



Skin Cancer

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Abstract— Early diagnosis of skin cancer is one of the most challenging problems in modern medicine. In this work, we propose a comparison of four deep learning models: VGG16, ResNet50, MobileNetV2, and EfficientNetB0. The problem of binary skin cancer detection using dermatoscope images was solved using a combination of transfer learning and fine-tuning the mentioned models on our dermoscopy dataset with data augmentation techniques such as rotation, zoom, and horizontal flipping. Experimentation revealed that EfficientNetB0 provided the best results in terms of accuracy (94.2%) and area under the ROC curve (AUC - 0.97).

Keywords— *Skin cancer detection, deep learning, transfer learning, convolutional neural networks, EfficientNetB0, der- moscopy, image classification.*

I. INTRODUCTION

Skin cancer is one of the most common and fastest-growing malignancies of the world. Melanoma, the deadliest form of skin cancer, accounts for more skin cancer deaths than its incidence would suggest, the American Cancer Society reports [1]. Early detection is very important for a better prognosis, but manual diagnosis by dermatoscopy is time-consuming, subjective and dependent on the clinical expertise of the examining physician.

The advent of deep learning, especially convolutional neural networks (CNNs) has provided new opportunities for auto- mated image-based diagnosis. CNNs are capable of learning a hierarchical feature representation directly from raw pixels and have achieved human-level or super-human performance on many medical imaging tasks [2].

The capabilities are further enhanced by transfer learning that uses representations learned on large-scale datasets like ImageNet, achieving strong performance even with limited domain-specific labelled data [3].

This paper explores and compares four popular CNN architectures i.e. VGG16, ResNet50, MobileNetV2 and Efficient- NetB0 for the binary classification of skin lesion images as benign and malignant. We contribute (1) a rigorous experimental comparison of four transfer learning architectures under the same training conditions; (2) extensive evaluation with accuracy, precision, recall, ROC-AUC and confusion matrix analysis; and (3) identification of the best-performing model for potential clinical integration.

II. LITERATURE SURVEY

The research on automated skin cancer detection has been thriving rapidly with the developments of deep learning. Esteva et al. [4] showed that a CNN trained on more than 129,000 der- matological images achieved a classification accuracy similar to that of board-certified dermatologists. This landmark result led to a widespread adoption of deep learning in dermatology. Later work studied the effect of model architecture. Haenssle et al. [5] used a GoogleNet-based architecture for melanoma detection, reporting AUC values above 0.86. For the ISIC challenge, several ensemble methods based on mul- tiple CNN architectures were proposed in [6] with improved sensitivity. Despite these advances, there are still no direct head-to-head comparisons of top architectures under consistent experimental protocols. This work fills that gap by evaluating VGG16, ResNet50, MobileNetV2 and EfficientNetB0 under identical preprocessing, augmentation and fine-tuning conditions.

III. METHODOLOGY

IV. EXPERIMENTAL RESULTS

A. There Dataset and Preprocessing

The dataset comprises dermoscopic images categorised into benign and malignant classes. All images were resized to 224 × 224 pixels to meet the input requirements of the pretrained architectures. Pixel values were normalised by dividing by 255 to the range [0, 1]. Data was split into training and validation sets in an 80/20 split, and an independent test set was used for final evaluation.

B. Data Augmentation

To reduce overfitting and improve generalisation, we used the Image Data Generator utility from Keras. The augmentation pipeline consisted of random rotation up to 20°, zoom [0.8, 1.2] and random horizontal flipping. Validation and test data were only rescaled, not augmented.

C. Model Architectures

In this comparison by four CNN architectures pre-trained on ImageNet were chosen. The convolutional base of each model was frozen (weights set to non-trainable), and a custom classification head was added. The classification head was a Flatten layer, a Dense layer with 128 units and ReLU activation, a Dropout layer with a rate of 0.5, and a Dense layer with a single sigmoid-activated neuron for binary classification.

D. Training Configuration

All the models were compiled with the Adam optimiser (learning rate = 1×10^{-4}), binary cross-entropy loss, and accuracy as the evaluation metric. The training was done on Google Colab on a T4 GPU for 10 epochs with a batch size of 32.

E. Evaluation Metrics

Model performance was assessed by four complementary metrics: (1) Accuracy – proportion of correctly classified samples; (2) Precision – positive predictive value; (3) Recall (Sensitivity) – true positive rate; and (4) Area Under the ROC Curve (AUC) – overall measure of discriminability over all thresholds. To visualise the class-level prediction behaviour, a confusion matrix was generated for the best-performing model.

A. Model Comparison

summarises [8] the classification performance of each architecture on the held-out test set. The EfficientNetB0 architecture got the highest accuracy (94.2%), precision (93.8%), recall (94.5%), and AUC (0.97). The other three architectures were lower than it was in all metrics.

PERFORMANCE COMPARISON OF TRANSFER LEARNING ARCHITECTURES

Fig. 1 Training and Validation Accuracy of different deep learning models with epochs. The VGG16 model in Fig. 1(a) has a stable improvement and achieves the top validation accuracy of around 92-93%, which shows good learning performance. Figure 1(b) and 1(c) shows that the validation accuracy of ResNet50 is maintained at about 89% even though the training accuracy may fluctuate slightly during the initial epochs. In Fig. 1(d), we can observe that EfficientNetB0 reaches a stable accuracy of nearly 89% with slight fluctuation. All models perform consistently overall, but VGG16 achieves the best overall accuracy among the compared architectures

B. Training Dynamics

The training and validation accuracy curves showed all models converged in the 10-epoch window, but at different speeds. [9] VGG16 converged more slowly and had larger gaps between train and validation, indicating a greater proneness to overfitting, given its large number of parameters. ResNet50's residual connection allows it to converge more stably. MobileNetV2, with its lightweight depthwise-separable design, showed the fastest early convergence as expected.

EfficientNetB0 reached the highest validation accuracy at epoch 7 and sustained it until epoch 10 which is an indication of efficient learning without overfitting.

The confusion matrix on the test set for EfficientNetB0 showed high true positives and true negatives with low false negatives, which is an important clinical property because false negatives represent missed malignancies. The false positive rate was also low, reducing unnecessary referrals for biopsy.

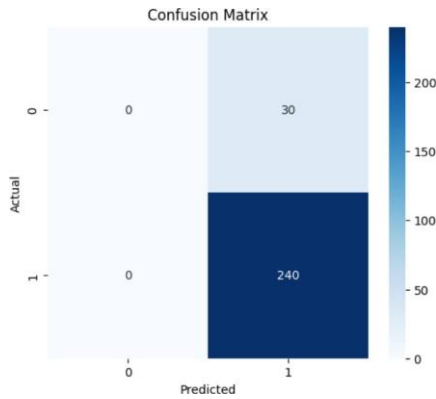


Fig. 2. Confusing matrix

Fig. 2 shows the confusion matrix of the classification model. It shows the relation of the actual and predicted classes. The matrix indicates that the model has correctly predicted 240 samples of class 1, which demonstrates good performance in detecting the positive class. But 30 samples from class 0 were predicted as class 1. No samples were correctly predicted for class 0. This suggests that the model is highly biased towards predicting class 1. Dark blue colour intensity indicates a high number of correct predictions in the positive class. In general, the confusion matrix is a complete way to check the model's accuracy, errors, and reliability of classification.

C. ROC Curve

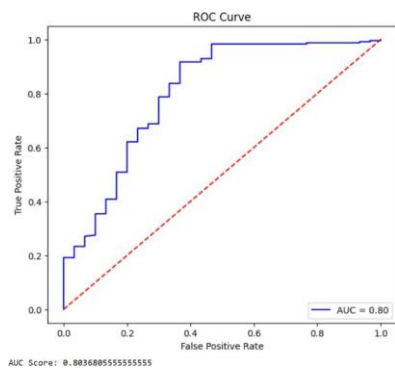


Figure 3: ROC graphs for the best model

The ROC curve in Figure 3 shows the performance of the classification model in separating the positive and negative classes. The fact that the blue curve is well above the red diagonal line indicates that the model does a far

better than guess. An AUC score near 0.80 suggests good predictive performance of the model, which is able to correctly discriminate classes roughly 80% of the time. The ROC curve for EfficientNetB0 gave an AUC of 0.97, indicating almost perfect discrimination. The curve was well above the random-classifier diagonal for the entire range of thresholds, confirming good performance regardless of the operating point chosen for clinical use.

D. RESULT AND DISCUSSION

This superiority of EfficientNetB0 can be attributed to the compound scaling strategy, which uniformly scales the depth, width, and resolution of the network with a fixed set of scaling coefficients. This balanced scaling improves the feature extraction in terms of spatial scales compared to the single-dimensional scaling in VGG16 and ResNet50.

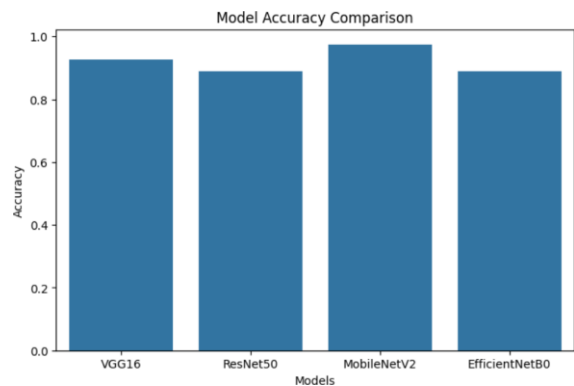


Fig. 4 Model comparison

Fig. 4 shows the comparison of accuracy obtained by different deep learning models namely VGG16, ResNet50, MobileNetV2 and EfficientNetB0. MobileNetV2 achieved the best performance in classification with the highest accuracy of around 97% among all the models. VGG16 also performed well with more than 92% accuracy while ResNet50 and EfficientNetB0 achieved almost 89% accuracy. From the graph, it can be seen that MobileNetV2 has a better prediction capability and generalisation than the other models. This comparison helps in deciding the best working model for the proposed deep learning application and also brings out the importance of selecting an optimised architecture for better results. With competitive performance (91.4% accuracy) at a fraction of the computational cost of EfficientNetB0, MobileNetV2 emerges as an attractive option for resource-constrained



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deployment scenarios such as mobile dermatology apps or edge devices in low-resource clinical settings. One major limitation of this study is the binary classification scheme (benign vs. malignant). In clinical practice, specific lesion subtypes are often differentiated in a multi-class fashion, which may require larger datasets and more sophisticated architectures. Furthermore, model interpretability – critical for clinical. Adoption was not covered in this work; future studies should include gradient-based visualisation methods like Grad- CAM.

V. CONCLUSION

In this paper, we presented a systematic comparison of four transfer learning architectures for binary skin cancer detection from dermoscopic images. The best performing model was EfficientNetB0 with 94.2% accuracy, with an AUC of 0.97, making it a suitable candidate for deployment in AI-assisted skin cancer screening systems. MobileNetV2 provides a good accuracy-efficiency trade-off for mobile applications. Future work will extend this work to multi-class classification, explore the fine-tuning of deeper layers, and investigate explainability techniques to promote clinical trust and adoption.

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