[1] **Hamsalekha R***

[2] **Glan Devadhas George**

[3] **T Y Satheesha**

# Fusion-Based Deep Learning Approach for Skin Cancer Detection Using DenseNet-121 and Transfer Learning

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***Abstract:*** - Skin Cancer is major type of cancer existing worldwide. In-order to improve the survival rates of infected person it is necessary to detect it in the Early stage. Earlier Traditional methods were used to detected the cancer but was more Time consuming and involved complex procedures like Biopsy, and to produce the output consumes more time. With the increase in latest technology in deep learning techniques like convolutional neural networks (CNNs) and other methods has increased the accuracy of detection of Melanoma skin cancer detection. This Research paper presents an approach which uses DenseNet-121 for classification of skin lesions into malignant and benign for binary categories. This methodology also employed transfer learning, data augmentation, and optimization techniques which helps in improved classification performance. The Proposed model achieves accuracy of 91%, Precision: 0.89, Recall (Sensitivity): 0.91, F1 Score: 0.90 on a custom dataset, that helps automating procedures that helps for assisting dermatologists in diagnosis and Treatment. This demonstrates a high performance in contrast to the performance of other cutting-edge networks. As a result, the proposed Deep Learning technique provide a less complex and more cutting-edge model pertaining to automatic detection and identification of melanoma skin Cancer, hence this method increases the likelihood of successfully saving a Person life.

The main aim of this research is to enhance binary skin cancer classification by using transfer learning with DenseNet-121, optimizing the hyperparameters, and applying data augmentation techniques to achieve robust and Accurate performance.

## I. INTRODUCTION

According to the World Health Organization (WHO), nearly 75% of the global population is affected by skin cancer, with the majority suffering from melanoma. Early detection and treatment are crucial for saving lives, particularly in aggressive forms of skin cancer like melanoma. Dermatologists typically rely on dermoscopic skin lesion analysis to identify and diagnose malignant skin lesions. However, this manual process can be prone to diagnostic errors. To reduce these errors, there is a growing need for automated systems that leverage machine learning algorithms, providing a more accurate and reliable tool for enhancing the diagnosis of dermatological lesions.

Melanoma is a particularly serious type of skin cancer that, if left untreated after it is detected, can spread to other areas of the body. It occurs when UV light damages DNA, which may cause the melanocyte cells to multiply out of control. It ranks 19th overall and is the 19th most common type of cancer in both men and women. In 2018, there were more than 3,000 new cases recorded. The ugly duckling sign and the ABCDE approach (asymmetry, border, color, diameter, and evolving) can be used to identify melanoma signs and indicators [1]

The process of maximizing decision support in the biomedical field is difficult, but many research communities are working to provide long-term solutions, including image processing, ROI extraction, attribute-based categorization using machine learning approaches, and much more. These methods have established a narrow validation support for the classification of skin cancer. Based on robust and random feature computation, we have presented a novel method in this research study for classifying and categorizing skin cancer. The suggested method is predicated on using attribute-feature mapping to identify ROI. These methods have produced encouraging outcomes for the categorization of skin cancer.

In the United States, melanoma skin cancer (MSC) is a common malignancy. Because MSC is a form of cancer that spreads, it leads to a greater infection rate. In a recent report, the World Health Organization (WHO) mentioned the growing worries regarding the form of skin cancer. Skin cancer and melanoma affect four out of ten US individuals. The American Academy of Dermatology (AAD) reports that 9500 Americans receive a skin cancer diagnosis every day. Medical infrastructure is probably being strained by the rising infection rate and complexity of treatment. Skin cancer is typically the 17th most prevalent type of cancer in the globe. Diagnosis and consultation are time-consuming and complicated processes. Delays in diagnosis and detection can result in false positive

[1] Research Scholar, SoET, CMR University, Bangalore, India

[*] Sr. Assistant Professor, Department of ECE, New Horizon College of Engineering, Bangalore, India. hamsalekha20@gmail.com

[2] Professor, ECE and DORI, CMR University, Bangalore, India, drglan.d@cmr.edu.in

[3]Associate professor, School of CSE, REVA university, Bangalore, India. ty.satheesha@reva.edu.in

* Corresponding Author Email: hamsalekha20@gmail.com

decisions in a number of situations. Existing trained models are used to filter the numerous diagnosis and skin cancer pattern variables that are produced.

A biopsy, a medical procedure used to identify skin cancer based on symptoms and characteristics, is performed to determine the precise stage of infected cells and determine whether the cancer is a tumor or an early stage. However, this type of surgery is also quite costly and inappropriate for older patients. There is a 92% probability that skin cancer can be cured if it is discovered early. A sophisticated autonomous diagnostic model is needed to streamline the process and achieve effective accuracy. This study's goal is to identify skin cancer by utilizing the cutting-edge methods of deep learning and neural networks to reach a conclusion with high accuracy. [Amit research]

In this study, we proposed a pre-trained DenseNet-121 Deep learning architecture, which is fine-tuned for binary classification of skin lesion images between benign and malignant skin lesions. Transfer learning reduces the requirement for a big dataset by adapting the general image recognition capabilities of the pre-trained network to the skin lesion domain. We employ optimization and data augmentation strategies to further enhance the model's performance. Our findings highlight the potential of deep learning in clinical applications by showing great accuracy in differentiating between benign and malignant tumours.

## II. Literature Review

Machine learning techniques, including deep learning models, have seen a significant rise in their application for analyzing medical images. Numerous key studies have concentrated on automating skin cancer detection using convolutional neural networks (CNNs).

Satheesha TY et. al., [1] proposed a novel Deep Convolutional Neural Network (DCNN) model specifically designed for classifying melanoma from input images. The system assists in distinguishing between malignant and benign lesions and emphasizes the importance of DCNNs in dermatology for achieving efficient results. The structure of the DCNN is intentionally designed to be lighter and simpler compared to existing methods, making it more suitable for practical applications in healthcare settings.

Luigi Di Biasi et. al., [2] introduced a hybrid architecture for melanoma detection and classification with Dataset modifications that improved classifier performance. The Performance of GoogleNet Algorithm performed robustly and to improve training and Performance Distributed architectures can be employed.

Mr. B. Sreedhar et. al., [3] showed that Early detection of skin cancer improves diagnosis performance and survival rates. AI based Automated diagnosis techniques helps in improved analysis accuracy of skin cancer. There are different image processing techniques are used for melanoma detection

Krishna Mridha et. al., [ 4] Developed a methos that performed as an optimizer such as CNN for skin cancer classification. Their study showed 82% of classification accuracy along with 0.47% loss accuracy on HAM10000 dataset employed for training and evaluation. They also Implemented data augmentation process to increase dataset size. Employed Grad-CAM technique for model interpretability. They also Proposed a smart healthcare system through Android application.

Seeja R D et. al., [5] proposed the U-Net algorithm, that achieved 77.5% Dice co-efficiency for image segmentation. SVM classifier was employed to produced 85.19% accuracy in melanoma skin cancer classification. SVM classifier performed best in classifying and obtained good accuracy and F1 score.

Vigneswaran Narayanamurthy et. al., [6] proposed a Skin cancer diagnosis that depend on non-invasive techniques. They also employed High-resolution imaging tools that helped in capturing skin lesions.

H. L. Gururaj et. al., [7] said Early detection of skin cancer is very important for effective treatment. Deep learning methods like Convolutional Neural Networks (CNN) performed good in skin lesion Analysis and classification. They used the dataset that consists of 10,015 skin lesion images. model performance was improved significantly by employing

T. Y. SATHEESHA et al. [8] proposed a 3-D skin lesion reconstruction technique by analysing the estimated depth obtained from regular dermoscopic images. On basis of the 3-D reconstruction, depth analysis and 3-D shape features were extracted.

Ruchi Mittal et. al., [9] used DermCDSM to enhance skin disease detection and classification accuracy. Employed Chameleon Swarm Optimization technique that optimized segmentation processes. This model showed superior performance on the ISIC 2017 dataset.

Shahbaz Sikandar et. al., [10**]**: proposed a SCDet technique, which identifies tiny tumours with maximum precision. SCDet outperforms VGG16, AlexNet, and SqueezeNet in accuracy. SCDet consumes fewer resources during training than pre-trained models.

Muhammadinranfaizi et. al., [11] proposed a model that Utilized normalized cross-correlation-based k-means clustering for segmentation.

Hassan Ashraf et. al., [12] Proposed a hybrid method that is combination of Utilized UNet, ResUNet, and ResUNet++ models for segmentation

E.D.Rosha et. al., [13] proposed a Truncate threshold segmentation, that effectively separates skin cancer lesions from normal skin.

Current research introduces an innovative method for Melanoma Skin Lession classification task, DenseNet-121- A Deep learning Technique and data augmentation to improve performance in a Melanoma Skin Lesion classification task. This approach proves effective for Melanoma Skin cancer Detection at its early stages.

## III. DATA ANALYSIS

### *3.1 Dataset*

In the research, we have used the custom dataset which was obtained from a clinical source and organized into two categories: Benign Lesions and Malignant Lesions. The dataset consists of 2,000 images, with 1,500 images used for training and 500 images for testing.

### *3.2 Data Processing*

Since the Dataset relatively small in size, transfer learning and data augmentation was employed to improve the generalization of the model. Then the images were resized to 224x224 pixels in size, in order to match with the input requirements of the DenseNet-121 architecture. Later Augmentation techniques like random cropping, horizontal flipping, and color normalization methods were used to increase the dataset's size and variability of the original Dataset image. In Normalization, The Input images were normalized with the mean and standard deviation of the ImageNet dataset. Then the input images were Resized and Cropped according to the requirements. Finally Horizontal Flipping is performed in order to prevent the model from overfitting. The Process of Data augmentation is only applied, to the training Data set, while the test set remains in original form.


**Figure 1.** Data Processing

### *3.3 DenseNet-121 architecture*

Each convolutional layer of a conventional feed-forward convolutional neural network (CNN), with the exception of the first one, which receives input, gets the output of the preceding convolutional layer and creates an output feature map, which is subsequently sent to the subsequent convolutional layer. As a result, there are 'L' direct connections for 'L' layers, one between each layer and the one after it.

However, the 'vanishing gradient' issue appears as the CNN's layers grow in number, or as it becomes deeper. This implies that certain information may "vanish" or be lost when the information pipeline from the input to the output layers lengthens, which lowers the network's capacity for efficient training.

By altering the conventional CNN architecture and streamlining the connectivity pattern across layers, DenseNets address this issue. The name Densely Connected Convolutional Network comes from the fact that every layer in a DenseNet architecture is intimately connected to every other layer. There are L(L+1)/2 direct connections for 'L' layers.

There are four Average Pool layers, one 7x7 Convolution, 58 3x3 Convolution, 61 1x1 Convolution, and one Fully Connected Layer in DenseNet-121. Compared to their conventional CNN or ResNet equivalents, DenseNets have achieved state-of-the-art performances and better outcomes across competing datasets because they require fewer parameters and permit feature reuse, resulting in more compact models. The figure 2 shows the General block diagram of Densenet-121 Architecture

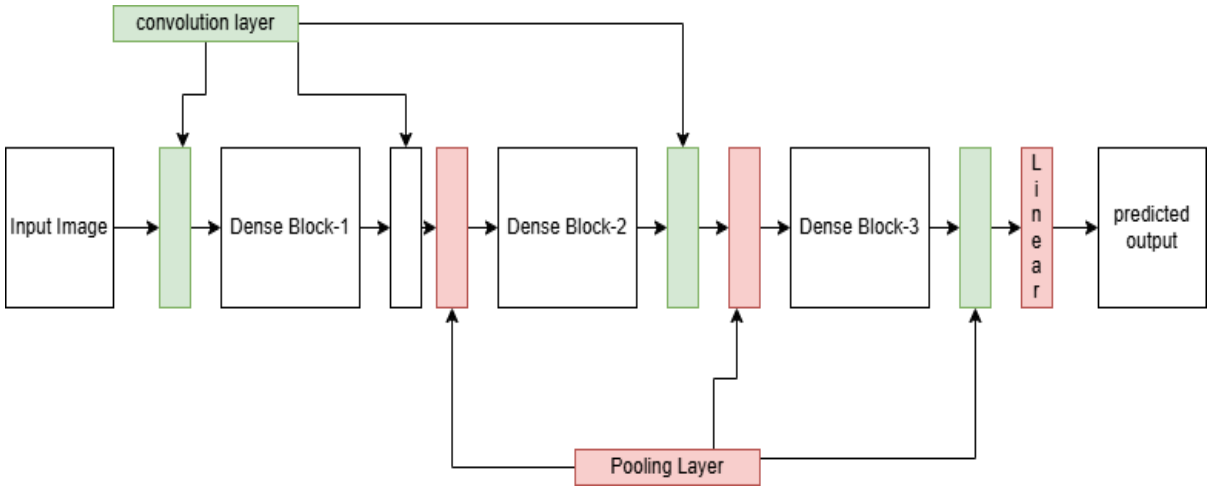


**Figure 2.** General block diagram of Densenet-121 Architecture

## IV. PROPOSED METHODOLOGY

The layers of DenseNet-121 include one 7x7 convolution, 58 3x3 convolution, 61 1x1 convolution, four average pool, and one fully connected layer.

We employ the DenseNet-121 architecture, a cutting-edge convolutional neural network renowned for its deep structure and effective feature reuse, for feature extraction and classification. The model can capture a wide range of features thanks to DenseNet's densely connected layers, each of which receives inputs from all layers before it. In order to reduce the number of parameters and increase computational performance, the design is composed of four thick blocks connected by transition layers. Feature maps are transferred directly between levels. The ImageNet dataset, which comprises millions of photos from different categories, is used to pre-train the DenseNet-121 model. Our transfer learning methodology is based on this pre-trained model. Figure 3 shows Block Diagram of Proposed Methodology.

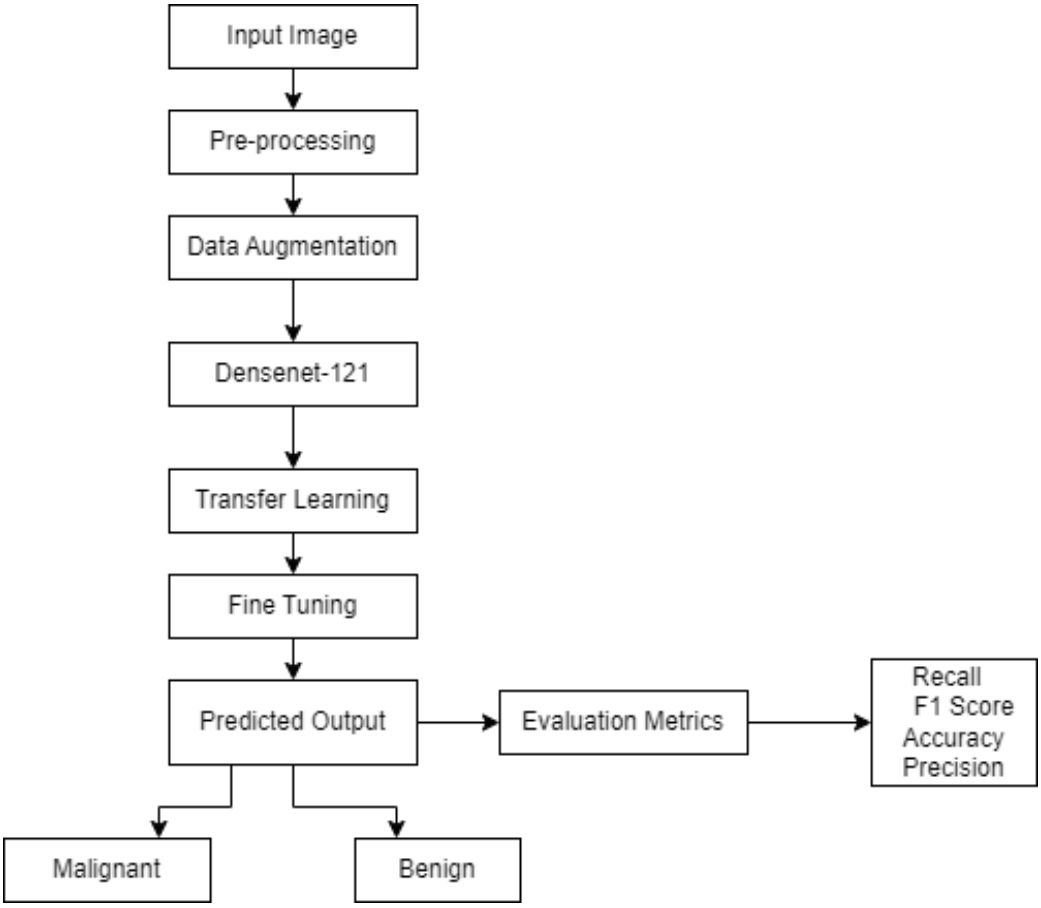


**Figure 3.** Block Diagram of Proposed Methodology

### *4.1 Transfer Learning with DenseNet-121*

Prior to being refined on the skin lesion dataset, the DenseNet-121 model was pre-trained on ImageNet. A new layer specifically designed for our binary classification task took the place of the last completely connected layer. In particular, a single-layer fully connected (FC) network with two output neurons—corresponding to benign and malignant classes—replaced the original DenseNet-121 classifier, which had 1,000 output neurons (for ImageNet's 1,000 classes).

To speed up convergence, we used stochastic gradient descent (SGD) with momentum (0.9) when training the model. The model was trained over 12 epochs with a learning rate of 0.001. The error between the predicted and actual labels was computed using the cross-entropy loss. PyTorch was utilized for both training and evaluation.

Transfer learning is a most important method that, uses a model that has already been trained on a huge dataset for a new task with a smaller amount of data. Here, the DenseNet-121 model has already learnt rich, low-level picture properties like edges, textures, and patterns because it was pre-trained on ImageNet. We may apply these attributes to our objective of classifying medical images.

The steps for transfer learning are as follows

1. Freeze the Early Layers: To preserve the pre-trained characteristics that are helpful for general picture recognition, the DenseNet-121 model's initial few layers are frozen. A fixed feature extractor is what these frozen layers do.
2. Adjust the Classifier: ImageNet's 1,000 classes are intended for the original DenseNet-121 classifier. We substitute a new classifier designed for binary classification (benign vs. malignant) for the last fully linked layer. A fully connected layer with two output units (representing the two classes) and a softmax activation function to produce class probabilities are features of the updated classifier.
3. Fine-tuning: To adjust the weights of the top layers of the DenseNet-121 model, we unfreeze them after swapping out the classifier. The model can adjust the learned features to the particular domain of skin cancer diagnosis by fine-tuning. To avoid making abrupt changes to the pre-trained weights, we fine-tune at a slower learning rate.

## V. RESULTS AND DISCUSSIONS

The model was Evaluated by using accuracy, precision, recall (sensitivity), and F1-score, as well as visualizations like the confusion matrix and ROC curve. The proposed model showed good generalization from the training set to the test set, achieving 93% training accuracy and 91% test accuracy. The confusion matrix provides a detailed breakdown of classification performance, showing correct and incorrect predictions across benign and malignant classes. The model showed minimal confusion between the classes, with the following metrics: Precision- 89%, Recall (Sensitivity): 91%, F1-Score- 90%, Accuracy- 91%.

**Precision** is defined as the ratio of true positive predictions to the total predicted positives.

**Recall (Sensitivity)** tells the ratio of true positive predictions to the total actual positives

**F1 Score**: The harmonic mean of precision and recall, providing a balanced measure of model performance.

**Confusion Matrix**: gives us a detailed breakdown of true positives, false positives, true negatives, and false negatives.

The evaluation also include ROC (Receiver Operating Characteristic) curve analysis which is used to measure the model's performance across various thresholds.

The Receiver Operating Characteristic (ROC) curve and the area under the curve (AUC) were computed to evaluate the model’s performance at various classification thresholds. The AUC was found to be 0.97, indicating a strong ability to differentiate between benign and malignant cases.

The DenseNet-121 model performed favorably, particularly in handling data augmentation and improving feature extraction through its dense connections. The test accuracy of 91% surpasses traditional CNN models trained from scratch. The model shows the accuracy of 93% using training Phase and Accuracy of 91% during testing Phase. Figure 4: plot of Accuracy vs Epoch and Training Loss Vs Epoch.

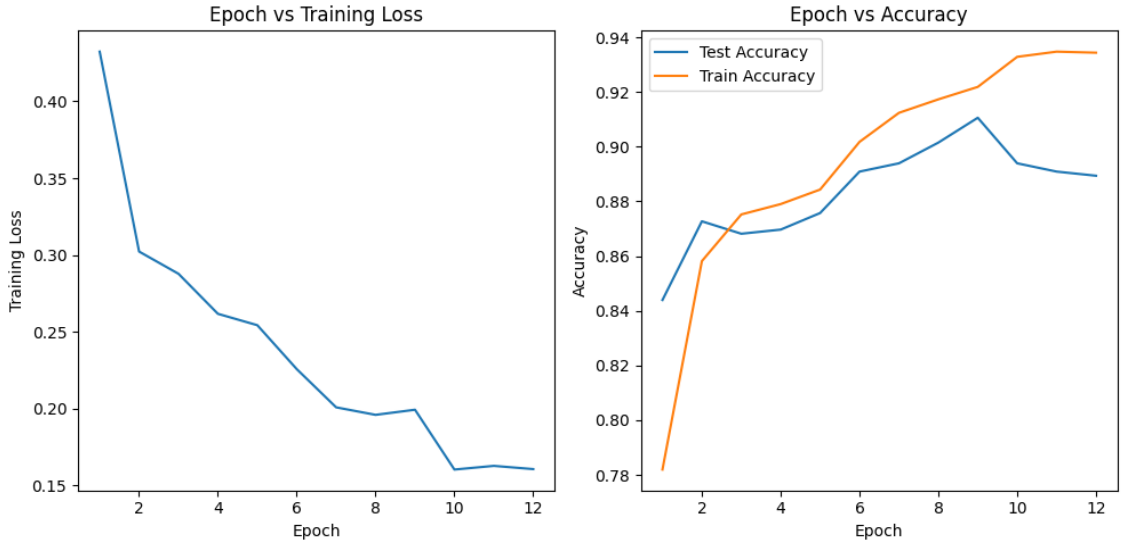


**Figure 4.** plot of Accuracy vs Epoch and Training Loss Vs Epoch

## VI. CONCLUSION

This research demonstrates the potential of using DenseNet-121 and transfer learning for binary classification of skin lesions. By utilizing data augmentation and optimization techniques, the model achieved high accuracy and generalization, even with a relatively small dataset. The use of transfer learning significantly reduced the computational burden and training time while maintaining robust performance. Future work could explore multiclass classification (e.g., melanoma, basal cell carcinoma) and address class imbalance using advanced techniques such as Synthetic Minority Over-sampling Technique (SMOTE).

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