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Dermatoscopic Analysis of Skin Lesions

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***Abstract*— In a world witnessing an increase in skin cancercases, early identification is pivotal for improved treatment outcomes. Skin cancer, propelled by factors like increased sun exposure and evolving lifestyles, manifests in various types, each requiring tailored treatment approaches. With different types of skin cancer being either malignant or benign, it can become crucial to identify the type to prepare a roadmap for its treatment. Our approach underscores the critical need for under-standing and addressing skin cancer, emphasizing the importanceof early detection. It integrates machine learning and image analysis, enabling users to promptly identify and understand skinconditions through simple image capture. This project explores the development, implementation, and evaluation of machine learning models for skin cancer detection, emphasizing their potential to revolutionize early diagnosis.**

***Index Terms*— CNN, ResNet50, Inception Networks, HAM10000.**

I. INTRODUCTION

Skin cancer, a global health concern, is escalating due to factors like increased sun exposure, changing lifestyles, and environmental challenges such as ozone layer depletion. This research emphasizes the critical importance of early detection, which significantly improves treatment outcomes and survival rates. It seeks to harness advanced technology to revolutionize early detection and enhance treatment outcomes using machine learning approaches that play a central role, allowing rapid analysis of extensive data to identify subtle patterns and detect skin irregularities that may elude human observation. Beyond technological advancement, the project aspires to contribute meaningfully to healthcare outcomes by creating a future where improved detection methods are accessible to all, ultimately promoting a healthier society. The objectives of the research paper include the implementation of a tailored machine learning model for skin lesion diagnosis accurate differentiation between malignant and non-malignant skin pigments, reduction of manual effort through automation in clinical settings, and the enhancement of user experience through better data visualization techniques. The collaborative efforts of medical professionals, researchers, and the public are underscored as crucial in developing effective strategies for prevention, early detection, and treatment. The paper advocates for a holistic approach, recognizing the transformative role of machine learning in healthcare and envisioning a future where advanced technologies contribute to better chances of staying healthy in the battle against skin cancer.

II. RELATED WORKS

A. Traditional Image Matching Approaches

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In the previous decade, CNN-based approaches emerged as a breakthrough in computer vision. These approaches, including architectures like AlexNet, VGGNet, and ResNet, focused majorly on capturing spatial relationships and hierarchical features in images. Additionally, the survey shows that CNNs can be combined with Recurrent Neural Networks (RNNs) for image captioning, generating accurate descriptions. The paper "Convolutional Neural Networks for Image Classification and Captioning" [2] addresses the use of attention mechanisms to improvise image captioning by focusing on relevant image regions and incorporating contextual information. Evaluation is performed using benchmark datasets such as ImageNet and MS COCO, assessing accuracy, caption quality, and generalization capabilities. Although the pooling layers and spatial hierarchies solved the concerns regarding translation invariance and hierarchical feature representations, as networks get deeper, training becomes challenging due to the vanishing gradient problem.

The gradients diminish as they are back-propagated through layers, making it difficult for the network to learn effectively. This gives rise to the issue of overfitting data. The CNN model almost memorizes the training dataset, causing issues when it encounters a different image, and hence does not provide high testing accuracy.

Shifting the survey towards the field of skin cancer detection, "Skin Cancer Detection: A Review Using Deep Learning Techniques" described the global health concern of skin cancer by leveraging deep learning methods. The survey provided details of traditional diagnostic approaches, emphasizing the paradigm shift facilitated by deep learning in analyzing dermatoscopic images for early and efficient detection.

Next, "Modified Topological Image Preprocessing for Skin Lesion Classifications," introduces a novel preprocessing methodology based on a modified Topological Data Analysis(TDA) approach. This innovative technique aims to revolutionize the processing and analysis of skin lesion images, showcasing consistent performance enhancement through a comprehensive evaluation using advanced deep-learning architectures. Within the domain of medical image segmentation, the paper titled "A hybrid approach for improving U-Net variants in medical image segmentation" provided evaluations on existing U-Net variants such as MultiResUNet and Attention U-Net. The primary focus of this is on addressing challenges related to overfitting and increased inference time, proposing a hybrid approach that leverages depthwise separable convolutions. The objective is to maintain or improve segmentation performance, particularly in skin lesion segmentation tasks, while mitigating parameter-related complexities associated with U-Net variants utilizing attention systems and residual connections.

TABLE I A COMPARATIVE ANALYSIS OF SKIN CANCER DETECTION USING CNN-BASED APPROACHES

Skin Cancer Diagnoses	**Classifier and Training Algorithm**	**Dataset**	**Description**	**Results (%)**
Melanoma/benign keratosis/ melanocytic nevi/BCC/AK/IC/atypical nevi/dermatofibroma/ vascular lesions	Deep CNN architecture (DenseNet 201, Inception v3, ResNet 152 and InceptionResNet v2)	HAM10000 and PH2 dataset	Deep learning models outperformed highly trained dermatologists in overall mean results by at least 11%	ROC AUC (DenseNet 201: 98.79–98.16, Inception v3: 98.60–97.80, ResNet 152: 98.61–98.04, InceptionResNet v2: 98.20–96.10)
Melanoma/BCC/melanocytic nevus/Bowen's disease/AK/benign keratosis/vascular lesion/dermatofibroma	InceptionResNetV2, PNASNet-5-Large, InceptionV4, and SENet154	ISIC dataset	A trained image-net model was used to initialize network parameters and fine-tuning	Validation Score (76)
Melanoma/non melanoma	ResNet-50 with deep transfer learning	3600 lesion images from the ISIC dataset	The proposed model showed better performance than InceptionV3, Densenet169, Inception ResNetV2, and Mobilenet	Accuracy (93.5), precision (94) recall (77), F1_ score (85)

A. ResNet50

ResNet is a type of deep neural network architecture designed to address the vanishing gradient problem in very deep networks. ResNet introduces a novel approach to deal with the issue of vanishing gradient by using residual blocks. ResNet50, a variant of ResNet that encapsulates 50 layers, is composed of an initial convolutional layer, followed by multiple residual stages, each containing several residual blocks.

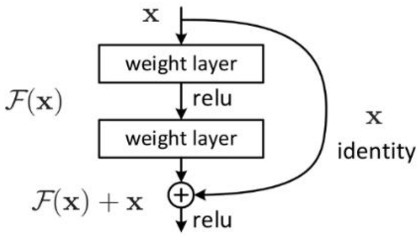

Figure 1 ResNet residual block implementation

The residual blocks utilize a bottleneck architecture with skip connections, and the network concludes with global average pooling and fully connected layers for classification. ResNet-50 is made up of several residual blocks, and its overall design may be broken down into several phases. A certain number of residual blocks exist in each stage; the quantity of blocks varies according to the network's total depth The building component of the 50-layer ResNet is designed like a bottleneck. A bottleneck residual block minimizes the number of parameters and matrix multiplications by using 1×1 convolutions, also referred to as a "bottleneck." This makes training each layer considerably faster.

B. Inception Networks

Inception Networks is a type of deep convolutional neural network designed to achieve high accuracy on image classification tasks while keeping the computational cost low. The Inception architecture achieves this by using a combination of convolutional layers with different filter sizes (1x1, 3x3, 5x5) and pooling layers to extract features from the input image at different scales. These insights are then combined, giving the network a holistic view of the image, from fine details to the bigger picture.
Inception Networks also use a technique called "dimensionality reduction" to reduce the number of parameters in the network and prevent overfitting, resulting in achieving state-of-the-art performance on a variety of image classification tasks while being computationally efficient.

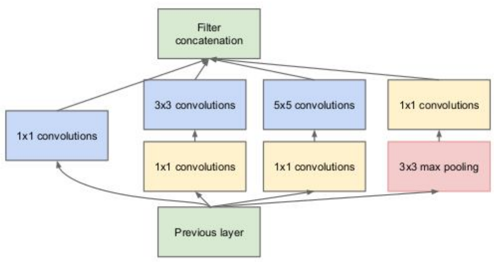

Figure 2 Architecture of Inception Networks

InceptionResNet-v2 is a hybrid model merging Inception and residual connections. It features a stem module, Inception-ResNet-A/B blocks, and a final layer. Each block includes 1x1, 3x3, 5x5 convolutions with shortcuts.

III. Inferences And Results

Our baseline approach involves utilizing a Convolutional Neural Network (CNN) architecture for robust skin cancer detection. The dataset underwent preprocessing to enhance features before being input into the CNN model, which incorporates multiple convolutional and pooling layers for effective feature extraction.
Encountering overfitting issues with the base CNN model as image dimensions increased, we increased epochs, exacerbating the problem. Recognizing this challenge, we shifted our approach to the ResNet variant of CNN, specifically ResNet50 with 50 layers and residual blocks. This choice aimed to address the vanishing gradient problem through skip connections. The ResNet model exhibited improved testing accuracy while maintaining alignment with training accuracy.
Additionally, we explored Inception Networks, which demonstrated exceptional performance. However, their computational demands emerged as a concern, particularly in resource-constrained environments or on less power.

A. Dataset

The datasets used to train the proposed model was the HAM10000 dataset. It contains 10, 015 dermatoscopic pictureswhich are divided into 7 categories, as shown below:

- *Melanocytic Nevi:* Abnormally dark birthmarks or molesthat are noncancerous.
- *Melanoma:* A type of cancer that begins in melanocytes,which are the cells that control skin pigments. Melanomais usually characterized by dark skin lesions.
- *Benign Keratosis-like Lesions:* Non-cancerous skin growths that are usually a waxy brown, black, or tan.
- *Basal Cell Carcinoma:* A type of cancer that usually develops on areas of skin exposed to the sun.
- *Actinic Keratoses:* Noncancerous, rough/scaly patch of skin caused by years of sun exposure.
- *Vascular Lesions:* Relatively common abnormalities of skin and underlying tissues. Commonly known as birth- marks.
- *Dermatofibroma:* Common, benign fibrous nodules mostcommonly found on women.

B. Parameters

There were different parameters on which we trained the models to get varying accuracy. We further made modifications as required to increase the accuracy of our mode.

TABLE II TRAINING PARAMETERS FOR DIFFERENT MODELS WITH VARYING SPECIFICATIONS

Model	**Specifications**	**Epochs**	**Training Accuracy**	**Testing Accuracy**	**Test Loss**
CNN	64 x 64 dimension	4	93.6	85.27	0.41
CNN	325 x 200 dimension	10	81.76	65.15	1.08
CNN	224 x 224 dimension	30	97.6	62.8	5.05
ResNet50	-	4	78.43	71.44	0.92
ResNet50	-	10	87.5	67.8	1.39
ResNet50	Used Focal loss with alpha = 0.25	10	85	68	0.19
ResNet50	Focal loss with alpha = 0.75	10	82.1	68.7	0.53
ResNet50	70-30 train test split	10	83.6	62.5	0.49
ResNet50	60-40 train test split	10	81.3	73.2	0.33
ResNet50	Implemented learning rate and Dropout (0.5)	30	78.1	77	0.63
ResNet50	Learning rate with initial = 0.001	30	92.5	81.92	0.5
ResNet50	Learning rate with initial = 0.0001	20	99.2	85.4	0.3
Inception Resnet-v2	299*299 image size Learning rate with initial = 0.01	36	96.70	90.88	0.47

A. Experimentation Results

Initially, we had started with a base CNN model, whichon reduced dimensions provided us with adequate testing accuracy. However, as we increased the dimension of theimages, the training accuracy was increasing, but the testing accuracy was not. After increasing the number of epochs, it had become evident that our model was overfitting the data, meaning that it was learning the training data too well, and unable to predict new, unseen images. Hence we had to shift our approach. We turned our attention to the ResNet variant of CNN, which implements a skip connection to solve the issue ofthe vanishing gradient. We have used ResNet50 for our project, which has 50 layers, with residual blocks. This model showed an increase in the testing accuracy, which was also in check with the training accuracy.

Furthermore, we explored InceptionNetworks which exhibited outstanding performance yet their efficacy came at the expense of demanding substantial com- putational power, posing challenges for resource-constrained environments or devices.

Effect of epochs: While in the CNN model, as we increased the number of epochs, the training accuracy increased significantly, however the testing accuracydeteriorated further, implying that the model was overfitting the data.

TABLE III EFFECT OF EPOCHS ON CNN TRAINING

Epochs	Training Accuracy(%)	Testing Accuracy (%)
10	81.76	65.15
30	97.6	62.8

Influence of focal loss: Focal Loss is a modification to the standard cross-entropy loss function, designed to address the problem of class imbalance. By implementing this loss function in contrast to the generic 'categorical cross-entropy', there was an unprecedented drop in the test loss for ResNet50 models. However, this had little effect on the accuracy of the models.

Effect of train-test split ratio: We had also tried to change the train-test split ratio from 80-20 to 70-30 and even 60-40, to see how it would impact the training and model accuracy. While the training accuracy was mostly unchanged, the testing accuracy had surprisingly increased.

TABLE IV EFFECT OF TRAIN-TEST SPLIT ON TRAINING AND TESTING ACCURACY

Train-Test Split	Training Accuracy(%)	Testing Accuracy(%)
80-20	82.1	68.7
70-30	83.6	62.5
60-40	81.3	73.2

Learning Rate variations: Learning rate is a hyperparameterthat determines the size of the steps taken during the optimization process of a model. It plays a critical role in controlling how quickly or slowly a model learns from the data. It consists of initial learning rate, decay steps and decay rate. Initial learning rate determines the rate at which learning will take place. Decay steps explains after how many iterationsthe learning rate will be reduced and decay rate is the rateby which it will reduce. The introduction of learning rateslows down the model training process, however a drasticchange was seen in the training and testing accuracy. At learning rate = 0.001, the training accuracy reached 92 % and at learning rate = 0.0001, it reached a staggering 99 %, while the testing accuracy also reached a record 85 %, indicatingthe best performing model yet.

IV. CONCLUSION AND FUTURE WORKS

Looking into the future, the project has a significant future scope in several aspects. The increasing demand for computational power can be addressed, necessitating efficient algorithms and hardware solutions to accommodate the growing complexity of dermatological image analysis. The ongoing refining and enhancement of the Convolutional Neural Network (CNN) model is required, leveraging advances in deep learning approaches and adding cutting-edge techniques such as transfer learning. The model's flexibility and dependability are ensured by the continual growth of the dermatoscopic image collection to include a larger spectrum of skin diseases and demographics.

Exploring real-time deployment in clinical settings for quick feedback during patient examinations and seamless connection with telemedicine systems resonates with the changing healthcare landscape. Furthermore, the initiative might progress into AI-assisted decision support systems, which would provide complete insights for treatment planning.

V. DISCUSSION

Initially we started by using the CNN model, as it is one of the most commonly used architecture for object detection. Due to its convolutional layers - which provide set of learnable filters on the input image, and pooling layers - which reduce the spatial dimensions of the feature maps generated, CNN provides a great base for object detection.

We trained the model by resizing our images, after preprocessing them, to 64x64 dimension for 4 epochs. The training accuracy was around 81.76% and testing accuracy was around 85%. However, this could not be considered as viable as the dimensions were significantly reduced.
Hence, we augmented the dataset to normalize the dataset and then we trained the model by resizing images to 325 x 200 (50% size of image). The training accuracy we got was around 81%, however the testing accuracy got reduced to 65%.
Later we used general dimensions of ResNet model (224 x 224) to train the images for 30 epochs. The training accuracy was a staggering 97%, however the testing accuracy was still around 63%.
This confirmed our hypothesis that our CNN model was over-fitting the data. Overfitting basically means that the model captures noise and irrelevant data during training and hence is unable to perform well to unseen data, hence we see no increase in testing accuracy, despite a significant increase in training accuracy.
This is when we decided to use ResNet50 model. ResNet50 prevents overfitting primarily through the use of skip connections, also known as residual connections. These connections allow the model to learn residual functions, capturing the difference between the input and the desired output. This mechanism facilitates the training of much deeper networks by mitigating the vanishing gradient problem.
Initially the training accuracy was around 80% mark and testing accuracy was around 68-70%. However, the testing loss was not reducing. This is when we decided to implement focal loss instead of categorical cross entropy loss. Focal Loss is a loss function designed to address the class imbalance problem. We implemented it for our model as our data was not evenly spread. If value of alpha is near to 1, the model focusses on less frequent classes and vice versa. After implementing focal loss, we saw a significant decrease in the test loss, hence we decided to move forward with focal loss.
However, we didn't see any significant increase in the testing accuracy. We further experimented by changing the train-test ratio to 7:3 and even 6:4, but even this only increase the testing accuracy by about 5% to 73-75%. We then decided to implement a Dropout layer as well, to further prevent overfitting of data. Dropout is typically applied after fully connected layers or convolutional layers to randomly drop a certain proportion of neurons during training.
Even after no significant increase in testing accuracy, we decided to implement learning rate. Learning rate is a hyperparameter that determines the size of the steps taken during the optimization process of a model. Using learning rate schedules, such as step decay, we can dynamically adjust the learning rate during training.
We used initial learning rate = 0.001 for 30 epochs. This helped increase our training accuracy to 93% and our testing accuracy reached 82%. This meant that the data was not being overfitted. After further decreasing the initial learning rate to 0.0001, our training accuracy reached a record 99% and our testing accuracy reached a new high of 85%.
In conclusion, this is how we optimized our model by applying multiple parameters and testing various methodologies and finally selected a model which performed well. of the Convolutional Neural Network (CNN) model is required, leveraging advances in deep learning approaches and adding cutting-edge techniques such as transfer learning. The model's flexibility and dependability are ensured by the continual growth of the dermatoscopic image collection to include a larger spectrum of skin diseases and demographics.

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