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A Fused Architecture for Binary Classification of Melanoma Skin Cancer Using Deep Learning Model

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Abstract: *Early detection of melanoma skin cancer is critical for reducing the diagnostic delays. There are various traditional deep learning models like MobileNet, ResNet50, EfficientNet, which offers advantages in its own way but also comes with underlying limitations when applied independently. These models often prone to overfitting on limited dataset, computationally heavy or lack stability in performance. To address these disadvantages, this study proposes a fusion based architecture using the existing deep learning models for binary classification of melanoma skin cancer into two categories that is benign and malignant. The model is trained on melanoma skin cancer dataset and integrates the InceptionV3 and MobileNetV2 as parallel fixed feature encoders that uses individual strengths. After which the features extracted are concatenated. Despite a slightly higher validation loss, the proposed model has shown exceptionally well in performance metrices like accuracy, precision and f1 score when compared to other models. This proposed model combines data from both encoders to give more nuanced and robust melanoma skin cancer classification, enabling clinical workflows with improved prediction reliability.*
Keywords: *skin cancer classification, fused model, deep learning, inceptionV3 model, mobilenet model, binary classification.*

1. INTRODUCTION:

Cancer is the deadliest, if not treated on time. In classification of cancer, skin cancer is categorized as one of the most common forms of cancer globally. It is defined as the abnormal growth of skin cell [1]. Its development is most commonly triggered by prolonged exposure to ultraviolet (UV) radiation, whether from natural sunlight or artificial sources such as tanning beds and sunlamps. UV radiation damages the DNA in skin cells, which can lead to abnormal cell growth and, over time, malignant transformations [2]. Unlike many other forms of cancer that are confined to specific organs or tissues, skin cancer has the unique distinction of potentially occurring on virtually any part of the body. However, it predominantly affects regions that receive the highest levels of sun exposure such as the face, neck, arms, and lower legs. There are three primary subclasses of skin cancer: basal cell carcinoma (BCC), squamous cell carcinoma (SCC), and melanoma. BCC and SCC are classified as non-melanoma skin cancers and generally exhibit slower progression and lower risk of metastasis. In contrast, melanoma is the most aggressive and life-threatening form due to its remarkable ability to metastasize rapidly to distant organs if not detected and treated early [1]. Melanoma arises from melanocytes, the pigment-producing cells of the skin and can initially appear as an irregular mole or pigmented lesion. What makes melanoma particularly dangerous is its capacity to invade surrounding tissues and enter the lymphatic or circulatory system, often before noticeable symptoms emerge [3]. Given its high mortality rate when diagnosed in later stages, early detection of melanoma is critical. The diagnosis of such subclass of cancer needs to be given earliest attention. Melanoma, one of the most aggressive forms of skin cancer, can become potentially fatal if not diagnosed at an early stage. However, when detected early, skin cancers are highly treatable. Traditionally, diagnosis has relied on visual inspection and dermoscopic analysis by trained dermatologists. While effective, these manual methods are time-intensive and susceptible to subjective interpretation. In recent years, various deep learning models such as InceptionV3, ResNet50, MobileNetV2, and EfficientNet have been implemented for classification of skin cancer [4]. Despite their strengths, each presents notable limitations: InceptionV3's depth may introduce computational overhead; MobileNetV2, although efficient, may compromise on feature richness; ResNet50 can exhibit inconsistent performance across diverse lesion types; and EfficientNet tends to overfit when trained on imbalanced or limited datasets. These drawbacks highlight the necessity of a more targeted and balanced architecture. To address the limitations of traditional deep learning architectures in skin cancer classification, this fusion-based architecture combines the InceptionV3 with the efficiency of MobileNetV2, enabling robust feature extraction without excessive computational cost. Trained on the Kaggle Melanoma Skin Cancer Dataset. A weighted loss function addresses class imbalance. By resolving key limitations in traditional models, this model provides a reliable and scalable approach for early melanoma detection. In summary, the proposed fusion-based architecture can classify the benign and malignant categories of melanoma skin cancer.

2. LITERATURE REVIEW:

The significant improvements in the Deep learning models have transformed the course of classification of various objects. One such advancement is observed in skin cancer classification. There were many traditional methods that have proven advantages for the classification task in this area but they all come with a significant disadvantage. Among many skin cancers, the melanoma is found to be aggressive. Hence a significant study needs to be carried out in context of this skin cancer. From the paper [5], it is evident that EfficientNet models have been used widely by researchers recently. Also, EfficientNet-based classification models have displayed better results than other state-of-the-art CNN models. In the study [6], the authors have implemented an effective deep learning and transfer learning technique for the classification. They have proposed a fine tuning of the pre trained MobileNet on the HAM10000 dataset. Their approach has yielded significantly stronger accuracy, along with precision and recall. Hence suggesting this approach for diagnostic reliability in medical applications There were many studies that has implemented the power of transfer learning. In the paper [7], the authors have suggested two models, and they compared both the models with both traditional machine learning and deep learning models. They compared their proposed model with Artificial Neural Networks (ANN), k-Nearest Neighbors (KNN), Support Vector Machines (SVM), Naïve Bayes (NB), and Decision Trees (DT)—were employed using Gray-Level Co-occurrence Matrix (GLCM), which focus on feature extraction. Similarly, pre trained networks like AlexNet, VGG-16, VGG-19, EfficientNet-B0, ResNet variants (18, 50, 101), DenseNet-201, Inception-v3, and MobileNet-v2, were also included. They concluded that even though traditional machine learning model focusses on feature extraction, their accuracy and ability to classify is significantly lower. These finding give us insight that pre-trained networks are more reliable in terms of classification tasks as they can capture complex patterns in medical imaging tasks especially in skin cancer images. In the research paper [8], the authors have focused on the various optimizer's algorithms and their impact on the deep learning models that are used for classification and detection of skin cancers. They conducted study on ResNet50 and MobileNet architectures under the observation of various optimizers like Stochastic Gradient Descent, RMSProp, and Adam Stochastic Gradient. Their main intension was to understand how these optimizers are going impact on the evaluation metrics. Which highlighted that the selection of each parameter including the optimizers is crucial part as these all directly impact the metric of the model. In the paper [9], the authors have introduced a feature extracting framework for skin cancer detection. They have used the Anisotropic diffusion filtering to reduce the noise and enhance the image. In paper [10], the authors have worked and introduced a novel framework that is tailored for skin cancer classification. They have used two custom convolutional neural network architecture. Their model's main characteristic are reduced depths and small filter sizes. They have mainly solved the issue of class imbalance in the dataset; hence they suggested to start with data augmentation. The first layer in their architecture used four residual blocks. While the second one has five residual blocks which is again optimized for capturing only the fine features in the image. Although there have been significant number of models that can perform the classification, the various limitations of the models still persist. The fused method as the authors have done in the paper [10], which have shown better classification and this method can also be used for pre-trained networks. So, in this paper this fused method is employed to the pre-trained network in the deep learning context.

3. RESEARCH METHODOLOGY:

3.1 DATASET

The dataset consists of 10,000 images of melanoma skin cancer [11]. The dataset is collected from Kaggle. The dataset is divided into two categories, benign and malignant. Each image is in format of JPEG with a resolution of 300 by 300. The dataset is structured, with separate directories of each category. All images are in RGB color, capturing the most prevailing textures, pigmentation and irregularities.

3.2 DATASET PREPROCESSING

Before presenting the model with images, these images were undergone a series of preprocessing steps. The dataset was automatically resized from their original 300 by 300 resolutions to 244 by 244 resolution.

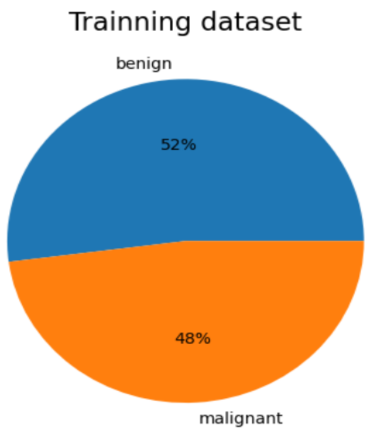


Fig. 1. Training dataset split

This resizing is done in order to ensure compatibility with the input shape of the expected convolutional neural network and this helps standardize the images dimensionality across all the datasets. The training dataset was further reduced to 5000 benign and 4605 malignant images, while the test set is kept with 500 images of each category. This training dataset was also undergone splitting accordingly. This reduction is used to optimize the training efficiency, control memory consumption. Further improvements are done to increase the generalization such as data augmentation is implemented which helped in stimulation of natural variability that can encounter in real world dermoscopic imaging. Altogether these preprocessing and augmentation helps in creating a critical step in building a resilient and high performing classification model.

3.3 MODEL ARCHITECTURE:

From the Fig 2 the image shows a framework designed for binary classification of skin cancer dermoscopic images into benign and malignant. The model fuses the InceptionV3 model and MobileNetv2 model as parallel fixed extractor. These networks were pretrained on ImageNet. While training the weights were frozen to avoid overfitting. The input images were preprocessed before feeding to the model.

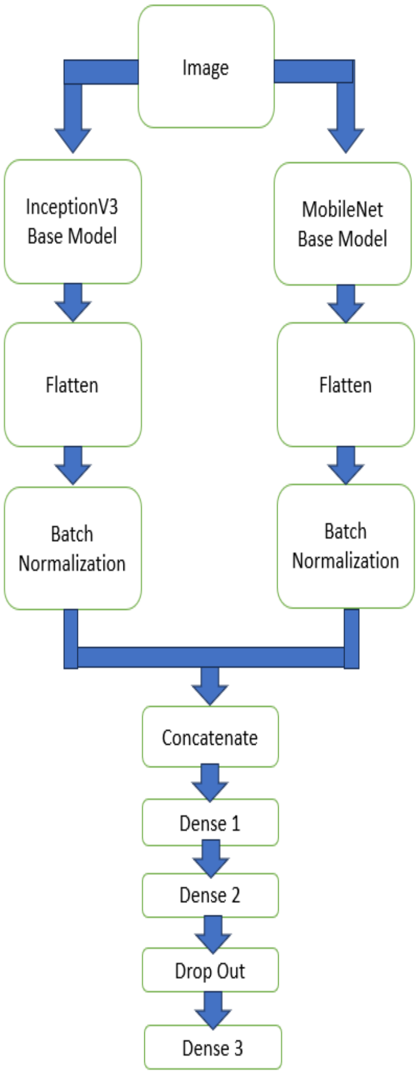


Fig. 2. Proposed model architecture

This preprocessing includes augmentation and resizing. These images were processed by both the networks. After which the output of these networks is flattened and normalized using batch normalization layer. These vectors were then concatenated so that these can be created a fused representation that captures the semantic context of this combined flow through a custom classification block that has multiple dense layers that have simultaneously dropout layers and regularization layers. Which helps in generalization ability of the model. In summary, the proposed model has a double deep learning model fused together so that their advantages can be used simultaneously. This approach elevates the classification robustness in the model while maintaining the computational efficiency.

4. RESULT ANALYSIS:

In Fig 3, it is evident that the output produced by the proposed model exhibits better predicted image with higher accuracy compared to other models. Similarly, from Table 1, performance analysis of five deep learning models, MobileNet, InceptionV3, ResNet50, EfficientNetB0, and a Proposed Model that are based on Precision, Recall, and F1 Score. From the graph we can infer that among all the model's, the proposed model has surpassed in terms of accuracy. We can understand that InceptionV3 has shown lowest metric values, followed by MobileNet and ResNet showing the moderate metric performance, and EfficientNet scoring the highest precision rates. The Proposed Model achieved the highest overall performance with accuracy and a balanced precision-recall profile, making it the most reliable classifier. While

MobileNet and ResNet50 also showed consistent metrics, InceptionV3 and EfficientNetB0 underperformed, particularly in F1 Score, due to lower precision and recall trade-offs. It is clear that even with a significant validation loss the proposed model has good generalization and prediction rates.

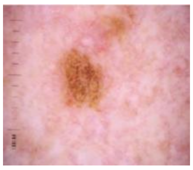
MOBILENET	INCEPTIONV3	EFFICIENTNET	RESNET50	PROPOSED MODEL
				
PREDICTED - Benign (89.6%)	PREDICTED - Malignant (94.3%)	PREDICTED - Benign (51.0%)	PREDICTED – Benign (58.7%)	PREDICTED - Benign (96.9%)

Fig. 3. The predicted images of various models

Table 1. Performance results of the models

MODEL NAME	ACCURACY	PRECISION	RECALL	F1 SCORE
MOBILENET	90.05	48.49	48.5	48.4
INCEPTION V3	91.22	33	33	32.97
RESNET50	78.17	48.79	48.8	48.74
EFFICIENT NETB0	51.75	25	50	33.33
PROPOSED MODEL	92.34	50	48.4	49.2

Table 2. The validation loss of various models

MODEL NAME	LOSS
MOBILENET	0.2765
INCEPTION V3	0.4391
RESNET50	0.5709
EFFICIENT NETB0	0.7906
PROPOSED MODEL	1.3007

5. CONCLUSION:

The proposed fusion-based convolutional neural network presents a comprehensive and effective strategy for binary classification of skin lesions. The proposed model presents a comprehensive and effective way for binary classification of melanoma skin cancer. By using the strengths of the inceptionV3 and MobileNetV2. The model was benefitted from both spatial feature extraction and computational efficiency. The fusion of these two models followed by a custom designed regularized dense classification layers head, made the model to learn the pattern underlying in the images. Additionally, the model showed an amazing performance in terms of accuracy, precision, recall and F1 score, even though the model gave a significantly higher validation loss, the model is strong in generalizing capabilities and diagnostic reliability. Given the models proven accuracy, this model can be useful for real-world deployment as a decision-support tool in skin cancer screening workflows.

6. FUTURE SCOPE:

Although the model gave strong performance across various evaluation metrices, future work will focus on reducing the validation loss while maintain the generalization ability. Such as optimizing the model parameters. Additionally, experimenting with more diverse data augmentation strategies may help improve the convergence stability and loss.

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