JETIR.ORG ISSN: 2349-5162 | ESTD Year : 2014 | Monthly Issue
JOURNAL OF EMERGING TECHNOLOGIES AND INNOVATIVE RESEARCH (JETIR)
An International Scholarly Open Access, Peer-reviewed, Refereed Journal

Deep Learning (CNN) techniques for the Classification of Breast Cancer using Ultrasound Images – A Review

Archana Singh[1] , Surya Prakash Mishra[2] , Prateek Singh[3]
[123] Department of Computer Science & I.T, SHUATS, Prayagraj, India

Abstract – *Breast Cancer, one of the main causes of death for women globally, highlights the vital need of an early and precise diagnosis. Ultrasonography, the first and primary diagnosis clinical investigating method lacks precise decision due to noise, shadow, contrast, and variations in tumor appearance. Convolutional Neural Networks (CNNs) in particular have shown remarkable achievements in medical image processing using deep learning models. In this paper, we have analyzed five popular pre-trained deep learning models— ResNet50, EfficientNetB0, VGG16, MobileNetV1 and DenseNet121 on publicly available dataset comprising 780 ultrasound images of both benign and malignant breast tumours from Baheya Hospital, Egypt. According to the results, the EfficientNetB0 network emerged as the best model for determining whether breast cancer is benign or malignant. In the study conducted, the Efficient-Net B0 model demonstrated impressive results with an accuracy rate of 96.80% among all the models with considerably less training time and minimal parameters. The ability of the transfer learning from Imagenets database module has also remarkably improved the accuracy of breast tumour categorization using ultrasound images.*

Keywords— Convolutional neural network, deep learning, breast cancer, ultrasound imaging (US), transfer learning (TL), classification, computer-aided diagnostic systems (CAD).

Introduction: Breast cancer continues to stay tall among cancer-related deaths in women worldwide, amounting to around 670,000 deaths in 2022 alone and 11.7% of all new cancer diagnoses [1]. Every year, up to 2.3 million new diagnoses are made, and better patient outcomes depend on early and precise diagnosis. For example, a five-year survival rate of up to 99% is achieved with early detection, while 28% is achieved with advanced-stage diagnosis [2]. Conventional imaging techniques like mammography, ultrasound, and magnetic resonance imaging (MRI) have limitations with low sensitivity for all of these extremes, especially in women with dense breasts, where detection rates is as low as 25–58% for mammography and 33–52% for ultrasound as documented [3]. These difficulties highlight the critical need for reliable and automated diagnostic methods that can help radiologists in making an accurate diagnosis of breast cancer.

The availability of automated, objective, and extremely accurate methods for classifying cancer has transformed medical image analysis and recent developments in machine learning and deep learning [4, 5]. Convolutional neural networks, or CNNs, are frequently employed to accurately learn complicated characteristics from unprocessed picture data (up to 92% in ultrasound pictures) [6]. But even with all of these achievements, deep learning models are usually limited by their high computing cost, reliance on massive volumes of labelled data, and vulnerability to overfitting on small datasets [7, 8]. Transfer learning has become a useful technique for addressing these issues. It involves pre-training models like VGG16, ResNet, and DenseNet201 using sizable datasets like ImageNet, then using the pre-trained models to transfer learned features for subsequent medical imaging applications [9]. Due to its densely linked architecture, which permits a richer gradient flow and efficient feature transfer, DenseNet201 has performed very well among these [10].

Moreover, hyperparameter tuning of the following classifier is still a difficult problem, despite the fact that transfer learning greatly enhances the model. When exploring high-dimensional spaces, conventional methods such as grid search or random search for parameter optimization—such as learning rate, dropout rate, and network size—are computationally costly and ineffective [11]. A more efficient option is Bayesian optimization, which effectively fine-tunes model parameters and enhances generalization performance by using probabilistic models to direct the search for the best-performing hyperparameters [12]. Lightweight classifiers such as the Fast Learning Network (FLN), may achieve high accuracy with shorter training durations when tuned, benefit greatly from this technique [13].

2. Related Works: Breast cancer is the fatal category of cancer in the world if not detected in early stages. The goal among the scientific and medical community is to find a way to detect breast cancer during an early stage. Additionally, scientists are looking at artificial intelligence methods to create a potent system that lowers the death rate [14]–[17].

The authors of this research paper [18] have put up a method for classifying ultrasound images of breast cancer. Using a fusion of the two datasets with an increase, this method is based on two deep learning approaches (CNN Alex-Net and Transfer Learning). When applied to the whole dataset and with a DAGAN augmentation, the NASNet model yields an accuracy of 99%. A novel classification approach was presented in [19] that distinguishes between benign and malignant tumours in US images of breast cancer by combining an unsupervised technique (fuzzy c- means clustering) with a supervised technique (back-propagation artificial neural network). The method produced a 95.86% accuracy rate.

To further enhance the performance of the original Deep Polynomial Network (DPN), the authors of [20] applied a Stacked DPN (S-DPN) method. Based on textural feature learning stain, S- DPN was then applied to ultrasound breast tumour classification. They made use of a limited collection of data. With a classification accuracy of 92.40%, the S-DPN performs the best in terms of the experimental findings.

A CAD method was proposed for tumour diagnosis in a research by [21]. The system is built using a combined ensembled approach of a variety of convolutional neural network (CNN) designs in conjunction with image fusion. In this, Three networks of CNN approaches were utilized in the study: DenseNet, ResNet, and VGGNet. According to the experimental findings, the suggested CAD system had an F1 score of 91.14%, accuracy of 94.62%, sensitivity of 92.31%, specificity of 95.60%, and precision of 90%. The authors proposed a CAD system that seeks to identify malignancies in a different study. . The three well-known CNN architectures used in the study VGGNet, ResNet, and DenseNet demonstrated the high accuracy with performance measures including accuracy, sensitivity, specificity, precision, and F1 score reaching 94.62%, 92.31%, 95.60%, 90%, and 91.14%, respectively.

The study [22] suggested a deep learning-based method for fine-tuning the images of breast tissue stained with hematoxylin and eosin (H&E) using an Inception-v3 convolutional neural network. The images were segregated into four categories: invasive carcinoma, benign lesions, in situ cancer, and normal tissue. The class of the overall picture is determined by a majority vote among the nuclear classes. The results demonstrated an average accuracy of 85% for all four classifications and a 93% accuracy rate for non-cancer (normal or benign) vs malignant (in situ or invasive carcinoma).

Multi-modal Transformer (MMT), a neural network presented in the study [23], identifies cancer patients and determines the risk of cancer development for individuals who are currently cancer-free by combining mammography and ultrasound. In order to track changes in tissues over time, MMT aggregates multimodal data using self-attention and compares the current inspections to earlier pictures. After being trained on 1.3 million tests, MMT outperforms strong unimodal baselines in identifying pre-existing cancers, with an AUC-ROC of 0.943. For 5-year risk prediction, MMT performs better than previous mammography-based risk models, with an AUC-ROC of 0.826. A Computer-Aided Diagnostic (CAD) system that can generate an ideal algorithm by itself was suggested by the study [24]. Machine learning is trained on 13 of the 185 characteristics that are accessible. Five machine learning classifiers were used to differentiate between tumors that were benign and those that were malignant. The experimental results include Bayesian optimization utilizing a tree-structured Parzen estimator for tenfold cross-validation, based on a machine learning classifier. However, LightGBM classifier outperforms the other four classifiers, achieving 99.80% FI score, 99.86% accuracy, 100.0% precision, and 99.60% recall.

The various Deep-learning algorithms for classifying images of breast cancer histology were investigated in the study [26]. Models like ResNeXt, Dual Path Net, SENet, and NASNet have been considered to yield the most sophisticated results for the ImageNet database. The Inception-ResNet- V2 architecture was also examined in the study; it yielded the best results for binary and eight classifications and superior comparative results.

The study [27] suggested a new deep model to classify breast cancer in order to improve the detection of breast cancer classification. It was inspired by two state-of-the-art deep networks, residual block and GoogLeNet, and was successful in acquiring a number of novel features. The proposed model demonstrated 93% and 95% accuracy on ultrasound and breast histopathology images.

A Meta-Learning Ensemble Method for Breast Cancer Classification Using Convolutional Neural Networks was proposed in the paper [28]. The suggested method combines multiple CNN models, including InceptionV3, ResNet50, and DenseNet121, using a meta-learning framework to improve generalization and reach 90% accuracy , particularly when detecting malignant tumors.

Study [29] evaluated and contrasted the classification accuracy, precision, recall, and F1 scores of five different machine learning approaches using a main dataset. To get the best results five different supervised machine learning techniques: XGBoost, logistic regression, naive Bayes, decision trees, and random forest were used. The final assessment of this investigation showed 97% accuracy rate, and XGBoost was confirmed as the best model.

The study [30] proposed a way to build an efficient deep neural network model that considers context from neighboring image segments in order to detect breast cancer on digital breast tomosynthesis (DBT). On the test set of 655 DBT trials, two 3D models performed better in categorization than the baseline models. The proposed transformer-based model depicted considerable improvement in AUC (0.88 vs 0.91, P = 0.002), sensitivity (81.0% vs 87.7%, P = 0.006), and specificity (80.5% vs 86.4%, P < 0.001) at clinically meaningful operational points as compared to the single-DBT-section baseline. The transformer-based model only used 25% of the floating-point operations FLOPs per second with respect to the 3D convolution model and attained similar classification results.

A Dilated Semantic Segmentation Network (Di-CNN) was presented by Irfan et al. [31] for the purpose of detecting and categorizing breast cancer. They employed transfer learning technique to create a pre-trained DenseNet201 deep model, which was then used for feature extraction. They also categorized the nodules using a 24-layered CNN and parallelly fused feature information with the previously trained model. The findings demonstrated that the fusion process increased the accuracy of recognition.

A contextual level set approach for breast tumor segmentation was introduced by Hussain et al. [32]. They created an encoder-decoder network in the UNet approach to extract high-level contextual information from semantic input.

A deep doubly supervised transfer learning network for the classification of breast cancer was introduced by Xiangmin et al. [33]. Using the Maximum Mean Discrepancy (MMD) criteria, they implemented the Learning Using Privileged Information (LUPI) paradigm. Later, they increased performance by combining the two methods using a new doubly supervised TL Network (DDSTN).

A computerized diagnosis approach for classifying breast cancer based on ultrasound images was presented by Woo et al. [34]. They presented an image fusion approach and integrated it with several CNN models with picture content representation. The experimental procedure produced comprehending noteworthy results when run on both private and BUSI datasets.

3. Materials and Methods of our study:

***A. Dataset Description*:** Images of ultrasound(US) from Baheya Hospital dataset taken for this study [26] are in grayscale. A total of 600 women aged 25 to 75 were the subjects of this data collection yielding 780 images, each having an average size of 500 × 500 pixels. The US dataset is separated into three groups: normal, malignant, and benign. Only 780 of the 1100 photos that were initially collected were left after the data preparation. It includes ultrasound pictures of breast cancers, both benign and malignant. The sample data from the database utilized in this work is shown graphically in Figure 1. The pictures are 224 × 224 pixels in size and are in PNG format.

Figure1: Samples of breast US images from the dataset used. (a) Benign. (b) Malignant.

The instruments used in the scanning process are the LOGIQ Agile and LOGIQ E9 ultrasound systems. These instruments are usually used in radiological, cardiac, and vascular high-quality imaging applications. They produce pictures with a 1280 x 1024 resolution.

B. Deep Learning CNN Models (DL-CNN)

DL-CNN has enormous capability in addressing medical imaging difficulties. We are utilizing models like ResNet50, EfficientNetB0, VGG16, MobileNetV1, and DenseNet121 for the classification of breast cancer from ultrasound pictures. Deeper models like ResNet50 and DenseNet121 enable strong feature extraction via residual and dense connections necessary for ultrasound images since they often include low contrast features and nuanced textures. EfficientNetB0 proved efficient for such situations having constrained resources because it provides a good compromise between accuracy and processing economy. Despite being an older architecture, VGG16's simplicity and track record of performance in image categorization make it a useful baseline model. MobileNetV1's speed and portability make it ideal for deployment on embedded or mobile devices with limited processing power. We can determine the best practical and efficient model for precisely identifying breast cancer in ultrasound images by evaluating these diverse designs. A brief summary of these models are presented below:

ResNet50 Model

ResNet50, a 50-layered deep renowned CNN for inventing the idea of residual connections, emerging as shortcut pathways that bypass layers so the network may learn differences (residuals) rather than complete transformations. The issues related to vanishing gradients frequently impede very deep networks, and are resolved using this solution. In order to gradually deepen the network while keeping the computational cost under control, the design is upgraded to compose four groups of bottleneck residual blocks after an initial convolution layer and pooling layer[35]. Because ResNet50's depth enables it to catch intricate details, which makes it applaudable to be frequently utilized in medical imaging tasks like categorization of breast ultrasonography carcinoma.

EfficientNetB0 Model

As compared to previous models, EfficientNetB0 CNN design is small yet powerful and is able to deliver good accuracy with significantly fewer parameters. In order to maximize performance without incurring undue computing costs, it presents a novel compound scaling technique that evenly grows the network's depth, breadth, and resolution. In order to effectively extract rich features, it has an MBConv block, which combines depthwise convolutions(DC), squeeze-and-excitation(SE) attention, and inverted residual(IR) connections[36]. EfficientNetB0 is ideally suited for medical imaging applications where computing resources may be constrained, such as ultrasound image classification, because of its exceptional speed-accuracy balance.

VGG 16 Model

A typical deep CNN network with 16 weight layers, VGG16 is well-known for its straightforward yet efficient architecture that stacks several 3x3 convolutional layers sequentially, with sporadic max pooling layers to minimize spatial dimensions. It has three fully linked layers remaining at the end of the network before final output. Though VGG16 emerged as a great success in computer vision tasks, it is incredibly massive and computationally demanding (with over 138 million parameters), which makes it less feasible for contemporary applications unless there is robust hardware [37]. In tasks, such as the identification of breast cancer from ultrasound pictures, it is still a helpful baseline architecture for comparison.

MobileNetV1 Model

MobileNetV1 approach uses depthwise separable convolutions to significantly reduce computation and model size. It was particularly made for mobile and embedded devices. Rather than carrying out a complete convolution over all channels, it divides the process into two parts: a pointwise convolution, which combines channels using 1×1 filters, and a depthwise convolution, which filters each channel independently. While keeping a respectable level of accuracy, it leads to considerable performance and memory savings [38]. MobileNetV1 is especially helpful in situations where quick inference on low-resource devices is necessary, such as ultrasound categorization.

DenseNet121 Model

With 121 layers, DenseNet121 is a deep neural network distinguished by its distinct dense connection structure, in which each layer gets inputs from every layer that came before it inside the same thick block. Compared to conventional designs, it helps the model in learning richer representations with fewer parameters, resulting in greater gradient flow and more effective feature reuse. Transition layers(TL) minimizes the size and quantity of channels in feature maps between dense blocks [39]. Because DenseNet121 is comparatively light and can capture small features, it demonstrated great efficacy in medical image analysis, including breast ultrasound cancer categorization.

Table below gives a brief comparison of these model showcasing their strengths and weakness:-

Model	**Params (approx)**	**Speed**	**Strengths**	**Drawbacks**
ResNet50	~25.6M	Medium	Deep residuals, strong feature learning	Larger than lightweight models
EfficientNetB0	~5.3M	Fast	High accuracy vs. size	Needs careful tuning on small data
VGG16	~138M	Slow	Simple and well-known	Huge size, inefficient
MobileNetV1	~4.2M	Very fast	Lightweight, fast	Lower max accuracy
DenseNet121	~8M	Medium-Fast	Dense connectivity, good for medical	Higher memory use due to concatenation

Table-1: Comparison of deep learning models for Breast cancer detection

C. Methodology

The first stage in the suggested method for categorizing US images of breast cancer is pre- processing the image database. The goal of this preprocessing stage is to clean and normalize the images, which is essential for deep learning. Training and validating five transfer-learning models— ResNet50, EfficientNetB0, VGG16, MobileNetV1, and DenseNet121 is then done using the obtained pre-processed images Figure 2 illustrates how these models are trained using the ultrasound training dataset.

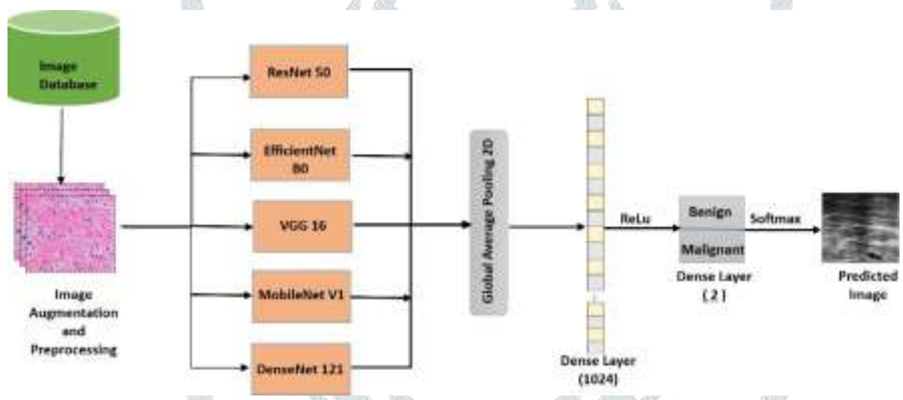

Figure2: Flowchart of the proposed model used for CAD system

Each of the models are pretrained from the "Imagenet" database and then transfer learning was used to transfer knowledge gained from a pre-existing model to a new model, thereby reducing the need for large amounts of new data. By utilizing the transfer learning concept, the new model can leverage the features learned from the previous task and helps in better generalization of the new task, even with limited data, making it a valuable tool for solving complex machine learning problems [40].

To ensure that the models are not overfitting, validation of the dataset is done during the training process. In our model we have split the training, testing and validation dataset of each class in the ratio of 70% 20% and 10% respectively. Finally, the performance of each model is evaluated on the test dataset. To determine the best performing model, confusion matrices including various performance metrics are calculated. This helps to identify the best model with most accurate classification results.

Each CNN processes the dataset images to create high-dimensional feature maps, which are then compressed by a Global Average Pooling (GAP) layer. By calculating the average of all spatial positions, GAP breaks down each feature map into a single integer, thus, drastically reducing the number of parameters and the chances of overfitting in our model while preserving crucial information. Through this transformation, complex spatial feature maps are broken down into easily handled one-dimensional feature vectors that highlight the main pattern presented throughout the image. We used ReLU activation function, so as to introduce non-linearity by passing this consolidated feature vector through a dense layer of 1024 fully connected neurons. By learning more complex feature combinations and interactions, this thick layer improves the model's capacity to discern minute variations between benign and malignant instances.

Finally, the model employs a smaller dense layer with only two neurons, which correspond to either benign or malignant categorization groups, after the dense layer. The raw output values are converted into probabilities using a softmax activation function, which shows how confident the model is in each class. A precise and understandable diagnosis to help medical professionals in making well-informed judgments is made possible by the final prediction being made by the class with the highest likelihood.

4. Performance Evaluation

Python 3.11.8 with TensorFlow 2.15.0, and Keras 0.20 as software and Intel Core i7 11th generation processor with 16Gb RAM and a 4 GB Nvidia GeForce RTX3050-Ti graphics card in hardware was used for all experiments. Table-2 displays the learning algorithms assessment and training hyper parameters. The size of each breast cancer image used in this research is 224 by 224 pixels.

Network	Learning Rate	Batch Size	Optimizer	Loss Function	Epochs
All-5 CNN Networks	0.0001	32	Adam	Categorical Cross Entropy	20

Table-2: Studied Pre-trained model Hyperparameters

Next, we present the results of our experiments. First we will show the validation accuracy and loss curve for all the CNN models under our research study , followed by the confusion matrix curves for each model. Our study is based on the training of five CNN pre-training models ResNet50, EfficientNetB0, VGG16, MobileNetV1, and DenseNet121 on the same database by the transfer learning method with of course a comparison of our classification system.

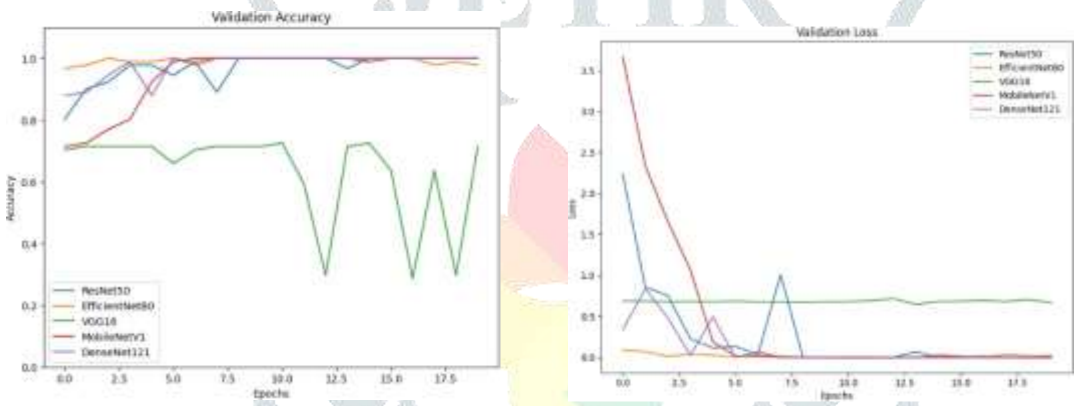

Figure-3: (a)Validation Accuracy and (b)Validation Loss of the five models.

As shown in Figure-3(a), The graph compares validation accuracy across all five models over 20 epochs. DenseNet121 and EfficientNetB0 achieved consistently high accuracy close to 100%, showing excellent and stable performance. ResNet50 and MobileNetV1 also achieve high accuracy but with some fluctuations. In contrast, VGG16 performs poorly, with lower and unstable accuracy throughout training. Overall, modern architectures like DenseNet and EfficientNet clearly outperform older models like VGG16 on this task.

The graph in Figure-3(b) shows how validation loss changes for five models during training. EfficientNetB0 and DenseNet121 achieved the lowest and most stable loss, nearly zero after a few epochs, indicating excellent performance and minimal overfitting. MobileNetV1 starts with a very high loss (~3.6) but quickly drops and stabilizes nearing zero, showing effective learning after an initially poor start. ResNet50 shows some spikes in loss across epochs, suggesting occasional instability despite overall low loss. VGG16 maintains a relatively high and flat loss curve around 0.6–0.7, indicating it struggles to improve during training. Overall, modern architectures like EfficientNetB0 and DenseNet121 clearly outperform VGG16, achieving both low loss and stable training behavior.

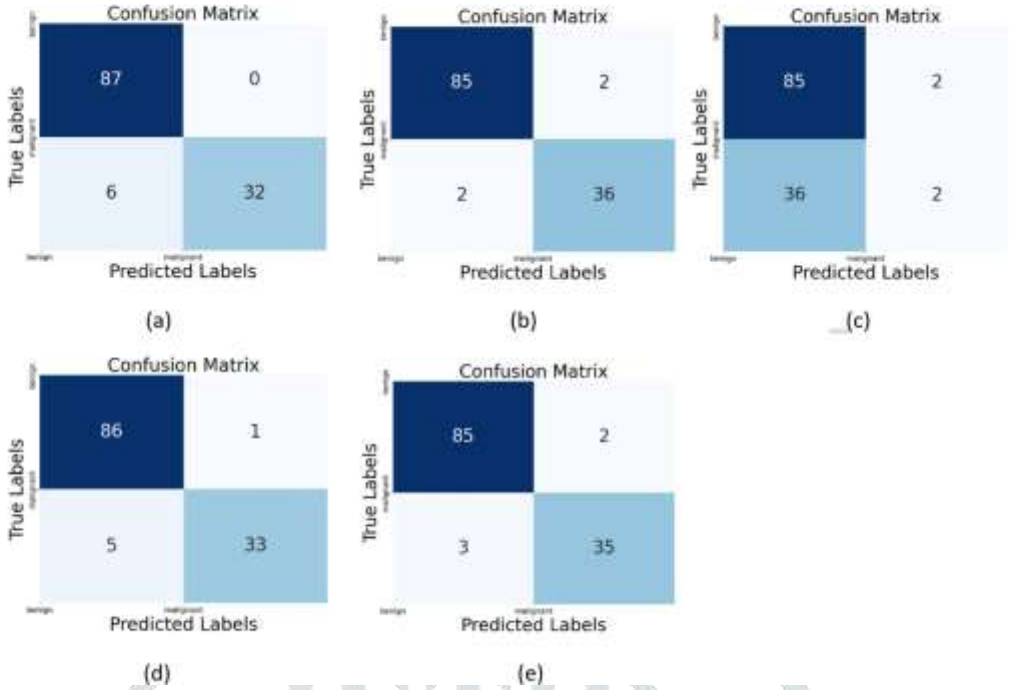

Figure-4: Confusion matrix of (a) ResNet50, (b) EfficientNetB0, (c) VGG16, (d) MobileNetV1 and (e) DenseNet121 for predicting Benign and Malignant Tumors.

The confusion matrices of the various CNN models obtained from the experiment are shown in the figure-4 which summarizes all the five confusion matrices that compare model performance in classifying benign and malignant cases. Most models, shown in matrices (a), (b), (d), and (e), achieved high accuracy, by correctly identifying the majority of benign and malignant samples with only a few misclassifications. However, matrix (c) stands out for poor performance, it accurately predicted benign cases but misclassified a large number of malignant samples as benign, which is critical in medical diagnoses. Overall, while benign cases are classified reliably across all models, distinguishing malignant cases remains more challenging. It highlights the importance of selecting models that minimizes false negatives in this context.

Model	RESNET-50	EFFICIENT NET-B0	VGG-16	MOBILENE T-V1	DENSENET-121
Test Accuracy	95.20%	**96.80%**	69.60%	95.20%	96.00%
Validation Accuracy	100.00%	100.00%	72.53%	100.00%	100.00%
Precision	**96.77%**	96.22%	60.12%	95.78%	95.59%
Sensitivity	92.10%	**96.21%**	51.48%	92.84%	94.90%
Specificity	92.15%	**96.25%**	51.50%	92.85%	94.92%
Recall	0.9211	**0.9622**	0.5148	0.9285	0.9502
AUC	0.9958	0.9973	0.5284	**0.9976**	0.9921
F1 score	0.9405	**0.9621**	0.4562	0.9415	0.9524
Total Training Time (s)	539.32	354.64	1194.55	787.52	**167.57**
Avg. Training Time per Epoch (s)	26.96	17.73	59.72	41.20	**8.38**
Total parameters	25,687,938	5,363,365	15,242,050	**4,280,514**	8,089,154

Table-3: Comparative Performance analysis of the CNN models using BUS dataset

The Table-3 compares all five models in our study based on classification performance and computational cost. **EfficientNet-B0** achieved the highest test accuracy (96.80%) and strong metrics across the board, with excellent sensitivity (96.21%), specificity (96.25%), and the highest F1 score (0.9621), while also being relatively fast to train. **DenseNet-121** follows closely with 96.00% test accuracy, high precision, recall, and the fastest average training time per epoch (8.38s), making it both accurate and efficient. **ResNet-50** and **MobileNet-V1** both reach 95.20% test accuracy with solid precision and recall, though ResNet-50 takes less time to train than MobileNet-V1. **VGG-16** performs poorly, with much lower test accuracy (69.60%) and the weakest metrics overall, while also requiring the longest training time. Among all models, **MobileNet-V1** has the smallest number of parameters, indicating lower model complexity, but DenseNet-121 offers the best balance of high performance and speed.

5. Summary and Conclusion

Transfer learning approach offers remarkable performance by transferring the knowledge gained from a pre-existing model to a new model and is remarkable in reducing the need for large amounts of new data. Overfitting and underfitting was avoided thereby, generating a robust performance. Our approach of preprocessing and image augmentation for cleaning and normalizing the data was successfully implemented and proved beneficial on Baheya Hospital dataset of780 images where each image is 224 × 224 pixels in size and are in PNG format. The formatted data is fed in the considered CNN models: ResNet50, EfficientNetB0, VGG16, MobileNetV1, and DenseNet121. ReLU activation function was used to introduce non-linearity. The validation accuracy and Validation loss curve is plotted to show the results. For fine-tuning, the hyperparameters include Adam optimizer with a learning rate of 0.0001, the batch size yielding maximum performance was 32 with 20 epochs. Categorical Cross Entropy was implemented. Confusion matrix for predicted benign and malignant class is also considered for the final result. The validation accuracy for all the models achieved was 100%. Analysis of performance comparison listed in table 3 above shows EfficientNet- B0 as emerging winner with attest accuracy 96.8%, sensitivity 96.21%, specificity 96.25% and the highest F1 score of 0.9621. DenseNet 121 with its deep network took the lowest training time of 8.38s per epoch. MobileNet V1 operated with the lowest number of parameters 4.3 million. ResNet 50 has the highest precision rate 96.77% among all CNN models . The above stated and implemented facts proved our claim of EfficientNet-B0 to be the best model with a transfer learning approach among all the other considered CNN networks.

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