Skin Lesion Analysis Towards Melanoma Detection using Deep Learning

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***Abstract*—Skin diseases, constituting 40% of global cancer cases, persist as a prevalent and potentially perilous health concern, impacting 56 lakh peoples in the preceding annum.Programmed grouping of skin injuries, an enduring challenge due to their nuanced variability, finds promise within the realm of Deep Learning. This innovative approach, particularly employing Convolutional Neural Networks, explores the intricate scene of fine-grained picture based investigation, showcasing exceptional precision.The research unfolds across three pivotal phases: hearty information assortment and expansion, precise plan of model engineering. The culmination in predictions across seven distinct categories of the skin diseases—melanocytic-nevi, basal-cell-carcinoma, dermato-fibroma,melanoma-lesion,vascular-lesions, actinic-keratoses and benign-keratosis-lesions.**

Building upon this foundation, an advanced Transfer Learning Approach seamlessly integrates with PyTorch.These models are prepared start to finish straight-forwardly from pictures, not only to enhance scalability but as it may, early determination can likewise really diminish costs.The essential target of this exploration paper is to present painless evaluating for skin infections into routine practice, streamlining the diagnostic process. Through the fusion of cutting-edge technologies and innovative methodologies, the study envisions a paradigm shift, ushering in a new era where efficient and accurate screening becomes an integral part of routine healthcare practices.

Keywords—Melanoma, Deep Learning (DL),Convolutional Neural Networks(CNN),Batch Normalization, Visual Geometry Group-19 (V.G.G-19), Resnet-50, Densenet-121, Transfer Learning, Wide Resnet-101.

I. INTRODUCTION

The human skin serves as the intricate and resilient outermost barrier of the body, and serves as a multifaceted shield against environmental stressors, ranging from dust and pollutants to the relentless onslaught of UV radiation from the sun. Composing the epidermis and dermis, it is a complex matrix of connective tissues that regulates fluid balance and defends against microbial invaders.However, this perpetual exposure makes the skin susceptible to various disorders, with skin cancer emerging as a formidable adversary.

Skin cancer, marked by a malignant proliferation of cells in the dermal or epidermal layers, has the insidious potential to metastasize and pose life-threatening risks. Prolonged exposure to UV radiation, weakened immune systems, and fair skin complexion contribute to its escalating incidence, impacting millions globally. Within the spectrum of skin diseases, lesions play a pivotal role as diagnostic indicators, ranging from benign conditions like actinic keratoses to malignant lesions such as melanoma, non melanoma and other skin cancers.

The insidious nature of cancer lies in its ability to disrupt the body's immune function, underscoring the urgency for early detection and intervention. Despite commendable strides in skin cancer treatment, the average detection rate remains at 65% based on clinical judgment, necessitating a paradigm shift in diagnostic approaches. Enter the transformative potential of deep learning – a cutting-edge field characterized by its capacity to extract intricate patterns from vast datasets.

This research explores the convergence of deep learning and dermatology, focusing sharply on the characterization of skin lesions. By harnessing advanced ML techniques, we aim to develop a robust framework for early detection of skin lesions. This intersection of technology and dermatology offers a new frontier in the battle against skin cancer, providing practitioners with objective evaluations and enhancing their ability to make life-saving clinical decisions. In an era marked by unprecedented technological advancements, the marriage of deep learning and dermatology aims to bolster our ability to detect and combat this formidable adversary with greater precision and efficacy, ultimately contributing to improved patient outcomes and more effective treatments.

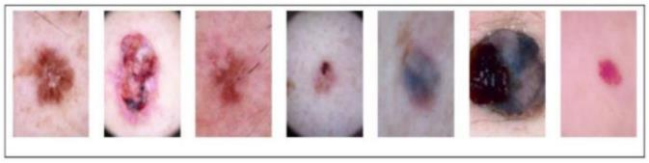

Figure 1: Types of Skin Lesions: Actinic Keratoses, Basal Cell Carcinoma, Benign Keratosis-like lesions, Dermatofibroma, Melanocytic Nevi, Melanoma and Vascular Lesions going from left to right.

II. LITERATURE REVIEW

Recognition and characterization of melanoma skin disease (MSC) through picture handling methods are fundamental for painless and proficient determination [1]. Alquran et al. (2022) present a strategy utilizing support vector machine (SVM) for this reason, accomplishing 92.1% precision through preprocessing, division, highlight extraction, and SVM arrangement.Different picture handling methods, including tissue counter examination and wavelet change-based models, have been explored for MSC identification [2]. SVM arises as a normally utilized characterization calculation because of its viability. The proposed technique by Alquran et al. offers equivalent exactness with diminished computational intricacy, promising functional application in determination.A profound learning-based approach is proposed for programmed skin sore division and order to upgrade melanoma conclusion precision [3]. Using convolutional brain organizations (CNNs) for division and component extraction, the strategy shows promising outcomes, particularly with SVM characterization. Past methodologies utilizing surface examination and wavelet techniques are talked about.The proposed PC supported demonstrative calculation uses profound brain organizations (DNNs) prepared on dermoscopy pictures to order threatening melanoma [4].

Dermoscopy upgrades perception by growing skin injuries. The man-made intelligence based approach accomplishes promising outcomes, highlighting the capability of simulated intelligence-driven frameworks in early discovery.Profound learning methods, especially CNNs, have shown guarantee in robotizing melanoma conclusion from dermatoscopic pictures [5]. This review proposes a two-stage order technique utilizing Cover R_CNN for sore restriction and ResNet152 for characterization. Critical upgrades in precision are illustrated, diminishing misdiagnosis rates.Utilizing CNNs, especially EfficientNet-B6, the review proposes a robotized model for examining skin sore pictures, accomplishing cutting edge execution [6]. Fruitful execution of move learning improves preparing proficiency. This exploration highlights the capability of CNNs in helping dermatological determination.

The examination proposes a strategy for programmed characterization of skin injury pictures into harmless or melanoma utilizing profound learning procedures [7]. The proposed philosophy includes picture pre-handling, division, and characterization utilizing CNNs, showing guarantee for fast melanoma discovery.The examination on skin malignant growth analysis involving CNNs for cell phone pictures tends to the basic requirement for available and exact demonstrative instruments [8]. Utilizing move learning and information increase strategies, the techniques show further developed execution, adding to propelling PC helped finding frameworks for skin disease.

III. PROPOSED WORK

The proposed framework is built upon a meticulously crafted architecture comprising five distinct modules: pre-processing, modeling, Deep Neural Network (DNN), model training, and deployment. This comprehensive framework, illustrated in Figure 2, has been intricately designed to seamlessly integrate and yield optimal outcomes. Notably unique in its approach, it undergoes rigorous testing utilizing five disparate models. Four of these models are bespoke modified transfer learning models developed using the PyTorch framework, while the fifth is a convolutional neural network (CNN) model meticulously trained from scratch.

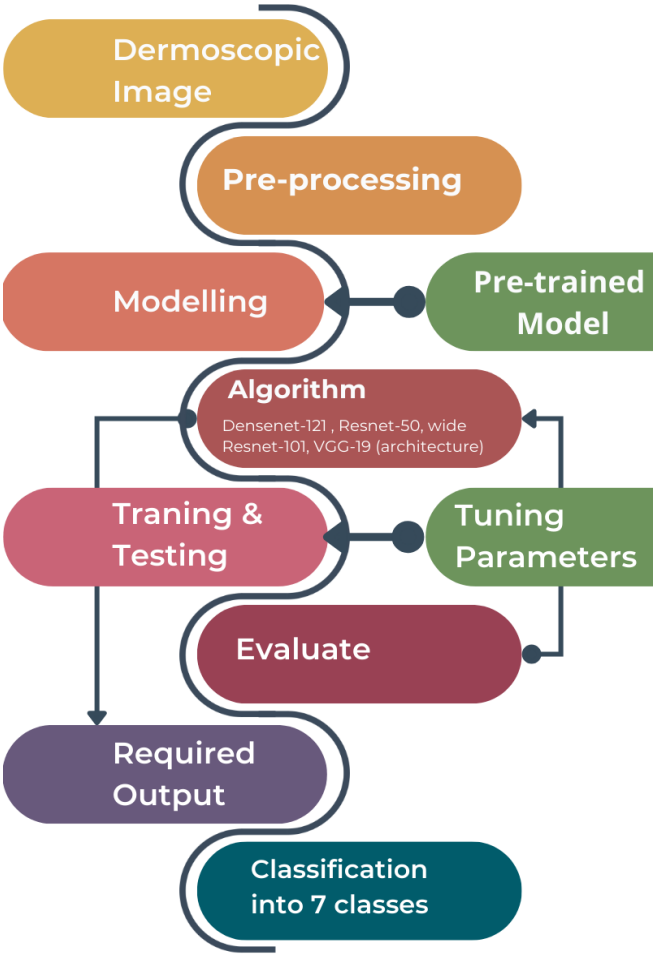

Figure 2: Diagram outlining the modeling procedure.

A. *Dataset*

The dataset utilized for training, known as "Skin Disease MNIST: HAM10000 (Human Against Machine with 10000 training images)," sourced from the "Harvard Dataverse," stands out as an invaluable resource.Featuring a vast array of 10,015 dermatoscopic images focused on pigmented lesions across seven distinct categories, it offers a diverse

representation of skin conditions. What sets this dataset apart is not only its size but also the meticulous validation process undergone by the lesions. Over half of the lesions have been histopathologically confirmed, ensuring a high level of accuracy.Additional instances were validated through follow-up evaluations, expert consensus, or confirmation via in-vivo confocal microscopy.This rigorous validation process guarantees the reliability and integrity of the dataset, making it a valuable asset for research and development in dermatology and artificial intelligence. Additionally, its rich variety of skin conditions facilitates robust training and testing of AI models for skin lesion classification tasks, enabling researchers and practitioners to develop more precise and efficient diagnostic tools, ultimately enhancing patient care and outcomes in dermatology.

B. Pre-processing

The preprocessing methodology employed aims to enhance the system's adaptability by reducing the number of steps while improving the modeling capacity when handling dermatoscopic images from diverse skin lesion datasets. This approach streamlines the preprocessing pipeline while ensuring effectiveness across various datasets. It applies standard preprocessing steps for transfer learning, focusing on three pivotal stages.

Firstly, duplicate images with the same lesion ID are removed from the dataset to maintain data integrity and reduce redundancy during training. This step is crucial for preventing bias and overfitting in the models. Following careful consideration of the split ratio,the dataset is partitioned into preparing and approval sets. For transfer learning models, a validation set ratio of 0.1 is utilized, while a ratio of 0.2 is used for the CNN model. This variation accounts for differences in model architectures and training requirements, optimizing model performance.

Image normalization is finally conducted by calculating the standard deviation and mean of values of the red, green, and blue color channels across the dataset, thus enabling the normalization of all images to a uniform scale, reducing bias and enhancing model robustness. This standardization process ensures that the models are trained on consistently formatted data, facilitating better integration and performance during training and inference.By prioritizing simplicity and effectiveness in preprocessing, this approach offers a distinct advantage in enhancing model adaptability and generalization across various skin lesion datasets. This streamlined preprocessing pipeline, coupled with careful parameter selection and standardization techniques, contributes to the overall efficacy and reliability of the proposed framework.

$$mean = \frac{1}{n}\left(\sum_{i=1}^{n} x_i\right) \quad (1)$$

$$std = \sqrt{\frac{1}{n}\left(\sum_{i=1}^{n}(x_i - mean)^2\right)} \quad (2)$$

Within the provided framework, addressing image noise is tackled through the implementation of augmentation techniques using the torchvision library.Incorporating rotations and horizontal & vertical flips, this function facilitates the augmentation of images within the training set, as depicted in Figure 3.

Additionally, adjustments to brightness, contrast, and hue are applied. The primary objective of augmentation is to foster network robustness, ensuring robust training that can produce accurate results even when confronted with suboptimal or unstable imaging conditions. This approach underscores a unique emphasis on preparing the models to effectively navigate real-world variability, thereby enhancing their performance and adaptability in practical dermatological applications.

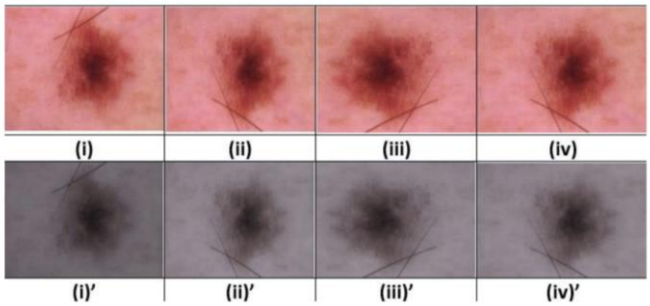

Figure 3: Preprocessed Images, after rotating, flipping and varying contrast, hue and brightness were fed-in to curtail biasing.

C. Modelling

Deep Learning Designs and Models customized specifically for categorizing skin lesions are explored in detail in this section. Furthermore, it offers a thorough evaluation of the underlying architectures of these networks, providing comprehensive insights for understanding their intricacies.

1. Convolutional Neural Networks

A Convolutional Brain Organization (CNN) [20] represents a sophisticated paradigm in deep learning, characterized by its sequential integration of convolutional and pooling layers, complemented by fully connected layers and a softmax layer. This intricate neural architecture is purposefully designed to harness the inherent 2D structure intrinsic to data. For each resized image within the dataset, with a resolution of (75x100) pixels per inch (ppi), the CNN extracts 22,500 distinctive features, showcasing its remarkable capability in effectively managing intricate image data.

The featured framework is composed of a structure incorporating six convolutional layers, delineated as follows:

$$S[m,n] = (a * b)[m,n] = \sum_j \sum_k b[j,k]\, a[m-j, n-k] \quad (3)$$

In this distinct context, S[m,n] denotes the feature map, with the indices m and n referencing the rows and columns of this map respectively. The variable 'a' signifies the input image, whereas 'b' represents the kernel, and 'j' and 'k' serve as summation variables.

The structural design of the organization comprises six convolutional layers, with the first two utilizing 128 and 64 filters respectively, each of size 3x3. The output of the second convolutional layer serves as input to the third layer, filtered with 256 filters, also of size 3x3. Subsequent layers utilize 128, 256, and 128 filters of size 3x3 respectively. A pooling layer of 2x2 with equal padding follows each even convolutional layer. Batch normalization is applied after each convolutional layer to enhance training stability. The Rectified Linear Unit (ReLU) activation function is consistently applied throughout the convolutional layers, renowned for its ability to alleviate the vanishing gradient problem and facilitate accelerated learning. Following the sixth convolutional layer, the feature maps are flattened and connected to a fully connected layer consisting of 512 units, which subsequently feeds into a softmax layer with 7 output classes. After experimentation with various learning rates, a stable and consistent performance was achieved with a rate set to 0.06737947. The Adam optimizer, recognized for its computational efficiency and robustness to gradient rescaling, is employed for gradient calculation and backpropagation. Its intuitive hyperparameters necessitate minimal tuning, making it an advantageous choice for optimization tasks.

2. *Transfer Learning*

Leveraging pre-trained models and adapting them to novel problem domains is the essence of transfer learning. Techniques such as feature transfer and fine-tuning are applied based on the resemblance between the original and new problems. Additionally, selectively freezing specific layers while retraining others provides flexibility in model adaptation. In scenarios with limited training data, incorporating an existing model from a related domain supplemented with additional training proves beneficial for addressing the new problem domain effectively. In all transfer learning setups, every resized image in the dataset, with a resolution of (224x224) pixels per inch (ppi), utilizes 150,528 features. The specific architectures employed in this approach are outlined below.

➢ *Densenet-121*

A distinguishing feature of this network lies in its ability to accumulate additional inputs from each preceding layer and append its own feature maps to all subsequent layers. The utilized pre-trained DenseNet architecture is structured with 4 dense blocks, each composed of varying numbers of dense layers: 6, 12, 24, and 16 respectively. Interconnecting each adjacent dense block are transition blocks, totaling three transition blocks in all. The dense neural network, featuring 1024 input features and 512 output features in its initial layer, seamlessly integrates with the pre-trained DenseNet architecture. Subsequently, two supplementary linear layers, incorporating a dropout factor of 0.3, are introduced. Finally, the modified architecture culminates with the output layer (softmax) comprising seven output classes. Achieving an impressive accuracy of 98.72%, this configuration is fine-tuned with a learning rate set to 0.0497870684, employing the Adam optimizer and cross-entropy loss function in conjunction with the modified DenseNet-121 architecture.The ReLU activation function is utilized to activate the neurons within the network, as depicted below:

$$R(z) = max(0,z) \quad (4)$$

In this specific scenario, the variable z encompasses any real number. When z is negative, the function R(z) yields 0, while for z greater than or equal to 0, R(z) equals z.

➢ *Resnet-50 and Wide Resnet-101*

ResNet and Wide ResNet architectures both incorporate BottleNeck blocks, akin to BasicBlocks, to enhance computational efficiency. A BottleNeck block strategically employs a 1x1 convolution to reduce input channels before executing a resource-intensive 3x3 convolution, followed by another 1x1 convolution to restore the original dimensions. ResNet comprises four consecutive blocks, each housing a specific number of bottleneck layers, optimizing GPU memory usage by minimizing the impact of computationally expensive 3x3 convolutions. The number of bottleneck blocks in these blocks are 3, 4, 6, and 3 respectively for ResNet. Wide ResNet, inspired by ResNet, diverges by featuring 23 bottleneck blocks within the third consecutive block. Additionally, Wide ResNet exhibits an increased number of channels in the convolutional layers compared to ResNet.

Furthermore, an innovative dense neural network with 2048 input features and 1024 output features in the initial layer is integrated with both pretrained ResNet and Wide ResNet architectures. Two additional linear layers incorporating a dropout rate of 0.3 are added, followed by the output layer (softmax) with seven output classes. The ReLU activation function is employed to stimulate the neurons. Achieving accuracies of 98.2% and 96.4% with ResNet and Wide ResNet networks respectively, both models utilize the Adam optimizer and cross-entropy loss function for

optimization. The weight updating mechanism of the Adam optimizer is outlined as follows:

$$w_t = w_{t-1} - \eta \frac{\hat{m}_t}{\sqrt{\hat{v}}_t + \epsilon} \quad (5)$$

In this particular scenario, wt represents the weight assigned to the t th training instance, m̂t denotes the average value of the moving gradient average, v̂t signifies the average value of the moving squared gradient average, and ε denotes the bias term.

➢ *VGG-19*

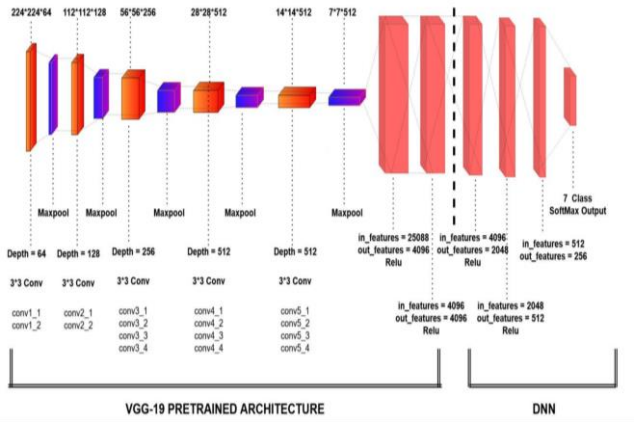

Figure 4: Modified VGG-19 Architecture

The development and optimization of the VGG-19 DCNN model were guided by the training data and experimental outcomes. VGG network architecture comprises numerous interconnected convolutional layers and fully connected layers, with sixteen convolutional layers and three fully connected layers specifically in the VGG-19 variant. Each convolutional kernel has dimensions of 3x3, and the input size is standardized to 224x224x3. Feature extraction from input images is facilitated by 64 filters from the initial convolutional layer. With its alternating design of convolutional and non-linear activation layers, the VGG network adeptly extracts image features, incorporates max-pooling for downsampling, and applies the ReLU activation function. The incorporation of downsampling layers aims to enhance the network's robustness against
distortions while preserving essential image features and reducing parameter count. During the training process, all layers in the network except the final five are kept frozen. The updated weights are then integrated into a new deep neural network featuring a sequential block with four linear layers. Activation is performed using the ReLU function, and the network is linked to the softmax output layer containing seven distinct output classes.

The adapted VGG-19 architecture attained a remarkable accuracy of 99.04%, depicted in Figure 4, surpassing the performance of all other classification models utilized.

Within Table 1, the classification report details the characterization of each of the seven types of skin lesions identified by the network.

Types of Skin Lesions	Precision	Recall	F1-Score
Melanocytic Nevi	1	1	1
Melanoma	0.99	1	0.99
Benign Keratosis	0.98	0.98	0.98
Basal Cell Carcinoma	1	1	1
Actinic Keratosis	0.98	0.95	0.97
Vascular Lesions	1	1	1
Dermatofibroma	0.98	1	0.99

TABLE I. Classification Report Table for Modified VGG-19

IV. RESULT ANALYSIS

BIn this segment, a comprehensive examination of the deployed models reveals emerging trends and crucial insights, gleaned from a thorough analysis of their classification reports.

A. Age vs Lesion Plot

Examining the age versus sore plot depicted in Figure 5 reveals a prominent surge in Melanoma cases, the most lethal among them, among individuals in their late 50s. Additionally, vascular lesions exhibit the highest incidence rates across all age groups, while instances of Basal Cell Carcinoma and Actinic Keratosis (precancerous conditions) are predominantly observed in individuals over the age of 40.

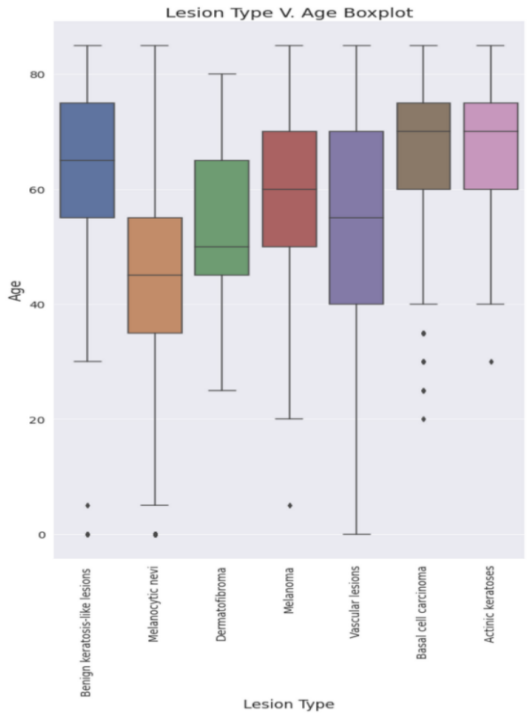

Figure 5: Lesion Type Vs. Age Boxplot

B. *Performance Analysis*

The rationale for the enhanced performance of deeper networks stems from their ability to grasp more intricate and nonlinear functions. When provided with ample training data, these networks become adept at discerning various classes effectively. Extending pretrained networks into deeper neural architectures is aimed at amplifying the system's capacity for feature extraction to its maximum potential. Upon analyzing the barplot depicted in Figure 6, it becomes apparent that the integration of an external DNN enhances the performance of pretrained networks. This augmentation leads to a notable improvement in both accuracy and precision. Particularly noteworthy is the exceptional performance observed with the integration of the VGG-19 Network and a DNN, achieving an impressive accuracy.

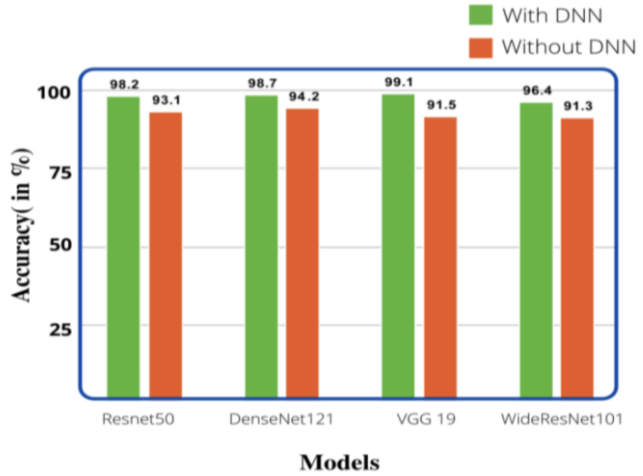

Figure 6: Accuracy comparison with and without DNN

C. *Confusion Matrix*

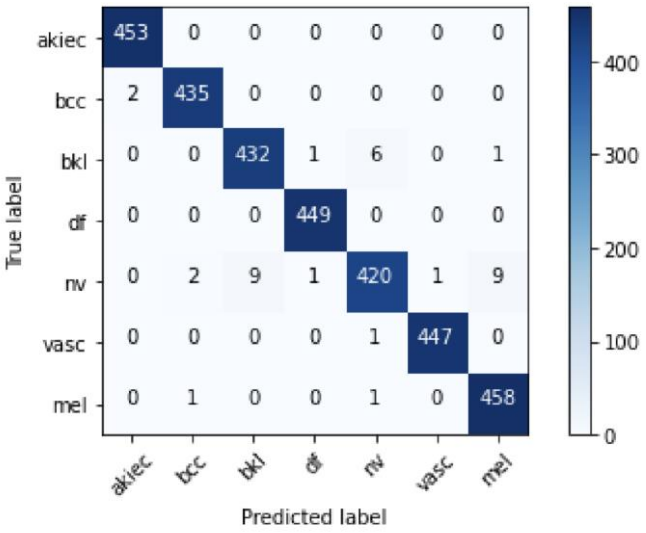

Figure 7: Confusion Matrix for VGG-19 Network

The Confusion Matrix, also known as an error matrix, provides a straightforward layout for visualizing performance metrics such as accuracy, recall, and precision. For instance, in Figure 7, the precision for the 'bkl' class is reported as 0.98, as outlined in Table 1. This precision is calculated based on the number of true positives and false positives, which are 432 and 8 respectively. The confusion matrix depicted in Figure 7 is the result of the execution of the VGG19 model.

Noteworthy insights gleaned from the confusion matrix include the accurate classification of Actinic Keratosis and Dermatofibroma with 100 percent precision, while the class of Melanocytic nevi exhibits the highest level of inaccuracy compared to other classes

V. CONCLUSION

Groundbreaking research in skin lesion classification has paved the way for this comparative analysis. What sets these networks apart from previous studies is their ability to surpass current benchmarks, with additional enhancement achieved through the integration of extended dense neural networks. Upon analyzing all five models, the most promising outcome was achieved with the VGG-19 Network, boasting an impressive accuracy. The CNN, Wide Resnet101, Resnet50, and Densenet121 models yielded accuracies of 81.24%, 96.40%, 98.20%, and 98.70% respectively.

These results demonstrate that utilizing these modified networks leads to improved visual diagnostic precision compared to human pathology experts. Moreover, these models address histological sampling bias and transform histopathology from a qualitative art into a quantitative science. They possess the capability to evaluate thousands of features efficiently and compare them to a vast library of known samples—a monumental challenge for human experts thus far.

The seamless implementation of these models underscores their true potential for integration into dermatoscopic systems and modern smartphones in the near future. The ultimate research objective aims to develop a state-of-the-art application for non-invasive skin cancer detection using computer vision and image processing, with the aspiration of establishing a global standard that is cost-effective compared to existing systems.

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