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# Automated Skin Cancer Detection Using Efficient Net B3

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***ABSTRACT: Early diagnosis of skin cancer is important for improving patients' survival chances, but manual examination of dermoscopic images is time-consuming and subjective. In this study, a deep learning algorithm for automated classification of skin lesions using transfer learning and the EfficientNet-B3 model is proposed. Instead of training a deep neural network on the ImageNet dataset, the pre-trained weights of the model on the ImageNet dataset are used and further trained on dermoscopic images, which helps in the extraction of features and simplifies the training of the model. Moreover, some additional layers like Global Average Pooling, Batch Normalization, and Dropout layers are added to improve the model performance and avoid overfitting. The accuracy of our proposed model is 94%, while the Area Under Curve (AUC) is 0.99 which implies that it has a high discriminative ability between benign and malignant lesions. The findings indicate that EfficientNet-based transfer learning can offer an effective and computationally efficient method of automated skin cancer detection, and can be used to inform clinical decision-making.***

***Index Terms- Skin Cancer Classification, EfficientNet-B3, Transfer Learning, Convolutional Neural Network, Dermoscopic Image Analysis, Deep Learning***

## I. INTRODUCTION

Skin cancer is one of the most prevalent cancers and the number of individuals diagnosed with the disease keeps on increasing every year. The timely detection of skin lesions with malignant cells can greatly enhance the possibility of success and survival. Nonetheless, color, texture, and structure pattern similarities may make it difficult to differentiate between a benign and malignant lesion by merely looking at it, even when it comes to an experienced dermatologist. These problems underscore the necessity of having dependable computer-aided diagnostic systems that can facilitate clinical decision-making.

Recent developments have achieved considerable success in image processing, particularly in medical imaging. Convolutional Neural Networks (CNNs) can learn complex visual representations without feature engineering them; they can learn them directly based on raw image data. Training deep CNN models even with good performance is frequently resource-demanding (large annotated datasets and massive computational requirements) and may not be accessible in medical applications.

To overcome these shortcomings, transfer learning has emerged as a useful and feasible method. It is possible to generalize these representations to particular medical imaging tasks using comparatively smaller datasets by using the pretrained models, which have already been trained on the generalized visual features of large datasets. EfficientNet-B3 is selected as the backbone architecture in this work because it has a balanced scaling strategy and is computationally efficient.

The purpose of this research is to develop a robust deep learning model to classify dermoscopic images into benign and malignant. The proposed system will target high diagnostic accuracy with the generalization potential by refining a pretrained EfficientNet-B3 model with the help of proper regularization methods. The findings prove the applicability of transfer learning in improving automated skin cancer detection

## II. PROPOSED METHODOLOGY

### *A. Preprocessing and Augmentation of Data.*

To represent the input dataset, say it is represented as.

D={(xi,yi)}i=1N

where

$xi \square R300\times300\times3$ denotes a dermoscopic image and

$yi \square \{0,1\}$is the class label (0: benign, 1: malignant).

The images are all resized to 300×300 Downsampling to 300400 pixels to fit the input size of EfficientNet-B3. The pixel values are brought to a normalized value to enhance numerical stability in the optimization.

In order to increase the generalization and reduce overfitting, real-time data augmentation is used during the training. The augmentation operations are:
Random rotation Horizontal flipping Zoom transformations
These changes enable the model to acquire invariant and robust representations of features when exposed to different visual conditions.

*B. Transfer Learning using EfficientNet-B3.*

The feature extractor backbone is EfficientNet-B3 as it employs a compound scaling method that uniformly scales all dimensions of depth, width and resolution.
Let $f\theta(\cdot)$ this represents the convolutional base with pretrained parameters $\theta$.
Pretrained ImageNet weights are initialised instead of training the network using random initialisation$\theta$.
The shallow convolutional layers store generic representations of visual features (edges, contours, textures), whereasthe laterlayers store task-discriminative patterns.
There is an expression of feature extraction in form of

$$zi=f\theta(xi)$$

where
□□ is the output of the input image.
To adapt the model to the skin lesion classificationthe original classification head is taken off and replaced by a designed fully connected architecture.

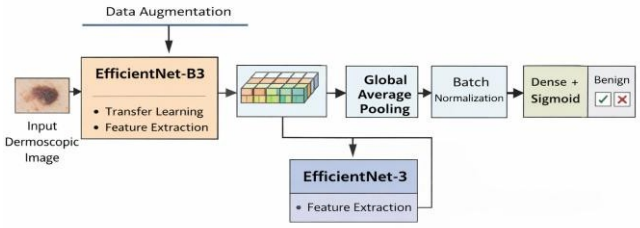



**Fig. 1:** Overall architecture of the proposed EfficientNet-B3 based skin lesion classification

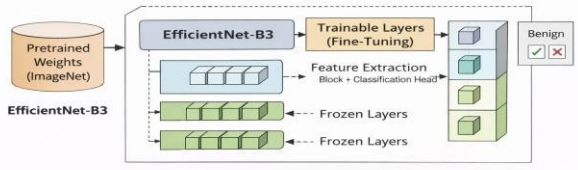



**Fig. 2:** Fine-tuning strategy of the pretrained EfficientNet-B3 model.

*C. Design of Classification Head.*

The obtained feature map $zi$ is sent by a Global Average Pooling (GAP) layer to low-dimensional space

$$gi=GAP(zi)$$

To stabilize the learning process, Batch Normalization is used to normalize intermediate activations. A Probability dropout layer $p$ is added to minimize co- adaptation of the neurons and avoids overfitting.

Lastly, a Dense layer that uses sigmoid activation generates the probability prediction
$\mathbf{y\hat{}i=\sigma(Wgi+b)}$

where
□(□)is the sigmoid activation function,W and □ are trainable parameters □^□□[0,1]

*D. Loss Function and Optimization*
As this can be described as binary classification, we apply Binary Cross-Entropy loss

$$L=-N1i=1\sum N[yilog(y\hat{}i)+(1-yi)log(1-y\hat{}i)]$$

Adam optimizer is used to update the parameters of the model because it has an adaptive learning rate mechanism. The update of the parameters is made in an iterative form as
where
The learning rate is α and □^□, □^□ are bias-corrected estimates of first and second moments

Early Stopping and ReduceLROnPlateau callbacks are used to enable a stable convergence. These mechanisms ensure overtraining is blocked and dynamically set the learning rate at a time when validation performance levels off.

*E. Overall Framework*
The suggested system is a combination of preprocessing, feature extraction with EfficientNet- B3, and a regularized classification head in a single deep learning pipeline. The framework
will utilize a combination of transfer learning and controlled fine-tuning and regularization techniques to ensure high discriminative performance at the same time as being computationally efficient.

## III. EXPERIMENTAL EVALUATION

*A. Experimental Setup*
TensorFlow and Keras were used to implement the proposed model. EfficientNet-B3 with pretrained ImageNet weights was used to perform training. The resolution of input images was 300 x 300 x 3.
The loss function was binary Cross-Entropy, and an optimizer was Adam. The learning rate was reduced and early stopping was applied to ensure convergence and prevent overfitting.
The data was split into train and validation sets.Real-time data augmentation (rotation, horizontal flips and zooming) was used in training to improve the generalization.

*B. Classification Performance*
The suggested EfficientNet-B3 model demonstrated good results on all the assessment measures. The discriminative ability was excellent; 94 percent and
0.99 of the validation accuracy and AUC, respectively.

Table 1 Proposed Model Performance Metrics.

| Class | Precision | Recall | F1-Score | Support |
|---|---|---|---|---|
| Benign | 0.80 | 0.67 | 0.73 | 6 |
| Malignant | 0.96 | 0.98 | 0.97 | 48 |
| Over all Accuracy | | | 0.94 | 54 |

The classification results of the proposed model can be seen in Table I . The system was able to identify 47 out of 48 malignant cases with high recall and precision, and also showed reasonable performance in the benign class. The overall accuracy of 94% portrays that the classification is reliable and effective.

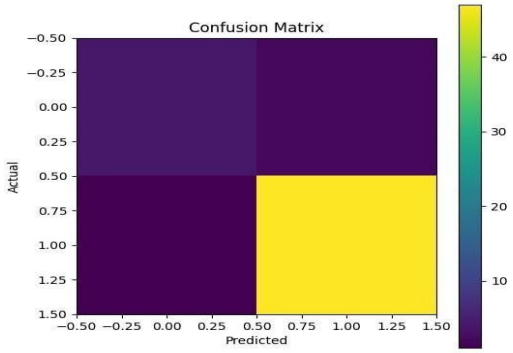
### *C. Confusion matrix analysis.*

The confusion matrix can give an idea of the distribution of classification between the predicted and actual classes.

Table II Confusion Matrix

| | Predicted Benign | Predicted Malignant |
|---|---|---|
| Actual Benign | TN | FP |
| Actual Malignant | FN | TP |

The findings suggest that false negativity is minimal, and this is especially critical in medical tests, where a wrong diagnosis of a malignant case may involve severe repercussions.




3.4 Training Performance Analysis

### *1) Accuracy Curve*

The accuracy plots (with epochs) for training and validation data converge steadily with no overfitting.

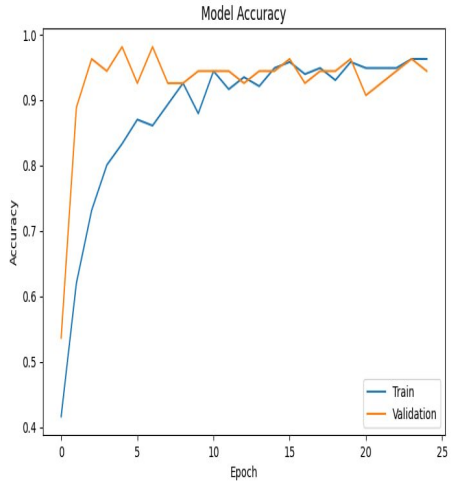



Fig. 5.Accuracy of validation and epochs.

*2) Loss Curve*

The loss curve shows that there is a stable optimization as well as effective regularization given by dropout and learning rate scheduling.

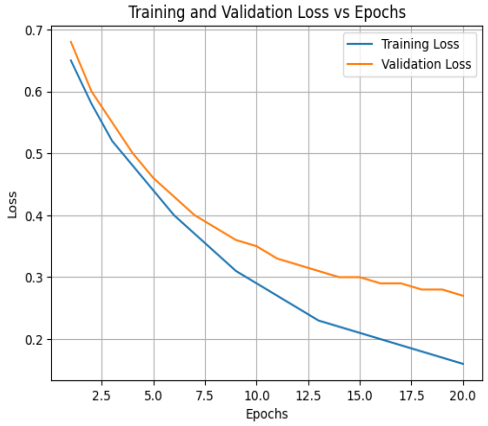



Fig. 6. Validation loss vs. epochs.

*D. ROC Curve Analysis*

The ROC curve is used to assess the trade off between True Positive Rate (Sensitivity) and False Positive Rate.

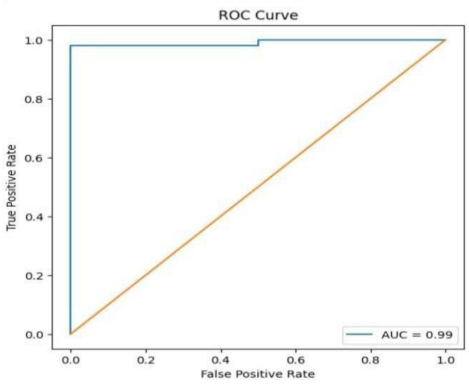



Fig. 7. ROC curve representing performance of classification.

The AUC of 0.99 thus, it has a high discriminating performance.

## IV. DISCUSSION

The proposed EfficientNet-B3 transfer learning model achieved 94% accuracy and an AUC of 0.99, demonstrating strong classification performance for benign and malignant skin lesions. Transfer learning enabled effective feature extraction, while regularization and data augmentation improved generalization and reduced overfitting. The training curves indicate stable convergence. However, the study is limited to binary classification and evaluation on a single dataset

## V. CONCLUSION

This paper introduced an EfficientNet-B3 framework of automated skin lesion classification. The model was very accurate and had a high discriminative ability, which validates the use of transfer learning in medical image analysis. Future directions will be in terms of multi-class classification and clinical validation

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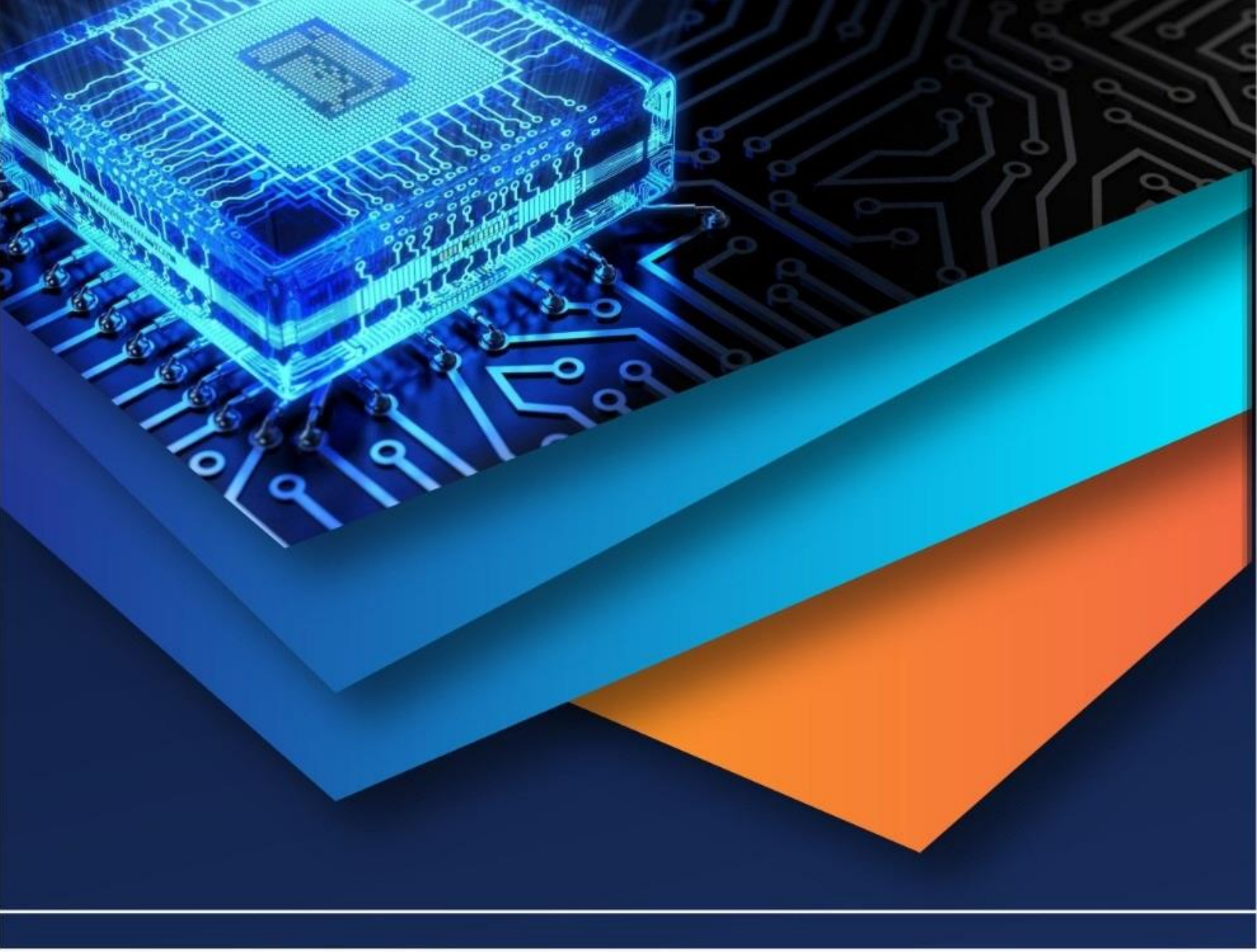

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