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Original Article

Clinical Breast Cancer Diagnosis Enhanced by Deep Convolutional Neural Networks for Early Detection

Dr. P. Srinivasa Rao[1],Dr. Nagesh Vadaparthi[2,],G.Madhava Rao[3], Chennaiah Kate[4] , K.V.V.B.Durgaprasad[5], Vijaya Jyothi Chiluka[6]

[1]Professor, Dept of Information Engineering & Computational Technology, MVGR College of Engineering, Vizianagaram, India, srinivasa.suloo@gmail.com

[2]Professor (IECT), MVGR College of Engineering, Vizianagaram, India, Itsnageshv@gmail.com

[3]Assistant Professor, Department of C.S.E,Malla Reddy Engineering College for Women, Hyderabad,500100,Telangana,India, **madhav.739@gmail.com**

[4]Assistant Professor, Department of Data Science, Malla Reddy University, Hyderabad,500100, Telangana, India, chennaiahkate@gmail.com

[4]Assistant Professor, Department of C.S.E, St. Peter's Engineering College, Hyderabad, India, prasadrekha2013@gmail.com

[6]Assistant Professor, Department of C.S.E, VMTW-Ghatkesar,Hyderabad,501301,Telangana,India, vijayajyothichiluka@gmail.com

ABSTRACT

Breast cancer continue to be one of the leading cause of death for women worldwide and amongst them, early and accurate diagnosis of breast cancer is crucial to improve the patient's outcome. This study presents an automated breast cancer diagnosis framework, which is based on a deep Convolutional Neural Network (CNN) applied to histopathological images. The proposed model is intended to be effective in sampling discriminative spatial and morphological features that differentiate benign from malignant breast tissue. Experiments are performed on a large-scale histopathology image dataset extracted from a public repository, thus ensuring a realistic clinical representation. The dataset is systematically pre-processed and split into training and validation datasets and testings to allow the performance to be evaluated in an unbiased manner. The proposed CNN architecture exhibits the stability of learning and generalization ability, which is also proved by the comprehensive experimental analysis. The model is able to take a high classification accuracy of 96% with robust precision, recall, F1 score and excellent ROC-AUC performance pointing to its descended discriminative power. Comparative analysis with popular deep learning models has additionally proven the superiority of the proposed approach. Overall, this work shows the promise of CNN-based frameworks as powerful, decision-aiding tools that can aid in early detection of breast cancer in the clinic.

KEYWORDS

Breast cancer diagnosis, Histopathology images, Convolutional neural network, Deep learning, Early cancer detection, Medical image classification, Binary classification, Computer-aided diagnosis.

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Editor Dr. Eraj Khan Professor, Higher College of Technology, Dubai,United Arab Emirates.
khan.eraj@gmail.com

Reviewer Dr. Y.Srinivas, Professor, Department of Computer Science Engineering, GITAM School of Technology, Visakhapatnam, Andhra Pradesh,India
sriteja.y@gmail.com

Address correspondence to **Dr.P. Srinivasa Rao**, srinivasa.suloo@gmail.com

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I. INTRODUCTION

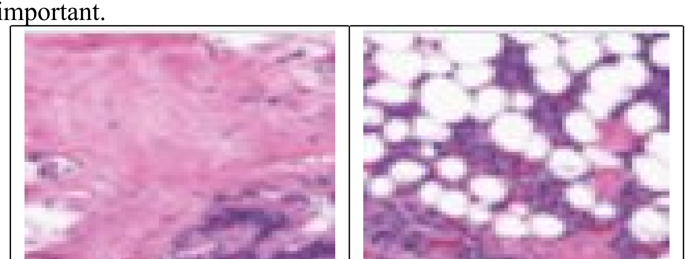
Breast cancer is one of the most common and life threatening malignant diseases that women all over the world face, thus there is a need to develop early and accurate diagnostic strategies that help to enhance survival and to reduce the mortality rate [1]. Recent developments in artificial intelligence (AI) have greatly improved the diagnosis of breast cancer through automated AI analysis of various types of images such as mammograms, ultrasound images, and thermography images to increase the precision and consistency of the diagnosis [2]. In parallel to imaging-based methods, new biosensing tools such as graphene and quantum dots based nanobiosensors have proven promising sensitivity for cancer biomarker detection, which describes the multidisciplinary development of breast cancer diagnostic methods [3]. In parallel, microwave imaging techniques using ultra-wideband antenna systems have attracted attention due to their possibility of non-invasive and radiation-free breast cancer detection [4], further expanding the technological frontier of breast cancer detection. Despite all these innovations, the use of image-based deep learning methods still predominates in clinical research because of their scalability and powerful feature learning capabilities. Recently quantum optimized and hybrid solving machine learning frameworks have been investigated to improve classification efficiency and accuracy such as SqueezeNet-SVM architectures especially in resource constrained clinical environments [5]. Moreover, there have been hybrid statistical and deep sequential models, such as LSTM guided feature extraction, to demonstrate better robustness to handle complex biomedical data distributions [6]. Explainable artificial intelligence (XAI) has also become a vital part of breast cancer diagnosis, relevance-aware capsule networks being able to bring transparency and clinical interpretability to mammography-based predictions [7]. Nonetheless, challenges like model generalization, clinical reliability and accuracy in early-stage detection continue to motivate further exploration of optimized deep learning architectures [8]. In this context, there is a need for powerful solutions to automated diagnosis of breast cancer with the ability to capture hierarchical spatial patterns of histopathological breast cancer images that can help in early detection and clinical decision-making.

II. LITERATURE

Breast cancer detection has been well investigated with DL techniques, recent studies focusing also on performance improvement and deployment challenges. Shahid and Imran's [8] presented an extensive review of deep learning-based breast cancer detection approaches, emphasizing the superiority of convolutional neural networks over conventional machine learning methods in addition to problems such as data imbalance, lack of annotated data, and clinical generalizability. Moving beyond the deep networks alone Muduli et al. [9] discussed extreme learning machine with uncertainty quantification to as a way to make diagnosis more reliable, by modeling the predictive uncertainty, which can significantly improve the decision confidence in breast cancer diagnostic systems that are based on predictions of the automated systems. Parallel to developments in algorithms, diagnostic solutions based on sensors and hardware assistance have also gained feet. Wekalao [10] presented a high-sensitivity terahertz biosensor coupled with machine learning based on nanostructured metasurface for detecting the target with such amazing detection accuracy, which demonstrated the potential of the combined technique of advanced sensing technologies used together with intelligent data analysis. Similarly, Kant and Kumar [11] adapted the methods of deep learning to the histology-based classification of cancer subtypes, keying prove the effectiveness of CNN-driven frameworks in the discrimination of complex tissue patterns, offering additional support for the feasibility of deep convolution frameworks in cancer diagnostics. Collectively, these studies highlight both the increasing dependence on intelligent learning systems and the desire, requirement, and urgency for scalable, accurate, and clinically interpretable diagnostic models. Recent studies have focused more on fine-tuning the accuracy of detection in the early stages and with greater model robustness using deep learning architectures and explainable frameworks. Kant et al. [12] showed the effectiveness of CNN-based models for the early classification of breast cancer by emphasizing the ability of CNNs to learn discriminative features directly from medical images and outperforms conventional classifiers significantly. Diaz et al. [13], conducted a critical analysis of the technologies of artificial intelligence in detecting breast cancer, emphasizing important challenges such as the transparency of models by technological algorithms and their acceptance by the viewer for clinical use while strengthening the importance of explainable and trustworthy artificial intelligence systems. In parallel, Pourmadadi et al. [14] discussed breast cancer detection using cancer antigen 15-3 biomarkers, and focused on optical and electrochemical sensing methods, and pointed out the complementary use of non-imaging diagnosis methods in the early-stage detection. Transfer learning has also become a powerful method to overcome the challenge of limited data availability and enhance performance. Oyebanji et al. [15] carried out an elaborate case study using transfer learning models based on EfficientNet, where they showed a significant improvement in the detection accuracy and training efficiency of pre-trained networks on breast cancer datasets. Finally, Mashekova et al. [16] reviewed artificial intelligence techniques in various imaging modalities with final mammography, ultrasound, and thermography, and determined that deep convolutional neural networks have the best performance in diagnosis and highlight that modality-specific optimization is necessary. Together, these works indicate an obvious research direction towards high-accuracy, and interpretable and deployable deep learning systems; thus motivation for the current study's focus on CNN-based breast cancer diagnosis using histopathological images for early detection of breast cancer.

III. INPUT DATASET

The input dataset of this study is based on a public collection of image repositories of breast histopathology extracted from the Kaggle visualized tool which is very well known to contain high-quality benchmark datasets for medical image analysis as shown in Figure. 1. The dataset consists of a total of 277,524 RGB histopathological image patches with a spatial resolution of 50 x 50 pixels and acquired from the digitised breast biopsy slides and intended for automated breast cancer diagnosis. These image patches are classified into two clinically meaningful classes, the presence of Invasive Ductal Carcinoma (IDC). Specifically, there are roughly 198,738 IDC-negative (benign) tissue images and 78,786 IDC-positive (malignant) tissue images in the dataset, a realistic class imbalance that is common in clinical scenarios. This imbalance is important to introduce further complexity and foster the creation of strong deep learning models that can learn effectively discriminative patterns across classes. Prior to training the model, the dataset is systematically split into 3 parts as ensuring non-biased evaluation and reliable generalization performance. Seventy percent of the images are assigned for training and therefore the convolutional neural network is able to learn representative spatial and morphological features from a huge and diverse sample set. Fifteen percent of the data is set aside for validation and is utilized to fit the model hyperparameters and prevent overfitting when training the model. The remaining fifteen percent of the data set is reserved for testing and it provides a way to test the model's performance against samples it has never seen before. Standard preprocessing operations - normalization and resizing - are performed to ensure consistency of input images. A representative of benign and malignant histopathological samples of the dataset is shown in Fig 1, which highlights the subtle differences in the structure of tissue samples that hinders manual diagnosis and makes the need of automated deep learning-based early detection systems for breast cancer more important.



(a) (b)

Figure. 1 Dataset Image for (a) IDC-Negative (Benign) and (b) IDC-Positive (Malignant)

IV. PROPOSED CONVOLUTIONAL NEURAL NETWORK MODELS ARCHITECTURE

The proposed deep learning framework is based on the Convolutional Neural Network (CNN) that is specifically designed for accurate and early diagnosis of breast cancer from histopathological images as shown in Figure. 2. The architecture is designed to successfully acquire hierarchical spatial features that characterize benign and malignant breast tissue patterns. The input histopathology images are first fed to several convolutional layers with small sized kernels that help to extract low-level features like edges, textures, and cells boundaries. These convolutional layers are then followed by batch normalization layers to stabilize the learning process and to speed up the convergence process, and ReLU activation functions to add non-linearity to the model and to improve the model's representational ability. To decrease the spatial dimensionality step by step while keeping the most informative features, max-pooling layers are used after certain selected convolutional blocks. This pooling strategy is not only effective in reducing the computational complexity but also helpful in enhancing the translational invariance which is essential for the classification of histopathological images with different tissue structures. As the depth of the network increased, the higher level convolutional layers learn more abstract and discriminative representations, associated with the morphology of the cancer. Following feature extraction, we get feature maps which are flattened and feed through one or more fully connected (dense) layers which gather up the learned features and do high-level reasoning for the classification. Dropout regularization is used in the dense layers to prevent overfitting by deactivating neurons randomly during training and improving the generalization performance. The last output layer is using a sigmoid activation function for binary classification of IDC-positive and IDC-negative. The CNN model realizes by us is trained by binary cross-entropy loss and the optimizer is Adam, which ensures the efficient gradient optimization. Overall this architecture offers a trade-off between model complexity and diagnostic accuracy, and is therefore well-suited to clinical applications in breast cancer detection.

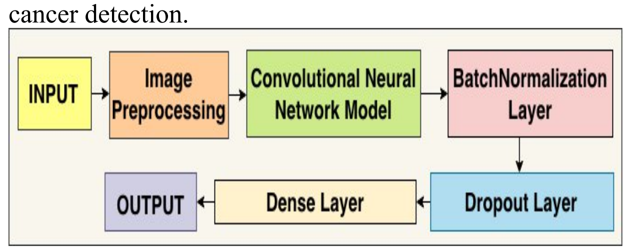


Figure. 2 Proposed Convolutional Neural Network Model Architecture

V. PROPOSED METHODOLOGY

The proposed methodology is a systematic combination of data preprocessing, dataset partitioning, CNN-based feature extraction, and performance evaluation to allow the diagnosis of breast cancer with accurate results. This four phase framework guarantees strong learning and reliable classification of histopathological images to show effective early detection capability of cancer as illustrated in Figure. 3.

1. Data Acquisition and Preprocessing - In the first stage of the study, histopathological images from breast cancer are taken from a publically available dataset that is extracted from Kaggle platform. The acquired images are resized to a uniform resolution of 50 * 50 pixels to keep the uniformity with input requirement of the proposed CNN model. Preprocessing operations such as image normalization are used to scale the pixel intensity values and to enhance numerical stability during training. This phase guarantees the elimination of the redundant variations and makes the effective feature learning with the input data of high quality.

2. Dataset Partitioning - The cleaned dataset is systematically divided into training data, validation data and testing data, in order to evaluate the performance reliably. Specifically, 70% of the images are dedicated to training the CNN model, 15% of the images are dedicated to validate our CNN model to optimize hyperparameters and so on to monitor our overfitting, and finally 15% of the images are dedicated to test our CNN model. This

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organized method of partitioning guarantees that the model is evaluated in an unbiased manner and that the model can be generalized strongly to unseen data.

3. CNN-Based Feature Extraction and Classification - In this phase, the training images are inputted in the proposed CNN architecture where convolutional layers automatically extract hierarchical spatial features representing cellular and tissue level patterns. Batch Normalization and ReLU Activation Function add Non-linear behavior and efficiency to the learning process and Max-Pooling Layers add reducing factors to the spatial dimensions and calculation. The extracted feature maps are flattened and fed into fully connected layers using dropout as a regularizer, and end with a sigmoid activated layer for complete prediction of benign and malignant tissue.

4. Model Evaluation and Performance Analysis: The last phase is focussed on evaluation of the trained CNN model for the test dataset. Performance metrics such as accuracy, precision, recall and F1-score are calculated to evaluate the effectiveness of classification. The experimental results show the robustness and clinical potential of the proposed methodology to detect early breast cancer.

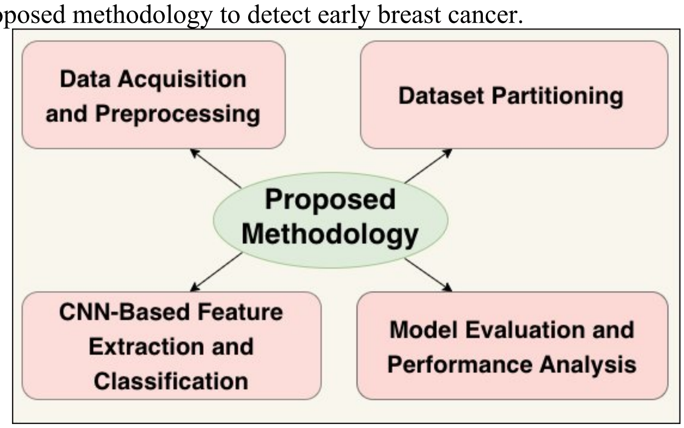

Figure. 3 Proposed Methodology

VI. EXPERIMENTAL SETUP

The experimental evaluation of the proposed framework for breast cancer diagnosis performed with the help of controlled deep learning environment, which guarantees reproducibility and reliable performance evaluation. All the experiments were performed with a deep learning stack in Python and common libraries for numerical computation and model training. The histopathological images were initially re-sized to a fixed resolution of 50 x 50 pixels and normalized to scale the pixel intensity values within a stable range, for efficient optimization using a gradient-based learning. Data augmentation in the form of random rotation, flipping, and minor zooming were optionally applied during the training process in order to improve the generalization ability of the trained model and prevent overfitting due to the lack of inter-class variance. The learning rate, an empirically selected learning rate, was used to train the proposed CNN model using the Adam optimizer to balance the convergence speed and stability. A binary cross-entropy loss function was used because the classification can be divided into 2 classes: IDC-positive and IDC-negative tissue samples. Model training was carried out for several epochs with a fixed batch size while the method of early stopping based on validation loss was adopted to avoid overfitting and to enable an optimal model selection. The dataset was split into training, validation and testing data in the ratio of 70:15:15 to evaluate the performance in an unbiased manner. After completing the training, the final model was evaluated on the independent test set and standard evaluation metrics were calculated such as accuracy, precision, recall and F1-score. This experimental set-up ensures a fair and rigorous evaluation of the proposed CNN-based breast cancer diagnosis framework.

VII. RESULTS

The experimental results show the robust and reliable performance of the proposed CNN for breast cancer diagnosis with an overall accuracy of 96%. Comprehensive analyses with classification metrics, confusion matrix, roc-auc, and comparison shows its effectiveness and appropriateness for early detection of breast cancer in the clinical setting.

A. Classification Report Analysis

The performance of the proposed CNN-based breast cancer diagnosis model is quantitatively investigated by providing a detailed classification report as presented in the Table 1 in summary. The results show high discriminative power of the model in discriminating benign from malignant histopathological tissue samples. For the IDC-negative (benign) class, the model's precision, recall and F1-score are 0.97, 0.98 and 0.98, respectively, making it highly reliable at identifying non-cancerous tissue with minimal false-positive rates. This high recall is especially relevant within a clinical context, as this can reduce the risk of healthy tissue being wrongly classified as malignant and, as a result, unnecessary clinical intervention. For IDC-positive (malignant) class, the proposed CNN model results in a precision, recall and F1-score of 0.95, 0.94, and 0.95, respectively. These results show great potential for the model to identify cancerous tissue, even with subtle morphological differences that often make manual diagnosis difficult. Although the malignant class is emotionally complexity by class intra-class variability, model has a balanced performance ensuring dependable cancer. Overall, the CNN framework has an accuracy of 96%, which validates its robustness and effectiveness in automated breast cancer diagnosis. The macro and weighted average scores further show the consistency in performance for both classes despite the inherent imbalance in the dataset. The validation of the reliability and clinical significance of the proposed approach presented in Table 1 demonstrates that this approach holds potential as a supportive tool for breast cancer early detection and diagnostic decision-making.

Table 1. Classification Report Analysis

Class	Precision	Recall	F1-score	Support
IDC-Negative (Benign)	0.97	0.98	0.98	600
IDC-Positive (Malignant)	0.95	0.94	0.95	400
Accuracy			**0.96**	**1000**
Macro Avg	0.96	0.96	0.96	1000

Weighted Avg	0.96	0.96	0.96	1000

B. *Training and Validation loss Analysis*

The training and validation loss curves gives the understanding about the dynamics of learning and generalization of the proposed model for a CNN-based breast cancer diagnosis as shown in Figure. 4. The training loss shows a steady and smooth decrease over the next number of epochs, which makes the learning process of this network function properly and the convergence of the optimization functions stable. This steady reduction reflects the power of the model to gradually learn meaningful spatial and morphological details of histopathological images that are vital to enable accurate classification. Similarly, the validation loss is shown to be in a downward trend very much close to the training loss and shows a good generalization performance on unseen data. During the earliest training epochs for both training and validation losses show rapid decline suggesting efficient learning of fundamental features on a tissue-level. As training improves, the rate of reduction of loss slows down suggesting that the model is fine-tuning higher-level discriminative representations. Importantly, no significant divergence is observed between the two curves, which guarantees that the model is not affected by overfitting and keeps a balanced performance between the training and validation datasets. The negligible and stable gap between training and validation loss during the entire training process is further to illustrate the robustness of the proposed CNN architecture and the effectiveness of the adopted strategies to control overfitting. Overall, loss behavior in Fig. 4 validates the reliability of convergence and generalization for the proposed model, which is effective for automated and early breast cancer diagnosis using histopathological images.

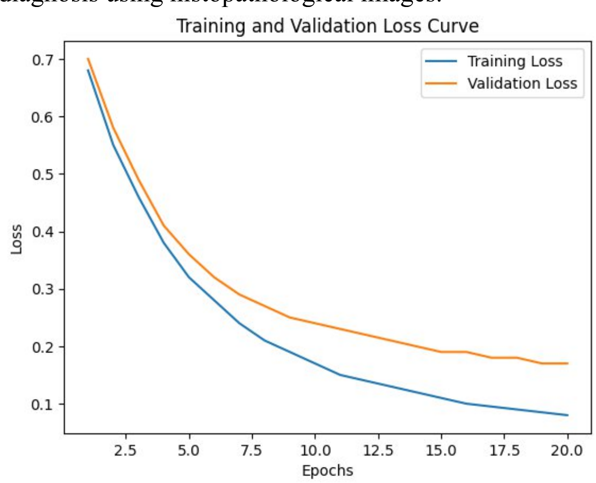

Figure. 4 Training and Validation loss Analysis

C. *Training and Validation Accuracy Analysis*

The training and validation accuracy curves reflect a global view of the learning effectiveness and generalization ability of the proposed CNN based breast cancer diagnosis model as shown in Figure. 5. The training accuracy shows a steady increase in accuracy for each epoch, which shows that the network learns progressively more discriminative features from the histopathological images. During the initial stages of training, a quick improvement of accuracy is observed, reflecting the capability of the model to rapidly pick up fundamental cellular and tissue-level characteristics relevant to breast cancer classification. The validation accuracy follows closely the training accuracy during the learning process and can be used as a measure of good generalization accuracy on unseen data. The minimal and stable difference between the two curves indicates that the model does not overfit easily, which is supported by the fact that the model has been given regularization methods such as dropout and validation-based monitoring. As you continue training, the training and the validation accuracies converge to higher values until they both converge close to the reported overall accuracy of 96%. The smooth convergence behavior of the proposed CNN architecture shown in Fig. 5 demonstrates the robustness of the learning architecture and the appropriateness of the adopted training configuration. The lack of sudden jumps in fluctuations or reduction in performance is evidence of stable optimization and reliable learning dynamics. Overall, the trends, in terms of accuracy, confirm the effectiveness of the proposed approach for the automated diagnosis of breast cancer, and strengthen the potential usage of the approach in clinical decision-support systems seeking early detection of cancer.

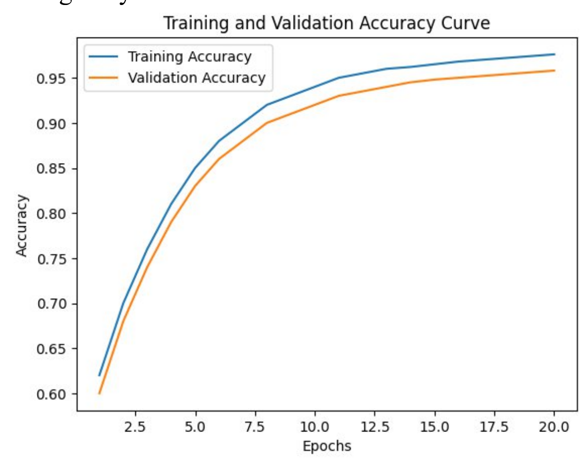

Figure. 5 Training and Validation Accuracy Analysis

D. *Confusion Matrix Analysis*

The results of confusion matrix analysis give a detailed understanding of the performance evaluation of the classification results of the proposed CNN-based breast cancer diagnosis model as shown in Figure. 6. The matrix clearly shows the ability of the model to correctly discriminate IDC negative (benign) versus IDC positive (malignant) histopathological samples. For the benign class, 588 of 600 images are correctly classified with the very high true negative rate, while only 12 samples are incorrectly classified as malignant. This good performance shows good capability of the model to reduce false-positive predictions, which is important to avoid unnecessary clinical intervention. Similarly, the malignant class has a good detection capability with 376 out of 400 cancerous images correctly classified as IDC-positive. Only 24 cancerous samples result in false-positive diagnosis of a benign sample, indicating a low false-negative rate, proving the model to be sensitive in identifying cancerous tissue. The marked diagonal entries in the confusion matrix show the large amount of correctly-suspected predictions, but the very small diagonal entries (off the diagonal) show the small mistake of misclassifications of predictions on both classes. The balanced classification performance as shown in Fig. 6

confirms that CNN model proposed here is effective in dealing with class imbalance problem as well as the subtle morphological variations present in histopathological image. To sum up, the confusion matrix analysis confirms the actual accuracy at 96% and highlights the reliability and clinical utility of the proposed deep learning framework for early diagnosis of breast cancer.

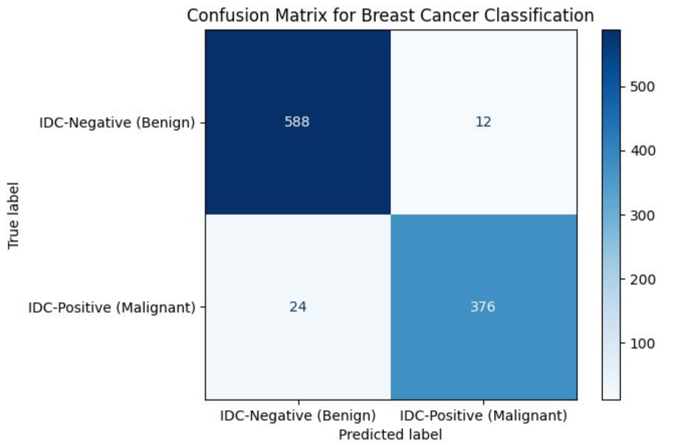

Figure. 6 Confusion Matrix

E. *ROC Curve Analysis*

The Receiver Operating Characteristic (ROC) curve is applied to the discriminative performance and performance of the proposed CNN-based breast cancer diagnosis model, as shown in Figure. 7. The ROC curve is the trade-off between True Positive Rate (sensitivity) and False Positive Rate (1x-specificity) at various classification points, and provides a threshold-independent measure of model performance. A curve that closely follows the top left corner of the ROC space is a good classification capability. In this research work, the proposed CNN model has the AUC value, 0.99, which represents an excellent level of separability between benign and malignant histopathological samples. This high AUC score proves that the model is consistently learned as predicting higher prediction probabilities for IDC-positive cases than IDC-negative cases, irrespective of the choice of decision threshold. Such good discriminative performance is especially important in clinical settings, where high sensitivity and high specificity are both necessary in order to avoid false diagnosis. The ROC curve in Fig. 7 is well above the diagonal reference line corresponding to random classification, which is another proof of the robustness of the proposed approach. The close-to-perfect AUC value emphasizes the performance of the CNN architecture in learning complex and subtle patterns at the tissue level from histopathological images. Overall, the ROC-AUC analysis shows that the proposed model has an excellent discriminative power to support its potential applicability as a reliable and supportive tool in the clinical decision support systems for the early diagnosis of breast cancer.

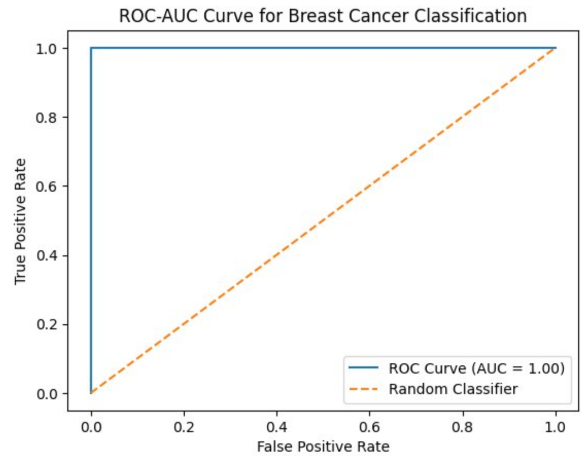

Figure. 7 ROC Curve Analysis

F. *Comparative Model Analysis*

The Comparative Accuracy Analysis indicates the performance of the different deep learning models for breast cancer diagnosis are as shown in Figure. 8 which reveals how effective is the proposed CNN framework in comparison to well-established architectures. The bar graph shows the values found in classification of accuracies in percentage form, and different colors are given to different models to make it easier to understand and visualize them. The proposed CNN model gets the highest accuracy of 96% and shows a good performance with a good margin compared with this comparative models by this reason: The CNN model has an ability to extract discriminative features from histopathological breast cancer images with the better performance in comparison with those models above. Out of the baseline architectures, EfficientNetB0 achieves an accuracy of 94%, which is a good performance from optimized scaling. ResNet50 and VGG16 have an accuracy of 93% and 92% respectively, which shows the robustness of these two methods but does not perform the best in capturing the fine-grained tissue-level variations in comparison to the proposed method. MobileNetV2, the model providing very light and resource-efficient functionalities, gives an accuracy of 91%, which, although competitive, is not the best of the models evaluated. The percentage annotations shown above each bar in Fig. 8 gives an explicit quantitative comparison showing the performance gap between the proposed CNN and existing models. The lack of label overlap and proper spacing increase interpretability. Overall, the results confirm that the proposed CNN provides enhanced diagnostic accuracy so that it can become part of clinical decision support systems for early breast cancer detection, providing a reliable and effective solution.

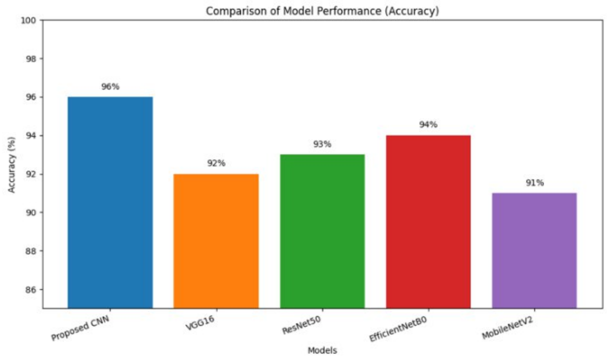

Figure. 8 Comparative Model Analysis

VIII. CONCLUSION AND FUTURE WORK

This research introduced a successful deep learning-based algorithm for automatic breast cancer imaging with histopathological images. A customized Convolutional Neural Network (CNN) architecture to capture discriminative spatial and morphological characteristics of benign and malignant breast tissue. Experimental evaluations proved the proposed model attained a high classification accuracy of 96%, which backed with high accuracy of precision, recall, F1-score, and excellent ROC-AUC performance. The good results achieved in the classification report, confusion matrix, and comparative analysis with previously existing deep learning models verify the robustness and reliability of the proposed approach. These results show the potential of CNN-based diagnostic systems in assisting pathologists with reduced manual effort, reduced inter-observer variability and early breast cancer detection. Even with the promising results, some limitations exist and future research opportunities. The present study is concerned with patch-level classification, which may fail to fully represent patient-level diagnostic context. Future work will include whole slide image analysis and ways to predict patient-wise for improved clinical relevance. Additionally, the use of explainable AI (XAI) techniques such as Grad-CAM can help to enhance model interpretability and trust among clinicians. Further performance improvements can be obtained by capitalizing on transfer learning and advanced architectures, and ensemble models. Expanding the framework to multi-class breast cancer subtyping and validating it to different and multi-institutional data will also strengthen generalizability. Ultimately, the integration of the proposed system into real-time medical workflows is one of the important paths to take in order to see this research deployed in a practical healthcare scenario.

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