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An Efficient Approach towards Skin Cancer Diagnosis with EfficientNetB3

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Abstract

Skin cancer has been identified as the most widespread and well-documented type of malignancy worldwide. Its origin lies in the irregular growth of melanocytic cells, often referred to as melanoma. Exposure to ultraviolet radiation and genetic factors leads to melanoma appearing on the skin. Identification at an early stage increases the chances of successful treatment. However, the conventional biopsy method used for detecting skin cancer is both invasive and painful. It involves extensive laboratory procedures that consume a considerable amount of time. Computer-aided diagnosis systems can help to address these challenges. In this work, two distinct models has been developed based on EfficientNetB3, with varying additional layers. To conduct a comparative work, various cutting-edge techniques have been evaluated. The suggested approaches surpass the majority of these techniques by achieving an overall test accuracy of 91% and 93.25% for Model 1 and Model 2 respectively.

Keywords: Skin Cancer detection, Benign, Malignant, EfficientNetB3.

1. Introduction

Skin cancer, especially melanoma, has become a significant risk to human life due to the abnormal proliferation of melanocytic cells. Major factors include exposure to UV radiation and genetic factors. In response to the limitations of invasive biopsy methods and the critical need for early identification, the development of robust computer-aided diagnosis systems has arisen as an essential domain of research. The primary goal of this work is to detect skin cancer through a computer-aided recognition. The objective is to classify the input data into two

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groupings: ‘benign’ (non-cancerous) and ‘malignant’ (cancerous) skin lesions. In this work, two models have been developed based on EfficientNetB3. The first one aimed for comprehensive feature extraction with multiple layers, while the second pursued efficiency with a simpler architecture. The simplification was aimed at developing a model that achieves a balance between high performance and practicality, rendering it more appropriate for real-world applications, especially in situations with limited computational resources. Also, it has been observed that the second model has achieved better accuracy having simpler architecture. So, it is clear that simplifying the architecture has helped to reduce overfitting by creating a more generalized model.

In this study, main contribution lies on the utilization and optimization of the widely recognized pre-trained EfficientNetB3. Image quality within the dataset is enhanced through the application of various augmentation and filtering techniques. Two models have been developed, with model 2 demonstrating superior performance compared to model 1 by carefully reducing certain additional layers. This outcome highlights the notion that the incorporation of numerous layers in model architecture, while capable of extracting more features, may introduce drawbacks. Model 2, through a thoughtful reduction of additional layers, strikes a balance between optimal performance and practicality. This aligns with the time-honoured principle that complexity should be weighed against resource constraints, making Model 2 a pragmatic choice for practical applications.

The structure of the work is outlined as – section 2 covers a discussion on prior similar research works in this field. Suggested methodology is presented in section 3. In that section description of dataset, techniques for image pre-processing, and custom structure of CNN models have been discussed. Section 4 outlines the experimental findings alongside a relative examination of prior studies, while section 5 offers the conclusion.

2. Related Work

In the realm of melanoma skin carcinoma recognition, numerous researchers have been actively engaged in recent years. They have predominantly employed a diverse array of computer vision techniques, including image pre-processing, augmentation, and image classification. These techniques represent the most commonly utilized methodologies documented in the literature.

Alom et al. [1] have used the “ISIC 2018” dataset. The researchers have tested on 3,005 skin images for seven different skin cancer types. The “Inception Recurrent Residual Convolutional Neural Network (IRRCNN)” has been employed there. This model has produced 81.12% testing accuracy for a dataset when data augmentation was not performed, but after training, the IRRCNN with augmented skin images achieved 87.09% testing accuracy. The research has extended its scope by exploring different feature fusion strategies in decoding units, showcasing adaptability to various architectural configurations. The effectiveness of the proposed may come at the cost of enhanced estimation complication which could pose challenges in terms of training time and resource requirements.

Milton [2] has worked with various convolutional neural network such as InceptionResNetV2, PNASNet-5-Large, InceptionV4, and SENet154. The experimenters properly processed the skin images and also performed augmentation techniques before using them for training the model. The dataset collected from “International Skin Imaging Collaboration (ISIC) 2018” has been used for testing. The “PNASNet-5-Large” has attained the best performance, yielding a validation score of 0.76. This work has illustrated the effectiveness of employing a deep neural network for the cataloguing of dermoscopic pictures showing potential for automated skin lesion detection. Challenges include dataset imbalance, advocating for improved balance and size. Despite achieving the highest validation score achieved by PNASNet-5-Large, refinement opportunities exist, emphasizing the need for further validation on diverse datasets.

Ali et al. [3] have conducted classification on the ISIC 2018 dataset, employing a combination of Deep CNN and Handcrafted Features. These hybrid features have better discrimination ability rather than features with single methods. These features are utilized as inputs to a multiclass Support Vector Machine (SVM) classifier. The experimenters evaluated their technique on online validation databases. The model has achieved a score of 0.841 on the validation dataset. The research has introduced a powerful dermoscopy image classification system using hybrid features which have led to achieve significantly improved accuracy. However, potential challenges like scalability and generalizability need further exploration.

In the study by Mahbod et al. [4], the findings indicate that image cropping outperformed image resizing as a technique. The “MSM-CNN algorithm” has achieved a

accuracy rate of 86.2% for multi-class classification on the “ISIC 2018” challenge test set. The research has investigated the effects of the size of images on skin lesion cataloguing, favouring cropping over resizing. While achieving excellent performance with the “three-level fusion tactic MSM-CNN”, limitations and scalability concerns require further exploration.

A unified baseline for skin carcinoma cataloguing has been planned by Sun et al. [5], with data augmentation details incorporated as further patient data. The metadata employed in this work has encompassed various data augmentation such as colour normalization gain, random cropping, and properties of image size. On the “ISIC 2018” skin cancer cataloguing encounter test set, the procedure attains an accuracy of 88.7% with individual algorithms and 89.5% for the embedding result for multi-class classification. The algorithm's practicality for real-world applications is highlighted by its low computational complexity. However, the research lacks an explicit discussion of potential limitations. Hence, it has necessitated further scope of exploration of the generalizability of models and sturdiness in diverse contexts.

Both machine learning as well as deep learning have been settled by Bechelli and Delhommelle [6]. They worked on Kaggle dataset, “Skin Cancer: Malignant vs Benign”. “Gaussian Naïve Bayes (GNB)”, “K-Nearest Neighbour (K-NN)”, “Classification and Regression Trees (CART)”, “Linear Discriminant Analysis (LDA)” and “Logistic Regression (LR)” have achieved an accuracy of 63.7%, 65.8%, 68.9%, 71.1%, and 72.1% respectively. Using deep learning, they found an accuracy of 80%, 88%, and 87% for Xception, VGG16, and ResNet50 respectively. The research highlights that deep learning (DL) systematically outperforms machine learning (ML) in terms of performance, particularly when utilizing Convolutional Neural Networks (CNN). CNN models have proved to be especially effective in capturing the intricate details and nuanced variability present in dermoscopic images.

Demir, Yilmaz and Kose [7] have also used Kaggle dataset, “Skin Cancer: Malignant vs Benign”. They have achieved an accuracy of 84.09% with the “ResNet-101” and an accuracy of 87.42% with the “Inception-v3”. The training process for both architectures is concluded within 60 epochs. The initial learning amount is set to 0.001 at the foundation of training and it progressively decreases as training advances through each stage. It is indicated by the results that superior classification performance is exhibited by the Inception-v3 when compared to the ResNet-101.

Anand et al. [8] have conducted their study on the Kaggle Dataset, "Skin Cancer: Malignant vs Benign." This method has undergone analysis with diverse group proportions, including 8, 16, 32, 64 and 128, utilizing the “Adam optimizer” and completing 10 epochs. The proposed work has accomplished the maximum accuracy rate of 89.09% with a batch size of 128. There is still room for further improvement in the general accuracy of the suggested architecture. This enhancement can be accomplished through concurrently growing both “true positives” and “true negatives”.

Agarwal and Singh [9] have worked on Kaggle dataset, “Skin Cancer: Malignant vs Benign”. The proposed architecture was skilled using the “Adam optimizer” with a varied learning proportion. The preliminary learning proportion was set at 0.0001 but was adjusted, specifically reduced, when the validation loss has surpassed a predetermined patience level, with a reduction factor of 10^-1. The functioning of the model was assessed using “accuracy” metric and “Early Stopping” was implemented to mitigate the risk of overfitting or overtraining. In this case, the monitored hyperparameter for “Early Stopping” was the validation loss, with a set patience level for yielding high performance. The accuracy of 86%, 86.57%, 82.57%, and 80.85% has been achieved using DenseNet, Resnet, XceptionNet, and MobileNet respectively.

Gokila Brindha et al. [10] have used Kaggle dataset, “Skin Cancer: Malignant vs Benign”. In this research work, both SVM and CNN have been employed for predicting skin cancer types, and the experiments are conducted using Python programming. TensorFlow is utilized for image processing and algorithmic accuracy is computed. The findings reveal that CNN outperforms SVM with higher accuracy. Future endeavours could involve optimizing various parameters derived from applying deep learning methods to further enhance algorithmic accuracy. The researchers have achieved maximum accuracy of 83% and 61% using CNN and SVM respectively.

The dataset employed in this work is named as “Skin Cancer: Malignant vs Benign” and it has been collected from Kaggle website [11]. This dataset consists of total 1800 images of the two types - Malignant and Benign.

Nagarajan et al. [12] has worked for the diagnosis of Oral Squamous Cell Carcinoma. Swarm Intelligence Optimizer has been used in their work with the intermediate layer. They

have applied InceptionV2, MobileNetV3, and EfficientNetB3 CNN architectures. This accuracy has been further increased to 0.95 by using Modified Gorilla Troops Optimizer as an intermediary layer.

Dildar et al. [13] have conducted a review on skin cancer detection. They have emphasized different deep learning-based techniques like ANN, CNN, GAN for skin cancer detection. They have discussed CNN-based approach for the detection of skin cancer. Different datasets used by different researchers have also been discussed in their review. They have conducted 82 related past works.

Non-invasive procedures for recognition of skin cancer have been explored by Narayanamurthy et al. [14]. Dermoscopy, photography, confocal microscopy, sonography, fluorescence spectroscopy, Raman spectroscopy, optical coherence tomography, terahertz spectroscopy, thermography, the multispectral imaging technique, tape stripping, electrical bio-impedance, and computer-aided analysis have been considered by them as the non-invasive procedure for recognition of skin cancer. 252 research articles have been considered for the review work.

Nahata and Singh [15] have worked on different deep learning approaches for skin cancer recognition and classification. CNN have been emphasized in their work. They have worked with ISIC 2018 and ISIC 2019 dataset. CNN were applied by them after data augmentation and image normalization to predict the category of input image as benign or carcinoma. CNN has been trained by the transfer learning from the pre-trained weight of ImageNet cataloguing. They have considered Inception V3, ResNet50, VGG 16, Inception-Resnet, MobileNet as network architecture. Accuracy, Recall, Precision, and F1 Score have been considered as performance metric in their work. Nahata and Singh [15] have been able to achieve best accuracies of 90% and 91% with Inception V3 and InceptionResnet CNN models respectively.

These studies utilize diverse datasets and algorithms for skin cancer classification. While Alom et al. [1] have focused on adaptability with feature fusion, Milton [2] has explored various CNN models. Ali et al. [3] have uniquely combined deep CNN and handcrafted features, achieving a high score with SVM. Mahbod et al. [4] have favoured image cropping over resizing, Sun et al. [5] have proposed a unified baseline with low computational complexity while Bechelli and Delhommelle [6] have illustrated the dominance of deep

learning over machine learning methods. Additionally, works carried out by Demir, Yilmaz and Kose [7], Anand et al. [8], Agarwal and Singh [9] and Gokila Brindha et al. [10] have contributed to this landscape with distinct findings on model architectures, training processes, and algorithmic accuracy. These works collectively highlight the dynamic approaches employed in skin cancer research each with its strengths and considerations.

In conclusion, the literatures have accentuated the promising trajectory of utilizing deep learning, particularly CNNs in skin cancer detection. The field is dynamic and the synthesis of findings suggests a need for continued research to refine methodologies, overcome the limitations, and achieve even greater accuracy in detecting skin cancer. In this research work, pre-trained EfficientNetB3 has been used and the proposed concept has accomplished an overall test accuracy of 93.25%. Accuracy of the proposed work has been evaluated in comparison to that of several prior research endeavours. The detailed comparative analysis with previous research works is shown in detail in sub-section 4.2.

3. Proposed Work

In this work, the median filter has been applied to the skin images for noise removal. Subsequently, various data expansion practices have been applied to boost the diversity and variability of the dataset. The phases of the proposed method are detailed in Figure 1. Initially RGB skin images are fed to the system as input. Then under the pre-processing steps, first median filter has been used for noise removal and then data augmentation has been performed for increasing volume of dataset. After the completion of pre-processing steps the model is trained and finally the model classifies the input skin images either as “Benign” or “Malignant”.

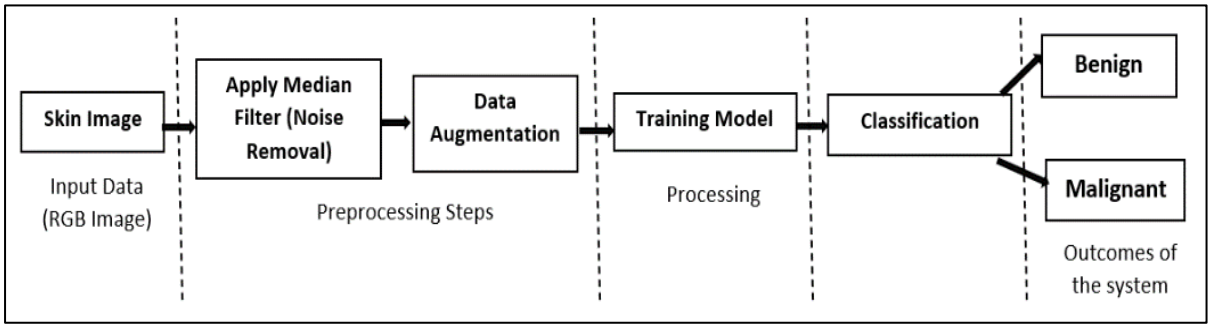

Figure 1. The Fundamental Concept of Proposed Method

3.1 Dataset Used

The dataset utilized in this work is obtained from Kaggle website [11]. Name of the dataset is "'Skin Cancer' Malignant vs. Benign"

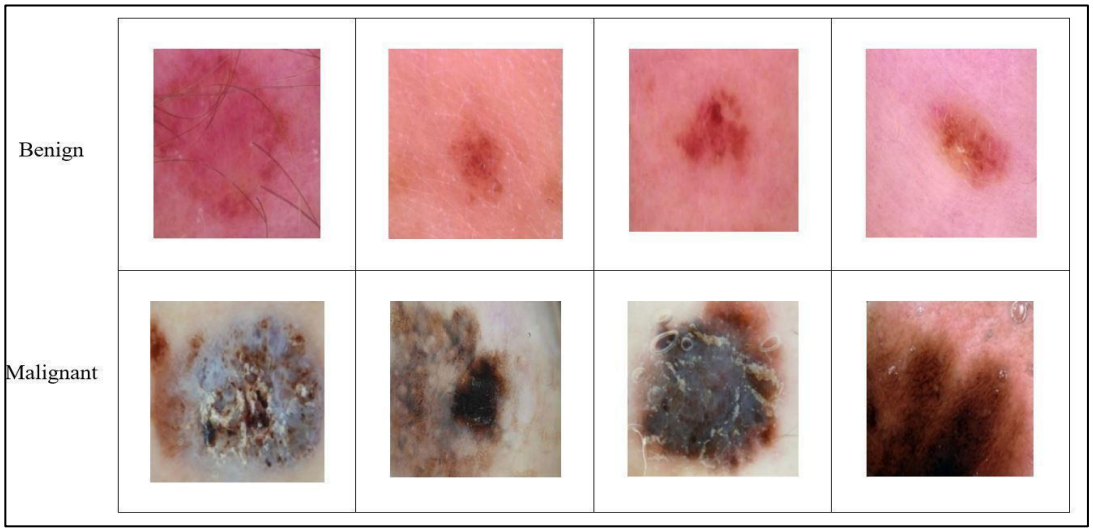

Figure 2. Example Images of the "'Skin Cancer' Malignant vs. Benign" dataset

The dataset contains RGB images of two types - Benign and Malignant. The training dataset comprises of 1440 benign images along with 1197 malignant images, whereas the testing dataset includes 360 benign images besides 300 malignant images. Sample images from the dataset is depicted in Figure 2.

3.2 Median Filter

In skin images, the presence of noises is quite natural. Therefore, to make these images workable they are required to be free from noise as much as possible. The median filter is able to perform that job. Hence, to get images with improved quality with free from noise as much as possible, a median filter has been applied to the skin images as a pre-processing step. The median filter reduces noises with considerably less blurring of edges. It helps to reduce noise while preserving essential edge information. It is one of the major reasons for which median filter have been chosen for noise removal. Sample images using a median filter have been depicted below Figure 3.

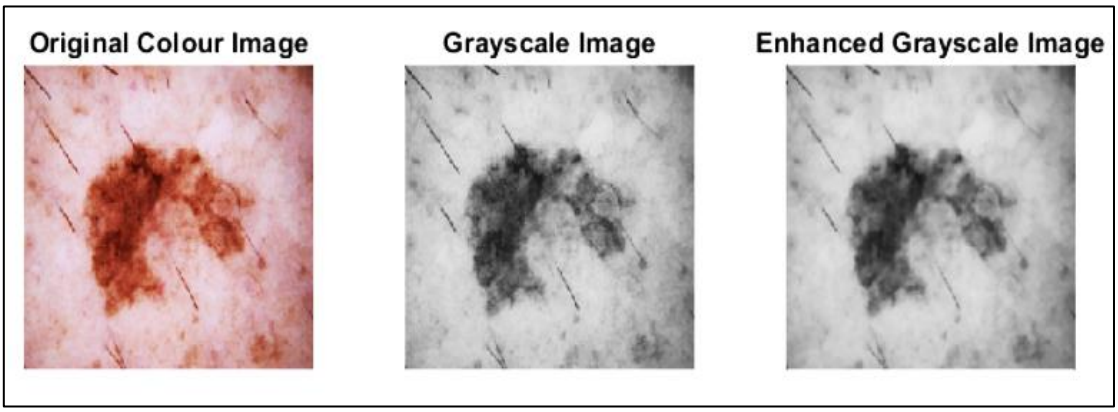

Figure 3. Sample Median Filtering Results

3.3 Data Augmentation

"Data augmentation" is a strategy which increases the size of the training dataset by implementing various transformations on the original data. Data augmentation technique artificially increases the size as well as diversity of the training dataset. Rotation, flipping, and scaling are some common augmentation usages. It enables the models for better generalization and accurately classifies the unseen data. In this work, following data augmentation techniques have been used:

- Rotation Range (15 degrees)
- Zoom Range (0.95,0.95)
- Horizontal Flip

3.4 Model Developed using EfficientNetB3

While creating the custom CNN architetures, the pre-trained EfficientNetB3 has been used. The methodology adopted by Nagaranjan et al. [12] on EfficientNetB3 in oral cancer has been adopted here to create the framework for skin cancer cataloguing. Here, two distinct models have been developed using EfficientNetB3. As per Keras 3 API documentation, EfficientNetB3 has 12.3M parameters and the depth of the model is 210.

3.4.1 Model 1

The first model has been structured for comprehensive feature extraction. It has employed a deeper architecture with multiple dense layers and comprehensive regularization techniques. Despite its complexity, this model may potentially capture intricate details but might face challenges related to computational demands and overfitting due to its deeper structure.

The comprehensive explanation of Model 1 is as follows:

Base Model: The pre-trained EfficientNetB3 was utilized as the base and was fine-tuned to adjust to the particular task. It is pre-trained on ImageNet and is configured not to include the top (classification) layer.

Additional layers: BatchNormalization, Two Dense layers (256 units each, ReLU activation), Two Dropout layers (rate: 0.45), Output layer (Dense Layer with softmax activation for classification).

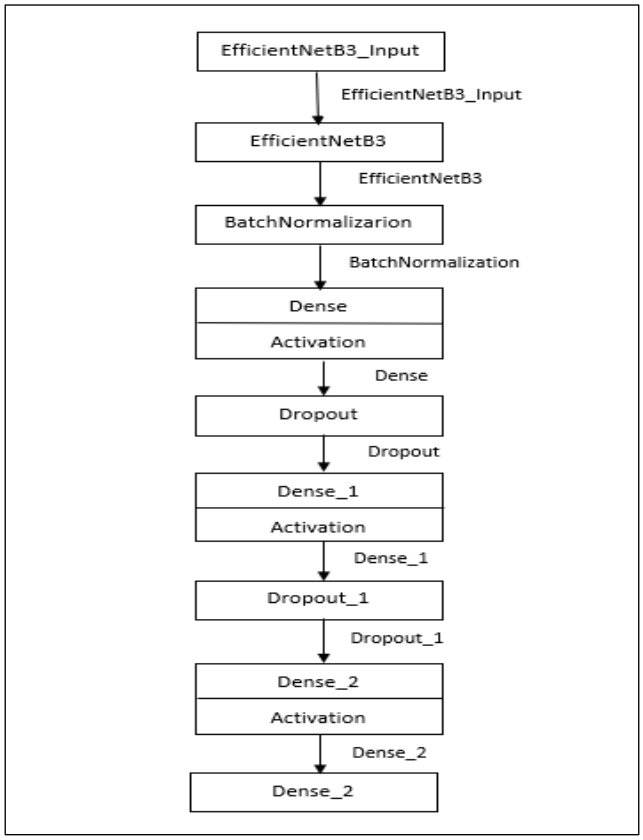

Figure 4. Layer-wise Configuration of Model 1

Model Compilation: The model is set up through the “Adamax optimizer”, employing a learning amount of 0.001. The loss function employed here is categorical cross-entropy and accuracy is chosen as the evaluation metric.

The layer-wise structure of this model is portrayed in Figure 4.

3.4.2 Model 2

The subsequent model has been designed for efficiency. It has streamlined the architecture by simplifying the layering. While maintaining competitive accuracy, this simplified structure has potentially reduced the burning issue of overfitting concerns. The simplicity of the model might facilitate improved generalization and efficiency, making it more adaptable for real-world deployment where computational resources are limited. In this model, one dense layer and one dropout layer has been removed which were earlier present in Model 1. Thus, the second one simplifies the model architecture.

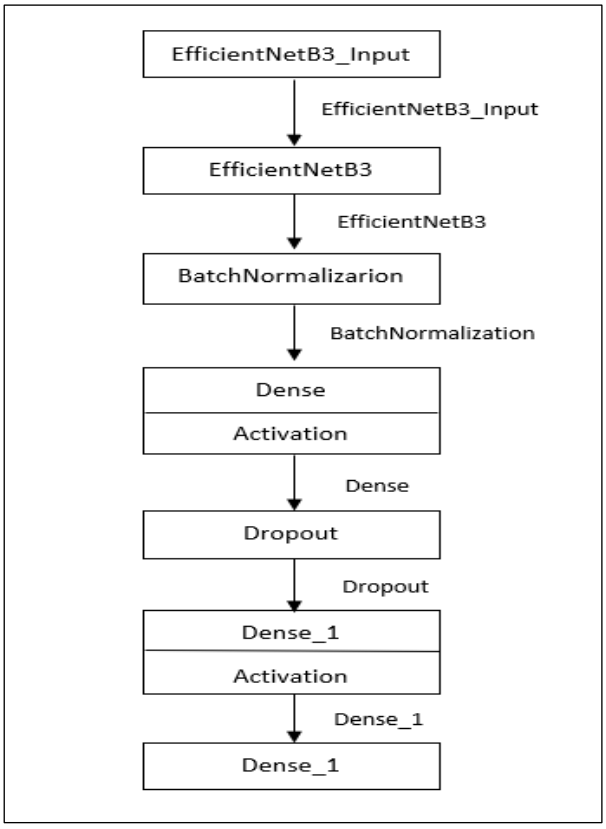

Figure 5. Layer-wise Configuration of Model 2

The comprehensive explanation of the proposed Model 2 is as follows:

Base Model: EfficientNetB3 is remained as the foundation and was made trainable to adapt to the specific task.

Additional Layers: BatchNormalization, Dense (256 units, ReLU activation), Dropout (rate: 0.45), Output (Dense Layer with softmax activation for classification).

Model Compilation: This remains the same as model 1.

The layer-wise structure of this proposed model 2 is depicted in Figure 5.

Both these Models showcase distinct trade-offs: The proposed model 1 is aimed for comprehensive feature extraction at the cost of complexity whereas the proposed model 2 has sacrificed the depth for efficiency. The proposed model 2 has been able to potentially reduce the overfitting issue and computational demands while maintaining competitive accuracy levels at the same time

4. Experimental Results

In the test dataset of "'Skin Cancer' Malignant vs. Benign", there are total 660 skin imageries - 360 "Benign" besides 300 "Malignant" imageries. Both the proposed models 1 and 2 are tested on this dataset and test accuracy is obtained. The test accurateness of the proposed two proposed models is presented in Table 1. Table 1 yields that the proposed models 1and 2 are able to identify skin cancer with 91% accuracy and 93.25% accuracy respectively. It is observed that performance of model 2 is better as it comprises of 1 less Dense Layer and 1 less Dropout Layer compared to that of proposed model 1.

Loss and accuracy curves of both the proposed model 1 and model 2 are also depicted in Figure 6 and Figure 7 correspondingly. Loss curves illustrate how well the model learns by showing loss reduction and the accuracy curves display how the accuracy changes across training epochs.

For a better understanding of the results, different performance metrics apart from accuracy like Precision, Recall, and F1-Score are calculated both for "Benign" and "Malignant" categories. For implementation of this work the following tools have been used: Visual Studio Code, Google Colab and Python 3.9.1.

The accuracy mentioned in below Table 1 is achieved based on the following training hyperparameter configurations: Adamax optimizer as optimizer, Learning rate as 0.001, categorical_crossentropy as Loss function, Accuracy as metric with batch size 32. The hyperparameter values are set empirically. Both the models have completed 50 epochs.

Table 1. Test Accuracy (in %) of the Proposed Models

Models	Test Accuracy
Proposed Model 1 (with more additional layers)	91.00
Proposed Model 2 (with less additional layers)	93.25

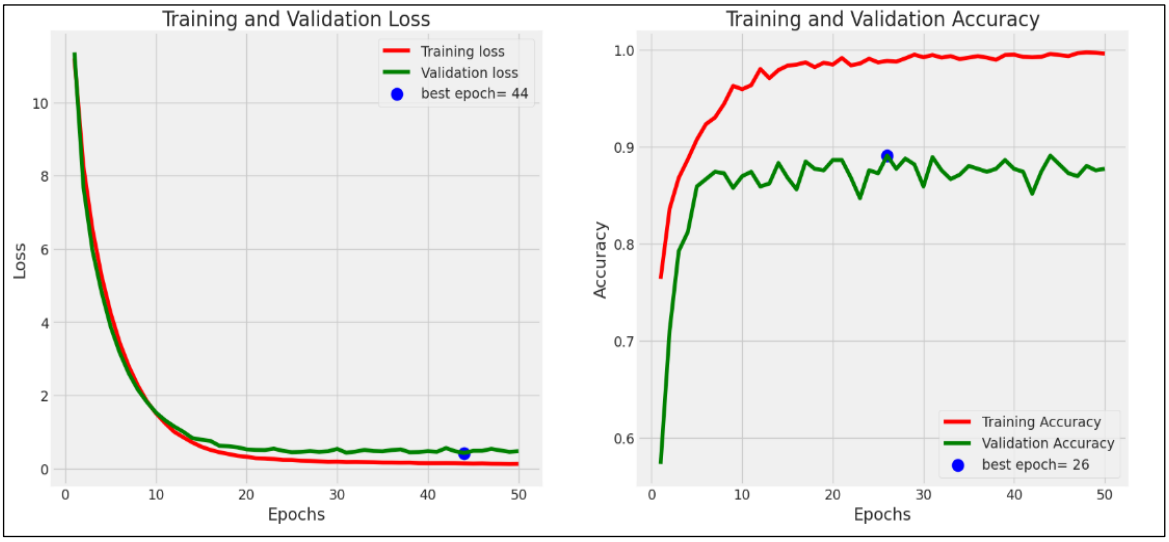

Figure 6. Loss and Accuracy Curves for Model 1

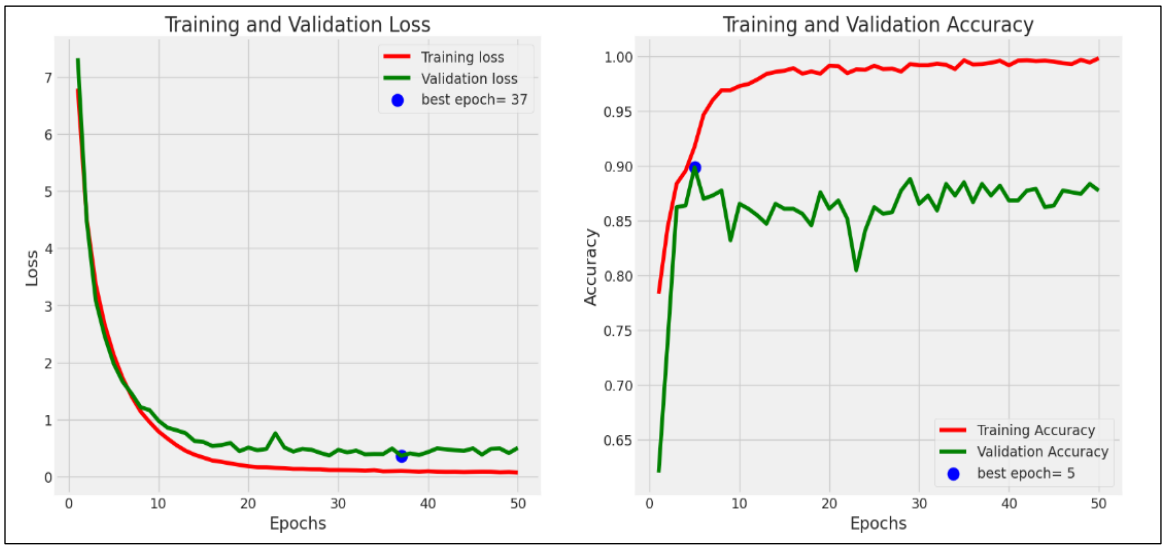

Figure 7. Loss and Accuracy Curves for Model 2

From the Figure 6 and 7 it is very much understandable that for both the models "Training and Validation Loss" gradually decreases with the increase of epochs. Best epochs for models 1 and 2 are 44 and 37 respectively. From Figure 6 and 7 it is also very much clear that for both the models "Training and Validation Accuracy" gradually increases with the increase of epochs. Best epochs for model 1 and model 2 are 26 and 5 respectively.

4.1 Precision, Recall, and F1-Score

For measuring the training and testing performance of the proposed models, Precision, Recall as well as F1 score have been used in this work.

a) *Precision: It is measured as the proportion of appropriately forecasted positive examinations to the entire forecasted positives.*

$$\boldsymbol{Precision = \frac{True\ Positive}{True\ Positive + False\ Positive}} \qquad (1)$$

b) *Recall: It is measured as the proportion of appropriately forecasted positive examinations to all authentic positives.*

$$\boldsymbol{Recall = \frac{True\ Positive}{True\ Positive + False\ Negative}} \qquad (2)$$

c) *F1-Score: It is measured as the "harmonic mean" of "precision" along with "recall".*

$$F1 - Score = \frac{2 \times Recall \times Precision}{Recall + Precision} \quad (3)$$

Table 2. Precision, Recall as well as F1-Score for Model 1

Class of Skin Image	Precision	Recall	F1-Score
Benign	0.86	0.92	0.89
Malignant	0.90	0.83	0.86

Table 3. Precision, Recall as well as F1-Score for Model 2

Class of Skin Image	Precision	Recall	F1-Score
Benign	0.84	0.96	0.89
Malignant	0.94	0.78	0.85

The “Precision”, “Recall” in addition “F1-Score” for both the proposed models 1 and 2 are represented in Table 2 and Table 3 respectively.

4.2 Comparative Analysis

The accuracies of the proposed models have been compared to that of several previous research studies and are tabulated in Table 4.

The research work suggested by Bechelli and Delhommelle [6], Demir, Yilmaz and Kose [7], Anand et al. [8], Agarwal and Singh [9], Gokila Brindha et al. [10] have been utilized on the dataset used in this work. The relative analyses among their work and proposed method have been documented in Table 4.

Table 4. Comparative Analysis

Method Used	Accuracy (in %)
Bechelli and Delhommelle [6]	88.00
Demir, Yilmaz, and Kose [7]	87.42
Anand et al. [8]	89.09
Agarwal and Singh [9]	86.60
Gokila Brindha et al. [10]	83.00
Proposed Method	93.25

From Table 4 it is clear that our proposed method can detect skin cancer better than other popular approaches.

5. Conclusion

In this work, two deep learning models have been developed based on EfficientNetB3. Model 1 and Model 2 have achieved a test accuracy rate of 91% and 93.25% respectively. The proposed model 2 has outperformed model 1 when some additional layers have been reduced which were earlier present in model 1. It has revealed that creating complex models with multiple layers not only helps to extract more features but there can be drawbacks also. Complex model architecture with more layers can also be affected by the problem of overfitting. The proposed model 2 strikes a balance between high performances and practically makes it more suitable for real-world applications where computational resources may be limited. While the current implementation of model 2 shows promising results, there are still some opportunities for further enhancement, including data augmentation, Model optimization and integration of clinical data, transfer learning, multi-modal fusion, and real-time deployment. These improvements may contribute to more accurate and reliable diagnosis of skin lesions, thereby assisting healthcare professionals in early detection and treatment planning.

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