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CLASSIFICATION OF SKIN CANCER USING DEEP NEURAL NETWORK WITH MOBILENET

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Abstract: The classification of skin diseases has become essential in contemporary healthcare, necessitating precise and effective approaches. While many different neural network and machine learning models have been used, overfitting and poor accuracy are common problems with them. This study suggests a method using Convolutional Neural Network (CNN) models to overcome these issues.
We use the ISIC 2019 dataset, which has inherent imbalances but is a well-known resource in the field. We guarantee the dataset's equilibrium by using threshold balancing techniques. Using the MobileNet model in conjunction with regularization and data augmentation methods, we obtain an impressive 97% accuracy.
Furthermore, we create a web application to make things easier for people to access and utilize. By making it easier for people to evaluate their skin condition, this platform improves access to healthcare resources. Our method encourages the development of accessible healthcare solutions while also improving the classification accuracy of skin diseases.
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***Index Terms*—Skin Disease Classification , Convolutional Neural Network , ISIC 2019 Dataset, Data Augmentation,MobileNet**

I. INTRODUCTION

The classification of skin diseases has grown in importance in the field of medicine in the modern period. On the other hand, overfitting and decreased accuracy rates have been identified as problems associated with this task's dependence on machine learning and neural network models. This research suggests a novel method that makes use of Convolutional Neural Network (CNN) models to handle these problems.

Our study attempts to address the difficulties in skin illness classification, much as steganography provides a solution for information security concerns by hiding dangerous data behind ostensibly innocent cover media, such as photographs. We concentrate on using the ISIC 2019 dataset, which is a popular resource in this field but has imbalances by nature. By using careful dataset balancing methods, we guarantee the equilibrium required for precise classification.

Moreover, we improve the mobility of the MobileNet model—a keystone of our methodology—by taking cues from the idea of data augmentation and regularization techniques. Similar to a key component of photo steganography, the MobileNet model is essential to our quest for precise skin disease

classification.
Therefore, this research explores the complexities of classifying skin diseases and emphasizes the value of using sophisticated neural network models, such as MobileNet, in healthcare applications.

II. LITERATURE REVIEW

Different scholars have looked into a range of classification techniques for skin diseases. These approaches are categorized in this part according to the datasets that were utilized, the feature extraction and selection techniques, and the classification algorithms that were applied. The review that follows summarizes a number of important studies, emphasizing their approaches and resources while also identifying current research needs.

Using fuzzy clustering and wavelet analysis, among other image processing techniques, Jagdish and colleagues developed a framework for the diagnosis of skin diseases. The framework was evaluated on a dataset of fifty photos, and the classifiers used were K-Nearest Neighbor (KNN) and Support Vector Machine (SVM). Their results showed that KNN outperformed SVM in terms of performance, recognizing two distinct skin disorders with an accuracy of 91.2% [9].

Naeem and colleagues developed an algorithm that predicts skin cancer by combining feature extraction with the GLCM approach with image processing to improve image quality and lower noise. To distinguish between benign and malignant tumors, they used SVM [10].
In order to further improve it into an ensemble deep learning strategy, Kalaivani et al. presented a novel approach that combined two distinct data mining techniques. Their approach successfully divided skin disorders into seven different categories when it was applied to the ISIC2019 dataset [12].

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A diagnostic model for skin diseases such psoriasis, acne, melanoma, and cherry angiomas was created by AlDera and colleagues. They used Gabor, Entropy, and Sobel filters in Otsu's technique for picture segmentation and feature extraction. SVM, Random Forest, and K-NN were among the classifiers they examined; the results showed accuracies of 90.7%, 84.2%, and 67.1%, respectively [13].

III.METHODS

1. Dataset Description and Processing

1.1 Initial Dataset Overview

The original dataset, which includes a variety of skin lesions, was gathered in order to investigate the automated classification of dermatological disorders through the application of machine learning techniques. There is a notable imbalance in the dataset among the eight categories, which are as follows along with the corresponding sample counts:

Melanocytic nevus: 12,875
Melanoma:4,522
Basal cell carcinoma: 3,323
Benign keratosis:2,624
Actinic keratosis: 867
Squamous cell carcinoma: 628
Vascular lesion: 253
Dermatofibroma: 239

Because of the uneven presence of classes, this imbalance makes it difficult to train machine learning models effectively because it can result in biased predictions that favor the majority class.

1.2 Addressing Class Imbalance via Resampling

We used an undersampling technique to solve the problem of class imbalance and make sure the model learns to accurately identify and distinguish between all forms of skin lesions. By lowering the number of samples in the overrepresented classes to equal the counts of the underrepresented ones, this technique seeks to balance the dataset, with a particular focus on achieving an equal class distribution where practical. The following adjustments were made to the resampled dataset sizes for each class:

Basal cell carcinoma: Reduced to 867 samples
Melanocytic nevus: Reduced to 867 samples
Actinic keratosis: Maintained at 867 samples
Benign keratosis: Reduced to 867 samples
Melanoma: Reduced to 867 samples
Squamous cell carcinoma: Maintained at 628 samples

1.3 Methodology of Resampling

In order to carry out the undersampling process, samples from the majority classes were randomly chosen without replacement until each majority class's size equaled the predefined target minority class count. This method improves the model's ability to generalize across less common diseases and helps to reduce potential bias towards more often occurring lesions.

2.ResNet50:

A deep neural network architecture called ResNet50 is well-known for having 50 layers, including residual learning capabilities. When skip connections—also known as residual connections—are introduced, training deeper networks advances significantly. Even with very deep networks, these connections help to mitigate the problem of vanishing gradients, resulting in better training results.

Residual blocks are the main building block around which ResNet50 is constructed. The intermediary layers in every block are made to learn a residual function related to the block's input. ResNet50 consists of four stages, each of which processes three-channel inputs that meet a minimum size multiple of 32.

To set up the later layers, the design starts with a 7x7 convolution and then moves on to a 3x3 max-pooling phase. Three residual blocks, with three layers within each block, make up each stage of the network. One 1x1, three 3x3, and once more 1x1 convolutions make up these. One of the most important functions of the 1x1 convolutions is to manage the computational load by first reducing the dimensions and then restoring them. As a bottleneck, the 3x3 convolution operates on reduced dimensions to enhance efficiency.

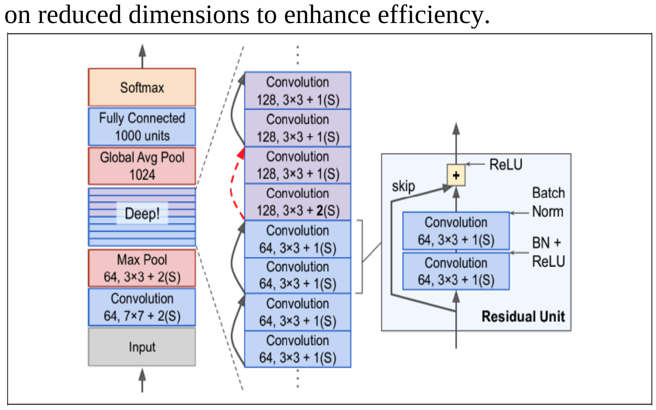

Fig:ResNet50 Architecture

3.AlexNet:

In the realm of deep learning, AlexNet is a groundbreaking architecture that had a big impact on convolutional neural networks' (CNNs) development. AlexNet was developed to tackle the ImageNet Large Scale Visual Recognition Challenge (ILSVRC) and was first presented by Alex Krizhevsky, Ilya Sutskever, and Geoffrey Hinton in 2012. It significantly decreased the error rate when compared to the state of the art, showcasing the potential of deep neural networks in computer vision tasks.

Eight layers make up AlexNet: three fully linked layers and five convolutional layers. An RGB image with a fixed size of 227 by 227 is fed into the network. Rectified Linear Units, or ReLUs, are used in the design as the activation function. This was a significant innovation at the time and sped up the

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training process by addressing the issue of vanishing gradients.

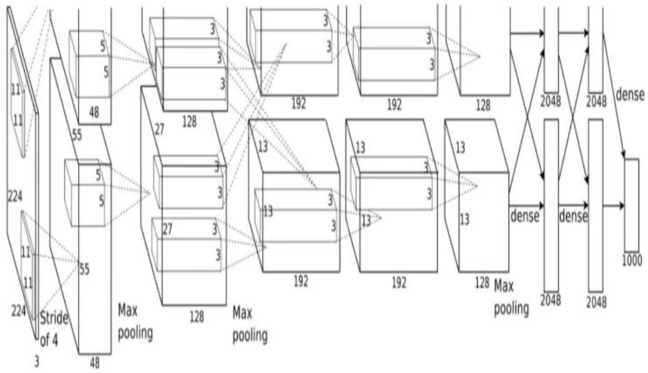

Fig: AlexNet Architecture

4.MobileNet

Convolutional neural network (CNN) architecture that is specifically designed for mobile and embedded vision applications is called MobileNet. MobileNet, which was first presented by Howard et al. in 2017, is perfect for contexts with limited resources since it balances model efficiency, computational performance, and accuracy.

MobileNet's inventive use of depthwise separable convolutions is the key to its efficiency. The depthwise convolution and pointwise convolution phases of the conventional convolutional operation are separated out in this method. In order to capture spatial information inside each channel, the depthwise convolution independently applies a single convolutional filter to each input channel. Then, employing 1x1 convolutions, the pointwise convolution aggregates the outputs of the depthwise convolution across channels, therefore lowering the computational complexity without sacrificing representational capacity.

Pointwise convolutional layers are dotted across a sequence of depthwise separable convolutional layers that make up MobileNet's architecture. When compared to conventional convolutional architectures, this arrangement enables MobileNet to achieve significant reductions in both the number of parameters and calculations. Additionally, MobileNet adds two new hyperparameters that allow users to adjust the width and input resolution of the model, respectively: the width multiplier and the resolution multiplier. By varying these hyperparameters, MobileNet becomes extremely flexible in meeting the demands of a wide range of applications by allowing trade-offs between model size, accuracy, and computational performance.

Input	Operator	t	c	n	s
$224^2 \times 3$	conv2d	-	32	1	2
$112^2 \times 32$	bottleneck	1	16	1	1
$112^2 \times 16$	bottleneck	6	24	2	2
$56^2 \times 24$	bottleneck	6	32	3	2
$28^2 \times 32$	bottleneck	6	64	4	2
$14^2 \times 64$	bottleneck	6	96	3	1
$14^2 \times 96$	bottleneck	6	160	3	2
$7^2 \times 160$	bottleneck	6	320	1	1
$7^2 \times 320$	conv2d 1x1	-	1280	1	1
$7^2 \times 1280$	avgpool 7x7	-	-	1	-
$1 \times 1 \times 1280$	conv2d 1x1	-	k	-	

Fig: MobileNet Architecture

IV.PROPOSED MODEL

Dataset Preprocessing:

To begin our skin illness classification project, we download the ISIC 2019 dataset, which consists of pictures of eight different skin conditions. But seeing that the dataset is inherently unbalanced, we use threshold balancing and divide it into six balanced classes, each enhanced by 867 examples. Additionally, we use picture preparation techniques, downsizing all photographs to a fixed dimension of 64x64x3, to standardize the input data and guarantee uniformity. Preprocessing lays a solid basis for later model training by ensuring uniformity throughout the dataset and facilitating computational efficiency.

Basal cell carcinoma: Reduced to 867 samples
Melanocytic nevus: Reduced to 867 samples
Actinic keratosis: Maintained at 867 samples
Benign keratosis:Reduced to 867 samples
Melanoma: Reduced to 867 samples
Squamous cell carcinoma: Maintained at 628 samples

Model Training:

We choose the MobileNet architecture, which is well-known for its effectiveness in picture classification problems, as the central component of our classification work. After splitting our dataset into training and validation sets, we use the preprocessed photos to train the MobileNet model. We use data augmentation approaches to increase the diversity of our training data during the training process, which helps the model generalize to new examples. Additionally, we incorporate regularization approaches into our training pipeline to prevent overfitting and improve model robustness.

Evaluation and Model Selection:

We use the validation set to rigorously evaluate our classifier after it has been trained on the model. We determine the quality of our model's classification of skin diseases by carefully examining accuracy metrics and performance indicators. We also investigate other architectures, such

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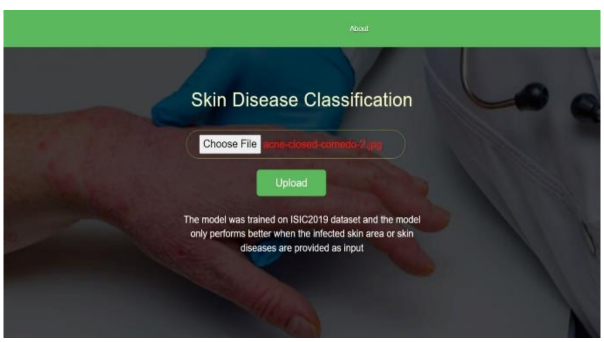
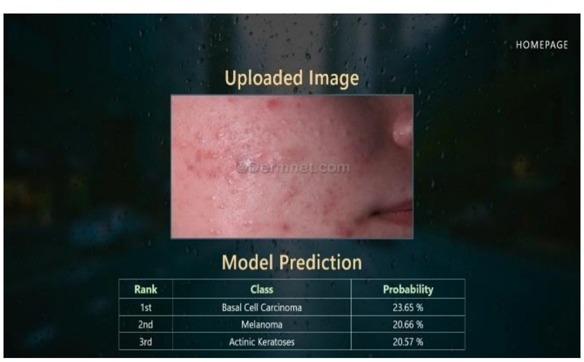
ResNet and AlexNet, in order to compare their respective performances and choose the best model for implementation.

Web Application Development:
In addition to our strong classification model, we are developing an intuitive web application to enable anyone to obtain a skin health assessment. We create a user-friendly and accessible platform by using Flask for backend implementation and JavaScript for frontend development. Users can easily upload skin photos for disease classification through the web application interface, which closes the distance between patients and healthcare resources. When a user uploads an image, the web application uses a trained model to assess the input and quickly provides the user with the skin disease diagnosis.

Deployment and Accessibility:
The web application is deployed to enable global accessibility after extensive development and testing. The application is accessible to users from any device with an internet connection, making dependable diagnostic tools easily accessible. Our implemented solution encourages proactive skin health management and advances inclusion in healthcare accessible by giving users the tools to obtain accurate diagnoses and make knowledgeable decisions about their skin health.





V.CONCLUSION
Skin illness classification is a comprehensive strategy that promotes proactive skin health management and improves healthcare accessibility. Through threshold balancing, we have effectively rectified the underlying imbalance in the ISIC 2019 dataset, guaranteeing fair representation across six balanced classes. Through the application of preprocessing techniques and standardizing image dimensions, we have established a strong basis for training the model.
Our use of the MobileNet architecture, together with regularization and data augmentation methods, has produced a very accurate classification model that can accurately identify a wide range of skin conditions. We have chosen the most successful model for deployment after conducting a thorough review and comparative study. This model yields 97% accuracy and ensures optimal performance in real-world circumstances.
A user-friendly web tool that bridges the gap between people and healthcare resources is being developed to further democratize access to skin health assessments. We have developed a user-friendly portal that allows users to easily input skin photos and get timely classification results by utilizing JavaScript and Flask.

Our web application guarantees global accessibility upon implementation, allowing customers to access trustworthy diagnostic tools from any internet-enabled device. Our approach encourages proactive management and diversity in healthcare accessibility by supporting well-informed decision-making about skin health.

All things considered, our project is a big step toward using cutting edge technologies to improve healthcare results and provide people the ability to take charge of their own wellbeing. We want to significantly increase the impact of our solution in enhancing skin health management on a worldwide scale through ongoing improvement and growth.

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