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Research Article

A Deep Learning Based Approach to Breast Cancer Detection

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Abstract: Breast cancer is the most frequent malignancy in women worldwide. Lack of understanding and late tumor diagnosis increase women's mortality. Early discovery, therapy, and periodic check-ups may reduce mortality. Breast tissue cells proliferate too quickly, causing cancer. Numerous researchers calculate breast cancer tumor accuracy and prediction using different machine learning models on different datasets. Researchers employ CNN and other deep learning algorithms. This study classifies benign and malignant cancers using inceptionv3 deep learning model and a convolutional neural network using convolution layers. The DDSM Mammography dataset comprises 11170 pictures, while the BreakHis dataset has 7909 images. This study trains the CNN model inception V3. A PCA-based logistic regression classifier outperformed other machine learning algorithms. This study uses transfer learning on a pre-trained proposed model, Inception V3, which has a testing accuracy of 96% on the DDSM dataset and on the WCBD dataset the accuracy of 96.24%. The third dataset, the Breast Cancer Histopathological Database (BreakHis), has 7909 microscopic pictures, and the CNN model had 98.8% accuracy, the best of all datasets in this study. Cross-validation of accuracy, precision, recall, and f1 score on deep learning approaches improves results.

Keywords: Breast cancer; malignancy; mortality; early discovery; CNN; deep learning;

1. Introduction

Breast cancer is caused by the hasty progress of cells in the breast tissue. These tissues are tumors, which can be benign or malignant. Noncancerous is benign, while cancerous is malignant. Malignant is more dangerous because it spreads quickly to other parts of the body, resulting in death. Research states that “2.3” million new breast cancer patients are diagnosed globally and over “650,000” die from it [1]. Globally, one woman gets breast cancer every 20 seconds and dies every 5 minutes. Over “170,000” new cancer cases are expected in Pakistan this year. Before it spreads and kills, breast cancer must be stopped. Machine learning (ML) is crucial to medical image categorization. In recent years, ML approaches have been developed for manual and automatic illness identification. ML algorithms are advancing, including deep learning. Deep learning (DL) is a smarter, more advanced machine learning area. DL approaches significantly impact medical image classification models [2].

Images are classified using mammography, magnetic resonance imaging (MRI), ultrasound, and biopsy in medical science. A biopsy determines if a bodily component is malignant. Different sources said 80% of women are breast cancer-free after a biopsy. A mammogram diagnoses breast cancer via an X-ray. If the

X-ray diagnoses the afflicted area, the doctor proposes evaluating the breast tissue. When a suspicious breast area is found, the doctor orders an ultrasound. If the ultrasound does not show considerable tissue, the doctor may recommend an MRI to better see the breast [3]. Breast cancer tumors are detected by taking numerous breast MRI pictures and syndicating them on the computer.

Breast cancer is diagnosed via screening, when physicians or nurses look for tumors using mammography and other imaging methods. Early cancer detection is possible with screening [6]. Mammography is the best early breast cancer diagnostic method due to its low cost and quickness. In mammography, anomalies like masses and calcifications are analyzed to diagnose breast cancer. Physicians estimate mammography accuracy at over 90%. Doctors may miss 11%–16% of breast cancer cases. Cross-validation requires two doctors to evaluate the same mammogram at separate times [7]. Although cross-validation improves breast cancer diagnosis to 14% with single checking, this procedure is time-consuming and costly. Computer-aided detection reduces this cost. In medical analysis, computers can be used. Databases, machine learning, image processing, and data analysis are used for this detection [8].

How might the computer-aided design (CAD) system reduce mammography breast cancer false positives?

Classifying pictures with image processing and computer vision reduces early breast cancer false-positives. Breast cancer mammography diagnosis is supported by these two machine learning methods. Edge detection, noise reduction, picture pre-processing, and region of interest are used to detect breast abnormalities in mammograms. After picture pre-processing, find characteristics to develop an algorithm to accurately diagnose breast cancer. These methods' precision is still a challenge.

This research presents a mammogram-based breast cancer detection method. The technique has two main aspects. Image processing is utilized to extract features from the DDSM and BreakHis datasets in the first portion. InceptionV3, a neural network model, predicts model accuracy using extracted features. On the WCBD dataset, logistic regression and the other three machine learning algorithms are trained and assessed in Part 2. This research aims to improve breast cancer diagnostic accuracy by integrating image processing and supervised machine learning classifiers like logistic regression into the new PCA model. This research also aims to eliminate the false positive probability from the breast cancer detection confusion matrix on WCBD and DDSM.

This section provides an introductory summary of breast cancer, including its detection methods and research objectives. Section 2 provides a comprehensive assessment of recent relevant studies. Section 3 presents a thorough and inclusive examination of the proposed methodology. In the fourth section, we learn about the trials that were run to assess the efficacy of deep learning models and machine learning algorithms in breast cancer diagnosis using the DDSM dataset. The fifth section provides a comprehensive account of the findings and recommendations for future research.

2. Related Work

S.V. Sree reviews breast cancer studies in this paper. The CNN deep-learning algorithm detected breast cancer [14]. Input, output, and hidden layers make up a deep neural network. The model's intermediate layer is hidden. CNN comprises four layers: convolution, max pooling, Relu, and SoftMax. X-ray mammograms are among the many diagnostic tests. This article concludes that deep learning performs better on image data.

B. Jaafar [15] utilized deep learning to interpret mammogram pictures. Alex Net has 5 convolutional, 3 pooling, and 2 FC layers. Resnet is the latest deep learning algorithm with greater shortcuts and batch normalization. Auto-encoders and decoders are used to segment and detect tasks in this paper. Classification using CNN. Deep learning expanded mammography analysis. Mammography and CNN breast cancer detection still struggle with massive data.

K. S. Krishna estimated in this research that 2,778,850 people will have breast cancer by 2040. This paper diagnoses breast cancer using machine learning and deep learning. In machine learning, RVM outperforms SVM, and in deep learning, AUC outperforms. This research evaluates three machine learning models: Random Forest, Naïve Bayes, and KNN, calculating accuracy, precision-recall, and f1 score using the Wisconsin Diagnosis Breast Cancer dataset [17]. KNN excels in accuracy (94%), precision-recall, and f1 score compared to Random Forest (92%), and Naïve Bayes (87%). Using supervised learning could help detect breast cancer early.

N. Khuriwal employed CNN and a deep learning algorithm to diagnose breast cancer early with 98% accuracy on the Mias dataset [18]. Mias has 200 photos and 12 features. The author employed adaptive mean filtering, color-enhancing, and watershed segmentation for pre-processing. The author plans to test on a large image dataset and various cancers like lung "lips," etc.

U.Khasana employed the ultrasound image modality for breast cancer detection, but the picture quality was low; therefore, he applied segmentation and the watershed transform method to improve image quality and get 88.6% accuracy with about 11% error [19].

This research recommends the automatic Diverse Features-based Breast Cancer Detection (DFEBCD) algorithm to classify mammograms as normal or benign [20]. Emotional Learning-inspired Ensemble Classifier (“eliec”) and Support Vector Machine (SVM) on the IRMA mammography dataset Diverse Features-based Breast Cancer Detection (dfebcd) were used to test CNN and other classifiers. CNN was good for three people, but hybrid and dynamic characteristics made “eliec” the best classifier.

ML approaches for breast cancer detection are discussed in this research. Mr. Rathi suggested a mixed strategy. They compared MRMR feature selection with four machine learning classifiers (Support vector machine, function tree, Naïve Bays, and end meta) based on characteristics such as absolute error, accuracy, Kapa statics, specificity, and sensitivity [21]. The author tests these methods using two UCI repository binary and multi-classification datasets. SVM performed better than the other three algorithms in this research [21].

Machine learning is crucial in medicine. A Bharat proposed a breast cancer prediction machine learning system [22]. This research compared the accuracy of four algorithms: k nearest neighbors, support vector machine, decision tree, and naïve bays. K nearest neighbors had the best accuracy of the three algorithms. Multi-SVM can be used for multi-class datasets, although support vector machine techniques only operate for binary classes.

M.Jannesari's fine-tuned deep neural network for four cancers had 99.8% accuracy. On Breakhis, use Resnet V1 50 and V1 152 [23]. The author suggested automated multi-classification breast cancer detection. Convolutional networks for biomedical image segmentation, deep labv3, and U-net are suggested for future research [24].

M.O.F. Goni uses probabilistic neural network (PNN) classifiers and Gaussian mixture models for segmentation. Future neural network classifiers for cancer prediction: benign or malignant probability the author wants cloud-based data for faster access and time savings. These algorithms—Adaptive Mean, GMM, and PNN—help doctors diagnose and cure breast cancer early, saving lives [25].

P. Kathale devised a random forest model to predict breast cancer in normal and cancer patients [26]. The RF model classifies a dataset with 95.8% accuracy after image pre-processing in 6.25 seconds and 3.16 seconds, respectively. GLCM, entropy, and mean image processing features. Future training should use larger datasets for improved accuracy.

M. Kumari presented two breast cancer detection machine learning models in this research. Breast cancer is the most common kind in women and raises the death rate owing to late detection and treatment. KNN and SVM algorithms were applied to the WBCD dataset and yielded 99.28% accuracy. First-stage breast cancer detection with a trained and improved model can save many lives [27]. WBCD data from the UCI repository has 699 values and 11 features, 16 of which are missing. The dataset distributes 65% malignant and 35% benign values. Confusion matrix and cross-validation assessed classifier accuracy. Its accuracy is higher than that of the KNN classifier. Physicians and patients saved time and money using the proposed system. In the future, the author wants a more accurate, cost-effective dataset with more values.

Researchers say more than 2 million women worldwide are diagnosed with breast cancer each year, and the rising death rate causes major health difficulties. Gerald SZE improves classifier accuracy by reviewing Python code for basic algorithms using the Wisconsin breast cancer database. The author chooses the best supervised machine learning algorithm for early breast cancer detection [28]. SVM's linear performance was 97% better than other algorithms, but when dealing with people's lives, a near-perfect model is needed for further investigation.

P.S. Shekar employed the SVM model to manually classify breast cancer histology images as benign or malignant [29]. This article identifies benign and malignant breast masses quickly and precisely. This reduces the risk of bareness and improves survival with several drugs. The paper aimed to create an SVM classifier that can diagnose breast cancer as benign or malignant with 97% accuracy and 95% precision.

C. Singhala introduced deep neural network (DNN) and contrast-limited-based histogram equalization for early breast cancer diagnosis [30]. All MIAS dataset photos were processed using both methods. In experiments, the DNN-based strategy had a lower mean square error (MSE) than the peak signal-to-noise ratio (PSNR), which was high. The author concluded that the DNN-based strategy is the best method for breast cancer detection on the MIAS Database because it performs better.

Z. Wang advocates using computer-aided diagnostics to detect breast cancer early on mammograms. The radiologist still struggles with CAD system accuracy [31]. The CNN learning model can categorize images using deep features and ELM clustering, according to the author. Using an extreme learning machine classifier, the author fused deep density, morphological, and texture data to classify breast tumors as benign or cancerous. The dataset included 400 mammography pictures, 200 of which were benign and 200 malignant. The CNN feature model's ELM specificity, sensitivity, and accuracy are best in a single feature model, suggesting this paper's model is superior. The CNN model with the texture feature in double feature detects breast cancer tumors with the highest specificity, sensitivity, and accuracy.

F. Yilmeez compared dense net-201 with Xception-net for early breast cancer diagnosis [18]. This research evaluates approaches using the breast cancer dataset, which comprises 20748 training images and 5913 testing images. Dense Net-201 has F1 accuracy of 92.24%, while Xception has 92.41%. Both methods have good accuracy and are similar.

To detect benign or malignant cancers, mammography screening is effective. The biggest challenge is identifying benign or malignant patients. Machine learning could improve breast cancer diagnosis. K closest neighbor (KNN) ML algorithm accuracy for early breast cancer diagnosis varies in research publications [32]. S. E. Khorshid said KNN is the easiest ML algorithm to construct and has the best accuracy (99.12%). Using diverse algorithms' accuracy could improve prediction efficiency in the future.

A pre-trained Resnet-50 model and class activation map technique were proposed by Wael E. Fathy to diagnose breast cancer [5]. The suggested method had 82.1% specificity, 99.8% sensitivity, and a 96% AUC. In this paper, a model diagnosed cancer with 93.67% accuracy and 0.122 false positives per image. This study classified pictures as benign or cancerous using the DDSM database. The author plans to add a threshold value to improve the model's accuracy, specificity, and sensitivity.

X Yu and W Pang suggested a pre-trained deep fusion learning model to diagnose benign and normal tumors [33]. The author proposed two deep fusion learning models: model 1 and model 2. The model extracted the ROI from the database. The models have two steps. First, ROI patches were modeled to diagnose normal and tumor, and model 2 integrated the feature using 1*1 convolution. Model 1 has 0.89 accuracy, 0.91 recall, and 0.80 precision. Model 2 gave the tumor 0.87 accuracy, 0.95 recall, and 0.75 precision.

Globally, one woman gets breast cancer every 20 seconds and dies every 5 minutes. Over “170,000” new cancer cases are expected in Pakistan this year. Before it spreads and kills, breast cancer must be stopped. ML is crucial to medical image categorization. In recent years, ML approaches have been developed for manual and automatic disease identification. ML algorithms are advancing, including deep learning. Deep learning (DL) is a smarter, more advanced machine learning field. DL approaches significantly impact medical image classification models [2].

P. Danaee detected breast cancer using deep learning. P. Danaee utilized a stacked denoising auto-encoder to extract gene features and test a supervised classification model to detect cancer with the new features [34]. These two qualities are ideal for early breast cancer screening, according to the author. The author plans to diagnose more breast cancer types using a larger dataset.

D. Selvathi introduced a sparse auto-encoder (SAE)-based breast cancer detection system that is error-free and quick compared to previous methods that learn feature representations from image datasets and classifiers [35]. The SAE performs in Random Forest Classifier, Support Vector Classifier (SVC), and K Nearest Neighbour. Random Forest performed best in this research. After pre-processing on SAE unsupervised learning, the Random Forest model gives 98.9% accuracy on publicly accessible MIAS dataset mammograms.

In [36], Y.J. Tan suggested a convolutional neural network model for early breast cancer diagnosis using pictures. Normal, benign, and malignant tumors exist. Classifying mammograms: MCCNN and BCDCNN improved image classification. Up to 87% system accuracy. 322 mammograms are in the dataset. CNN has the highest accuracy and the fastest diagnosis.

In this reference, Omondiagbe examines support vector classifiers, artificial neural networks, and naïve Bayes approaches on the WCBC database [37]. The author incorporates all machine learning approaches with an early feature selection strategy and examines their performance. The proposed model reduced dataset dimensionality using linear discriminant analysis and a hybrid technique. The model's accuracy is 98.42. The author plans to analyze more breast cancer detection machine learning algorithms and construct a model that predicts other breast cancer-related disorders.

S. Karthik proposed computer-aided detection for early breast cancer analysis utilizing a deep learning neural network with many layers on a support vector machine classifier for improved accuracy [16]. This study uses Wisconsin breast cancer detection. The dataset analysis yielded 98.62% accuracy, better than the other state-of-the-art systems's designs and tests. The author wants to work on particle swarm optimization to save time and enhance accuracy.

A Breast Ultrasound (ABUS) by Y. Wang uses 3D CNN for computer-aided cancer screening [13]. The author claimed to have pioneered 3D CNN deep learning. ABUS provided a 3D representation of the breast and an independent image that a radiologist could understand. The author proposed using 3D CNN for cancer diagnosis in automated breast ultrasound. The author detected cancer with excellent sensitivity and low false positives using a multilayer feature. The voxel-level adaptive threshold distinguishes benign and malignant tumors. The author tested this method on 900 volumes of 745 malignant and 144 healthy women. This experiment yields 95% sensitivity and 0.84 false positives. Breast cancer detection using ABUS is sensitive and has few false positives.

This research employed the DDSM and CBIS-DDSM datasets and tested multiple deep learning models. Deep convolutional neural networks (CNNs) are investigated for breast cancer CAD. CNNs are built and tested on two mammographic datasets, with ROIs showing harmless or worrisome mass sores [12]. The exhibition assessment of each inspected network is done in two ways: with pre-prepared loads and arbitrarily. Broad test findings illustrate the maximum exhibition achieved by adjusting a pre-prepared organization versus preparing without preparation. This research's best models were Alex Net and Resnet 50.

3. Proposed Methods

The process consists of four steps. Grab a dataset first from the UCI Repository. Second Pre-Processing a dataset and extracting its features Third Data splitting, training, and testing come last. Data classification and evaluation using deep learning and machine learning algorithms. Model of deep learning CNN and an analysis of a few logistic regression, SVM, and KNN classifiers for machine learning. The UCI repository's WCBD dataset is used to test machine learning algorithms. In cross-validation tests, the logistic regression classifier model yields the best accuracy, nearly 98.25 percent. Our deep learning CNN model is trained using the Keras technique, with 70% of the data used for training and 30% for testing. The accuracy of the neural network model l is 97.66%. Model 2 fig 4-3 displays the process for the other two datasets. When compared to the inceptionV3 model on the DDSM dataset, the sequential model's accuracy on the BreakHis dataset was superior. The percentages for testing and training are 20% and 80%, respectively.

The proposed model 1, which we applied to WCBD after acquiring the dataset, is depicted in figure 1 below

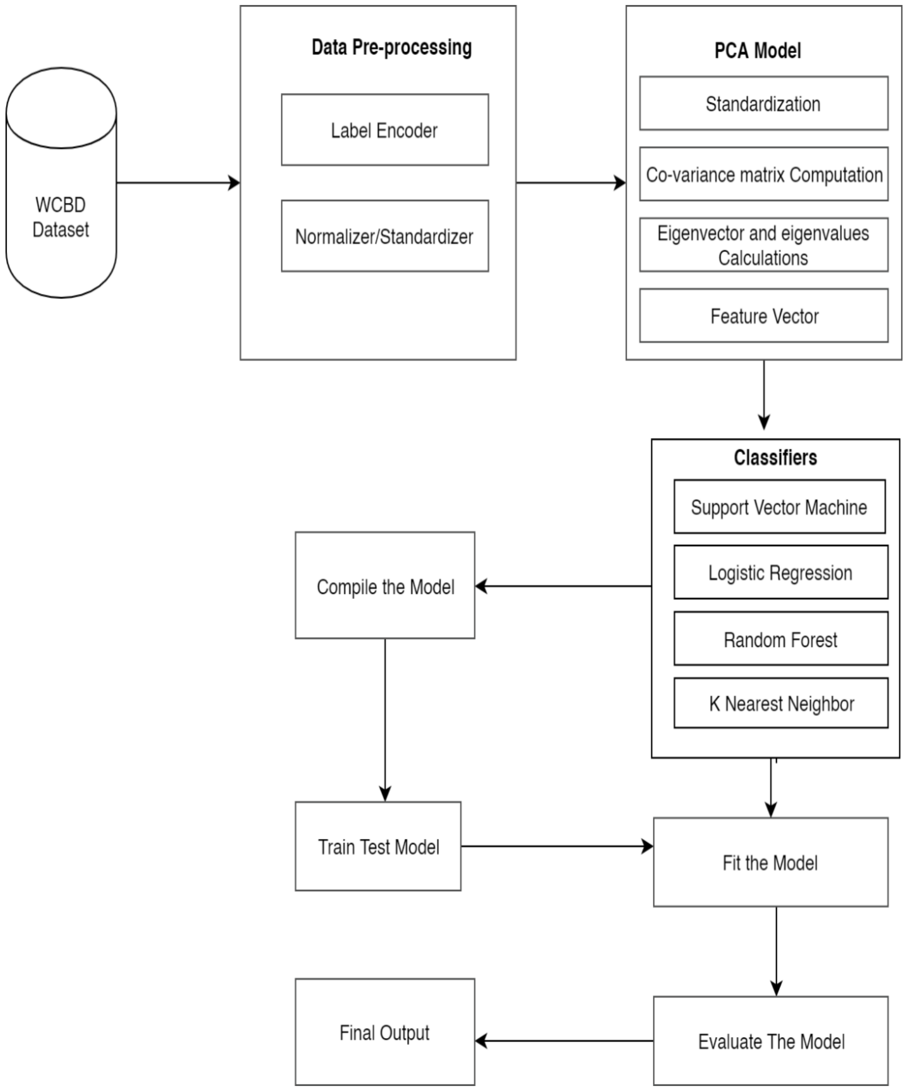

Figure1: Methodology on WCBD Dataset with the PCA (model1a)

In Figure 2, an approach to describing WCBD without the use of a PCA model is demonstrated.

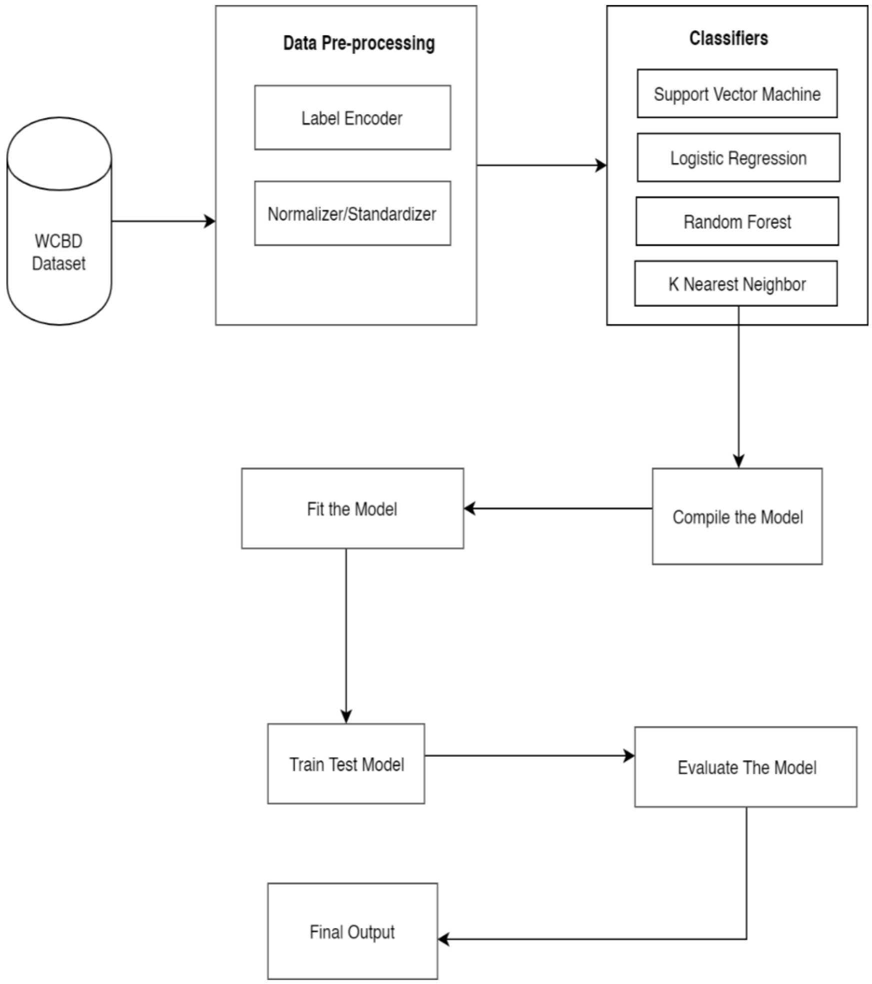

Figure 2: Methodology on WCBD Dataset Without the PCA (model1b)

The methodology of our proposed model2 is displayed in figure 2. We have performed pre-processing on the DDSM and Breakhis datasets, including reshaping and resizing the images. We then applied a CNN model to the DDSM dataset and an InceptionV3 model to the Breakhis dataset. When working with the inceptionV3 and CNN model, it's important to experiment with various layers such as convolution, pooling, and activation functions like Relu. Additionally, the fully connected layer with Sigmoid and SoftMax can be utilized to classify tumors as either benign or malignant.

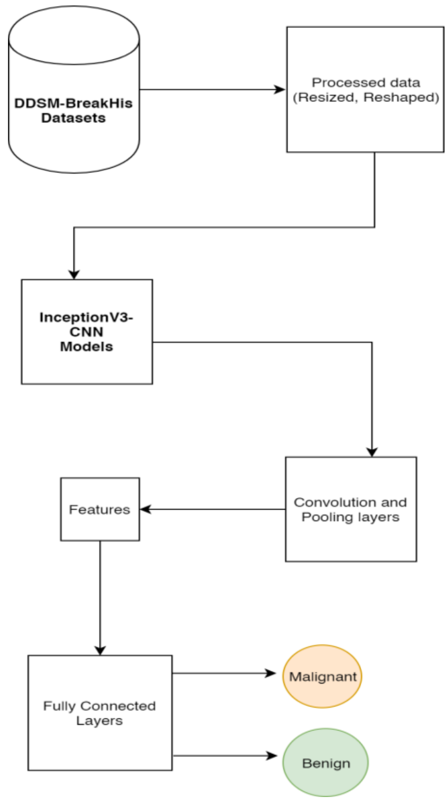

Figure 3: Methodology on DDSM and Breakhis Dataset (model2)

3.1. Datasets

3.1.1. The Wisconsin breast cancer database

The dataset covers 699 instances and 10 attributes. The dataset has a missing value which would be dropout Samples attained occasionally as Dr. Walberg stat in his clinical cases. The dataset replicates this consecutive group of the data. This group information seems immediately below, having been eliminated from the data itself. Benign is a non-cancerous tumour, whereas malignant is a cancerous tumour. We can write benign as 0 and malignant as 1.

3.1.2. DDSM Mammography

The DDSM dataset comprises images, which were pre-processed and subsequently resized to a dimension of 299*299 pixels. 86% of the "55890" training images in this dataset are negative examples, while the remaining 14% are positive examples.

- Pre-processing

There are two categories of images in the DDSM dataset: positive and negative. Positive images are included in the CBIS-DDSM dataset, while negative images are included in the DDSM dataset. During data pre-processing, images are resized to dimensions of 299 by 299 pixels. The negative image was initially 598 by 598 pixels and was subsequently resized to 299 by 299 pixels [11]. In order to extract the region of interest (ROI) from the positive images in the DDSM dataset, a mask with spacing is applied to specify the location of the image. Each image of the region of interest was arbitrarily cropped three times into 598*598 dimensions, with pre-processing including rotation, reversal, and resizing to 299*299.

The resized images are labeled into two binary and multi labels as:

- Binary class - 1 for malignant and 0 for benign

- Multi-Label - 0 for negative, 1 for benign calcification, 3 for malignant calcification, 2 for benign mass, and 4 for malignant mass

3.1.3. Breast Cancer Histopathological Dataset (BreakHis)

There are a total of 7909 images of benign and malignant breast cancer tumors in this dataset. A total of 82 patients were utilized to obtain these microscopic images at various magnification factors. Out of a total of 7909 images, 2480 are benign and 5429 are malignant samples. Each image is 740 by 460 pixels in dimension, in PNG format, and contains an 8-bit depth in the RGB channel [4]. The development of this database was facilitated by the Brazilian organization Pathological Anatomy and Cytopathology. The proprietors of a dataset are certain that this dataset will serve as the optimal resource for their investigations and prove beneficial in the detection of breast cancer.

3.2. Data Preprocessing

3.2.1. Categorical Variable Conversion

Attributing categorical information denotes discrete values that are members of a particular finite set of classes or groups. These are often referred to as "groups" within the context of expected attributes or variables generated by the model. These unique values are either textual or numeric. Definite data can be broadly classified into two classes: ordinal and nominal. The dataset combines categorical and numerical mechanisms. Thus, two distinct sorts of perceptions exist regarding breast cancer. M represents malignancy, while B represents benignly. Each classifier performs admirably with numerical data. Consequently, in order to convert non-numerical data to a numerical value, a "label encoder" was required.

3.2.2. Feature Scaling

When operating with a learning model, scaling the options to a value of variability that is close to zero is dynamic. This may be achieved by ensuring that the variation of the options remains consistent. If the variance of a single feature is orders of magnitude greater than the variance of other options, that feature could potentially result in distinct options within the dataset. We do not want this to happen with our model. The aim at this stage is to attain a mathematical expression that has a mean of zero and a variance of one unit. Although numerous practices exist in this regard, standardization and normalization are the most recent. By substituting their Z scores for the values, standardization occurs.

3.2.3. The Principal Component Analysis (PCA)

The PCA is a technique of correlational analysis that studies the full variance within the knowledge, that is the mutual correlational analysis, and converts the first variables into a minor set of linear mixtures. The diagonal of the matrix covers unions and therefore the full variance is transported into the tissue matrix. The term issue matrix is that the matrix that protects the factor loadings of all the variables on all the factors removed. The term, “factor loadings” is the unassertive correlation between the factors and the variables. The PCA could be a method used for the documentation of a smaller range of distinct variables stated as principal elements from a superior set of information. The technique is wide famine to emphasize variation and detentions well-made patterns in an exceptionally knowledge set. The principal element analysis is recommended once the researcher’s primary anxiety is to work out the minimum range of things that may account for the extreme variance within the knowledge in use in the detailed statistical process, like in city studies. The eigenvalues talk over with the whole variance enlightened by every issue. The quality deviation measures the variability of information. The job of principal part analysis is to advert the patterns within the data and to straighten the info by grace.

PC1 and PC2 represent the PCA model composition in Figure 4. Red spots indicate benign tumors, while green dots indicate malignant tumors. Based on the data presented in Figure 4, it can be observed that the majority of the cases extant at a given point (2.5 0.0) on PC1 and PC2 are benign in nature.

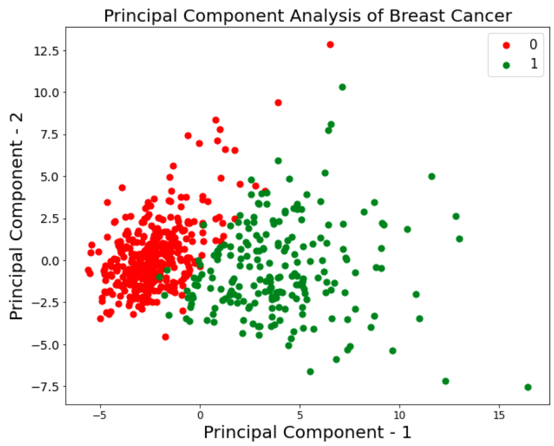

Figure 4: PCA Model Output on WCBD

4. Results and Evaluations

This study evaluates classification issues and classifier performance matrices. The binary variable 1(Malignant) indicates a positive breast cancer diagnosis. A negative instance (0) indicates no breast cancer. In this chapter, we compare machine learning classifier and deep learning model outcomes.

4.1. Models Performance

4.1.1. K-Nearest Neighbors (KNN)

The training set comprises 30% of the model and the evaluation set comprises the remaining 70%, for a total accuracy of 94.24%. However, by implementing Principal Component Analysis (PCA), we were able to improve both accuracy and recall. We attained a 98% recall rate, 99% precision, and 98% accuracy rate. The model obtained an accuracy of 98%, precision of 97%, and recall of 98% for both benign and malignant tumors. The confusion matrix after straightforward KNN and PCA application are compared below. 98% is the aggregate performance of the KNN classifier when applied to the PCA model.

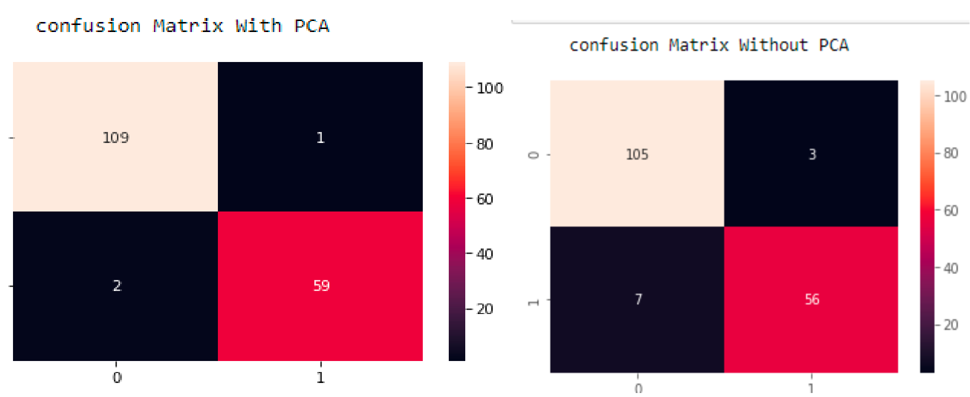

Figure 5: Performance Comparison of the KNN

4.1.2. Logistic Regression (LR)

The Logistic Regression (LR) classifier demonstrates an accuracy rate of 99.4%. Accuracy with the PCA model is 96.49%, whereas accuracy without the PCA model is 96.49%. Figure 5-2a illustrates that the implementation of Principal Component Analysis (PCA) resulted in enhanced precision, recall, and the f1 score. A 98% precision, a 100% recall, and a 99% F1 score. The PCA model obtained a precision of 100%, recall of 97%, and f1 score of 98% for both benign and malignant tumors. 96% is the accuracy of LR in the absence of the PCA model.

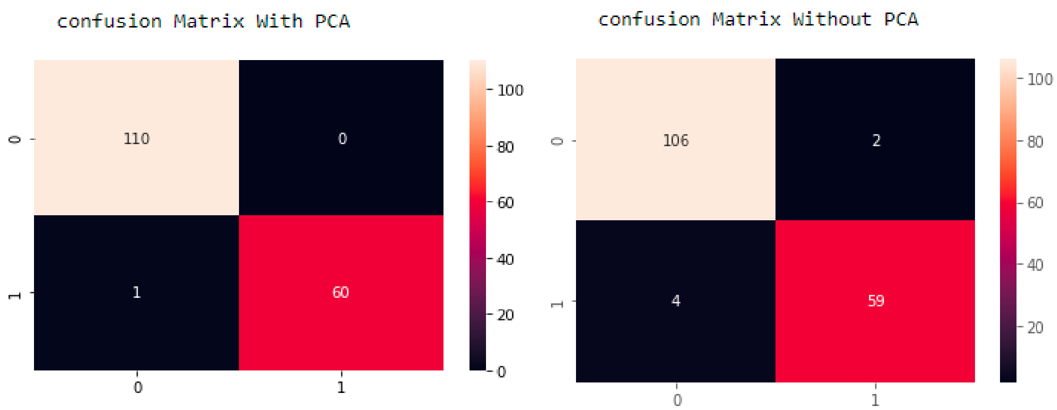

Figure 6: The Performance Comparison of Logistic Regression

4.1.3. Support Vector Machine (SVM)

The Support Vector Machine (SVM) model demonstrates a remarkable accuracy of 99%. The accuracy achieved using the PCA model is 98%, whereas its absence results in a lower accuracy of 98%. Upon implementing Principal Component Analysis (PCA), a marginal increase in the accuracy of the model was observed. The PCA model achieves an accuracy of 99%, precision of 99%, recall of 100%, and f1 score of 100% for benign tumors. For malignant tumors, the model achieves precision of 100%, recall of 98%, and f1 score of 99%.

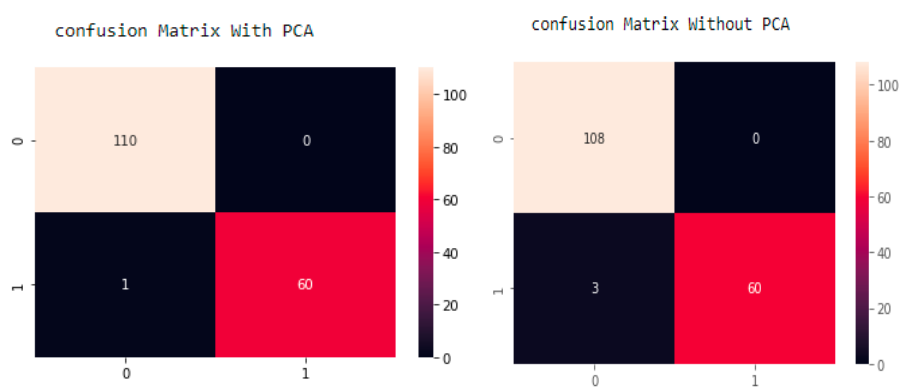

Figure 7: Performance Comparison of SVM

4.1.4. Random Forest (RF)

The Random Forest (RF) model demonstrates a 98% accuracy rate. Achieving an accuracy of 96% without the utilization of the PCA model is possible. We observed that by implementing Principal Component Analysis (PCA), our accuracy, recall, and f1 score all improved. The PCA model obtained an accuracy of 98.2%, precision of 98%, recall of 99%, and f1 score of 100% for benign tumors, and precision of 98%, recall of 97%, and f1 score of 97% for malignant tumors.

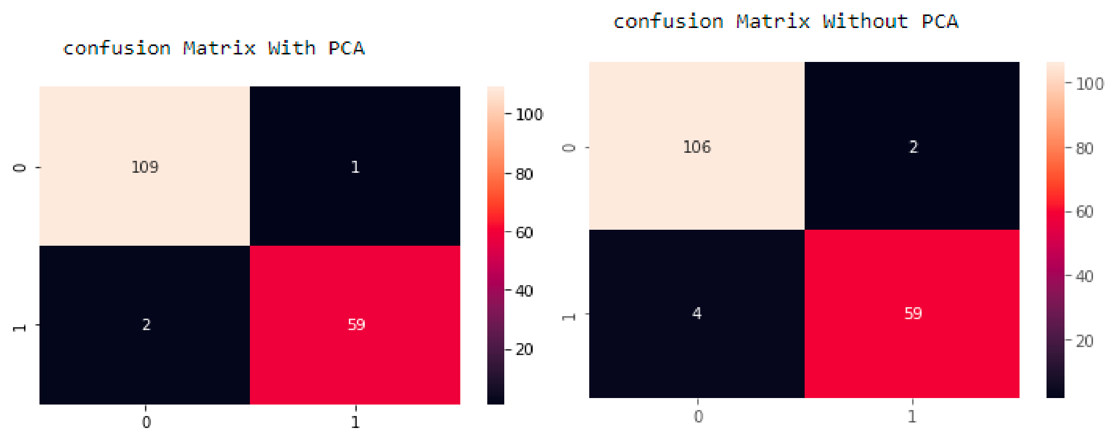

Figure 8: Performance Comparison of Random Forest

4.2. Comparison And Analysis Between the Algorithms

In this research paper, four ML algorithms are examined in depth. In this paper, we compare and contrast the fundamental characteristics and features of four machine learning algorithms. In our experiment, the efficacy of Logistic Regression is comparable to that of other models; both training and prediction are significantly improved by approximately 99 percent.

Table 1 presents comparisons of four machine learning models. Based on the data presented in the table, it can be concluded that the logistic regression model exhibits superior performance compared to the others, as it enables rapid and accurate predictions and has a commendable training speed.

Table 1: Comparison and analysis of ML Algorithms

	Accuracy Prediction	**Training Speed**	**Prediction Speed**	**Performance on a small observation**
Logistic Regression	Fast	Fast	Yes	Yes
Random Forest	High	Slow	Moderate	Yes
KN Neighbors	Low	No Training	Slow	Yes
SVM	High	Slow	Fast	Yes

4.3. Graphical comparison among the algorithms

In this study, we compared four distinct types of machine learning algorithms for accuracy with and without the PCA model. With the PCA model, logistic regression and SVM provided better accuracy than 98%, but without the PCA model, logistic regression and support vector machine produced 99% accuracy, both being the most accurate. The y-axis represents the accuracy rate, while the x-axis represents the algorithm names.

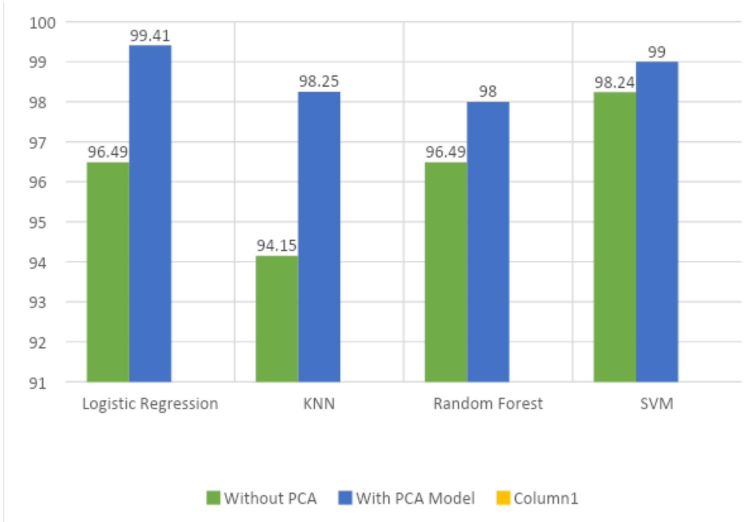

Figure 9: Graphical Representation of B and M Using PCA

Figure 9 illustrates graphical representations of model accuracy. The classification of benign and malignant tumors using various machine learning techniques is demonstrated. The x-axis displays algorithm names, while the y-axis displays accuracy rates. Logistic regression has the highest accuracy of the three classifiers when utilizing the PCA model.

4.4. Performance of Deep Learning Model on WBCD Dataset

The deep learning model performs well on Keras at 96.24%. We employ seven input layers with the activation function Rectified linear unit (Relu), and for output, we attempt two functions. In our scenario, SoftMax outperforms Sigmoid because it excels at binary categorization. We divide the dataset into two portions with varying weightages: 80% for training and 20% for testing. We run these layers for 50 epochs with a "128" batch size, and the model achieves 96.24% accuracy.

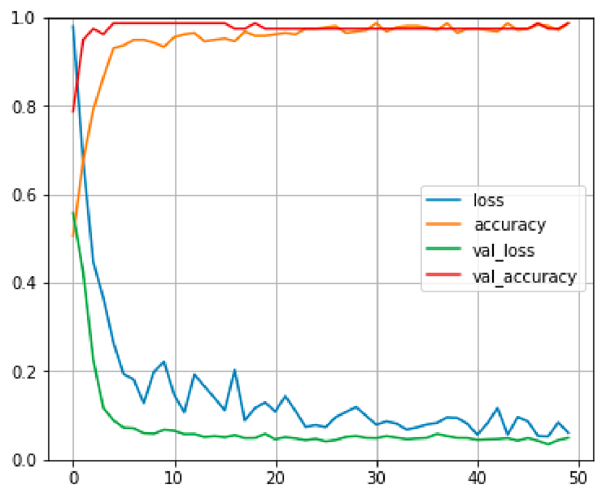

Figure 10: Accuracy Graph of DL Model on WCBD

Figure 10 shows that a deep learning model achieves 96% accuracy on the WCBD dataset. The value loss ranges from 0.2 to 0.3, the loss from 0.0 to 0.6, and the validation accuracy from 0.65 to 0.99, as indicated in the Accuracy Graph.

4.5. DDSM Dataset Performance

Following data pre-processing, we use the Inceptionv3 model to train our data using several input and output layers. In order to enhance the accuracy of a model, the training step incorporates the inclusion of hidden layers. 80% of the data is allocated for training, while the remaining 20% is reserved for testing. The activation function employed for the output is the sigmoid layer. Achieving an accuracy of 95.73% and a f1 score of 95.67% was seen across 36 epochs and 128 batch sizes. However, prior to our pre-processing and model training, the accuracy of Inceptionv3 was 92.22%. This accuracy subsequently improved to about 3%, which is considered satisfactory for predicting breast cancer tumors. Below are the classification reports of our model, as well as the results obtained from our training and feature extraction.

Classification Report:

	precision	recall	f1-score	support
0	0.97	0.98	0.98	9719
1	0.85	0.82	0.83	1458
accuracy			0.96	11177
macro avg	0.91	0.90	0.90	11177
weighted avg	0.96	0.96	0.96	11177

Figure 11: Classification Report After the Experiment

Figure 11 demonstrates a model accuracy of 96%, surpassing the accuracy of the initial InceptionV3 model, which was approximately 92%. Based on the findings presented in figure 11, it can be inferred that our trained model demonstrated enhanced precision in predicting and diagnosing breast cancer tumors as either benign or malignant.

Classification Report:

	precision	recall	f1-score	support
0	0.98	0.93	0.95	14579
1	0.65	0.89	0.75	2187
accuracy			0.92	16766
macro avg	0.81	0.91	0.85	16766
ighted avg	0.94	0.92	0.93	16766

Figure 12: Classification Report before the Experiment

Figure 12 displays the pre-training performance of the InceptionV3 model on the DDSM dataset. The training of InceptionV3 by the other author yields an average accuracy of 92%.

4.5.1. InceptionV3 Confusion Matrix on the DDSM Dataset

The Inception V3 model's confusion matrix on the DDSM dataset, as shown in figure 13, indicates that the model achieves an accuracy of 96% on this dataset. There were 208 false positives and 269 false negatives out of 11777 scan pictures, which are represented by the diagonal value.

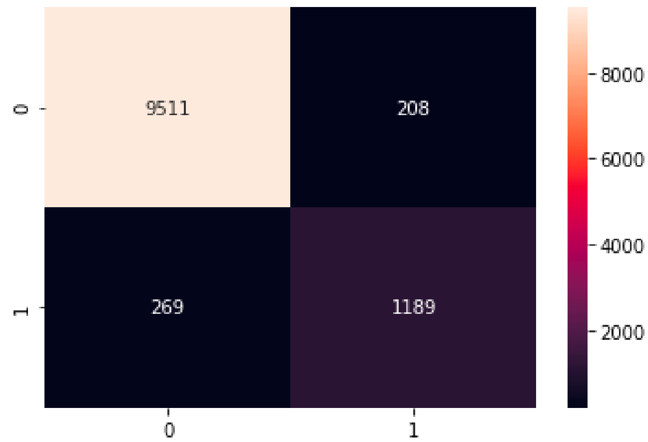

Figure 13: Confusion Matrix on DDSM Dataset

4.5.2. Graphical representation of Accuracy on DDSM dataset

Accuracy, validation accuracy, loss, and validation loss are graphically depicted in figure 14. With a validation loss of more than 0.2, a model's accuracy stays over 96%.

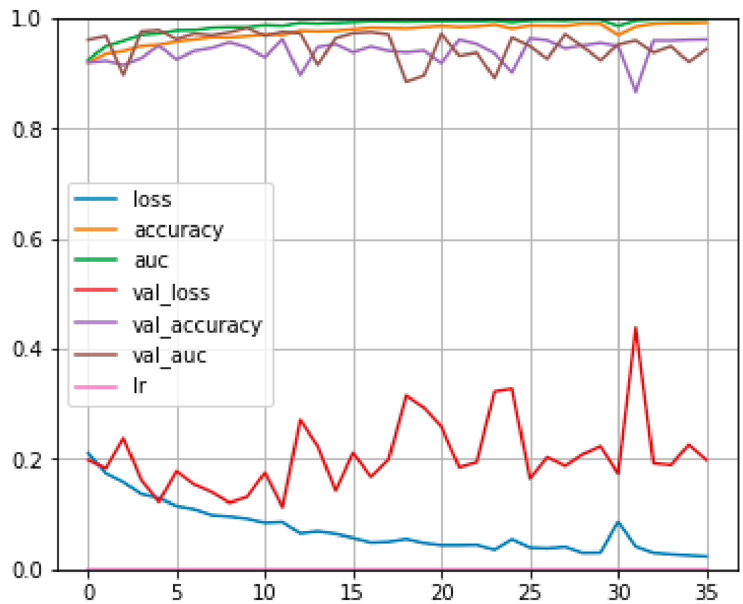

Figure 14: Graphical representation of Accuracy on DDSM dataset

4.6. Comparison of different Deep Learning models on DDSM dataset

Here in Table 5, we take a look at the DDSM Dataset and compare five distinct deep learning models. All of the models' average f1 and precision-recall scores are displayed. Our trained model, inceptionv3, outperformed the other four models with an accuracy of over 96%. Our model for the DDSM dataset was a pre-trained InceptionV3. Following picture pre-processing and segmentation, the model is executed on hundreds of photos. Author Li Shen discusses Resnet50 and VGG-16 in this study [10], although the inceptionV3 model outperformed both in terms of accuracy.

Table 5: Deep Learning Models Performance ON DDSM

Model Name	Accuracy	Precision	Recall	F1score
Inceptionv3	**96**%	**95**%	**95**%	**96**%
Resnet50	89%	89%	88%	88%
Densenet121	91%	90%	91%	90%
Mobile Net	90%	89%	90%	88%
VGG-16	84%	85%	83%	84%

4.7. Breakhis Dataset Performance

Once the data has been pre-processed, it is trained using a deep learning model with several input and output layers. To further enhance a model's accuracy, some hidden layers are also incorporated during the training phase. For training, we use 80% of the data, and for testing, we use 20%. As an activation function for output, the SoftMax layer is utilized. We get a 98.8% accuracy and a 99% F1 score over 5 epochs with 128 batch sizes, which is sufficient for predicting tumors associated with breast cancer.

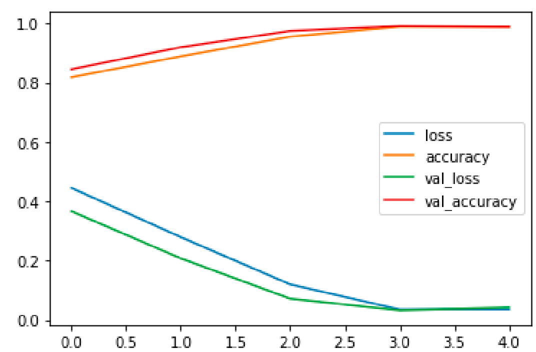

Figure 15: Accuracy Graph of BreakHis Dataset

In Figure 15, we can observe the accuracy curve of the BreakHis dataset on CNN. Both the validation accuracy and the accuracy on benign and malignant tumors reach 99%. From 0.4 to 0.01, loss and validation loss are decreasing at a steady rate.

```
              Classification Report:
              precision    recall  f1-score   support

           0       0.98      0.99      0.98      2019
           1       0.99      0.99      0.99      4308

    accuracy                           0.99      6327
   macro avg       0.98      0.99      0.99      6327
weighted avg       0.99      0.99      0.99      6327
```

Figure 16: Classification Report of BreakHis dataset

Figure 16 displays classification reports on the BreakHis dataset, which inform us that, out of a total of 6327 pictures, 2019 are predicted to be benign with a 98% precision and 4308 as malignant with a 99% precision.

4.7.1. Confusion Matrix of CNN model on BreakHis Dataset

Figure 17 displays the confusion matrix of the BreakHis dataset. It is evident that the diagonal location of the matrix exhibits a relatively low number of images, indicating a high level of accuracy in our predictions. Out of the total of 7909 photos, a mere 25 instances are classified as false positives, indicating that the model incorrectly predicts the presence of breast cancer in 25 patients who do not actually have breast cancer. Conversely, 51 instances are classified as false negatives, indicating that the model incorrectly predicts the absence of breast cancer in 51 patients who actually have breast cancer.

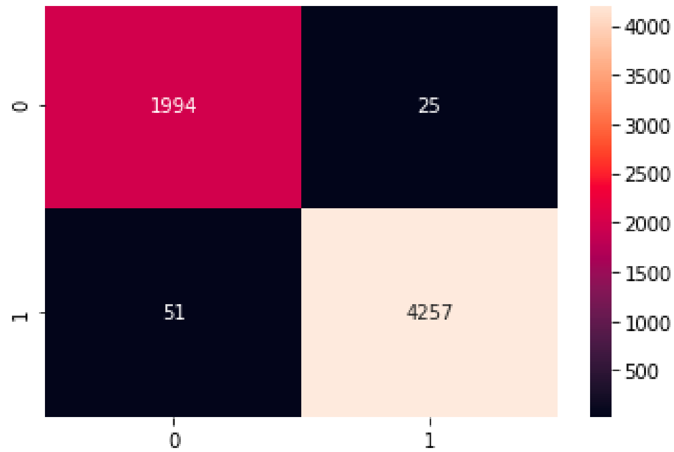

Figure 17: Confusion Matrix of CNN model on BreakHis Dataset

5. Conclusion

In conclusion, our research highlights the significant significance of prompt and precise breast cancer detection, particularly in poor countries where women have obstacles in accessing healthcare services. By utilizing advanced deep learning models like InceptionV3 and Sequential, we were able to attain impressive classification accuracies on several datasets. Specifically, we achieved a classification accuracy of 96.24% on WCBD and 98.8% on BreakHis. The investigation conducted on supervised machine learning techniques serves to underscore the effectiveness of deep learning methodologies, wherein Logistic Regression demonstrates greater performance. This research makes a valuable contribution to the advancement of healthcare outcomes on a global scale by highlighting the importance of strong diagnostic tools and the possibility of deep learning in enhancing breast cancer detection.

Future work in breast cancer detection might involve refining deep learning algorithms for use with parallel processing systems and publicly available medical picture datasets in order to increase accuracy, and the integration of physician verification to better safeguard patient care.

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