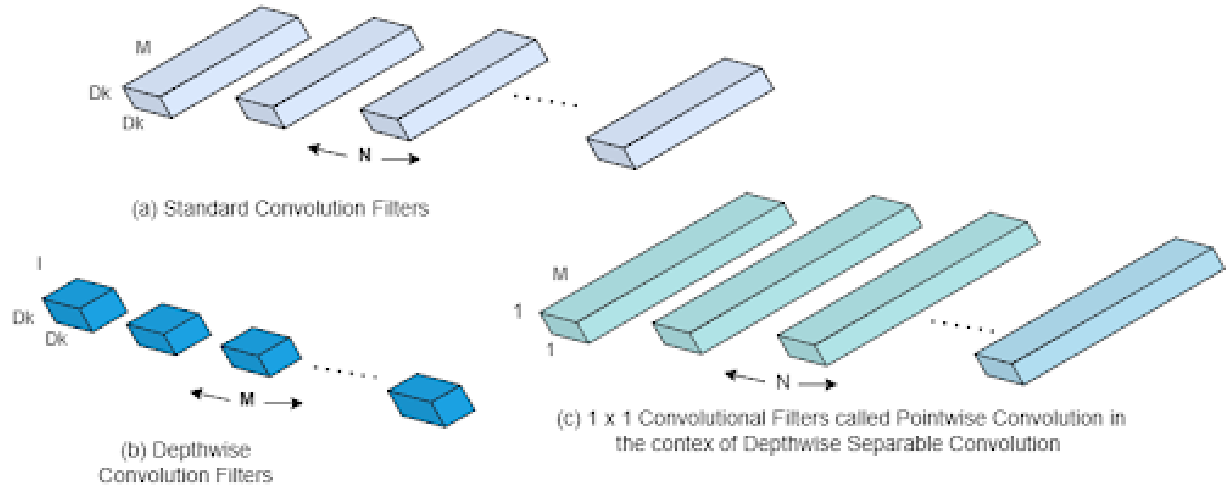


Figure 4.6: Standard convolutional filters and depthwise separable filters

Any image size bigger than 32×32 is supported by MobileNets, with larger image sizes providing better performance. This function returns a Keras image classification model, which can be loaded with pre-trained ImageNet weights if desired. MobileNet employs a depth-separable convolution. It decreases the number of parameters by a significant amount when compared to a network with convolutions of the same depth in the nets. As a result, lightweight deep neural networks are created. MobileNet is one of the smallest Deep Neural Networks on the market, and it's fast and efficient even on smartphones with low-end GPUs. Spatial separable convolutions and depth-wise separable convolutions are the two types of separable convolutions. Kernels that cannot be factored into two smaller kernels are used in depthwise separable convolution. Mobile Nets are built on a simplified design that builds lightweight deep neural networks using depth-wise separable convolutions. Its structure is built on depth-wise separable filters.

4.4.1 MobileNet Architecture

As mentioned above, mobilenet is built on depth-wise separable convolutions, except for the first layer. The first layer is a full convolutional layer. All layers are followed by batch normalization and ReLU non-linearity. However, the final layer is a fully connected layer without any non-linearity and feeds to the softmax for classification. For downsampling, stridden convolution is used for both depthwise convolutions as well as for the first fully convolutional layer. The total number of layers for mobilenet is 28 considering depthwise and pointwise convolution as separate layers.

Type / Stride	Filter Shape	Input Size
Conv / s2	$3 \times 3 \times 3 \times 32$	$224 \times 224 \times 3$
Conv dw / s1	$3 \times 3 \times 32$ dw	$112 \times 112 \times 32$
Conv / s1	$1 \times 1 \times 32 \times 64$	$112 \times 112 \times 32$
Conv dw / s2	$3 \times 3 \times 64$ dw	$112 \times 112 \times 64$
Conv / s1	$1 \times 1 \times 64 \times 128$	$56 \times 56 \times 64$
Conv dw / s1	$3 \times 3 \times 128$ dw	$56 \times 56 \times 128$
Conv / s1	$1 \times 1 \times 128 \times 128$	$56 \times 56 \times 128$
Conv dw / s2	$3 \times 3 \times 128$ dw	$56 \times 56 \times 128$
Conv / s1	$1 \times 1 \times 128 \times 256$	$28 \times 28 \times 128$
Conv dw / s1	$3 \times 3 \times 256$ dw	$28 \times 28 \times 256$
Conv / s1	$1 \times 1 \times 256 \times 256$	$28 \times 28 \times 256$
Conv dw / s2	$3 \times 3 \times 256$ dw	$28 \times 28 \times 256$
Conv / s1	$1 \times 1 \times 256 \times 512$	$14 \times 14 \times 256$
$5\times$ Conv dw / s1 Conv / s1	$3 \times 3 \times 512$ dw $1 \times 1 \times 512 \times 512$	$14 \times 14 \times 512$ $14 \times 14 \times 512$
Conv dw / s2	$3 \times 3 \times 512$ dw	$14 \times 14 \times 512$
Conv / s1	$1 \times 1 \times 512 \times 1024$	$7 \times 7 \times 512$
Conv dw / s2	$3 \times 3 \times 1024$ dw	$7 \times 7 \times 1024$
Conv / s1	$1 \times 1 \times 1024 \times 1024$	$7 \times 7 \times 1024$
Avg Pool / s1	Pool 7×7	$7 \times 7 \times 1024$
FC / s1	1024×1000	$1 \times 1 \times 1024$
Softmax / s1	Classifier	$1 \times 1 \times 1000$

Figure 4.7: MobileNet Architecture

4.5 Loss Function:

Here, we use a Mobile-Net model to segment digital mammograms using multiple labels in a semantic manner. In each image pixel, we attempt to classify it as normal, benign, or cancer. It's the normal pixels that dominate the breast's background and the labels that are predominant in the images. Cancer pixels, however, represent small abnormalities found in the breast. In other words, if we use the standard categorical cross-entropy loss function given in Equation 1, then the model will forecast the majority of the pixels normal since they represent the dominant class, and the evaluation will seem biased. Gradients will die quickly during training before correctly categorizing benign and cancer classes. Due to the imbalance between various classes, weights are applied to each class to increase the probabilistic penalty. Weights for classes are based on the percentage of total samples in the predominant class against that class's sample count. As a result, in Equation 2, for the categorical cross-entropy, the loss is weighted according to the weight assigned to each class. The standard categorical cross-entropy is given by:

$$J_c ce = -1/n \sum_{i=1}^{c} \sum_{j=1}^{n} y_j^i * log(h(x_j^i))$$

The weighted categorical cross-entropy is given by:

$$J_w cce = -1/n \sum_{i=1}^{c} \sum_{j=1}^{n} w_i * y_j^i * log(h(x_j^i))$$

4.6 Transfer Learning

Transfer Learning is a technique for adapting a pre-trained neural network by transferring the learnt characteristics to a new dataset. It's used to tailor a model to a certain set of requirements. A model that has been trained on a big dataset is referred to be a generic model. We can avoid having to start from scratch by employing these feature maps. It provides a number of advantages, including reduced training time and improved performance. Furthermore, it does not necessitate a large amount of data.

4.7 Overfitting

In machine learning and deep learning models, overfitting is a typical issue. It occurs when the model accurately predicts and classifies data in the training set, but fails to do so in the test set. In other words, the model overfits the data in the training set. For a better model, it is critical to remove overfitting. It can be detected by looking at the loss or accuracy measures, which are simply validation measurements. After a few epochs, it usually stops improving. The validation metrics then start to drop. If the training statistic improves over time in the training data, the model is attempting to find the best fit. There are some options for avoiding this issue. One possibility is to obtain more training data. However, due to time constraints, technical issues, and other factors, it is not always practicable in real-world scenarios. Overfitting can be avoided by using data augmentation, regularization, and dropouts. Another technique to avoid overfitting is to reduce the capacity to learn and memorize the training data so that it can generalize more effectively.

4.8 Early stopping

In our model, we used early stopping to avoid overfitting. As we know, too many epochs can lead to overfitting of the training dataset, whereas too few may result in an underfit model. Early stopping is a method that allows to specify an arbitrarily large number of training epochs and stop training once the model performance stops improving on a hold-out validation dataset. So, when our model performance stops improving on the validation dataset, early stopping detects it. It allows us to specify a large portion of training epochs and then it stops training our model.

4.9 Explainability

CNN is brilliantly intuitive and functional, but they fall short when it comes to mode description and interpretability. Between accuracy and interpretability, there

is always a trade-off. Due to a lack of decomposability, there are no models that can be described or grasped. Understanding is difficult because of the high amount of intricacy. As a result, we employed the concept of Explainability to solve these flaws.
Explainability, also known as interpretability, refers to the ability of a machine learning or deep learning model's output to be described in a way that validates and supports the accuracy of the identification. It deciphers and evaluates the outcomes of machine learning and deep learning models. Because it's difficult to show how a black-box model generated a particular decision, explainability is frequently used in these situations.

4.9.1 Gradient Class Activation Map (Grad-CAM)

As we all know that deep learning or machine learning just blindly tells us the result or gives the output but does not explain or illustrate the results and does not tell us how we get this type of output.
So, to avoid such black box testing we have implemented explainability to our model with the help of Grad-Cam. The Gradient Class Activation Map is a tool that improves the transparency of Convolutional Neural Network-based models by displaying the input regions that are critical for model predictions or visual interpretations. This representation is both high-resolution and class discriminating. It employs any target concept's gradients to build a localization map showing the critical regions in the image for predicting the concept. Grad-CAM requires no retraining and is broadly applicable to any CNN-based architecture.

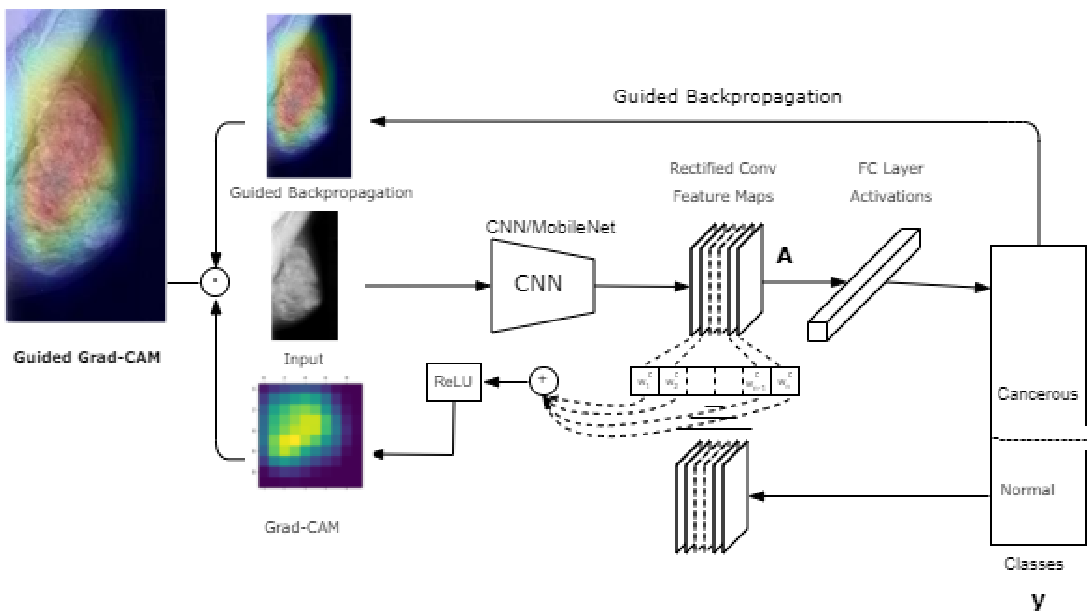


Figure 4.8: Grad-Cam

As the figure 4.8 shows that here our mammographic image is fed to the input layer of our CNN-based model then we take the last layer of the model as it signifies the most important features. Thus we took this layer and generated a heatmap on it. As you can see in the heatmap and these pictures, important features are highlighted.

Based on these features our model had predicted whether this mammography is cancerous or normal tissue.

Chapter 5

Result Analysis

5.1 Accuracy Calculation

The model's performance was evaluated after it was trained to determine how accurately it might predict. The actions we used to evaluate execution were based on the disorder lattice's four boundaries. The boundaries are TP, TN, FP, and FN, with True certain and Genuine negative indicating that the number of perceptions was correctly predicted. The proportion of precisely predicted examples to all-out examples is determined by precision. The classifier's correct anticipated pace is determined by the following condition:

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

Sensitivity refers to how well the model could predict test outcomes that differed from all of the actual results in the test set. When the model structured a perception as 'dependent,' the individual was powerless to fixation; affect ability saw the example of expecting the proper banner in our experiment. The following are the requirements for processing sensitivity:

$$\text{Sensitivity } = \frac{TP}{TP + FN}$$

Furthermore, Precision depicts the percentage of correctly predicted positive impressions that sum up to positive perceptions in the test group.

$$\text{Precision } = \frac{TP}{TP + FP}$$

The model's specificity is determined by how often it can predict false characteristics among all true regretful traits. When the model gave the answer 'calm,' indicating that the individual is not prone to compulsion, it projected how frequently the model could predict the correct negative outcome.

$$\text{Specificity } = \frac{TN}{TN + FN}$$

5.1.1 Validation on CNN

Here, we have used CNN with added dense layer(with transfer learning) that helps us to analyze our image data and push us to have a good classification. We have run this for Epoch=30. And find the accuracy and loss function shown in the figure 5.1 below.

```
Epoch 1/30
8/8 [==============================] - ETA: 0s - loss: 0.6771 - accuracy: 0.6055
Epoch 00001: val_accuracy improved from -inf to 0.60547, saving model to
/content/drive/MyDrive/Thesis work/bmodel.h5
8/8 [==============================] - 211s 27s/step - loss: 0.6771 - accuracy: 0.6055 -
val_loss: 0.6418 - val_accuracy: 0.6055
Epoch 2/30
8/8 [==============================] - ETA: 0s - loss: 0.6423 - accuracy: 0.6094
Epoch 00002: val_accuracy improved from 0.60547 to 0.66211, saving model to
/content/drive/MyDrive/Thesis work/bmodel.h5
8/8 [==============================] - 127s 17s/step - loss: 0.6423 - accuracy: 0.6094 -
val_loss: 0.5834 - val_accuracy: 0.6621
Epoch 3/30

.

.

.
Epoch 17/30
8/8 [==============================] - ETA: 0s - loss: 0.4127 - accuracy: 0.7891
Epoch 00017: val_accuracy did not improve from 0.78320
8/8 [==============================] - 28s 4s/step - loss: 0.4127 - accuracy: 0.7891 -
val_loss: 0.4074 - val_accuracy: 0.7754
Epoch 00017: early stopping
```

Figure 5.1: Accuracy after applying CNN

At the first epoch of our training our model started with gaining nearly 60% accuracy. CNN with transfer learning:the accuracy is 78%
Top accuracy:
Training: 83.4598% Testing: 78.92%

In neural network loss function is one of the most significant component. Loss is actually the prediction error. In other word, the difference between the predicted result and the acquired result is called loss. The way we calculate the loss is called loss function. So, if the difference is higher loss function will be very large number.

Here, the figure 5.2 shows that the predicted output line and actual output line deviated so far from each other after every epoch. So the difference between these two result is higher when we are applying CNN. As a result, we got an increasing loss trend in case of CNN.

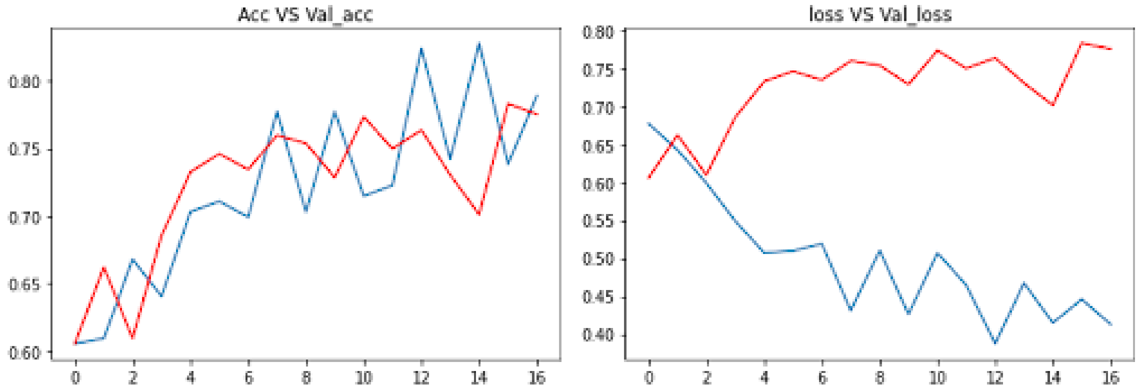


Figure 5.2: Training accuracy vs Test accuracy and Training loss vs Test loss of CNN

5.1.2 Validation on MobileNet

At the very beginning of our research, we have started feeding our data set to a simple CNN model. But in that case, our model accuracy was not that satisfactory. As we have to deploy it in the real-life medical sector we must have ensured high accuracy otherwise if our model mispredicts a sample that might cause death to the people. To fix this up, we have decided to use transfer learning. So in transfer learning what we do is transfer the learning of a pre-trained model to our new model. This helps us to improve our model thus we can achieve good accuracy. So, as a pre-trained model, we use MobileNet architecture. We did not train its layer rather we add a dense layer to it. After that we train our model with our training data which we previously separated for training from our data set. We have train our mobileNet based model for Epoch=30 And found promising accuracy. The accuracy that we have found and loss function shown in the figure 5.3 below:

```
Epoch 1/30
8/8 [==============================] - ETA: 0s - loss: 7.7885 - accuracy: 0.5781
Epoch 00001: val_accuracy improved from -inf to 0.73047, saving model to
/content/drive/MyDrive/Thesis work/bemodel.h5
8/8 [==============================] - 388s 48s/step - loss: 7.7885 - accuracy:
0.5781 - val_loss: 2.9390 - val_accuracy: 0.7305
Epoch 2/30
8/8 [==============================] - ETA: 0s - loss: 4.1014 - accuracy: 0.6367
Epoch 00002: val_accuracy improved from 0.73047 to 0.74023, saving model to
/content/drive/MyDrive/Thesis work/bemodel.h5
.
.
.
8/8 [==============================] - 183s 25s/step - loss: 4.1014 - accuracy:
0.6367 - val_loss: 1.8043 - val_accuracy: 0.7402
Epoch 3/30
8/8 [==============================] - ETA: 0s - loss: 3.1838 - accuracy: 0.6797
Epoch 00009: val_accuracy did not improve from 0.80469
8/8 [==============================] - 40s 5s/step - loss: 3.1838 - accuracy:
0.6797 - val_loss: 1.2153 - val_accuracy: 0.7852
Epoch 10/30
8/8 [==============================] - ETA: 0s - loss: 1.8184 - accuracy: 0.8008
Epoch 00010: val_accuracy improved from 0.80469 to 0.81250, saving model to
/content/drive/MyDrive/Thesis work/bemodel.h5
8/8 [==============================] - 40s 5s/step - loss: 1.8184 - accuracy:
0.8008 - val_loss: 1.2128 - val_accuracy: 0.8125
Epoch 11/30
8/8 [==============================] - ETA: 0s - loss: 1.0325 - accuracy: 0.8125
Epoch 00011: val_accuracy did not improve from 0.81250
```

Figure 5.3: Accuracy after applying MobileNet

At the first epoch of our training our model started with gaining nearly 60% accuracy. MobileNet with transfer learning:the accuracy is 82%
Top accuracy:
Training: 84.77% Testing: 81.25%

In neural network loss function is one of the most significant component. Loss is actually the prediction error. In other word, the difference between the predicted result and the acquired result is called loss. The way we calculate the loss is called loss function. So, if the difference is higher loss function will be very large number.

Here, the figure 5.4 shows that the predicted output line and actual output line remains close to each other after every epoch. Here, the difference between these two result is lower when we are applying MobileNet. As a result, we got the minimal loss in case of mobileNet.

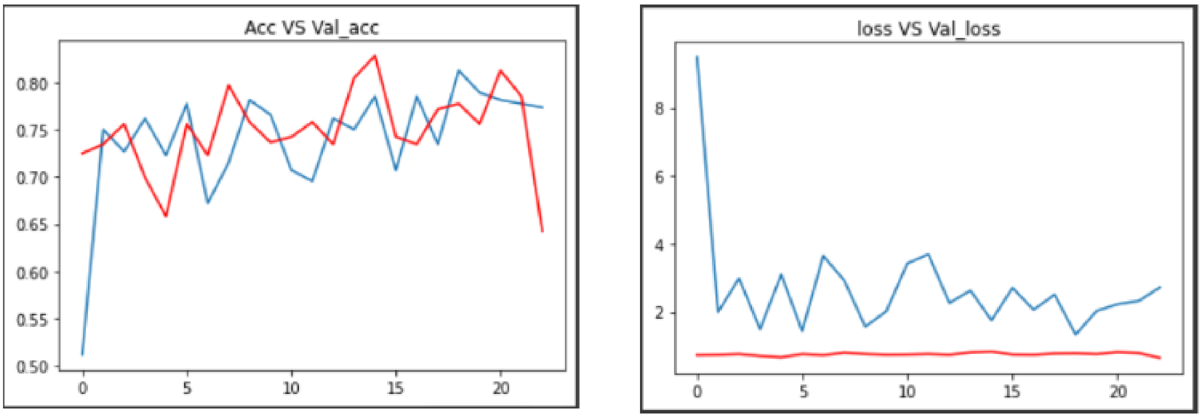


Figure 5.4: Training accuracy vs Test accuracy and Training loss vs Test loss of MobileNet

Here, we have tested some random mammography pictures those we separated from our data set before training. As shown in the figure 5.5, the first mammography belongs to cancer class and our model has predicted it accurately as it has cancerous tissues. In the second picture, we took the sample from mammography of a healthy breast. Our model has also predict this class accurately as it could able to identify that this mammography is normal. Thus we got the cross validation of our data set and found that our model shows very promising predictions.

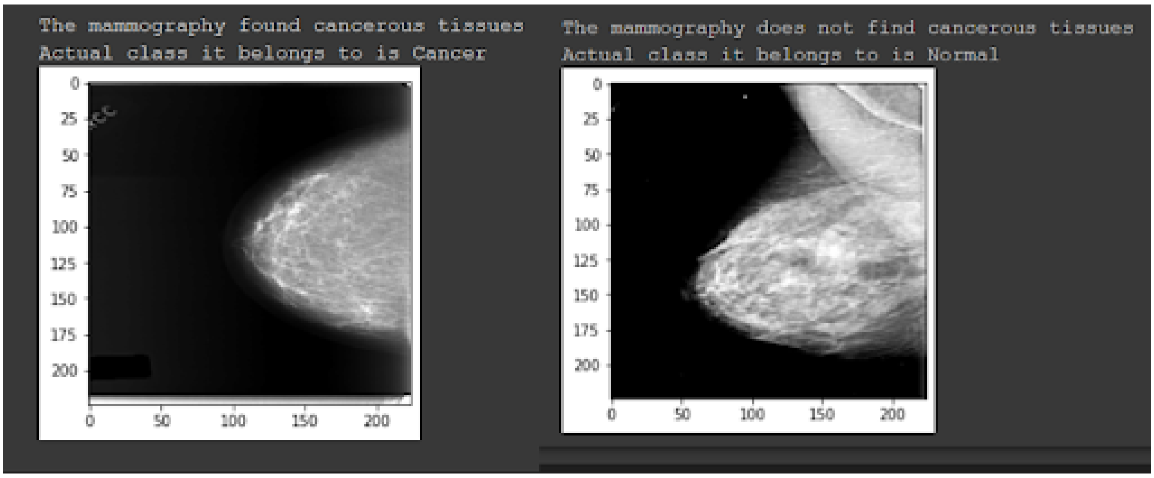


Figure 5.5: Result Analysis

5.2 Summary of Training and Testing Accuracy

So, in comparison, at the very beginning we have started with a simple CNN model. With this architecture we got 83.45% training accuracy and only 78.92% testing accuracy which is very unsatisfactory case as we are planning to deploy this model in medical sector where we have to deal with life. If a wrong predication happened this might cause death to the people. As long as this sector is very sensitive we must have to build a model that ensure us high accuracy. Keeping that on our mind, we have decided to use transfer leaning thus we can use learning of a pre-trained model to our base model by which we can reach to a promising model. For that here we used MobileNet architecture to build our model. Along with that we have added an extra dense layer with sigmoid activation function. From this modified MobileNet model we have got better accuracy. We got 84.77% training accuracy and 81.25% testing accuracy. We did not get much related work with this dataSet hence could not able to compare with all state of art models. But during our research we have found that comparing to other deep learning model we got better accuracy with mobileNet. Thus, here we are proposing this model in our research. So far, we have been successfully able to show the comparison with different models with our proposed model.

Name of the Model	Training Accuracy	Testing Accuracy
CNN	83.45%	78.92%
MobileNet	84.77%	81.25%

Table 5.1: Accuracy Table

5.3 Model interpretation with Grad-CAM

One of our main goals was to incorporate interpretation into our deep learning models. Deep learning model predictions are similar to black-box testing in most cases. One of the main concerns of data analysts is this. Along with predictions from our deep neural network models, we've included an explanation of why our model predicts that particular class in our suggested model. In the figure 5.6 shown the interpretation of two test images from our validation data.

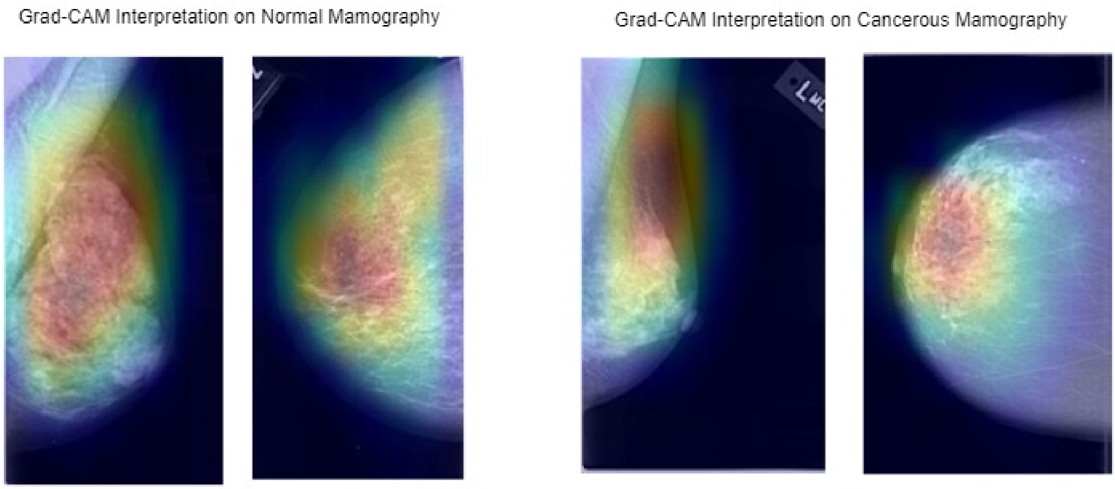


Figure 5.6: Grad-CAM implementation on medical mammography

Lastly, we show the visualization (figure 5.7) based on what features our model predicts whether this image contains cancerous tissues or not. This is how we transform the black-box model of our deep neural network into a dynamic and understandable representation. As a result, we have achieved our last goal, which is the interpretability of our deep learning model's expectations.

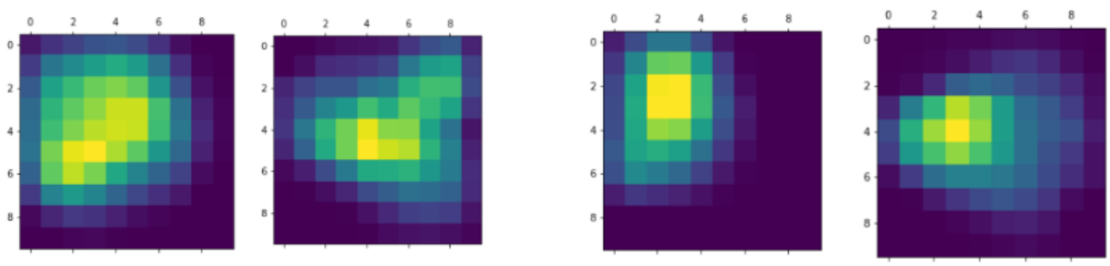


Figure 5.7: Grad-CAM heatmap on medical mamography the same subject (mammography)

5.4 Comparison with other related works

It's a good idea to employ a quick and efficient model architecture when integrating a neural network into your program. Especially if you want to make frequent predictions, such as on real-time video. A neural network like ResNet-50, which is a common backbone model used in research publications, consumes too much power and is inappropriate for real-time applications. Of course, there is a trade-off, as with most things in engineering: In general, the larger the model, the better the findings. However, the slower it operates, the more energy it consumes. Large models easily heat up and deplete the battery. That isn't a pleasant user experience.

VGG19 is a very heavier model. It takes more training time to catch everything. Moreover, it also has a Vanishing gradient problem. As it has so many parameters, its model weights are very large, weighing more than 550 MB. The main disadvantage was that there were quite a few parameters to be trained in such a network.

MobileNet[4] is a lightweight deep neural network with fewer parameters and greater classification accuracy than other deep neural networks. Dense blocks, as proposed in DenseNets, are integrated into MobileNet to minimize the amount of network parameters and increase classification accuracy. MobileNet outperforms other state-of-the-art convolutional neural networks in a variety of ways. MobileNets are small deep neural networks that are well-suited to mobile and embedded vision applications. MobileNets are built using depthwise separable convolutions and simplified architecture. MobileNet makes use of two basic global hyperparameters to effectively balance accuracy and latency. Object identification, fine-grain categorization, facial recognition, large-scale geolocalisation, and other applications could all benefit from MobileNet. It's a convolutional neural network with a short latency.

In the first place, this model makes use of both the global location and context simultaneously. Also, it offers better segmentation performance with fewer training samples. In terms of its architecture and its ability to segment images pixel-by-pixel using layers of convolutional neural networks, Mobile-Net[9] captures more of the functionality of conventional models. Even with small datasets, this method works well. The algorithm includes only Convolutional layers and no Dense ones, so it can process any size image. The "Mobile-Net" does not require multiple runs to perform image segmentation, and it is well suited to segmenting images in biology or medicine with very few labeled images.

Keeping the number of channels of the input matrix constant allows the pooling layer to reduce the height and width information. This step reduces complexity (each element of the image matrix is called a pixel). In short, a pooling layer represents a group of pixels with a single pixel. The output is pixel-wise (minus the validity margin of the convolutions). It should work without modifications since we are going to do segmentation here. Structured simply, it is easy to read. This is a repetition of essential components: down sampling, convolutions, tiling, pooling for the encoding path, and up sampling, convolutions, and tiling for the up sampling path. As a result, it should not pose a great deal of difficulty to implement. The performance is excellent. In segmentation challenges, it still ranks well. It won several benchmarks when it was introduced. Since we planned to use medical image data, Mobile-Net would be a good fit.

Chapter 6

Conclusion and Future Work

Every year many women suffer and die because of breast cancer. Mammograms are one of the best ways to detect cancer cells at an early stage. However, detecting cancer from these pictures is difficult. According to the American Cancer Society, one out of every five instances of breast cancer is overlooked by radiologists, and half of all women who receive screening for a 10-year period will have a false positive, in which cancer is mistakenly suspected.
Over treatment with invasive biopsies and undue stress for patients can result from a false positive. A false negative might lead to delinquency. But by using Artificial Intelligence the computer can detect cancer cells more accurately. As a result, the initial treatment can be started quickly and prevent death.
Cancer has always been a life taking disease among human beings. In the past medical science was not that advanced in detecting and curing cancer cells very easily. But nowadays the progression of technology has become so advanced that we can diagnose cancer very easily at our nearest hospital. Though the advancement of technology has been established, it's still not quite enough to diagnose all kinds of critical cancer. Moreover, the number of breast cancer patients has been increasing day by day. In Spite of having advanced technologies we are still not capable of finding cancer cells with higher accuracy because the diagnosis report is examined by humans and making errors is the nature of humans. Therefore to get better accuracy in detecting cancer cells from medical images we have tried to build a system by doing our research in this field. The main objective of our research was to find an optimal way to identify cancer cells from medical images so that if a doctor mistakenly misses examining medical images with his bare eyes our system can easily detect that cell. Besides, we have another in-built feature in our system which is grand cam. By using this feature it can specifically mark the cancerous cell and will let us know it's a benign or a malignant cell. In our research work we have trained our data using the mobileNet model and received a satisfactory accuracy result compared with others work on this data. Also, we have compared our model with other existing models such as VGG-19, restNet50, and inception3 and showed the efficiency of our proposed model. Even so, our collected data is open sourced and the patient data it has is from a specific community or a country. But in the future, we want to work on our research using our data from other countries also. In this way our research work will be more flourishing. In addition to this, we also want to work on a hybrid model to extend our knowledge where more complex algorithms will be used. Last but not the least, we want to see a world where people will not

die from misdiagnosis of cancer. Unwanted deaths from cancer are always painful and by minimizing the death rate we can make the world a better place.

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