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Skin Lesion Detection and Classification

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Abstract: Skin cancer has an overall mortality rate of 0.6 to 0.7% and accounts for 5.8% of cases worldwide (1.6% for melanoma). Globocan 2018 is challenged by Pakistan's Punjab Cancer Registry (PCR), which records an increased incidence. According to PCR, skin cancer is eighth and ninth most common in both males and females in 2017. It ranks in the top eight for Karachi according to the Karachi Cancer Registry (KCR). According to Dow University of Health Sciences (DUHS), non-melanoma skin cancer is the sixth most common type of the disease, which indicates a notable increase in Karachi. This study identifies key contributors among universities, research institutions, and cities and objectively assesses Pakistan's skin cancer research, examining output, types, and focuses. Additionally, it intends to identify the main institutions and cities that have made significant contributions to this field of research. The research presents a sophisticated computerized diagnostic method that apply Inception V3 architecture. This method achieves an impressive accuracy, when tested on the HAM10000 dataset, highlighting its effectiveness in identifying and diagnosing skin ailments. The hybrid machine learning approach, when applied to a dataset of 3672 categorized pictures, produces a diagnosis accuracy of 99.80% on testing while achieved validation accuracy of 84.27%. This shows promise for improving the categorization of skin cancer and potentially leading to advancements in diagnosis, treatment, and mortality rates.

Keywords: Skin Lesion Classification, Inception V3, DNN, Machine Learning.

1. Introduction

The skin, comprising layers such as the epidermis, dermis, subcutaneous tissues, blood vessels, lymphatic vessels, nerves, and muscles, is a vital organ. Skin diseases, arising from various factors, may lead to chronic conditions or progress into malignancies, necessitating prompt and accurate diagnosis for effective treatment. Imaging-based therapies are crucial for assessing skin conditions, but diagnosing skin diseases can be time-consuming, posing challenges for timely therapy.

Computer-aided diagnosis (CAD) has demonstrated efficacy in the identification and diagnosis of skin conditions, providing a cost-efficient resolution. Automated expert systems for early skin lesion categorization can serve as a solution in contexts where resources are limited, by addressing the disparity between the number of patients and the availability of expert knowledge. Various machine learning methodologies, including decision trees (DTs), support vector machines (SVMs), and artificial neural networks (ANNs), have been proposed for skin lesion classification.

Deep learning methodologies, particularly convolutional neural networks (CNNs), show promise in achieving precise and reliable diagnoses of various skin lesions. Skin cancer, with subtypes like basal cell carcinoma, squamous cell carcinoma, and melanoma, presents distinct challenges in diagnosis due to inter-class uniformity and intra-class variability. Deep learning models, like the enhanced CNN proposed in this study, contribute to improved skin lesion classification accuracy while addressing issues of parameter efficiency and reduced computing time.

In conclusion, the study emphasizes the need for advanced diagnostic tools in dermatology, particularly in distinguishing between benign and malignant skin lesions. The proposed enhanced CNN architecture, along with balanced class-wide data, demonstrates notable accuracy and efficiency in skin lesion classification, offering a valuable contribution to the field.

2. Literature Review

In the past, scholars have made substantial progress in automating the diagnosis process and improving the reliability of computer-aided systems for diagnosing skin lesions. A comprehensive investigation has been conducted on the binary categorization of melanoma, which is acknowledged as the most lethal dermatological condition [1]. However, it is important to acknowledge that there are six additional skin disorders, some of which have similar degrees of danger as melanoma if not detected promptly. Therefore, the prompt detection and accurate classification of skin lesions belonging to many categories are highly significant. The notable similarity detected across lesions from different classes and the significant differences reported among skin lesions within the same class make multiclass skin lesion categorization extremely difficult. Ongoing research is currently focused on studying the many components of a CAD system for multi-class skin lesion diagnosis, including preprocessing, segmentation, feature extraction, best feature selection, and classification [3]. There has been a significant amount of research undertaken on the use of deep learning-based automated systems to diagnose skin lesions, as demonstrated by studies referenced in the literature. Farhat et al. presented a refined method for the multi-classification of skin lesions in their study [11-15]. The researchers utilized transfer learning to extract deep features, which were optimized using a combination of hybrid whale optimization and Entropy Mutual Information (EMI) methods. After obtaining improved characteristics, fusion is performed using a modified canonical correlation-based method, resulting in classification based on extreme learning machines. The suggested methodology was assessed using the HAM10000 and ISIC2018 datasets, resulting in accuracies of 93.4% and 94.36% respectively [1][4][7]. The authors used picture preprocessing to remove artifacts and improve quality. They then utilized Geodesic Active Contours (GAC) for the purpose of region-of-interest segmentation. This study utilizes two different methodologies for feature extraction. The initial approach is obtaining score features by employing a Convolutional Neural Network (CNN), specifically leveraging the ResNet-18 architecture for transfer learning. The second approach entails extracting texture features through the utilization of the Gray-Level Co-occurrence Matrix (GLCM) and Histogram of Oriented Gradients (HOG) techniques. The procedure of classification is ultimately carried out by utilizing an SVM classifier. The team developed and deployed a deep convolutional neural network with many layers and different filter sizes, intentionally minimizing the number of filters and parameters to improve efficiency and performance. The datasets used to evaluate the current work include ISIC2017, ISIC2018, and ISIC2019 [5]. The primary objective of the study was to minimize the necessity for preprocessing operations. Khan et al. proposed a deep learning approach to detect skin cancer. The main aim of this study was to examine the preprocessing step and thereafter determine the feature with the greatest discriminant power. Both of these factors contributed to reducing the duration and intricacy of computations [7]. The tests were conducted using the ISBI2016 and ISBI2017 datasets. Similarly, another noted study utilized refinement and augmentation networks. Hasan et al. conducted a study that highlighted the importance of the preprocessing stage. At first, the photos were improved by applying the Gaussian Blur method. Consequently, the edges were identified in order to provide a clear delineation of the artifacts. Afterwards, the creation and recovery of the image mask were performed in the database, guaranteeing the absence of any imperfections. In order to tackle the problem of lesion contrast, researchers adopted a novel preprocessing technique in their reference study. The researchers employed a novel method to improve contrast in monochrome photographs by minimizing fluctuations in luminance within anomalous areas. They utilized a top hat filter and an inpainting technique in the preprocessing stage to accomplish this. Using genetics algorithm A deep investigation was performed for the purpose to improve the quality of motion graphs. Khan et al. instigated a method for abruptly segmenting and categorizing skin lesions using deep features. For improving the quality of the input image LCcHIV was used at the very first stage [7]. To achieve the purpose of developing robust and precise model Feature extraction and selection were considered as very important. To keep the performance at its peak, Arshed et al. developed the iteration-controlled Newton-Raphson (IcNR) technique. They used Deep neural networks to extract features using transfer learning which resulted a model for classifying skin lesion. For correct feature selection the technique also utilized kurtosis-controlled principal component analysis (KcPCA). The studies utilized the datasets HAM10000, ISBI 2017, and ISBI2016, resulting in accuracies of 80.8%, 83.60%, and 80.20%, respectively [5][6][8]. The authors outlined an approach in their study that successfully combines information from deep learning algorithms and manually built features, leading to improved accuracy on the selected datasets. Features that are manually designed, such as shape, texture, and local and global characteristics, are obtained by referring to a specific source. Afterwards, the combination of traits took place, followed by the identification of the most advantageous qualities using a genetic algorithm. The CNN model referred to was used to extract deep information from two primary output layers. Then, the decision-controlled parallel fusion method is employed to do feature fusion. The selection of the most optimal characteristics is determined by the application of a methodology based on window distance-controlled entropy. Several other studies have been conducted that employed pre-trained models for categorization. Multiple researchers have suggested several conventional approaches to attain the desired results. The aforementioned solutions should have prioritized the contrast enhancement stage, while giving greater attention to the data augmentation procedure. The data augmentation stage is commonly performed by flip and rotation operations. Nevertheless, empirical evidence has demonstrated that these methods yield positive outcomes on certain occasions, while occasionally causing a decrease in training accuracy, thereby leading to a reduction in classification accuracy. Furthermore, the researchers took into account the feature selection approach, which led to improved accuracy and reduced processing time. This work presents a new method that leverages improved deep-learning features and suitable feature selection to accurately classify skin lesions across many categories.

3. Proposed Methodology

The advent of deep neural networks (DNN) has been widely regarded as a significant breakthrough in machine learning, particularly in computer vision applications. Autonomous systems in computer vision can match or even surpass human visual capabilities in specific scenarios, mainly when employed for diagnostic purposes such as disease identification and diagnosis based on image analysis. Deep Convolutional Neural Networks (DCNNs) have demonstrated exceptional performance in image categorization tasks. Some wi (Muhammad Asad Arshed, 2023)dely recognized deep learning models include Inception v3, DenseNet 121, and ResNet 50. We have used Inception V3 model in this paper so will be discussing the same.

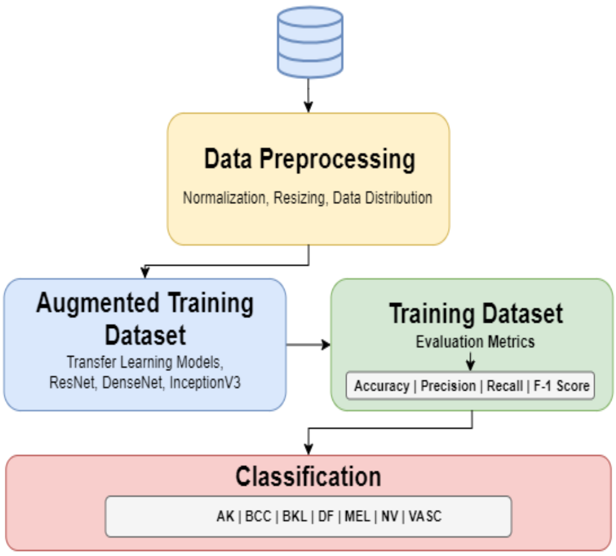

Figure 1. Proposed Methodology

3.1. Dataset Acquisition:

In this research, we employed an open-source benchmark dataset obtained from Kaggle, as depicted in Figure 1. Nevertheless, it is crucial to acknowledge that the dataset utilized in our study exhibited an imbalance, hence giving rise to potential problems, including over fitting or underfitting. To achieve an ideal performance of the model, it is imperative to effectively tackle the problem of data imbalances, particularly in the training phase.

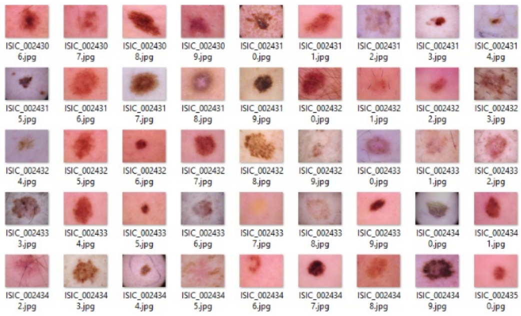

Figure 2: Dataset HAM10000

3.2. Data augmentation:

Data augmentation is a critical methodology for enlarging datasets, particularly in deep learning models, to ensure effective performance. In this study, we focused on rotation as an augmentation approach, implementing maximal left and right rotations of up to 8 degrees in computer vision [21-26].

The augmentation method comprised two primary categories: position augmentation and color augmentation. Position augmentation involved techniques like scaling, cropping, affine transformation, padding, flipping, translation, and rotation. Color augmentation included modifications to hue, brightness, saturation, and contrast. Augmented samples were created through a random selection and augmentation process on the original dataset, resulting in a well-balanced training dataset of 980 samples per class.

To address potential bias from class imbalance, we merged the augmented photos with the original data, resulting in a cumulative count of 980 images per class for training. For validation and testing, 140 distinct photographs were used in each set. To further mitigate data imbalance, we employed random under-sampling in addition to data augmentation, enhancing the effectiveness of the skin cancer classification models ResNet50, VGG16, and VGG19. This approach significantly improved overall classification performance.

3.3. Data visualization

Data visualization plays a crucial role in presenting complex information about skin lesions and their characteristics through graphical techniques. This approach enhances the clarity and comprehensibility of the extensive data gathered in the research. In our study, we employed data visualization to extract metadata, focusing on seven attributes to obtain the diagnosis count for each type of skin lesion.

The dataset includes seven possible diagnosis codes, representing various skin conditions. These codes include akiec, bcc, bkl, df, mel, nv, and vasc, each corresponding to specific skin conditions such as actinic keratoses, basal cell carcinoma, benign keratosis-like lesions, dermatofibroma, melanoma, melanocytic nevi, and vascular lesions, respectively.

After assigning codes to these types, we utilized data visualization to illustrate the age distribution, sex count, and localization count (indicating different skin areas) as integral aspects of our analysis. The visual representation aids in conveying insights and trends derived from the comprehensive dataset, contributing to a better understanding of the research findings.

3.4. Data Cleaning

Data cleaning, also known as data cleansing, is the methodical detection and resolution of errors, discrepancies, and inaccuracies within large datasets collected or obtained for analysis. This crucial step ensures that the data utilized is of exceptional quality, reliable, and suitable for analysis and modelling. Here are some considerations to consider when performing data cleansing in the context of this research.

3.5. Inception V3:

The Inception v3 model is an advanced deep neural network extensively utilized for the purpose of image analysis and classification. The architecture, designed by Google experts, has numerous essential components to enable optimal speed in visual processing. The input layer of the model is specifically intended to handle color images with dimensions of 299x299 pixels, serving as the initial stage for the neural network.

The voyage commences with the primary convolutional layer, utilizing 32 little filters (3x3 pixels) and a stride of 2 to extract essential visual characteristics. Inception v3 is characterized by its utilization of "Inception modules," which consist of parallel convolutional branches. These branches use filters of diverse sizes (1x1, 3x3, or 5x5 pixels) to capture details of different scales in the input picture, with 1x1 convolutions utilized for complexity reduction.

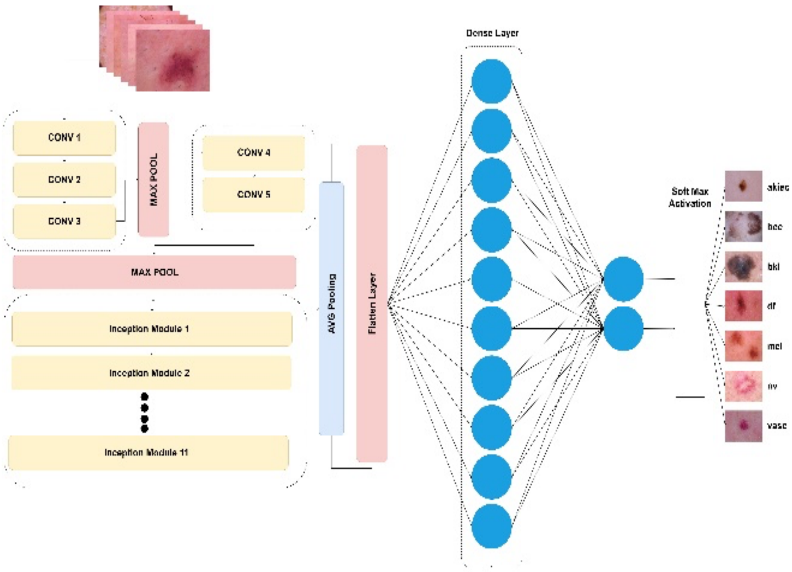

Figure 3. Inception V3

As the network advances, reduction blocks are incorporated following certain Inception modules. These blocks efficiently reduce spatial dimensions and enhance channel numbers through techniques such as max-pooling and 1x1 convolutions. The fully connected layers are positioned after the final Inception module and are responsible for the main objective of categorizing images. The objective of these layers is to produce probability for different classes using a SoftMax activation function.

4. Performance Evaluation Metrics

In order to improve the training process, Inception v3 strategically integrates auxiliary classifiers within the network, namely after the 5th and 11th Inception modules. These classifiers are essential for reducing the problem of vanishing gradients during training by incorporating regularization approaches. While not currently used in real-time scenarios, these components are essential during the training phase. The Inception v3 design integrates global average pooling as a more efficient option to replace extensive fully connected layers. This option mitigates overfitting hazards and simplifies computational complexity by reducing the feature map's dimensionality to a single number (1x1).

Softmax activation function is used in the output layer of neural networks. This function categorizes the input images and computes the anticipation of several classes and assign them to the classes. The idea behind Inception v3's design is to find a balance between model complexity and accuracy. It does well in picture categorization tests while also putting an emphasis on being computationally efficient. Applications with limited computing resources are particularly well-suited to make use of this capability.

This part goes into detail about how the experiment was set up and shows the results using measures like F1 score, confusion matrices, accuracy, precision, and recall.

- Accuracy=(TP+TN)/(TP+TN+FP+FN)
- Percision =TP/(TP+FP)
- Recall=TP/(TP+FN)
- F1 Score=(2×(Percision×recall))/(percision+recall)

After 28 iterations, the Inception V3 model got a training accuracy of 99.80% and a validation accuracy of 84.27% on the HAM10000 dataset, showing that it kept getting better. The model's loss in the training set was 0.0163, and its loss in the validation set was 0.6252. This shows that it was able to reduce errors during training. Accurate predictions are displayed at the diagonal of the confusion matrix, and there is a significant frequency of correct predictions (1305 instances). Off-diagonal zeros show how well the model avoids certain mistakes, while on-diagonal zeros show a frequent mistake in classification.

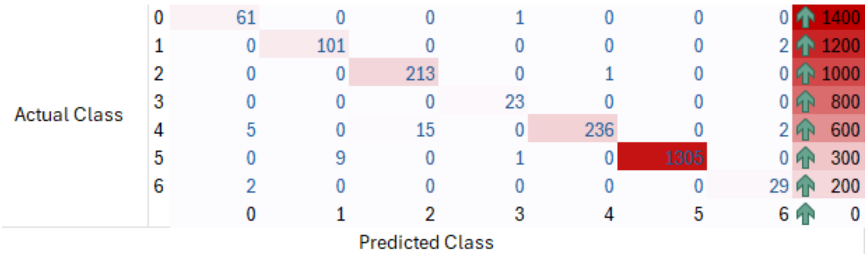

Figure 4. Confusion Matrix

The precision of certain classes like, 0, 1, 2, 3, … 6, which suggests a significant of accurate positive predictions. Recall is generally low, with the exception of class 5 which has a recall rate of 1.00. The F1-Score for class 5 is 0.79, indicating a harmonious compromise between precision and recall.

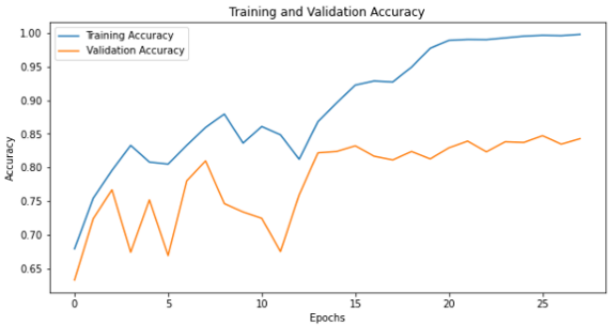

Figure 5a. Training and Validation Accuracy

Figure 5b. Training and Validation Loss

The overall accuracy is 0.12, while the macro-average precision, recall, and F1-Score are 0.09, 0.05, and 0.05, respectively. The weighted averages, which account for class imbalance, indicate a precision of 0.51, a recall of 0.14, and an F1-Score of 0.65. To summarize, the Inception V3 model faces difficulties in accurately predicting positive outcomes for the majority of classes, leading to subpar precision, recall, and overall accuracy. Additional analysis and refinement of the model may be necessary to improve performance.

5. Conclusion

This study uses a novel method to identify and classify skin lesions. The method uses Inception V3 deep learning architectures to process and analyze skin lesion images rigorously. Deep learning models eliminate manual feature analysis, making diagnosis faster. Our approach was tested using a benchmark dataset of many skin lesion pictures. Credible dermatology sources provided the photos. The empirical outcomes in this study show that our methodology improves skin lesion identification and categorization accuracy and performance. Our architecture, InceptionV3 models, outperforms current skin lesion diagnosis methods. A thorough analysis using four key performance measures validated our strategy's superiority. In conclusion, deep learning algorithms are used to precisely identify skin lesions in our work. Our study advances dermatology and offers a significant possibility to improve medical image analysis in numerous clinical contexts.

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