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A Transfer Learning Approach for Detection and Classification of Skin Cancer

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A B S T R A C T

Skin disease is one of the major problems in the world. Skin cancer, infection, acne, psoriasis, and eczema can significantly affect the health of a person. Skin cancers such as melanoma, squamous cell carcinoma, and basal cell carcinoma are the most concerning problems that require early attention to save lives and simplify the treatment. Other conditions like eczema and psoriasis, though not life-threatening, impact mental health and appearance, underscoring the need for timely intervention. Machine Learning and Deep Learning have become a transformative tool in dermatology, leveraging deep learning and computer vision to diagnose skin diseases effectively. In this paper, we presented a model that can classify between Melanoma and Benign types of skin cancer using EfficientNetB7 the Transfer Learning Model with a good test accuracy of 84.09% on the ISIC dataset. The proposed model achieves mean precision, recall, and F1-score is 96.11%, 79.15%, and 86.63% respectively.

1. INTRODUCTION

Skin is the essential organ of a human body and its plays a vital role in protecting against germs and environmental factors. Due to some environmental factors, there are many chances that people can get affected from skin disease such as Impetigo, Cellulitis, Folliculitis, Fungal Infections, Allergic problem, Heat Rash, Acne, Eczema (dermatitis) Psoriasis, Rosacea, Skin Cancer, Fungal Infections, Bacterial Infections, Hives, Vitiligo etc. Early and accurate detection of dermatological problem is an important for effective and preventive treatment, especially in the cases where the life of a person in risk such as skin cancer. The Skin cancers, including Basal Cell Carcinoma, Melanoma, Merkel Cell Carcinoma, squamous Cell Carcinoma, Kaposi Sarcoma and Cutaneous Lymphoma are the most common types of cancer worldwide [1, 2].

Therefore, timely identification of dermatological problems can not only save lives but also help avoid more complex treatments

and lower healthcare costs. In addition to skin cancer, other dermatological issues such as eczema, psoriasis, acne, and fungal infections can also cause significant distress, affecting an individual's appearance, mental health, and overall quality of life. These conditions, though not life-threatening, often require early intervention to minimize symptoms, prevent flare-ups, and avoid complications. Detecting these problems at an early stage is important for improving treatment outcomes and reducing the impact on patients' lives [3, 4, 5].

In today's era, Machine Learning and Deep Learning are the useful tools in dermatology, to detect the skin problems. Transfer learning applies pre trained data model on new or correlated problems [5, 6, 7].

In dermatology, large labeled datasets can create challenges due to the different types of skin diseases. To get out of this situation, Transfer learning is the solution by allowing models trained on large dataset. This paper looks into how transfer learning is applied to skin disease detection, its performance compared to traditional deep learning models, and the future outlook for this technology.

1.1 Types of Skin Cancer

There are many types of skin cancer few of them are Melanoma, Basal Cell Carcinoma, and squamous Cell Carcinoma, Merkel Cell Carcinoma, Kaposi Sarcoma and Cutaneous Lymphoma.

Important Information regarding skin cancer

- The skin cancer is mostly caused by ultraviolet radiation (UV) that is caused by sunlight. However a little bit of ultraviolet radiation is good for people to produce vitamin D.
- There are approximately 3 million cases of melanoma and approximately 130000 cases of non-melanoma are treating every year. More than 90 percent of people have non-melanoma due to fair skin.
- When a child is exposed to excessive sunlight during childhood, he/she may suffer from skin cancer later on.

Melanoma: It is aggressive type skin cancer which originates in the melanocytes cells of a body and spread metastasize to other parts of the body. Melanoma appears as a new mole or change in an existing mole (color, size, shape).

Basal Cell Carcinoma (BCC): The symptoms of BCC look as a small nodule or bump that grows slow and hardly spreads to other parts of body. BCC cancer starts in the basal cells, which are found in the lower part of the skin, also called epidermis.

Squamous Cell Carcinoma (SCC): This type of skin cancer starts in the squamous cells that comprise the skin's outer and middle layers. The symptoms of SCC appear as a flat lesion or as a red nodule.

Merkel Cell Carcinoma (MCC): The Merkel cells are the origin of this type of uncommon but touch sensitive skin cancer.

Kaposi Sarcoma: This is a cancer that originates in the blood vessels and lymphatic system, appears like purple, red or brown lesion on the skin. It can also affect internal organs.

Cutaneous Lymphoma: Cutaneous lymphoma skin cancer affects the skin and begins in the lymphocytes white blood cell.

Table 1. Representation of Skin Cancer with their symptoms, risk factor, and treatments.

Skin cancer	Symptoms	Risk factor	Treatment
Melanoma	Developing a new mole or changing the existing mole eg: colour, shape, size.	Excessive sun burn, fair skin, family history, large number of moles.	Surgical excision, immunotherapy, chemotheraphy.
Basal cell carcinoma (bcc)	Small, shiny bump or noudle	Chronic sun exposure, fair skin, older age, history of sun burn.	Surgical excision, cryotherapy, mohs surgery.
Squamous cell carcinoma (scc)	Red noudle or flat lesion with a scaly, crusted surface.	Exposure in sun, fair skin, older age, chronic skin condition, immunosuppression.	Surgical excision, mohs surgery, topical treatments like 5-fluorouracil.

Merkel cell carcinoma (mcc)	Painless, firm, rapidly growing nodule or tumor that is reddish or purple.	Exposure in sun, older age, fair skin, weekened immune system.	Radiation therapy, ammunotheraphy, chemotheraphy.
Kaposi sarcoma	Lesion appear particularly on the lower legs, face, and mucous membranes	Immunosuppression (e.g., hiv/aids, organ transplantation), and infection with human herpesvirus 8 (hhv-8).	Antiviral therapies, chemotherapy, radiation, and immune-modulating treatments. In immunocompromised patients, controlling the underlying condition (e.g., hiv) is crucial.
Cutaneous lymphoma	Patches, plaques, or tumors on the skin, often with a red, scaly appearance.	Weakened immune system	Topical steroids, chemotherapy, phototherapy (uv light treatment), radiation therapy, and in some cases, systemic chemotherapy or immunotherapy.

1.2 Worldwide Statistics of Skin Cancer

According to "International Agency for Research on Cancer", the incidence cases of Melanoma of skin cancer is 331722 in all over the world and the mortality of Melanoma of skin cancer rate is 58667 as shown in Figure 1.

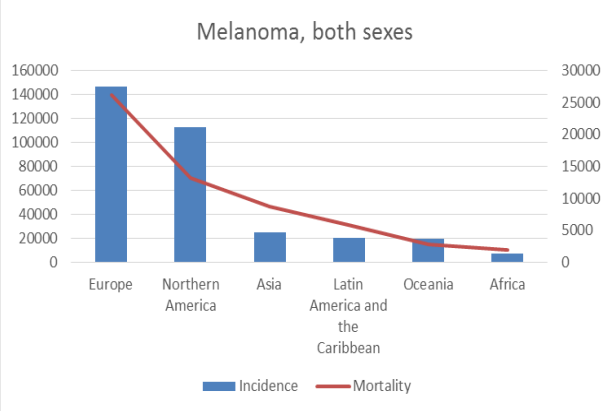

Fig. 1. Melanoma incidence (left-side y-axis) and mortality rate (right-side y-axis) all over the world [1].

Skin Cancer is the harmful type of skin lesion in which human life is directly connected to the life or death. Early detection and treatment are the keys for improving outcomes in all types of skin cancers.

2. LITERATURE REVIEW

Roberta et al. (2017) [8] has proposed SE-OPF, SEFS-OPF and FEFS-OPF algorithms to diagnose melanoma, which is a type of skin cancer. The model was classified using forest algorithm and combined with a widely held voting technique. The author used 1104 images as a dataset using a cross-validation technique. The computational system's accuracy, sensitivity, and specificity were 94.3%, 91.8%, and 96.7%, respectively.

Parvathaneni et al. (2021) proposed a model to classify seven type of skin lesion such as BCC, Melanoma, etc. The proposed model detect skin lesion using MobileNet V2 which is a Deep Learning Model and Long Short-Term Memory (LSTM). The MobileNet V2 model was able for classifying skin problems with better accuracy. For maintaining the record of disease, a grey-level co-occurrence matrix is used to keep the record of skin lesion. The author used HAM10000 dataset on the proposed model which provides more than 85% accuracy.

Farhat et al. (2022) [9] has proposed a deep learning model, ResNet-50 on three types of dataset Ph2, ISBI2016, and HAM1000 which contains three, two and seven skin cancer classes. The computational model achieved an accuracy of 95.40%, 91.1%, and 85.50%, respectively. Further an enhanced grasshopper optimization technique was used on learned features, which was later classified through the Naive Bayes classifier.

Viswanatha et al. *(*2022) [10] to identify melanoma skin cancer the author proposed a Neural Network model, CNN (Convolutional Neural Network) which achieves the accuracy of 88.83 percent on a well-known melanoma dataset.

Mostafiz et al. (2022) [11] has proposed an approach for classifying eight types of skin diseases, including melanoma (MEL), melanocytic nevus (NV), basal cell carcinoma (BCC), actinic keratosis (AK), benign keratosis (BKL), dermatofibroma (DF), vascular lesion (VASC), and Squamous cell carcinoma (SCC).The proposed approach contains four crucial steps: image pre-processing, segmentation, feature extraction and classification. The author used a digital Morphological Black-Hat Transformation method

to remove hairs and Gaussian Filter method to blur the images. The author employed an automatic Grabcut segmentation for accurately identifying and segmenting the skin lesion region. In the proposed model the author used Support Vector Machine (SVM), K-nearest neighbour (KNN) and Decision Tree (DT) algorithm to categorise the skin disease by using two common dataset ISIC 2019 challenge and HAM10000 imbalanced dataset. A random over sampling technique was used for balancing the dataset. The computational model achieved an accuracy of 95%, 94%, and 93% in the dataset of ISIC 2019 using SVM, KNN, and DT algorithms, respectively and achieves an accuracy of 97%, 95%, and 95% in the dataset of HAM10000 using SVM, KNN, and DT algorithms, respectively.

Aishwarya et al. (2023) [12] has proposed YoloV3 and YoloV4 version techniques to categorizing the nine type of skin cancer including vascular lesions, Pigmented Benign Keratosis, Seborrhoeic Keratosis, Melanoma, Nevus, Actinic Keratosis, Basal Cell Carcinoma, and Dermatofibroma. The proposed deep neural network models YoloV3 and YoloV4 achieve an accuracy of 88.03% and 86.52% respectively. You Only Look Once is a real-time object detection method which selects an area of interest in an image uses single neural network model by adapting conventional image classifier algorithm.

Deni et al. (2023) [13] has proposed a Convolutional Neural Networks (CNN) algorithm. The author used several models such as Single-Shot multibox Detector (SSD), CenterNet, and You-Only-Look-Once (YOLO) which used low memory dependence and gives fast result.

Javed Rashid in 2022 [14] has proposed a MobileNetV2 model for the classification of Melanoma. The Computational system is a deep convolutional neural network model that uses ISIC 2020 dataset and gives the accuracy of 98.2 percent. Jessica et al. (2023) [15] has proposed MobileNet model for the classification of skin lesion which achieves the accuracy of 94.1%.

Hari et al. (2020) [16] has proposed a transfer learning technique for skin lesion identification. The author used ResNet50 model for identifying seven distinct types of skin problems. The system used HAM10000 dataset with the accuracy of 90%.

Zhe et al. (2019) [17] proposed Inception-ResNet-v2 model which is a CNN based approach for the detection of skin cancers, including lupus erythematosus (LE), rosacea (ROS), seborrhoeic keratosis (SK), actinic keratosis (AK), basal cell carcinoma (BCC), and squamous cell carcinoma (SCC). The proposed model achieved average recall 77.0 percent and average precision 77.0 percent on Xiangya-Derm dataset that contain 150,223 clinical photos of 543 distinct skin problems.

Kamil et al. (2023) [18] implements a CNN based transfer learning algorithm for the classification of differnt skin conditions. For training and transferring the data the model is divided into two CNN models one is inner and the second is external model in which the preprocessing and data augmentation is not applied. The author obtained the skin lesion images by smartphones. It contains 2298 images with 1641 skin lesions. The proposed model uses ReLU activation function on CNN model for extracting the features of an image which activates only the positive values and removes the negative values for accelerates the convergence and decrease the model's cost.

Karen et al. (2015) [19] has proposed ImageNet and high-performance computing systems for instance GPUs for classification of skin problems. The author added convolutional layers to increase the depth of the network in the architecture design. The architecture used (3*3) filter in all layers. The hidden layers use ReLU non linearity, and the network does not contain Local Response Normalisation as such normalization does not improves the performance on ImageNet Large-Scale Visual Recognition Challenge dataset 2012, but increase space and time complexity.

Mawaddah et al. (2024) [20] proposed EfficientNet-B4 model for classifying Basal Cell Carcinoma (BCC), Squamous Cell Carcinoma (SCC), and Melanoma skin lesions with the accuracy of 79.69%. The author used preprocessed imbalanced dataset. The author compares the efficiency of EfficientNet model (B0-B7) and finds the EfficientNet B4 provides higher accuracy with 79.69 percent.

Kanchana et al. (2024) [21] proposed a CNN based EfficientNet model for classification of

skin cancer such as Benign Kertosis, Eczema, Melanoma, molluscum, psoriasis. The author compares the efficiency of EfficientNet B0-B7 model and finds the EfficientNet-B7 achieving different accuracy in different types skin cancer. The author used ISBI-2016 dataset which is introduced in 2016 provides high resolution images of various skin lesions.

Hritwik et al. (2024) [22] proposed an integrated model VGG16 and ResNet50 for classification of nine skin problems such as actinic keratosis, basal cell carcinoma, dermatofibroma, melanoma, nevus, pigmented benign keratosis, seborrheic keratosis, squamous cell carcinoma, and vascular problem on ImageNet imbalanced dataset. To balance the dataset data augmentation techniques were used. A high-performance computer system equipped with NVIDIA Tesla V100 GPUs with the speed of 125 TFLOPS was used in the proposed system. The activation function ReLU is used with 100 epochs with a batch size of 32 to balance the computational efficiency. The computational system achieves an accuracy of 97.50 percent.

Gurpreet et al. (2023) [23] implements a VGG16 model for the detection of skin lesion such as Herpes, Psoriasis, Acne, Dermatophy Tosis, and Warts with the accuracy of 90.1%, precision, recall and F1-score was identified as 86.7, 94.2, and 89.1% respectively.

Some research papers are summarized in Table 2.

Table 2. Summary of some research papers published on the skin cancer detection and classification.

References	Methodology	Skin Lesion	Dataset	Accuracy (%)
[24]	CNN	Melanoma	Dermnet	88.83
[25]	CNN	Melanoma and focal cell carcinoma	HAM10000	80
[21]	Efficientnet-B7	Skin diseases	Imagenet	90.7
[17]	Inception-resnet-v2	Actinic keratosis (AK), basal cell carcinoma (BCC), and squamous cell carcinoma (SCC), Seborrheic keratosis (SK), rosacea (ROS), lupus erythematosus (LE).	Xiangya–Derm	77.0
[22]	VGG16-resnet50	Carcinomas And melanomas	Imagenet	97.5
[26]	CNN, Resnet50, inceptionv3, Inception Resnet	Malignant and benign	ISIC2018	CNN-83.2, Resnet50-83.7, inceptionv3-85.8, inceptionresnet-84
[16]	Resnet50 model	Melanoma, Dermatofibrom, Actinic Keratosis, Basal cell carcinoma, Vascular Skin Lesion, Melanocytic Nevi, Benign Keratosis.	HAM10000	90
[27]	Efficientskindis	Kaposi Sarcoma, Basal Cell Carcinoma, Merkel Cell Carcinoma, and Cutaneous Lymphoma, squamous Cell Carcinoma Melanoma and more diseases.	HAM10000 dataset+ ISIC2018	87.15
[20, 28]	Efficientnet-B4	Basal Cell Carcinoma (BCC), Squamous Cell Carcinoma (SCC), and Melanoma	HAM10000	79.7
[23]	VGG16	Malignant and benign	-	90.1
[15]	Mobilenet	Chicken pox, eczema, pityriasis rosea, Tinea corporis , acne, vitiligo and psoriasis,	-	94.1

3. EXPERIMENTAL SECTION

Transfer learning is a deep learning technique that uses pre-trained models from one machine learning task or dataset to improve performance on a related task or another dataset.

3.1. Dataset

In this paper, we have used ISIC dataset from Kaggle that contains 1197 photos of Melanoma and 1440 photos of Benign as a training dataset and 360 images of Melanoma and 300 images of Benign cancer are tested on pretrained transfer

learning model using EfficientNetB7. Few raw images have been shown in Figure 2 [21, 29].

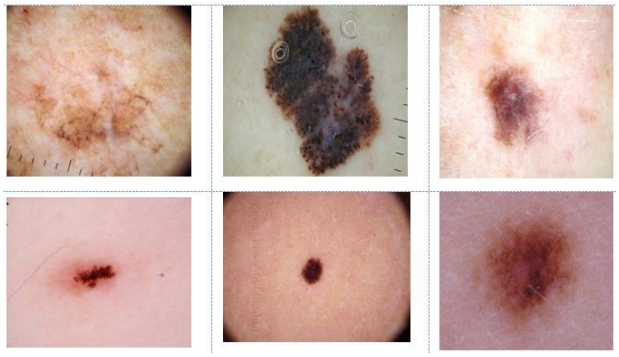

Figure 2. Raw images of the taken dataset that belong from Melanoma (first row) and Benign cancer (second row).

3.2 Data Pre-processing

In data pre-processing several steps has been included:

- Image Resizing: The images need to be resized to a consistent size, commonly used by the models (e.g., 224x224 pixels for VGG16, ResNet50, & InceptionV3, and 300x300 for EfficientNet).
- Normalization: Pixel values required to be normalized in a range of 0-1 which improves convergence during training of the model.
- Data Augmentation: To enhance model generalization and prevent over-fitting, data augmentation techniques including random rotations, flips, shifts, and zooms have been applied on the images.

3.3 Implementation of computer program

All the processes have been implemented in a single computer code written in Python language on the Anaconda environment. The algorithm used in the computer program is as follows.

Algorithm:

1. Load Dataset
2. Take Separate Dataset for Training and Testing
3. Preprocess Data
   - Resize images
   - Convert images to a specific format
   - Normalize pixel values
4. Create Data Generators
5. Build Model Architecture
   - Define layers (e.g., Convolutional, MaxPooling, Dense)
   - Specify activation functions (e.g., ReLU, Softmax)
   - Choose optimizer (e.g., Adam, Adamax)
6. Compile Model
   -Specify loss function (e.g., categorical_crossentropy)
   - Define optimizer
   - Select metrics (e.g., accuracy)
7. Train Model
   - Train the model on the training data
8. Evaluate Model
   - Evaluate on Training set
   - Evaluate on Validation set
9. Plot Training History (Optional)
   -Visualize training and validation loss and accuracy
10. Evaluate Model on Test Set
11. Generate Performance Metrics
    - Calculate accuracy, loss
    - Generate confusion matrix
    - Create classification report
12. Save Model

3.4 Evaluation Metrics

After training, the models have been evaluated on a test set (unseen data) to assess their generalization ability. Accuracy represents how close the produced value to the actual value, indicating the tool's capability to accurately measure the exact value. In the context of machine training, precision is the proportion of number of true cases to the total cases including true and false cases, providing insights into the classifier's ability to produce correct output within a class. Similarly, recall, also known as sensitivity, is given by dividing total number of true positive cases obtained by the classifier by total actual positive entities in the class. The F-measure referred to as the harmonic mean of sensitivity and precision which serves as a robust measure of model's classification performance. By computing the average of precision and sensitivity, the F-measure provides a balanced assessment that considers both the quantity and ability of classifications. The value of F-measure lies between 0 and 1. The F-value closer to 1 is showing an efficient classification model [29].

Mathematically, the performance parameters are defined as given below:

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} \quad (1)$$

$$Precision = \frac{TP}{TP+FP} \quad (2)$$

$$Recall\ or\ Sensitivity = \frac{TP}{TP+FN} \quad (3)$$

$$F-Measure = 2 \times \frac{Precision \times Sensitivity}{Precision+Sensitivity} \quad (4)$$

Where, *TP*, *TN*, *FP*, and *FN* are the abbreviations for true positive, true negative, false positive and false negative values respectively provided by the model.

Computational Efficiency: The training time and inference time have been measured to evaluate the efficiency of the model. The EfficientNet model is expected to demonstrate the highest computational efficiency while maintaining the accuracy.

Confusion Matrix: The confusing matrix is a necessary representation which helps to evaluate the model's performance in detail by identifying true positives, false positives, true negatives, and false negatives. The other evaluation parameters as given in equations 1 to 4 can be clearly calculated with the help of confusing matrix elements.

4. RESULT AND DISCUSSION

The whole model in the study was implemented using Keras with the Tensorflow libreries on Python platform. The pre-processing has been performed on the raw images from the training dataset of melanoma and benign cancer. The training images have been resized to fixed 300×300 size as shown in Figure 3 [30, 31].

A combination of various connected layers and fully connected layers is used in the model. Here, the softmax activation function is used. For the normalization of output image, we added normalization layers in the model which minimized over-fitting. To provide effective nonlinear transformations of the input image, the rectified linear unit (ReLU) is used as activation function for all the levels except the last layer. Further, we need to optimize the training process. Adam optimizer is used for optimization of the training procedure. Training procedure is extended over 30 epochs, each epoch processing a batch size of 165 instances. The ISIC dataset is trained on Transfer Learning based EfficientNet B7 model using Python programming language. For training the model Adamax optimizer was used as it is shown in the figure.

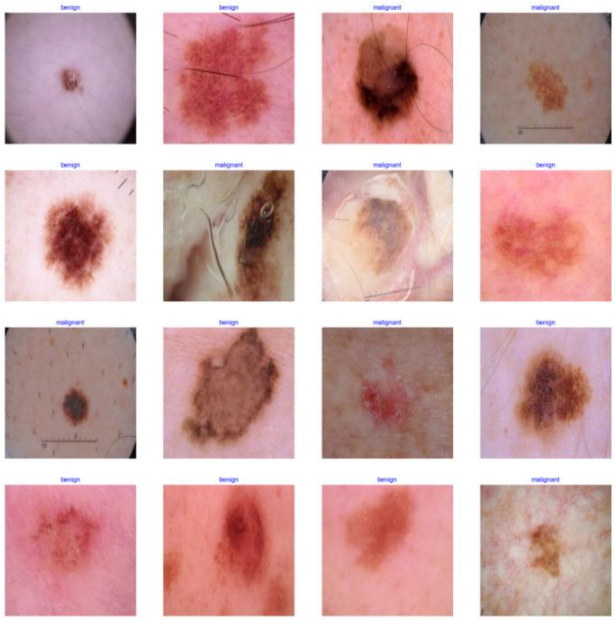

Fig. 3. Pre-processing of training images after resizing of Malignant and Benign cancer images.

The provided training and validation loss and accuracy curves reveal important insights into the machine learning model's performance. The training loss decreases steadily, suggesting that the model is learning to fit the training data. However, the validation loss decreases initially and then plateaus, indicating the model's generalization to unseen data is limited. The blue dot on the loss curve marks the epoch with the lowest validation loss, which is typically considered the best epoch, indicating optimal generalization before over-fitting starts.

The training and validation loss and accuracy are plotted in Figure 4. The training accuracy increases over 30 epochs, showing the model's improving performance on the training data, while the validation accuracy rises initially but then drops, signalling potential over-fitting as the model fails to generalize well to validation data. The best epoch for validation accuracy is marked by the blue dot, which may not coincide with the lowest validation loss, highlighting the trade-off between minimizing loss and maximizing accuracy. Overall, these curves indicate that while the model learns well on the

training data, it struggles with generalization, with the best balance between performance and generalization occurring around epoch 29 for accuracy and epoch 30 for loss, underscoring the importance of monitoring both metrics to prevent over-fitting.

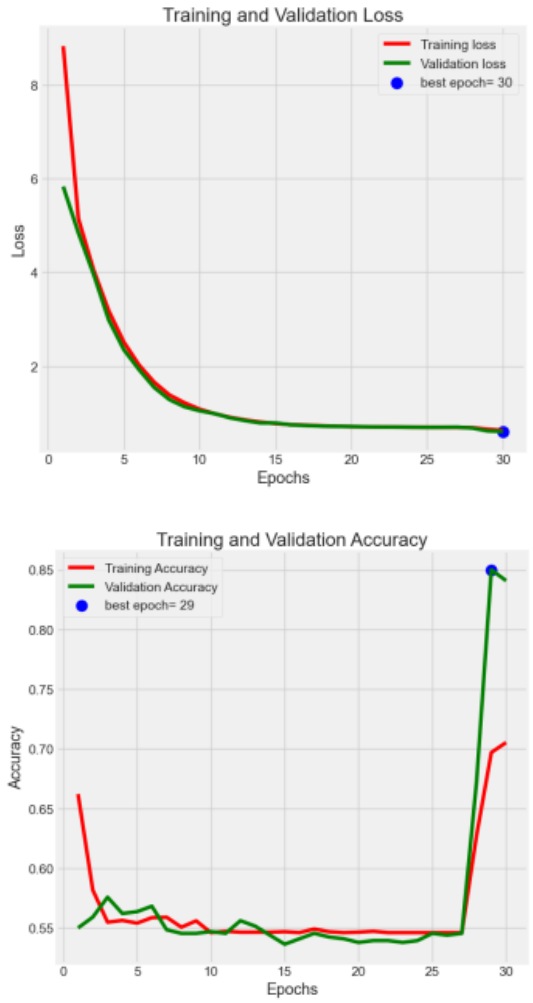

Fig. 4. Model Performance, Generalization, and Over-fitting using Training and validation loss (Top) and Training and validation accuracy (Bottom).

The confusion matrix (Figure 5) shows a detailed view of the performance of classified model by comparing the predicted classifications with the actual outcomes. In this study, the model accurately predicted 346 benign cases as benign (True Positives, TP), and 209 malignant cases as malignant (True Negatives, TN), which indicates good model performance in these categories. However, the model made some errors, mispredicting 14 benign cases as malignant (False Positives, FP) and 91 malignant cases as benign (False Negatives, FN). These off-diagonal values represent areas where the model failed to classify correctly, with False Positives indicating benign cases misclassified as malignant, and False Negatives representing malignant cases misclassified as benign. Ideally, a model should have high True Positives and True Negatives while minimizing False Positives and False Negatives. A higher number of True Positives and True Negatives suggest that the model is performing well in accurately classifying both benign and malignant cases. On the other hand, the lower the number of False Positives and False Negatives, the better the model's overall accuracy and reliability.

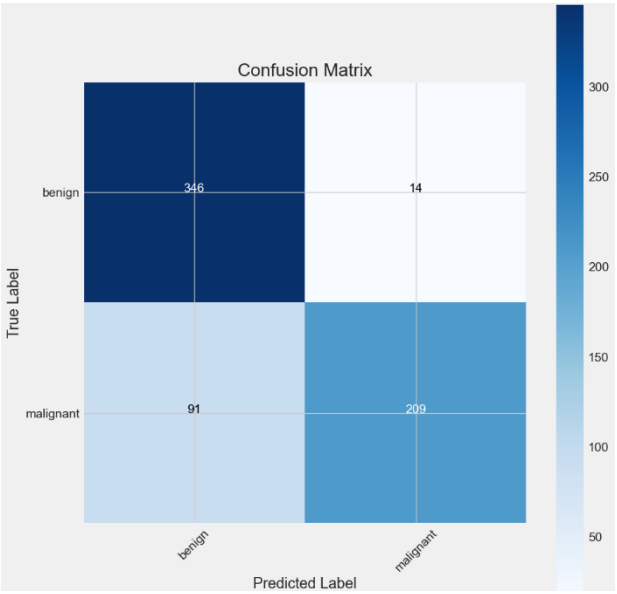

Fig. 5. Confusion matrix analysis: evaluating model performance in predicting benign and malignant cases.

The model's performance can be summarized through several key metrics derived from the confusion matrix. The accuracy is 84.09%, indicating that the model correctly classified 84.09% of all cases. Precision is 96.11%, meaning that when the model predicted benign cases, it was correct 96.11% of the time. Recall, at 79.15%, reflects that the model correctly identified 79.15% of all actual benign cases. The F1-score, which balances precision and recall, is 86.63%, suggesting a strong overall performance in terms of both correctly identifying benign cases and minimizing misclassifications. These metrics highlight the model's effectiveness in classifying benign cases, with a high precision, but it could benefit from improvements in recall to reduce the number of benign cases incorrectly classified as malignant.

5. CONCLUSION

This study shows the efficiency of transfer learning for skin cancer classification, achieving high accuracy with reduced resource requirements. In this paper the proposed model classify the Melanoma and Benign a type of skin cancer using EfficientNetB7 with a good training accuracy of 86.87 %, test accuracy 84.09% on ISIC dataset. The computational model achieves mean precision, recall, and F1 score is 96.11%, 79.15%, and 86.63% respectively. The findings suggest that transfer learning can be a valuable tool for developing automated diagnostic systems, particularly in resource-constrained settings. Future advancements in this field have the potential to revolutionize dermatological diagnostics, improving accessibility and outcomes for patients worldwide.

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