CLASSIFICATION OF 5 DIFFERENT KINDS OF SKIN DISEASES USING NEURAL NETWORKS

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ABSTRACT

Skin illness is a very prevalent human condition that affects people of all races and ages. Pakistan has few skin doctors and percentage of patients having skin diseases are increasing rapidly. Some forms of diseases like Psoriasis, Eczema and Ringworm looks quite similar and doctors have difficulties in detecting such skin disease. Some of these diseases may not be life threatening However, it has a significant impact on people's quality of life. The main idea of this project is to detect 5 different kinds of skin diseases (Psoriasis, Actinic keratosis, Benign Keratosis, Ringworm, Eczema) at an early level by using image processing and classification techniques and to spread awareness related to skin diseases among the people of Pakistan. Different preprocessing techniques were applied to the dataset after which a DenseNet201 model based on theory of transfer learning with a few customizations was trained for the classification. The model is evaluated on HAM10000 dataset and ultimately detects all skin diseases with an overall accuracy of 80% on test dataset.

INDEX TERMS Skin Diseases, Classification, Preprocessing, Images, CNN, DenseNet201, Detection.

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1. BACKGROUND

1.1. Motivation

The largest organ in the human body is the skin. Skin weighs between six and nine pounds and has a surface area of around two square yards. There are many people that are suffering from the skin diseases. These diseases may look similar but their effects and treatments differ and early identification of these diseases allows patients to receive appropriate treatment as soon as possible, halting the progression of the condition. There are many types of skin diseases such as Carcinoma, tinea corporis, poison ivy, Melanoma, Alopecia, Ringworm, and many more. All these diseases happen with no early symptoms. The same applies to Psoriasis, Eczema, Actinic Keratosis, Benign Keratosis and Tinea Corporis (Ring worm) which are likely to be experienced by people in Pakistan and the percentage of people having these diseases is increasing since 2015.

It is always a challenging task even for doctors to determine which kind of skin disease it is just by looking at the disease from naked eye. For example, Actinic Keratosis / Benign Keratosis and Melanocytic Nevi all look very much similar at an early stage with slight differences in shape and sometimes in color. Due to this reason, diagnosis and detection of skin diseases based on image analysis using Convolutional Neural Networks was proposed. As a result, computer-assisted diagnostic (CAD) systems are required for diagnosis of skin lesions.

Traditional Deep Learning techniques have been applied for the detection of skin diseases. The pipeline includes first image preprocessing of images followed by feature extraction and classification. Many CNN models were trained based on different architectures such as InceptionResnetV2, ResNet, VGG16 and Desnet201. The most accurate was found to be Desnet201 with test accuracy of 80%. In addition, transfer learning was used to improve the overall result accuracy.

1.2. Organization

The rest of this paper is organized as follows: Section 2 represents the Related Work (literature review). Section 3 discusses about challenges faced in detection of Skin Diseases. Section 4 represents the Materials and methods along with transfer learning. Section 5 represents evaluation, results and discussions followed by Section 6 where conclusion and future works are summarized.

2. RELATED WORK

A variety of techniques have been used to detect various skin diseases (Psoriasis, Eczema, Actinic Keratosis, Benign keratosis and tinea corporis (Ringworm). A variety of models previously utilized for skin diseases detection have been detailed in the following paragraphs, together with their challenges and performances. Several academics have proposed image processing-based methods for detecting different types of skin disorders. Seung Seog Han [1]. How to fine-tune the resnet-152's ImageNet pretrained model to increase CNN's understanding and visualize the features selected by it.

First of all, let’s talk about [1] Fine-tuned. It is a frequent strategy for transfer learning to fine-tune it. Except for the output layer, the target model duplicates all model designs and their parameters from the source model and fine-tunes them based on the target dataset. The feature extraction phase, the training phase, and the testing/validation phase procedures were proposed by Patnaik S. K, Sidhu M. S [2]. The suggested method employs pre-trained image recognizers that have been modified to identify skin images. Transfer Learning (the reuse of a previously learnt model on a new issue) and segmentation were proposed by Erol and Recep [3]. This process was started by first finding the super pixels using s Simple Linear Iterative Clustering (SLIC) to automatically detect the region of interest. Zhiwei [4] used A skin lesion style-based GAN-based data augmentation technology is established for improving the classification performance of skin lesion images, and a skin lesion style-based GAN-based data augmentation technology is established for synthesis of skin lesion images. The style-based GANs architecture is used to propose a GANs model. The proposed model modifies the original generator's style control and noise input structures, as well as the generator's and discriminator's progressive developing structures. It's good for creating high-resolution skin lesion photos with a lot of variety. Nandini Bhimanadhula [5] We learned how to resize images and improve image data in this paper. Automatic thresholding segmentation and masking operations in the red, green, and blue (RGB) planes were used to segment the images.

Latest research on this domain is [5] Threshold Segmentation is a technique for converting an image to a binary image (White or Black). Entropy, form, and energy characteristics are all retrieved. [6] Transfer Learning: Rather than beginning the learning process from scratch, the model builds on patterns gained while solving a separate problem. As a result, the model can make use of prior knowledge rather than having to start from zero. Transfer learning is commonly expressed in image classification through the use of pre-trained Models. A pre-trained model is one that has been trained on a big benchmark dataset to tackle a problem that is comparable to the one we are working on.

[7] [11] The practise of removing hair-like artefacts from skin photographs is known as noise removal. After that, the inpainting process is used to replace the pixel values with those of the neighbours. This morphological operation-based algorithm (each pixel in the image is adjusted based on the value of other pixels in its neighborhood). For improved outcomes, this research integrates Otsu's thresholding with CNN.

Otsu's thresholding: The threshold value is determined automatically rather than being chosen. It is taken into account a bimodal image (two unique image values). There are two peaks in the histogram that was generated. As a result, a generic condition would be to pick a threshold value that is halfway between both histogram peak values.

Soft Attention was proposed by Soumyya Kanti Datta [14], which discredits irrelevant portions of the image by multiplying the appropriate feature maps with low weights. As a result, the low-attention locations have weights that are closer to zero. Soft attention is used to concentrate more on the image's important features.

Soumya. [14] looked examined ten alternative techniques for evaluating deep learning models for skin lesion categorization in 2018. Among the eleven approaches they looked at were data augmentation, model architecture, picture resolution, input normalization, train dataset, segmentation, test data augmentation, extra usage of support vector machines, and transfer learning. Data augmentation, they claimed, had the largest impact on model efficiency. Soumya's [14] observation is also confirmed.

3. CHALLENGES OF SKIN DISEASE DETECTION

There are some challenges in detecting skin cancer due to differences in image types and sources. The fact that human skin tone varies makes skin cancer detection more difficult and complicated.

1) The main challenges in skin disorders are the various sizes and shapes of the images, which make reliable identification impossible. Pre-processing is necessary for accurate analysis in this case.
2) Some images contained a lot of hairs which were interfering with part of the disease. These images were creating distortions in analyzing the disease correctly.
3) Color illumination presents certain challenges due to issues such as color texture, light beams, and reflections.
4) The human skin contains moles which are not harmful but they share some similarities with a few diseases.
5) High similarity between all diseases.

4. PROPOSED METHODOLOGY

The approach of the suggested system for detecting, extracting, and classifying skin diseases using images is detailed in this section. DenseNet201 architecture with transfer learning, SoftAttention and few custom layers was trained for the classification of skin diseases. The complete architecture can be divided into multiple modules comprising of Data Collection, Preprocessing, Feature Extraction and Classification as described below.

4.1. Dataset

Human Against Machine (HAM10000), an excellent series of multi-source dermatoscopic images of common pigmented skin lesions, was one of the datasets used. This data was gathered from various populations and saved using various modalities. HAM10000 contains a comprehensive collection of all relevant illness images for our problem. The other dataset was from International Skin Organization (ISIC). It contained images of classes actinic keratosis, benign keratosis and melanocytic nevi. One other dataset was used and images were extracted from Dermnet website. The Preprocessing and augmentation of the dataset is discussed next.

4.2. Preprocessing and Data Augmentation

Image pre-processing is a critical stage in the detecting process for removing noise and improving the quality of the original image. It had to be used to narrow the search for irregularities in the background that had an impact on the outcome. The major goal of this stage is to improve the image quality by removing irrelevant and unneeded parts from the image's background so that it can be processed further. The accuracy of the system can be considerably improved by using the right preprocessing techniques. Few preprocessing techniques used are discussed below:

- Image scaling techniques are applied due to the lack of same and standard size of images. Since data was extracted from three different sources, size of images were differing, for this reason all images were combined and input size was transformed to 224x224x3 since it improves transfer learning model design and decreases training time.
- Since images were of skin, therefore some images contained too much hairs in them which were hiding the disease, these images were extracted manually and image inpainting techniques were applied to them to remove hair and distortions from images. This was not done to all images as images with no hairs were getting too much noise.
- Some blurry images were also found, these were also extracted manually and Weiner filter was applied to them to improve blurry and noisy images.
- To ensure that learning model is not affected by class imbalance problem, data augmentation techniques such as random rotation, shearing, cropping etc. techniques were applied to solve class imbalance problem and to increase size of overall data set. Details of this are shown below.

Types of skin disease	Sample number	Data Augmentation
Actinic Keratosis	1000	5000
Eczema	500	5000
Psoriasis	600	5000
Ringworm	600	5000
Benign Keratosis	1200	5000
Melanocytic nevi	5000	5000

Table 1 Detail of the dataset

5. Experimentation and Methods

5.1. Soft Attention

Only a small proportion of pixels in skin lesion images are important, as the remainder of the image is completely filled with different useless things such as hairs. Soft attention is used to focus more on certain important aspects of the image. soft attention is implemented. Inspired by the work proposed by Soumyya , Abuzar[14], where they used attention mechanism to detect cancerous images, in this paper, soft attention is used to distinguish between common skin diseases.

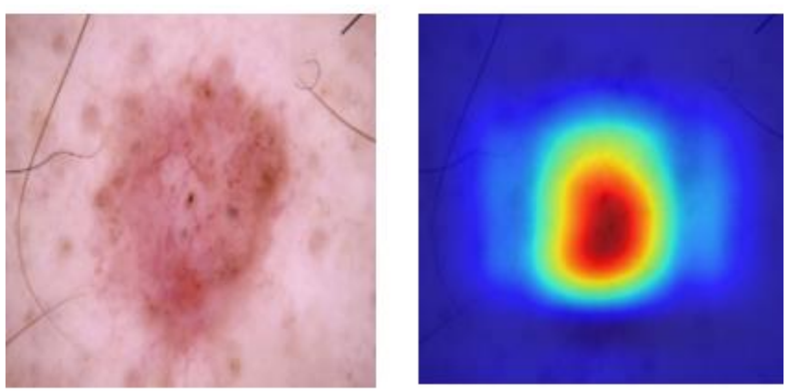

Figure 1 Before and after soft attention

The areas getting the most attention are highlighted in red in the figure above. Because soft attention multiplies the associated feature maps with low weights, it discredits irrelevant regions of the image. As a result, the low-attention regions have weights that are closer to zero. The model performs better with more focused inputs. Following is the architecture of Soft Attention made by Soumyya , Abuzar[18] that is also used by us to boost the performance of our model.

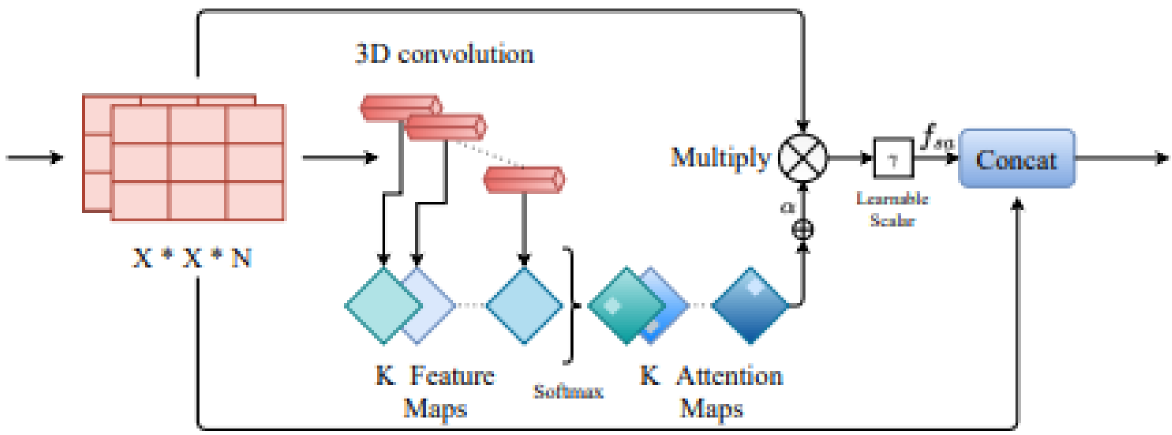

Figure 2 Soft Attention Unit

5.2. Transfer Learning and Architectures

To train a new DNN model, a large number of images are needed. Unfortunately, there is not any datasets with thousands of labelled skin lesion images. It is difficult to train a large number of medical datasets, such as ImageNet, using all of the parameters available in neural networks. Transfer Learning is useful in this situation. Transfer learning is a machine learning research problem that focuses on storing and transferring knowledge learned while addressing one problem to a different but related problem. Because it takes into account a pre-trained architecture with weights, transfer learning is prevalent and useful. Datasets containing millions of images are used for this. References [3,12,6] showed that for medical image analysis having a priori knowledge on the images, a pre-trained architecture seems to be the right approach. The base weights were taken from ImageNet, then fine-tuning was done to adjust some of the feature extraction layers by changing some network weights, then a new configuration of the of few custom layers followed by a final Dense Layer was proposed.

The architectures of ResNet50, VGG16, Inception ResNetV2 and DenseNet201 were used for Transfer Learning and trained after customizing them with few custom layers and regularization techniques. The architecture that worked the best and selected for further optimizations and tuning was of DenseNet201 with a Soft Attention layer.

5.3. Training with DenseNet20

The Convolutional Neural Network DenseNet201 has 201 layers. In a feed-forward approach, the Dense Convolutional Network connects each layer to every other layer. They operate on the idea that convolutional networks can be significantly deeper, more accurate, and efficient to train if the layers closest to the input and those closest to the output have shorter connections. One of the main reason that this architecture worked best on our problem is because they resolve vanishing gradient problem since it preserves information through additive identity transformations. Since every layer is connected to every other layer so no information is lost. We trained DenseNet201 with transfer learning after customizing it with few custom layers and then adding a Soft Attention block after the final Dense Block. The model architecture is shown below.

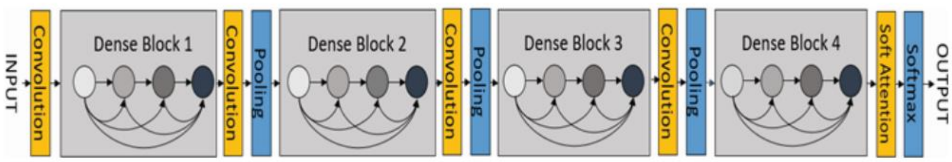

Figure 3 Architecture of the Model

The soft attention layer was introduced after the 4th Dense Block in DenseNet201, and the image's feature map was 7x7 in size. Following the soft attention layer is a MaxPooling layer with a pool size of 2x2, which is subsequently concatenated with the inception block's filter concatenate layer. After the concatenate layer, there is a relu activation unit. The activation unit is followed by a 0.5 dropout layer to regularise the output of the attention layer. The entire architecture of the Soft Attention block is shown below.

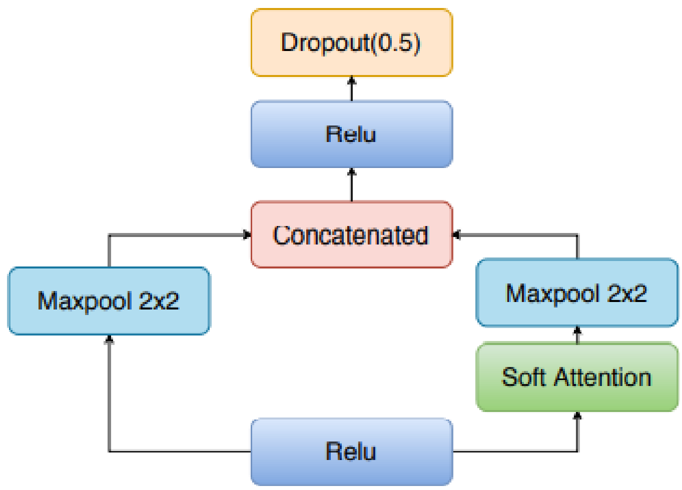

Figure 4 Schema for soft attention block

Layers till first Dense Block were freezed and final model was trained till 60 epochs with a batch size of 32 and Categorical Crossentropy as Loss Function. Adamax optimizer was used with initial learning rate of 0.001 that was adjusted with a factor of 0.05 after every epoch if validation accuracy was decreasing. Dataset was split into 25% validation data. Final accuracy achieved on validation data was of 82%.

6. EXPERIMENTS AND RESULTS

All the experiments related to solving the classification task of skin lesion images was done using architectures of ResNet50, VGG16, InceptionResNetV2 and DenseNet201. Transfer learning was used while training all the models. All the models were trained after preprocessing and balancing the dataset. The results obtained from each model after evaluating on test data is shown below.

MODEL	ACCURACY
ResNet50	67%
VGG16	69%
InceptionResNetV2	73%
DenseNet201	76%
DenseNet201 with SoftAttention	79%

Table 2 testing results

DenseNet201 performed the best out of all the models. Parameter tuning was then done on this model to further improve the accuracy on test data. Soft Attention was also used to boost the performance of the model. Further evaluation of this model using different evaluation metrics is shown below.

6.1. Confusion Matrix

A confusion matrix is a table that shows how well a classification algorithm performs. The confusion matrix shown below helps to observe the errors that the models must identify in some classes.

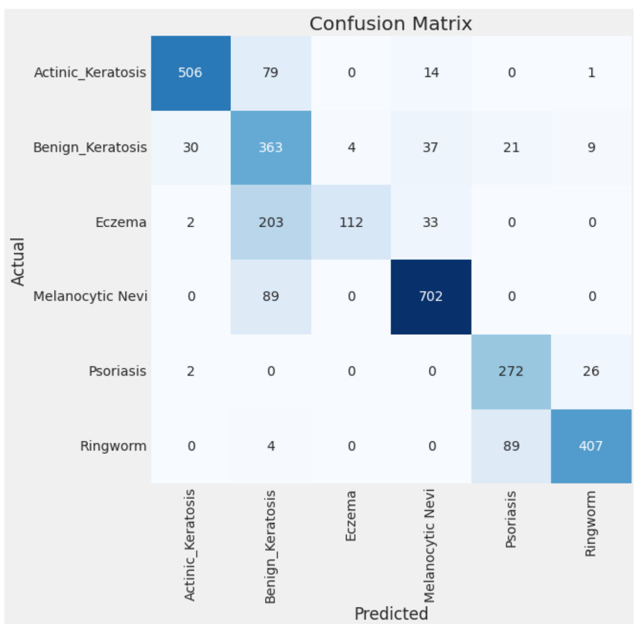

Figure 5 Confusion Matrix

6.2. Classification Report

A classification report is used to assess the accuracy of a classification algorithm's predictions. How many of the predictions are correct and how many are incorrect? True Positives, False

Positives, True Negatives, and False Negatives, as illustrated below, are used to predict the metrics of a classification report.

Classification Report:
----

	precision	recall	f1-score	support
Actinic_Keratosis	0.94	0.84	0.89	600
Benign_Keratosis	0.49	0.78	0.60	464
Eczema	0.97	0.32	0.48	350
Melanocytic Nevi	0.89	0.89	0.89	791
Psoriasis	0.71	0.91	0.80	300
Ringworm	0.92	0.81	0.86	500
accuracy			0.79	3005
macro avg	0.82	0.76	0.75	3005
weighted avg	0.83	0.79	0.78	3005

Figure 6 Classification Report

Our model is evaluated using Precision, Sensitivity, Specificity and F1-score of each label as shown above.

6.3. ROC Curve

It shows how better the model is at predicting each class. The AUC displays the methodological approach's ability to classify skin lesions using deep learning models based on transfer learning and hyper-parameters optimization.

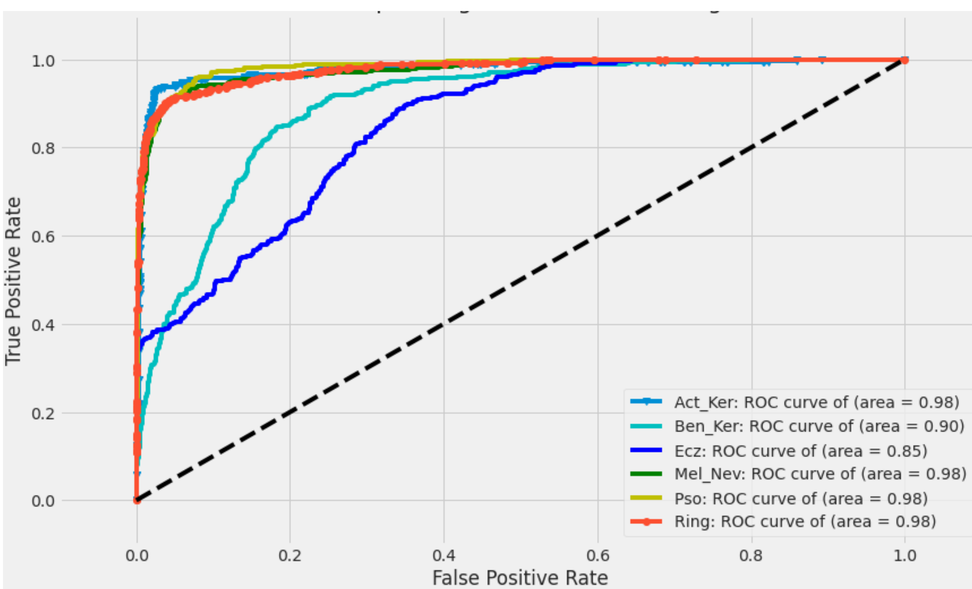

Figure 7 ROC Curve

7. CONCLUSION

In this paper, we presented a novel technique for early detection of provided skin diseases using Convolutional Neural Network. Many experiments were done using architectures of ResNet50, VGG16, InceptionResnetV2 and DenseNet201 out which DenseNet201 performed the best as it overcomes the problem of VGD. We demonstrated how to increase the model's capacity to detect skin lesions by using preprocessing, transfer learning, hyper-parameter optimization, and data augmentation. Soft Attention was also used to boost the overall performance of the final model. This shows the potential and effectiveness of Soft Attention in image analysis. Soft Attention focuses on relevant part of the image as well as adding the advantage of naturally dealing with image noise internally. We are not absolutely sure of any earlier work that has been done in the classification of all of the diseases classified in our work. While many work was found in which Actinic and Benign keratosis were classified and our proposed model outperforms almost all of them in terms of True Positive Rate. It is concluded that an innovative detection of skin lesions using CNN shows good performance in the medical field.

8. FUTURE WORK

In future we can work on a larger and locally provided dataset by hospitals to gain the best prediction and classification accuracy. The model can be used to help dermatologists in hospitals. This approach can also be used to classify data from other datasets with relative ease. Other medical image problems, such as brain tumors, can benefit from the proposed methodology.

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