Skin Cancer Detection Using Lightweight Deep Learning Models

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Abstract. Skin cancer is one of the most prevalent cancers in the world with an increase in the number of cases each year. Early detection significantly improves the prognosis for malignant melanoma patients but traditional diagnosis methods are time-consuming and invasive. This paper explores how lightweight deep learning models like MobileNetV2, NAS Net Mobile, ResNet50, and EfficientNetB0 can aid in the early and accurate detection of skin cancer. A Melanoma Skin Cancer Dataset of 10000 Images is utilized. The images first undergo pre-processing techniques that are initially applied to improve the performance of the model. The pre-trained models are fine-tuned by replacing the top layer with layers for specific functions of identifying malignant and benign skin lesions. The model's evaluation is conducted using metrics like accuracy, precision, recall, and F1 score alongside visualizing learning curves to assess the performance of the model. This study demonstrates that deep learning techniques can be very useful in supporting dermatologists in the diagnosis of skin cancer, therefore improving patient outcomes through early and accurate detection. MobileNetV2, NAS Net Mobile, EfficientNetB0, and ResNet50 have accuracies of 89.38%, 90.79%, 95.71%, and 90.46% respectively. EfficientNetB0 is the most efficient of all the models followed by MobileNetV2. NAS Net Mobile and ResNet50 need more fine-tuning.

Keywords: Convolutional Neural Networks, Deep Learning, Machine Learning, Skin Cancer Detection.

1. Introduction

Skin cancer is one of the most widespread forms of cancer. The number of skin cancer cases has been increasing year by year. It is caused by the development of abnormal cells that can invade or spread to other parts of the body. Early detection greatly improves the prognosis of patients with malignant melanoma. Usually, the diagnosis of skin cancer has been heavily relied on by the expertise of the doctor which often requires time-consuming and invasive procedures [1]. SC is the fifth most prevalent kind of cancer and one of the deadliest diseases of the current decade. In the next decades, it is also expected to overtake heart disease as the leading cause of death and the largest barrier to increasing life expectancy. In 2018, there were also over 9.6 million cancer-related deaths and 18.1 million new cases of cancer worldwide, according to the International Agency for Research on Cancer's annual status report. According to data provided by the American Cancer Society, the expected number of new melanoma cases among all malignancies in 2023 will be 4% for women and 6% for men [2], [3]. Additionally, it is anticipated that for the next 20 years, the total number of new cases will continue to increase. The primary cause is the aberrant proliferation of skin cells, which is made possible by the uncorrected DNA of skin cells due to genetic abnormalities or DNA mutations [4]. The tissue of the skin is separated into two layers: the bottom dermis, which is composed of a layer of connecting tissue that contains hair follicles, sweat glands, and blood vessels, and the top epidermis, which is composed of pigmented melanocytes and epithelial cells. Malignant melanoma is the name for cancer cells that arise from abnormalities in skin melanocytes [5], [6]. The most common kind of skin cancer throughout the world is non-melanoma skin cancer (NMSC), which arises from the epidermis. It is further divided into two categories based on the variety of cells involved: basal cell carcinoma (BCC) and squamous cell carcinoma (SCC). A mole that developed into Multiple Myeloma (MM) expanded and spread in around 25% of the documented instances. This kind of skin cancer is linked with a substantial chance of recurrence. If left undetected, NMSC seldom ever migrates through the deeper tissues of the epidermis [6], [7] Only when discovered early on can it be readily eradicated. Because SC has a detrimental impact on a person's social and psychological well-being, it needs substantial financing for therapy and technology. Radiation therapy, chemotherapy, and surgery are still used in the treatment. However, these therapies are uncomfortable for patients, have several drawbacks, and do not heal illnesses. They often have an impact on healthy, normal cells as well without being harmful enough to the cancer cells. The application of phototherapies, such as photodynamic therapy (PDT) and photothermal therapy (PTT), in clinical cancer therapy provides considerable promise since there are tumor-ablative and function-reserving oncologic therapies. During phototherapies, light irradiation may activate safe phototherapeutic chemicals that selectively kill cancer cells without having harmful side effects [8].

Deep learning-based methods have been proposed to aid Dermatologists in early and accurate diagnosis of skin cancer. Deep learning models have achieved great performance in tasks like computer vision including image classification, object detection, and segmentation. Amongst various deep learning models like MobileNetV2, NASNetMobile, ResNet50, and EfficientNetB0 can be very useful for the detection of various skin cancers. MobileNetV2 is a lightweight Convolutional Neural Network (CNN) architecture specifically used for mobile and embedded vision applications [9]. It has several features for enhanced efficiency and accuracy like depthwise separable convolution, inverted residuals, bottleneck design, linear bottlenecks, and squeeze-and-excitation (SE) blocks. NASNet stands for Neural Architecture Search (NAS) Network. This model is more complex than MobileNetV2 but is lightweight compared to other NASNet models. It provides a good balance between accuracy, efficiency, and computation requirements. ResNet50 is a part of the ResNet family of models that addresses challenges regarding training neural networks, ResNet50 is a mid-range model. EfficientNetB0 is based on an inverted-bottle neck in residual blocks of MobileNetV2 [10].

Before using these deep learning models, it first needs to prepare the input image data for the model using preprocessing techniques. Usually, CNNs with fully connected layers demand that all the images must be in an array of the same image size. For the image pre-processing tasks we can use OpenCV which is a prominent computer vision library. Image pre-processing techniques like Rescaling and Normalization, Image Resizing and Cropping, Image Augmentation, Color Space Conversion, and Noise Reduction are crucial for the proper functionality of the model. This paper explores the application of these models and techniques for skin cancer detection.

2. Literature Survey

The developments in the area of skin cancer detection proclaim major contributions that enhance the diagnosis accuracy of artificial neural networks and convolutional neural networks. Recent studies using deep CNN models based on NASNet prove that it is possible to differentiate between melanoma and non-melanoma skin cancers with desirable high accuracy. The potential for diagnosis using skin cancer classification becomes probable through the connection made between deep learning techniques and ensemble stacking of machine learning techniques. There has also come a focus on transfer learning, resulting in efficient models across various architectures, like EfficientNet and NASNet Mobile, and have shown their efficiency in melanoma detection by extended datasets. The use of NASNet in skin lesion classification with the use of data augmentation proves to provide better accuracy without the need for segmentation [11].

The author's research uses the ISIC public dataset to identify skin cancer using convolution-based deep neural networks. Cancer diagnosis is a delicate matter that is prone to mistakes if it is not identified promptly and precisely. The ability of each machine learning model to identify cancer is not very good. It is anticipated that the collective choice of the individual students would be more correct than the individual ones. To produce a better judgment, the ensemble learning approach makes use of a variety of learners. Therefore, by combining the choices of individual students for delicate topics like cancer diagnosis, the prediction accuracy may be improved. This study presents the development of a deep learning ensemble for skin cancer detection utilizing VGG, CapsNet, and ResNet learners. The findings demonstrate that, in terms of sensitivity, accuracy, specificity, F-score, and precision, the collective choice of deep learners outperforms the findings of individual learners. The study's experimental findings provide a strong argument for its application to other disease detection [12].

This analytical work provided a unique DL-based model that predicts the kind of lesion based on patient data, including age, gender, and the anatomical location of the lesion, in addition to the lesion image. The recommended model used a CNN that was trained for object identification using Inception-ResNet-v2. According to the findings, the suggested approach performed well for a range of skin disorders. Additionally, every case examined showed a minimum 5% increase in classification accuracy when the patient's information was included in addition to the lesion picture. The proposed approach performed 89.3%±1.1% in the categorization of benign vs malignant lesions and 94.5%±0.9% in the discriminating of four main skin disorders using a dataset of 57536 dermoscopic images. The encouraging results demonstrate the effectiveness of the suggested method and show that the performance of skin cancer diagnosis may be improved by including the patient's information with the lesion image [13].

It presented a novel dataset that consisted of patient clinical data and clinical photos that were gathered using mobile. Subsequently, it provides a simple technique to integrate characteristics from clinical data and photos that include an aggregation process. Finally, it conducts tests to evaluate the models' performance both with and without this technique. According to the data, using the aggregation approach improves balancing accuracy by around 7%. Overall, the performance of models is greatly impacted by clinical data, demonstrating the significance of including these variables in automated skin cancer diagnosis [14].

This paper uses a Convolutional Neural Network (CNN) method with four distinct transfer learning algorithms to identify skin pictures using dermoscopic analysis, allowing for quick detection. A CNN model is evaluated on 660 photos that reflect the deadliest types of skin cancer after being trained on a dataset of 3700 clinical photographs. A significant increase in skin cancer diagnosis accuracy by the use of deep learning architecture For early identification and treatment, ResNet34 offers a dependable method [15].

This study examines two automated methods for detecting skin cancer that employ deep learning techniques: Convolutional Neural Network (CNN) and Artificial Neural Network (ANN). The efficacy and performance of ANN and CNN in prompt and efficient skin cancer diagnosis were established by examining studies on skin cancer detection using these approaches. Using various data sets and hybrid models, the research discovered that ANN and CNN were effective in early skin cancer diagnosis, indicating the potential for these technologies to increase skin cancer detection accuracy. To save time and effort during the diagnostic process, the study emphasizes the need to develop an automated system for skin lesion identification and underlines the uniqueness of using deep learning methods for skin cancer detection. The creation of more effective and precise skin cancer detection systems, which might result in earlier diagnosis and more favorable treatment results, is one of the study's potential uses. This study emphasizes the value of using cutting-edge technologies, including ANN and CNN, in the battle against skin cancer and the potential benefits of these methods for enhancing patient outcomes [16]. Table 1 summarizes the objectives, methods, and findings of the studies on skin cancer detection using deep learning and CNN techniques:

Table 1: Represent studies on skin cancer detection using deep learning and CNN techniques.

Author	Objective	Method	Finding

M. M. Musthafa *et al.*	Enhance diagnosis accuracy of skin cancer detection using artificial neural networks (ANN) and convolutional neural networks (CNN).	Use of deep CNN models, especially NASNet, to differentiate between melanoma and non-melanoma skin cancers with high accuracy.	Deep CNN models based on NASNet achieve high accuracy in distinguishing melanoma from non-melanoma, leveraging transfer learning with architectures like EfficientNet and NASNet Mobile.
A. Imran *et al.*	Improve skin lesion classification accuracy without segmentation.	NASNet model with data augmentation on the ISIC dataset.	NASNet with data augmentation achieves high classification accuracy for skin lesion classification without requiring segmentation.
R. A. Mehr and A. Ameri	Develop a model that incorporates patient data for improved lesion classification.	CNN model trained on Inception-ResNet-v2 architecture with lesion images and patient data (age, gender, anatomical location).	The model achieves 89.3% accuracy for benign vs. malignant classification and 94.5% for main skin disorder classification, demonstrating the value of adding patient data to image-based classification.
A. G. C. Pacheco and R. A. Krohling	Assess the impact of clinical data integration on model performance.	Aggregation technique for combining clinical data with images, tested on a novel dataset collected via mobile devices.	Including clinical data improves model accuracy by 7%, highlighting the importance of clinical data in automated skin cancer diagnosis.
S. Sasikala	Evaluate the effectiveness of CNN models for rapid skin cancer detection.	CNN method with transfer learning (ResNet34) on a dataset of 3700 images for dermoscopic analysis of 660 skin images.	ResNet34 shows reliable early detection capabilities, enhancing the accuracy of skin cancer diagnosis.
A. Shah *et al.*	Compare ANN and CNN in terms of their efficacy in skin cancer detection.	Review of studies on ANN and CNN models using various data sets and hybrid	Both ANN and CNN demonstrate efficacy in early detection, with CNN being particularly effective, emphasizing the potential of

		approaches for skin cancer detection.	deep learning methods in enhancing skin cancer diagnosis accuracy and patient outcomes.

3. Methodology

To develop an efficient skin cancer detection system making use of deep learning techniques we first need a proper dataset. The Melanoma Skin Cancer dataset with 10,000 images contains 10,600 images out of which 9,600 images are designated for training and 1,000 are for testing the model. The pre-processing steps include resizing the images to a consistent size as per the requirements of the models used. Applying data augmentation techniques to increase the performances and generalization of the models used. Data augmentation techniques include random rotations, height, and width shifts, zooming, shearing, and horizontal flipping [17]. The usage of TensorFlow's Image Data Generator helps in real-time data augmentation. Converting the images in RGB color scale if required by the model and filters for noise reduction to enhance the quality of the image. Feature extraction also plays a huge part. It is important especially for the detection of skin cancer as it needs to detect edges, texture, coloration, and shape of the skin lesions [18].

For the model training step, we consider four different deep learning models which are MobileNetV2, NASNetMobile, ResNet50, and EfficientNetB0. All these models are considered lightweight in comparison to the other larger models available but each model has a different level of complexity. Each of these models maintains a good balance between efficiency and accuracy. These models are loaded as pre-trained models. By using these pre-trained CNN models, we can fine-tune them on the dataset by replacing the top layers of these models and compiling them with a suitable optimizer, loss function, and metrics for the detection of skin cancer. The final layers need to be replaced with new layers for the specific tasks for classifying images as malignant or benign skin lesions. Dividing the training dataset as 60% training and 40% validation of the model [19]. Using callbacks like early stopping and checkpoints while training the model we can reduce the instances of overfitting and have a model with relatively good performance. Hyperparameters like learning rate, batch size, and the number of epochs can be changed to optimize the performance. Figure 1 explains the methodology in a diagrammatic form.

Evaluation of the models is to be conducted on the test dataset using metrics such as accuracy, precision, recall, and F1 score. Also visualizing the learning curves of the model. These metrics and graphs of the learning curves help understand the accuracy, efficiency, and performance of a model for skin cancer detection.

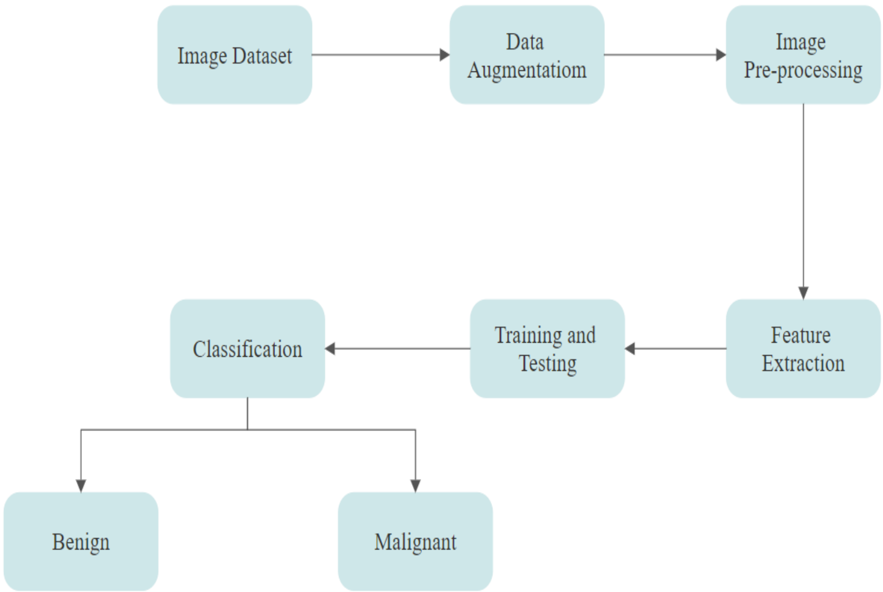

Figure 1: Flow chart of the Methodology

4. Results

The performance was evaluated on four deep learning models- MobileNetV2, NASNetMobile, EfficientNetB0, and ResNet50 -for the task of skin cancer detection. Utilizing the dataset comprising thousands of dermoscopic images, the assessment of each model was based not only on the accuracy and loss of the model but also on different metrics like precision, recall, and f1-score. These metrics were utilized to understand the strengths and weaknesses of the models to classify between malignant and benign skin cancer.

From Figure 2 it is observed that the first model MobileNetV2 was able to achieve an accuracy of 89.38% with a loss of 0.27. The model achieved high accuracy with a relatively low loss. The model provided a balanced performance to effectively identify both benign and malignant lesions. From Table 2 it is observed that it displayed slight caution in identifying malignant lesions resulting in a relatively larger number of true positives but eventually also leading to more false negatives. This cautious nature of the model could be useful in clinical settings where the cost of false positives is a lot higher, eventually reducing unnecessary worry among patients. However, MobileNetV2 proved robust as a model for skin cancer detection when resource efficiency became a concern. In comparison, NASNetMobile performed somewhat better with an accuracy of 90.79% and a loss of 0.22. The model's performance metrics show a major imbalance in the performance mainly in detecting benign lesions. The model's performance variables show that there is a large gap in the model's ability to detect malignant versus benign lesions. Because of the performance gap between both classes, this means that the model is prone to require further tuning, especially concerning optimization parameters or data augmentation techniques, to be able to enhance its performance in the detection of benign lesions. NASNetMobile is still competitive and may need some further refinement for its potential to detect benign lesions.

The best-performing model having an accuracy of 95.71% with a loss of 0.1219 was EfficientNetB0. Among the 4 models assessed, EfficientNetB0 was the most effective. It is extremely capable in skin cancer detection as the performance was characterized by consistency across both classes of lesions. A high-level performance for all metrics, besides maintaining the loss to minimum values, suggests its robustness and reliability. This model not only minimized the loss effectively but also had a superior ability to generalize across both lesions. On the other hand, ResNet50 has an accuracy of 90.46% but with a higher loss of 0.3498. The model demonstrated consistency in classifying benign cases. However, its metrics need some enhancement in detecting malignant cases. ResNet50 showed valuable characteristics but would be beneficiary if it is optimized further to enhance its accuracy and consistency for both benign and malignant lesions.

In summary, EfficientNetB0 outperformed the other models in terms of accuracy, loss, and balance between detecting both lesions. It is a better choice for a skin cancer detection task, as its design enables it to perform well in both efficiency and detection.

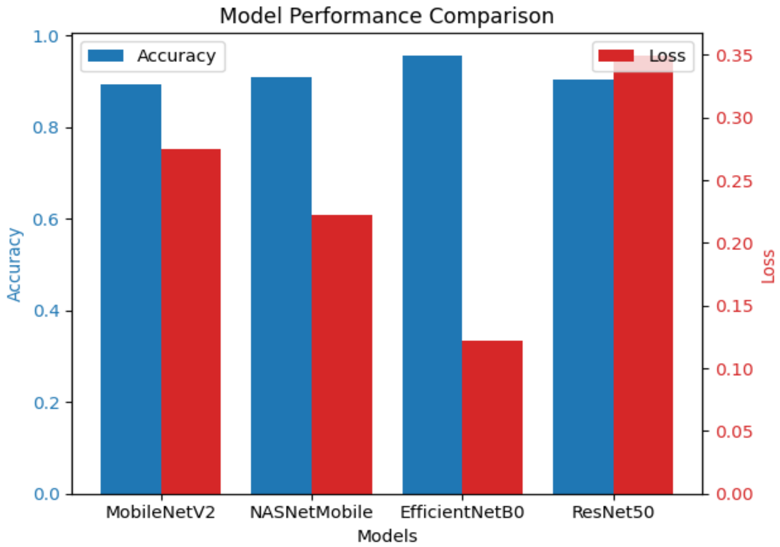

Figure 2: Accuracy and Loss of all 4 models

Table 2: Performance metric of all four models for benign and malignant lesions.

	Benign			Malignant		
Models	Precision	Recall	F1-score	Precision	Recall	F1-score
MobileNetV2	0.87	0.93	0.90	0.92	0.85	0.88
NASNetMobile	0.69	0.76	0.67	0.82	0.78	0.80

EfficientNetB0	0.90	0.97	0.94	0.96	0.89	0.92
ResNet50	0.87	0.79	0.77	0.88	0.75	0.73

5. Disussion

5.1. Type of Skin Cancer

An overview of the most common types of skin cancers.

5.1. Melanoma

Melanoma's propensity to spread has earned it the moniker "the most serious skin cancer." You may get melanoma anyplace on your body, whether it's in a healthy, normal skin or a malignant tumor that develops into cancer. Men who have melanoma usually have it on their trunks or faces. Men's and women's skin that has not been sufficiently exposed to the sun may develop melanoma. Early melanoma identification and treatment are crucial [20].

5.2. Dysplastic Nevi

Atypical moles, also known as dysplastic nevi, are similar to regular moles but can have certain traits of melanoma. In addition to being larger than normal moles, they often have an unusual form or color. Atypical moles may appear in typically covered areas of skin, such the scalp or buttocks, as well as on skin that is exposed to sunlight.

5.3. Basal Cell Carcinoma (BCC)

The most common kind of skin cancer is BCC. Fair-skinned people often get BCC. Darker-skinned people are more susceptible to skin cancer. BCCs often seem as a pinkish skin patch, a pearl-shaped lump, or a spherical, flesh-colored growth. BCCs usually show up after years of regular sun exposure or indoor tanning. The head, neck, and arms are where BCCs are most often discovered, although they may form anywhere on the body, particularly the chest, abdomen, and legs. Early diagnosis and therapy are essential for BCC. BCC has the capacity to proliferate. If it spreads by invading the bones and nerves, it may damage and distort them.

5.4. Squamous Cell Carcinoma (SCC)

The most common kind of skin cancer is SCC. Darker-skinned people may also have SCC, however those with lighter skin have a higher chance of getting it. SCC usually manifests as a solid, red lump, a scaly patch, or a healing sore that reopens. Skin that receives a lot of sun exposure, such the back, arms, chest, neck, face, and ear rim, is more likely to develop SCC. SCC may cause damage and deformity by severely penetrating the skin. SCC may be prevented from spreading to other body regions and from growing deeply by early identification and treatment. The growth of precancerous skin might result in SCC.

5.5. Actinic Keratoses (AKs)

Some patients develop dry, scaly skin lesions called actinic keratoses (AKs). Despite being caused by excessive sun exposure, an AK is not skin cancer. An AK is a precancerous skin growth that may progress to squamous cell carcinoma, the common kind of skin cancer. AKs usually appear on exposed skin, such as the hands, neck, forearms, and head. Since AKs have the potential to develop into a particular kind of skin cancer, treatment is crucial.

6. Conclusion

In this study, four deep learning models MobileNetV2, NASNetMobile, EfficientNetB0, and ResNet50 are assessed in terms of detection of skin cancer using a dataset of 10,600 images. All the models are evaluated based on accuracy, loss, precision, recall, and f1-score in terms of the determinations for how well the benign and malignant lesions are classified. The best model overall was EfficientNetB0, with a top accuracy of 95.71% and the lowest loss at 0.1219. This model consistently and strongly performed well in identifying both benign and malignant skin lesions; which makes it most appropriate for the detection of skin cancer in clinical practice. Its consistency can be observed in all metrics, proving that this model is reliable and robust. Followed by MobileNetV2, which obtained 89.38% accuracy and a loss of 0.27 with balanced performance on both types of lesion, suffering only slightly in recall on the malignant cases. The lightweight architecture is the most appropriate for applications when resources are less than plentiful as is the case with mobile devices, without sacrificing too much in the way of accuracy. NASNetMobile achieved an accuracy of 90.79%. Its highest failing was a bit more in benign lesion detection. Here, the precision for benign cases is 0.69 versus 0.82 for malignant ones. Potentially good but should be further fine-tuned for better performance on benign cases. The ResNet50 model accuracy was at 90.46%, though with a higher loss value of 0.3498, it points out the possibilities for some overfitting issues. Its precision and recall were not much different from MobileNetV2 but upon further optimization, generalization could be improved. Lastly, it can be said that the most effective models are EfficientNetB0 and MobileNetV2 while more refinement is required to be given to the NASNetMobile and ResNet50.

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