Custom Convolution Neural Network for Breast Cancer Detection

Thyagaraj T, Keshava Prasanna, Hariprasad S A

Abstract*: *Breast cancer remains a serious global health issue. Leveraging the use of deep learning techniques, this study presents a custom Convolutional Neural Network (CNN) framework for the detection of breast cancer. With the specific objective of accurate classification of breast cancer, a framework is made to analyze high-dimensional medical image information. The CNN's architecture, which consists of specifically developed layers and activation components tailored for the categorization of breast cancer, is described in detail. Utilizing the BreakHis dataset, which comprises biopsy slide images of patients in a range of cancer stages, the model is trained and verified. Comparing our findings to conventional techniques, we find notable gains in sensitivity, specificity, and accuracy. Gray-Level Co-Occurrence Matrix (GLCM) features extracted from the BreakHis dataset was used to analyze the performance on sequential neural network, transfer learning and machine learning models. After analysis, we have proposed hybrid models of CNN-SVM, CNN-KNN, CNN-Logistic regression and achieved accuracy of about 95.2%

Keywords*: *Breast Cancer Detection, CNN, MobileNet.

I. INTRODUCTION

Tumors are the result of unchecked cell growth in an organ. Benign and malignant tumors are the two types of tumors. Benign or non-cancerous tumors do not pose a risk to health or life. Conversely, malignant, or cancerous tumors are those that are expanding and pose a threat. Breast cancer is the second greatest cause of mortality for women worldwide and the number one killer of women between the ages of 40 and 55. Tumor assessment tests should be performed every 4-6 weeks. This makes benign and malignant identification based on classification features extremely important.

Although there is no known cause of breast cancer, early detection and treatment can reduce the death rates associated with it. In up to 71% of cases seen by clinicians without breast cancer expertise, misdiagnosis, delayed diagnosis, or failure to diagnose might occur. In instances seen by mammography-trained clinicians, this statistic drops to 3%. The death rate from breast cancer has been proven to be lower with careful diagnostics and early detection. When compared to a diagnosis provided by an experienced clinician (79.9%), a diagnosis produced with the help of technology such as deep learning and machine learning can be more accurate (91.1%) [1][17][18][19].

Several datasets have been published for detection of breast cancer like Wisconsin Diagnostic Breast Cancer (WDBC), Mammograph MIAS database, BreakHis database etc. In this work, BreakHis dataset containing Breast cancer histopathology images was chosen to train all the models.

This work has progressed in three stages: In the first stage, images from BreakHis dataset were used to train deep learning architectures of ResNet50 and Mobilenet. In the second phase, GLCM features were extracted and used to train MobileNet and a custom deep learning algorithm. The features extracted from these two models were used to train machine learning models in the third phase.

II. BACKGROUND

A. Literature Survey

Juanying Xie et al. [2] adapted Inception_V3 and Inception_ResNet_V2 architectures for binary and multi-class classification of BreakHis dataset. The dataset was expanded to avoid high false positive rate in classification and to solve the unbalanced distribution of samples which gave much better results than with raw datasets. Inception_ResNet_V2 network on augmented dataset offered a significant improvement. Further they used Inception_ResNet_V2 which defeated Inception_V3 to extract features for SVM and 1-NN classifiers. Jitendra Maan et al. [3] extracted features of histopathological images using CNN based technique for tumor cells detection. They implemented drop-out layer to overcome the problem of over-fitting. 4 different optimizers with 3 different learning rates was tried on the CNN model and they found that RMSprop Optimizer with learning rate 1e-3 gave more testing accuracy. The CNN model achieved train accuracy of 96.7% and test accuracy of 90.4%. In the research carried out by Yan Hao et al. [4], the extracted features using DenseNet201 are fused with the 3-channel GLCM features and classification is done through SVM. The results obtained are then compared with 7 baseline models AlexNet, VGG16, ResNet50, Google Net, DenseNet201, Squeeze Net and Inception- ResNet-V2. For 40x, 100x, 200x, 400x, the image-level recognition accuracies are 96.75%, 95.21%, 96.57%, 93.15% respectively and the patient-level recognition accuracies are 96.33%, 95.26%, 96.09%, and 92.99% respectively.

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The goal of Htet Thazin Tike and Khin Mo Mo Tun [5] is to provide a method for breast cancer treatment that differentiates between various breast cancer classifications. In this study, a feed-forward neural network is built, and the network is trained using an island differential evolution propagation algorithm. This research compares the outcomes of two alternative migration topologies using random-random policy. Hameed et.al. [6][20][21]. presented a deep learning approach on a dataset that they had collected which contained non- carcinoma and carcinoma breast cancer histopathology images. 5-fold cross-validation operations on all the individual models, namely, fully trained VGG16, fine-tuned VGG16, fully trained VGG19, and fine-tuned VGG19 models. Then, they followed an ensemble strategy by taking the average of predicted probabilities and found that the ensemble of fine-tuned VGG16 and fine-tuned VGG19 performed better in classification. This paper explores the application of Convolutional Neural Networks (CNNs) for breast cancer detection in histology images. The authors demonstrate the effectiveness of CNNs in automatically extracting relevant features from histopathological images, leading to improved accuracy in identifying cancerous regions Spanhol et.al [7]. explores the application of Convolutional Neural Networks (CNNs) for breast cancer detection in histology images. The authors demonstrate the effectiveness of CNNs in automatically extracting relevant features from histopathological images, leading to improved accuracy in identifying cancerous regions. Cruz-Roa et.al [8]. provides an overview of the state-of-the-art in breast cancer histopathology image analysis, with a focus on the application of deep learning techniques, including CNNs. The authors discuss various methodologies and challenges in utilizing CNNs for breast cancer detection.

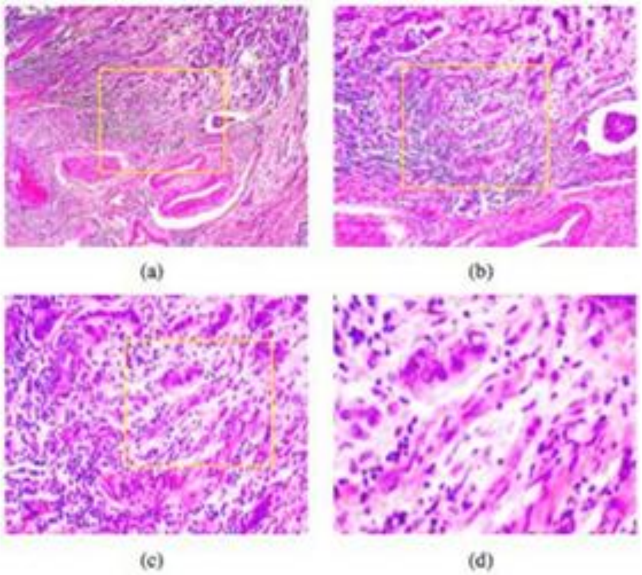

Figure 1. A Slide of Breast Malignant Tumour (Stained with HE) Seen in Different Magnification Factors: (A) 40X, (B) 100X, (C) 200X, and (D) 400X.

Islam et.al [9]. presents a study on the application of deep learning techniques, including CNNs, for breast cancer detection in mammography images. The authors compare the performance of CNNs with traditional methods, demonstrating the superior accuracy of deep learning in identifying abnormalities. Dhungel et.al. [10]. trained an improved CNN network and investigated the performance of the model on the IDC patch-based classification task. Experimental results show that our approach yields the best performance on the IDC dataset when compared to other published approaches. Our model achieves f-score of 85.28% and balanced accuracy of 85.41% with increase improvementof11.51% on f-score and 0.86% on balanced accuracy Romano et.al [11]. trained an improved CNN network and investigated the performance of the model on the IDC patch-based classification task. Experimental results show that our approach yields the best performance on the IDC dataset when compared to other published approaches. Our model achieves f-score of 85.28% and balanced accuracy of 85.41% with increase improvementof11.51% on f-score and 0.86% on balanced accuracy Setio et.al [12]. proposed architecture comprises multiple streams of 2-D ConvNets, for which the outputs are combined using a dedicated fusion method to get the final classification. Data augmentation and dropout are applied to avoid overfitting. On 888 scans of the publicly available LIDC-IDRI dataset, our method reaches high detection sensitivities of 85.4% and 90.1% at 1 and 4 false positives per scan [13]-[16]. showed that deep learning techniques are applicable to image-based medical diagnosis and improve the performance compared to traditional machine learning techniques. From Literature survey, it is found that breast cancer can be detected using machine learning and deep learning architectures and extracting features. Each method has its strengths. Thus, in this work key strengths of all are used with hybrid model that integrates feature extraction, deep learning, and machine learning algorithms. Further, the performances are compared in terms of metrics: Accuracy, Precision, Recall, F1-score, and loss function.

III. DATASET

The BreakHis (Breast Cancer Histopathological Image Classification) dataset is a collection of breast cancer histology images that are commonly used for training and evaluating machine learning algorithms in the field of digital pathology. The dataset contains 9,109 microscopic images of breast tumour tissue samples, captured at 40x magnification, and stained with Hematoxylin and Eosin (H&E). The images in the BreakHis dataset are divided into two main categories: benign and malignant, and further classified into four subtypes: ductal carcinoma in situ (DCIS), invasive ductal carcinoma (IDC), lobularcarcinoma in situ (LCIS), and invasive lobular carcinoma (ILC). The BreakHis dataset is a popular choice for researchers in the field of digital pathology and medical image analysis due to several reasons: (i) It is one of the largest and most diverse publicly available datasets of breast cancer histopathological images. (ii) The images are of high quality, providing clear and detailed views of the tissue samples. (iii) The images in the Break His dataset are annotated by expert pathologists, which ensures the accuracy and consistency of the annotations. (iv)

The BreakHis dataset has been used as a benchmark dataset for evaluating the performance of different algorithms for breast cancer classification, segmentation, and detection.

Overall, the BreakHis dataset is a valuable resource for researchers in the field of medical image analysis and digital pathology. Visual differentiation between benign and malignant tumors based on images in the BreakHis dataset can be challenging, as both types of tumours can have similar visual features. However, there are some general visual characteristics that can help differentiate between the two: (i) Malignant tumours tend to have irregularly shaped cells with abnormal nuclei, while benign tumours usually have regular cell shapes and nuclei. (ii) Malignant tumours tend to have a higher nucleus-to-cytoplasm ratio. In contrast, benign tumours tend to have a lower nucleus-to-cytoplasm ratio. (iii) Malignant tumours tend to have irregular or jagged margins, while benign tumours usually have smooth, well-defined margins. (iv) Malignant tumours tend to have invasive growth patterns that invade the surrounding tissue, while benign tumours tend to have more localized growth patterns.

IV. DATA PREPARATION

A common texture analysis method that offers details on the spatial distribution of gray levels in an image is the Gray Level Co-occurrence Matrix (GLCM). GLCMs are usually associated with texture. The recurrence of visual patterns may be noticed in texture. It makes sense that GLCMs may be used to extract details about textures existing in images using the proper positional operator. After all, recurring visual patterns might be interpreted as recurring sets of values with a certain orientation. The information in the GLCM is used in texture feature calculations to provide a measurement of the intensity variation, commonly referred to as image texture, at the pixel of interest. The features which are extracted are Dissimilarity, Correlation, Homogeneity, Contrast, ASM, and Energy. Finally, these 6 features are applied for all the augmented images with rotations 0, 45, 90 and 135. Therefore, there are 6 X 4 = 24 features which are extracted. The size of the extracted GLCM features is 7909 x 25. Splitting your dataset is crucial for a fair assessment of prediction accuracy. It is advised to divide the data into three subsets: Training set, Validation set, and Test set -in order to train a model utilizing the processed data.

- Training set: The training set is applied to train the model. For illustration, one uses the training set to find the coefficients, or optimal weights for Logistic regression, Linear regression, or Neural networks.
- Validation set: The validation set is used for impartial model evaluation during hyperparameter tuning. For illustration, when one wants to find the optimal number of neurons in a neural network or the finest kernel for a SVM, experiments with different values needs to be performed. For each considered setting of hyperparameters, one fits the model with the training set and reviews its performance with the validation set.
- Test set: The test set is demanded for an impartial evaluation of the final model.

The original dataset had 7909 images of benign and malignant together. GLCM features extracted from those images were divided into sets such that training set had 6406 images, test had 712 images and validation set had 791 image data. The dataset required pre-processing to ensure that learning and inference are based on the same picture attributes. It is initially upsampled. Upsampling is a technique used to insert fictitious or duplicate data points into the dataset (corresponding to the minority class). The numbers for each label are almost equal after this procedure. This equalization procedure prevents the model from inclining towards the majority class. Data augmentation [12] is a very potent method used to increase an existing image data collection by intentionally producing variances in existing images. This transforms the existing dataset, which represents a wide range of potential images, into new and unique images. Images are rotated by 0o, 45o, 90o, and 135o degrees to increase the number of images in the dataset and to train the model with large dataset. Benign images in training set have been upsampled to match with the 4404 images in malignant category. This is shown in the Figure 3 and Figure 4.

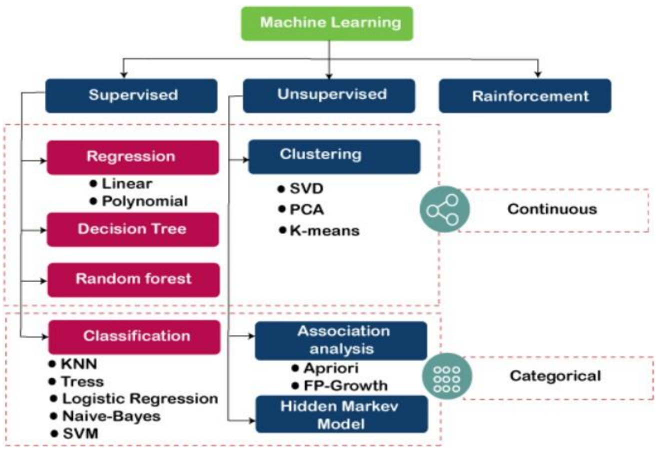

Figure 2. Types of Machine Learning Algorithms

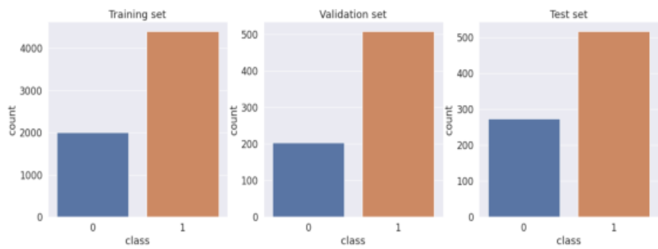

Figure 3. Image Data Separation Before up Sampling

V. CONVOLUTION NEURAL NETWORK MODEL DESCRIPTION

Computational models with numerous processing layers can learn representations of data at various levels of abstraction thanks to deep learning. These techniques have enhanced object identification, speech recognition, and visual object recognition capabilities. By employing the backpropagation technique to suggest changes to a machine's internal parameters that are used to compute the representation in each layer from the representation in the previous layer, deep learning can uncover detailed structure in massive data sets.

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Deep convolutional nets have made significant advances in the processing of pictures. Convolutional neural networks outperform other neural networks especially when given inputs are images. There are three basic categories of layers in them: Convolution layer, Pooling layer, FC (fully connected) layer.

The Convolutional neural network becomes more complicated with each layer, detecting larger areas of the image. Early layers emphasize essential elements like colors and borders. The more significant features or shapes of the object are first seen when the visual data moves through the CNN layers, and eventually, the intended object is recognized.

Resnet 50 architecture incorporates a residual learning framework to make it easier to train the neural network and solve the gradient descent problem. The fundamental idea of "skip connections" is at the heart of the residual blocks, which enhance the neural network.

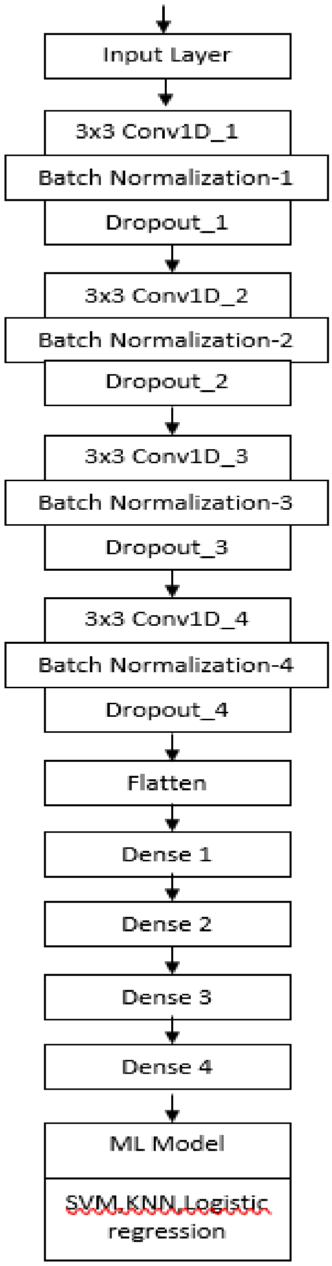

Figure 4. Sequential CNN Model Architecture.

Mobile Net was created to efficiently run embedded and mobile applications. It has a 28-layer deep linear design. To create a compact deep convolutional neural network, these layers employ depth-wise separable convolutions. The ReLu6 activation function is mainly used in two operations, depth-wise convolution (3x3) and pointwise convolution(1x1), to create a depth-wise separable convolution. The sequential convolution network that makes up sequential CNN model has a total of 17 layers. A 3x3 Convolution layer, a batch normalization layer, and a dropout layer are among the three layers of the four sets. A flattened layer and four dense layers come after these first four sets. The model uses an Adam optimizer, a Relu activation function, and binary cross entropy as the loss function. Resized to 256x256x3, the input image at the input layer. A bit more than 10,000 test and training photos were used to train this model. The model architecture is shown in Figure 4.

VI. MACHINE LEARNING ALGORITHM DESCRIPTION

A branch of computing algorithms called machine learning is constantly developing and aims to replicate human intelligence by learning from the environment. In the brand-new era of "big data," they are regarded as the workhorse. Machine learning methods have been effectively used in a variety of industries, including banking, entertainment, biomedicine, pattern recognition, computer vision, spacecraft engineering, and computational biology.

Programs that use machine learning algorithms can discover hidden patterns in data, forecast results, and enhance performance based on past performance. Machine learning uses a variety of algorithms that can be applied to various jobs. The categories and several ML algorithms are shown in Figure 5.

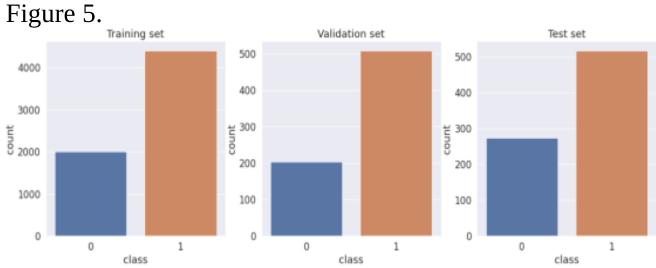

Figure 5. Image Data Separation After up Sampling.

One of the most well-liked supervised learning algorithms, Support Vector Machine, or SVM, is used to solve Classification and Regression problems. The SVM algorithm's objective is to establish the best line or decision boundary that can divide n-dimensional space into classes, allowing us to quickly classify fresh data points in the future. A hyperplane is the name given to this optimal decision boundary. SVM selects the extreme vectors and points that aid in the creation of the hyperplane. Support vectors, which are used to represent these extreme instances, form the basis for the SVM method. The k-nearest neighbors algorithm, sometimes referred to as KNN or k-NN, is a supervised learning classifier that employs proximity to produce classifications or predictions about the grouping of a single data point.

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Although it can be applied to classification or regression issues, it is commonly employed as a classification algorithm because it relies on the idea that comparable points can be discovered close to one another.One of the most often used Machine Learning algorithms, within the category of Supervised Learning, is logistic regression. Using a predetermined set of independent factors, it is used to predict the categorical dependent variable. In a categorical dependent variable, the output is predicted via logistic regression.

A supervised learning method called a decision tree can be used to solve classification and regression problems, but it is typically favored for classification problems. It is a tree-structured classifier, where internal nodes stand in for a dataset's features, branches for the decision-making process, and each leaf node for the classification result.

Gradient Boosting is a potent boosting approach that turns numerous weak learners into strong learners. Each successive model is trained using gradient descent to minimise the loss function of the preceding model, such as mean square error or cross-entropy. The algorithm calculates the gradient of the loss function with respect to the current ensemble's predictions in each iteration, and then it trains a new weak model to try to minimise this gradient.

XGBoost is a distributed gradient boosting library that has been optimised for quick and scalable machine learning model training. A number of weak models' predictions are combined using this ensemble learning technique to get a stronger prediction. Extreme Gradient Boosting, or XGBoost, is one of the most well-known and widely used machine learning algorithms because it can handle large datasets and perform at the cutting edge in many machine learning tasks like classification and regression.

The popular machine learning algorithm Random Forest is a part of the supervised learning methodology. It can be applied to ML issues involving both classification and regression. It is built on the idea of ensemble learning, which is a method of integrating various classifiers to address difficult issues and enhance model performance. According to what its name implies, "Random Forest is a classifier that contains a number of decision trees on various subsets of the given dataset and takes the average to improve the predictive accuracy of that dataset."

VII. METHODOLOGY

A. Phase 1: Training of CNN Models

To enhance the model's recognition, the histopathology images that are divided into train and validation have been resized to 256x256. ResNet50 and MobileNet models were trained for comparison. 20 epochs are used to train each model. Resnet50 and MobileNet, among the other transfer learning models, provided the highest prediction metrics for the H&E dataset used. Among the 2 models, it was observed that MobileNet gave better accuracy, hence, it was carried further to the next phase.

B. Phase 2: Training CCN Models with Extracted GLCM Features

GLCM features are extracted from the images in BreakHis dataset. These samples are split into 6406 in training, 712 in test, and 791 in validation datasets. The training images are highly imbalanced with 4404 malignant and 2002 benign samples. To improve generalization, the training set data has been upsampled to obtain 4404 samples in each class. A sequential CNN model with 18 layers was developed for experimental purposes. The MobileNet and sequential CNN models as shown in figure 2 are then trained on training data. The sequential CNN model has the highest degree of accuracy among the three. These models are each trained over 25 epochs.

C. Phase 3: Development and Training of hybrid models (MobileNet+ML and CNN+ML) with GLCM feature extraction

Both the hybrid models have similar basic structures. The features extracted from the trained CNN models are given to each of the ML models as shown in figure 6 one after the other, and their performances are compared.The output from sequential CNN and MobileNet is used to train the seven Machine Learning Algorithms-Support Vector Machine, Decision Tree, eXtreme Gradient Boosting, Logistic Regression, K-Neighbor Classifier, Gradient boosting algorithm, Random Forest classifier. Among the hybrid models, the highest accuracy achieved was 95% for the combination of sequential CNN and ML algorithms. The metric values indicate that this hybrid model provides the best result for prediction. Various performance indicators have been employed to examine the models in the three phases. Quantitative measurements of the model are taken to track its performance and quantify its quality of predictions. To do so six metrics functions have been made use of namely accuracy, precision, loss, recall, and AUC.

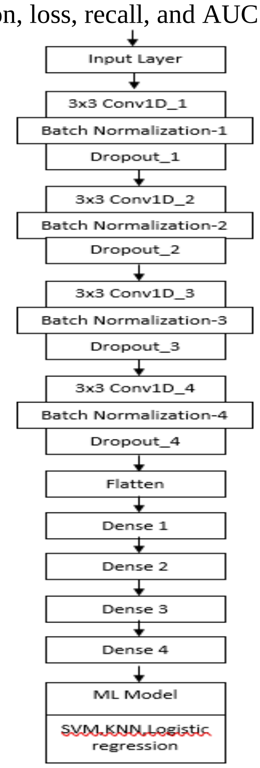

Figure 6. Sequential CNN + ML Model's Flowchart

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VIII. RESULT AND DISCUSSION

The work carried out was on histopathological images from the Break His dataset. Different techniques of transfer learning, machine learning and Convolutional Neural Networks have been experimented with. This section consolidates the results obtained in each of the phases.

A. Phase 1

The metrics values were obtained for transfer learning models trained on the dataset in this phase. The models of ResNet-50 and MobileNet were run for 20 epochs each. It was observed that MobileNet gave better accuracy of 93.32% on the test dataset, while on the other hand, ResNet50 gave a test accuracy of %. The overall metrics values are indicated in Table 1. Since the performance of MobileNet model was observed to be better, it was carried forward to the next phase.

Table 1: Metrics Values Obtained for Phase-1

Metrics	ResNet-50	MobileNet
Accuracy		0.9332
Precision		0.51
Recall		0.55
Loss		0.2147

B. Phase 2

To improve the performance of the models, six GLCM features were extracted in four directions each. A new sequential CNN model was also designed and experimented with in addition to the MobileNet model. Training the models in this stage was carried out for 30 epochs because it was observed that the minimum loss and maximum accuracies were obtained at these epoch values as shown in Figure 7 and Figure 8. The results obtained indicated that the sequential and MobileNet models did not differ much as shown in Table 2. Hence, both models have been further carried forward to the next phase.

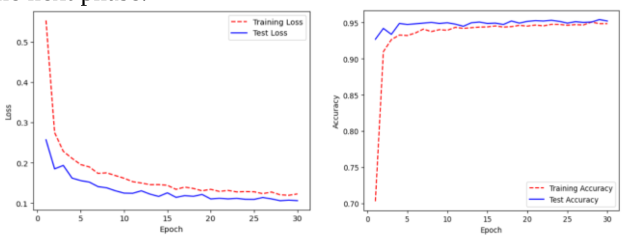

Figure 7. Sequential A CNN
(a) Loss vs Epoch (b) Accuracy vs Epoch

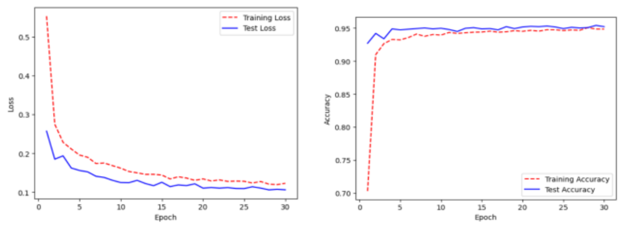

Figure 8. MobileNet
(a) Loss vs Epoch (b) Accuracy vs Epoch

Table 2: Metrics Values Obtained for Phase-2

Performance Metrics	MobileNet	Sequential CNN
Accuracy	0.9475	0.9484
Precision	0.9228	0.9175
Recall	0.9831	0.9915
Loss	0.1258	0.1228
AUC	0.9880	0.9875

C. Phase 3: Training of CNN Models

The accuracy of hybrid models which used sequential CNN along with ML models (SVM, Decision Tree Classifier, Logistic Regression, K Neighbors Classifier, Random Forest Classifier, Gradient Boosting Classifier, and XGB) trained and predicted using extracted GLCM features is shown in the Table 3.

Table 3: Metrics Values Obtained for Phase-2

Algorithm	Accuracy of MobileNet Hybrid	Accuracy CNN Hybrid
SVM	0.9495	0.9505
DT	0.5153	0.9505
LR	0.9404	0.9505
KNN	0.5153	0.9505
Random Forest	0.5153	0.9505
Gradient Boosting	0.9447	0.9505
XGB	0.5153	0.9505

SVM, Logistic Regression, and K Neighbour Classifier have the lowest accuracy using GLCM features, as indicated in the table. The features obtained from mobilenet and CNN are provided as an input to these models in order to increase their accuracy. For SVM, Logistic Regression, and K Neighbour Classifier, the accuracy of mobilenet feature extraction has improved, but it is still less accurate than CNN feature extraction. The accuracy has reduced for the remaining models, Decision Tree Classifier, Random Forest Classifier, Gradient Boosting Classifier, and XGB, using both feature extraction methods, but it has decreased significantly with mobilenet features.

Table 4: Performance Metrics of Different Feature Exaction Techniques for SVM Model

Performance Metrics	MobileNet+SVM	CNN+SVM
Precision	0.9123	0.9167
F1-Score	0.9539	0.9539
AUC	0.9481	0.9492
Recall	0.9981	0.9943
Loss	0.0504	0.0494

Table 5: Performance Metrics of Different Feature Exaction Techniques for Decision Tree Classifier

Performance Metrics	MobileNet + Decision Tree	CNN + Decision Tree
Precision	0.5153	0.9167
F1-Score	0.9539	0.9539
AUC	0.5	0.9492
Recall	1	0.9943
Loss	0.4847	0.0494

Table 6: Performance Metrics of Different Feature Exaction Techniques for Logistic Regression Model

Performance Metrics	MobileNet + Logical Regression	CNN + Logical Regression
Precision	0.9219	0.9167
F1-Score	0.9539	0.9539
AUC	0.9396	0.9492

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Performance Metrics	MobileNet + Logical Regression	CNN + Logical Regression
Recall	0.9661	0.9943
Loss	0.0596	0.0494

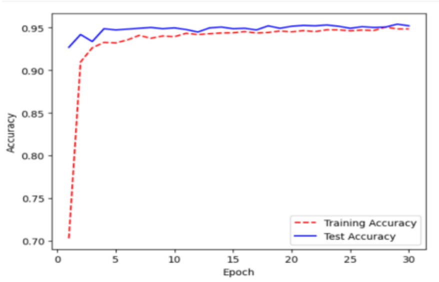

Figure 9 - Accuracy Versus Epoch Plot for CNN+Ml Architecture

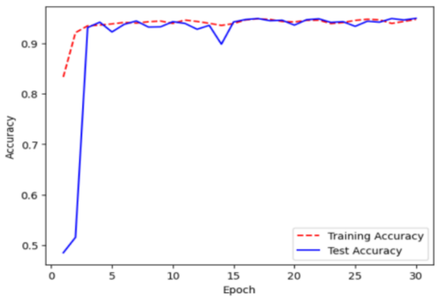

Figure 10 - Accuracy Versus Epoch Plot for CNN+Ml Architecture

Table 7: Performance Metrics of Different Feature Exaction Techniques for K Neighbours Classifier

Performance Metrics	MobileNet+KNN	CNN+KNN
Precision	`	0.9167
F1-Score	0.9539	0.9539
AUC	0.5	0.9492
Recall	1	0.9943
Loss	0.4847	0.0494

Table 8: Performance Metrics of Different Feature Exaction Techniques for Random Forest Classifier

Performance Metrics	MobileNet + Random Forest	CNN + Random Forest
Precision	0.5152	0.9167
F1-Score	0.9539	0.9539
AUC	0.5	0.9491
Recall	1	0.9943
Loss	0.4847	0.0494

Table 9: Performance Metrics of Different Feature Exaction Techniques for Gradient Boosting Classifier

Performance Metrics	MobileNet + Gradient Boosting	CNN + Gradient Boosting
Precision	0.9151	0.9167
F1-Score	0.9539	0.9539
AUC	0.9435	0.9491
Recall	0.984	0.9943
Loss	0.0552	0.0494

Table 10: Performance Metrics of Different Feature Exaction Techniques for XGB

Performance Metrics	MobileNet + XGB	CNN + XGB
Precision	0.5153	0.9167
F1-Score	0.9539	0.9539
AUC	0.5	0.9491
Recall	1	0.9943
Loss	0.4847	0.0494

Accuracy and loss versus epoch for MobileNet and CNN architectures are shown in Figure 9 and Figure 10.

SVM, Logistic Regression, and K Neighbour Classifier have the lowest accuracy using GLCM features, as indicated in Table 3. The features obtained from mobilenet and CNN are provided as an input to these models in order to increase their accuracy. For SVM, Logistic Regression, and K Neighbour Classifier, the accuracy of mobilenet feature extraction has improved, but it is still less accurate than CNN feature extraction. The accuracy has reduced for the remaining models, Decision Tree Classifier, Random Forest Classifier, Gradient Boosting Classifier, and XGB, using both feature extraction methods, but it has decreased significantly with mobilenet features which is depicted in Table 4,5,6,7,8,9,10. Therefore, the goal of this research is to increase the models' unsatisfactory accuracy. i.e., to improve SVM, Logistic Regression, and K Neighbour Classifier accuracy. It is clear from the data that CNN feature extraction outperformed mobilenet feature extraction in terms of outcomes. Figure 9 and Figure 10 show plot of the accuracy and loss versus epoch for sequential CNN + ML model and mobilenet + ML model.

IX. CONCLUSION

Based on features extracted from GLCM, mobilenet, and CNN, this work proposes machine learning models for the interpretation of histological pictures of breast cancer. Upsampling and data augmentation are used as pre-processing steps for the BreakHis dataset. The features may be extracted from this pre-processed data. These features are used to train the ML models. We show that, in comparison to features derived from mobilenet and GLCM features, our CNN extracted features delivered the greatest results when given to train SVM, Logistic Regression, and K Neighbour Classifier.

FUTURE SCOPE

- The model requires validation from domain experts.
- Interactive user interface development is required to create intelligent diagnosis tools.
- The present system of manual biomarker assessment is very prone to subjective differences amongst pathologists. According to academics, combining pathologist observation with digital image processing will improve the accuracy of cancer identification.

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