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Scalp disease analysis using deep learning models

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Abstract. Alopecia areata, folliculitis, hair loss, and dandruff are common scalp hair disorders caused by nutritional imbalances, stress, and pollution in the environment. Specialized treatments, such as hair physiotherapy, have arisen to address this issue. This paper proposes a deep learning model that can analysis the scalp diseases with high accuracy, using this model we can predict the scalp diseases which makes easier for them to treat the disease with good treatment using the mobile phones we can predict the diseases simply using its image. This paper deals with an advanced classification model which predicts scalp disease. More than 1100 images are used as training dataset, CNN is used for the classification and the high accuracy is achieved using VGG16, VGG19 and MobileNetV2**.**

Keywords: scalp, diseases, VGG16, VGG19, mobileNetV.

1. Introduction

The skin and subcutaneous tissue that cover the bones of the cranial vault are referred to as the scalp. Soft tissue layers cover the cranium and make up the scalp. It is an anatomical region bordered on the front by the human face and on the sides and back by the neck [1]. It runs from the supraorbital foramen to the superior nuchal lines and occipital turbulences. Deep learning is a sort of machine learning in which computers are taught to do things that humans do naturally. Deep learning is used to train a computer model to perform categorization tasks from images, text, or sound. Deep learning systems can attain 9 times the accuracy of humans and, in some situations, outperform them. To train models, a large amount of labeled data and neural network topologies with numerous layers are used. The scalp pictures dataset is utilized in this study to detect hair diseases using deep learning techniques VGG16, VGG19 and MobileNetV2**.** The 2014 ILSVRC(ImageNet) competition was won by the VGG16 architecture, a convolutional neural network (CNN). Currently, it's one of the most cutting-edge vision model designs available. VGG16 focused on having 3x3 filter convolution layers with a stride 1 and always used the same padding and maxpool layer of 2x2 filter stride 2, as opposed to having a lot of hype parameters. Throughout the architecture, the convolution and max pool layers are arranged in the same manner. Two FC (completely connected layers) and a SoftMax are the last components for output. The 16 layers of various weights in VGG16 are indicated by the number 16. With around 138 million parameters, this network is fairly large.

1. The volume is 224*224*64 because the first two convolutional layers have 3*3 filters and the first two levels have 64 filters because the same convolutions are used in both layers. The typical stride for filters is 3*3.

2. Then, using a pooling layer with a max-pool of 2*2 size and stride 2, the volume's height and width were decreased from 224*224*64 to 112*112*64.
3. Then, two further convolution layers with 128 filters are added. As a result, a new dimension of 112*112*128 is produced.
4. Volume is lowered to 56*56*128 once the pooling layer is implemented.
5. The image is then downscaled to 28*28*256 pixels by adding two more convolution layers with 256 filters.
6. A max-pool layer divides two more stacks, each comprising three convolution layers.
7. After the final pooling layer, the 7*7*512 volume is flattened into a Fully Connected (FC) layer with 4096 channels and 1000 softmax output classes.

The paper's model, VGG19, has a depth of 19 layers (16 convolution layers, 3 Fully connected layer, 5 MaxPool layers and 1 SoftMax layer). 19.6 billion FLOPs makeup VGG19. It was first proposed in 2014 by the Visual Geometry Group at Oxford University, which also achieved precise classification results on the ImageNet dataset[2].VGG19 is a sophisticated CNN with a strong grasp of image color, structure, and shape, as well as pre-trained layers. VGG19 is a deep learning system that has been trained on millions of pictures with difficult categorization problems.

1. The matrix was of shape because the input to this network was a fixed-size RGB picture (224 * 224). (224,224,3).
2. Only the mean RGB value of each pixel, which was obtained for the complete training set, was subtracted.
3. To cover the complete visual notion, they employed kernels with a size of (3 * 3) and a stride of 1 pixel.
4. Spatial padding was used to keep the image's spatial resolution.
5. Over a 2 × 2 pixel window, sride 2 achieved maximum pooling.
6. The Rectified linear unit (ReLu) was then introduced to provide non-linearity to increase model classification and processing speed, whereas previous models had relied on tanh or sigmoid functions.
7. The first two layers were 4096 layers, followed by a 1000-channel layer for 1000-way ILSVRC classification, and then a softmax function.

A 53-layer deep convolutional neural network specifically created for mobile devices is called MobileNet- v2. For locating and segmenting objects, it's a fantastic feature extractor. It functions by using residual links between bottleneck levels and an inverted residual structure. Lightweight depth-wise convolutions serve as a source of non-linearity in the intermediate expansion layer filters. A fully convolutional layer with 32 filters and 19 bottleneck layers is part of MobileNetV2's overall architecture.

MobileNetV2 models are significantly quicker than MobileNetV1 devices. On a Google Pixel phone, it takes two times less operations, is more accurate, requires 30% fewer parameters, and is 30-40% faster. MobileNet's benefits include: 17MB network size reduction. The number of parameters has been reduced to 4.2 million. They perform better and are more suitable for mobile apps. In the bottleneck residual block, there are 3 convolution layers. The final two layers of Mobile Net v1 are known to us. They are a depth wise convolution layer and a 1 x 1 point-to-point convolution layer. In MobileNetv1, the number of channels is kept the same or doubled. Using 1 x 1 convolution, however, the number of channels is minimized. The projection layer is what we call it. Because it limits the quantity of data that travels through it, this layer is also known as the bottleneck layer. A 1 x 1 expansion layer is the first layer. It increases the amount of data that passes via it (the number of channels). It has the exact opposite effect as the projection layer. According to the expansion factor, the data is expanded. This hyper parameter can be discovered through various architecture trade-offs. The expansion factor is set to 6 by default. The depth wise convolution layer is the next layer. The third layer is an 11-layer convolution with no non-linearity. The researchers found that if ReLU is repeated, deep networks only have the capability of a linear classifier in the non-zero volume output domain[3]. A residual connection is also a crucial component of the bottleneck residual block. It's just like ResNet.

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2. Literature review

Soft tissue layers cover the cranium and make up the scalp. It is an anatomical region bordered on the front by the human face and on the sides and back by the neck. It runs from the supraorbital foramen to the superior nuchal lines and occipital turbulences. It functions as a region for hair to grow as well as a physical barrier to protect the body from unwanted irritants. Without a healthy scalp, you can't have healthy hair. A Scalp or hair disease affects this very important tissue, which, in turn, can affect the personality of human beings. The early detection and ensuing treatment are essential to prevent hair and scalp damage[4]. A scalp biopsy is a quick, simple procedure that involves removing a sample of skin from your scalp for testing and analysis. It is an important component in both diagnosing and determining the best treatment.

The symptoms of hair-related disorders vary, but the majority of them cause irritation. Hair diseases can affect any part of your scalp which affect your hair follicle, and some can be serious enough to cause baldness. Common scalp conditions include Alopecia Areata, Folliculitis, Lichen Planopilaris. There are other issues that can occur, but these conditions are some of the most common and serious that a person can experience. There are several existing conventional methods which are simple and complex that take more time and require manpower round the clock to detect and classify Hair related diseases. Several Deep Learning models have also been used to classify hair diseases using well-known Deep Learning architectures[8]. Furthermore, several researchers have developed modified versions to increase the identification of retinal illness in a variety of situations.

Lee, S. H., & Yang, C. S [5] has presented a scalp hair inspection and diagnosis system based on deep learning for health. Deep learning was used to diagnose the hair and scalp. ScalpEye datasets were used to inspect and diagnose. The image of scalp hair is analyzed by a cloud-based AI training server. The ScalpEye system technique used the R- CNN Inception ResNet v2 Atrous model, which had a precision of 97.7%.

Researchers proposed that the automated evaluation of hair density using YOLOv4 be reviewed using a Deep Neural Network [6]. As a result, this research was carried out to assess the accuracy of several deep-learning-based HDM algorithms as well as the possibility of automating HDM [7]. Using cutting-edge deep-learning-based object detection technology, the feasibility of automated HDM was explored (specifically, EfficientDet, YOLOv4, and DetectoRS) [8]. YOLOv4 had the best performance in the experiments, with a mean average precision of 58.67.

Shakeel, C. S [9] has proposed an efficient hair damage detection system based on Convolutional Neural Networks in deep learning that will detect hair damage autonomously using SEM (scanning electron microscope) images. The Hitachi S-4700 SEM is used to achieve the best results. A stochastic gradient descent approach was used to train the network (SGD) Multiple residual attention modules were stacked to create the RCSAN network.

3. Proposed work

Research has been done related to our concept. Methodologies used in the base paper are R-CNN, YOLO - V4. We have implemented a concept using VGG19 which is 19 deep layers [10][11]. A pre-trained version of the network can be loaded using the ImageNet database, which has been trained on over a million images. Keyboards, mice, pens, and other animals are just a few of the 1000 possible item categories that can be used to categorize photographs [12][13]. The network has so picked up a variety of rich feature representations for a variety of images [14]. For the network, 224 224 pixels of picture input are required. We have used dataset images of 10 commonly occurring diseases such as Alopecia Areata, Contact Dermatitis, Folliculitis, Head Lice, Lichen Planus, Male Pattern Baldness, Psoriasis, Seborrheic Dermatitis, Telogen Effluvium, Tinea Capitis. This helps trichologists to predict the disease accurately and appropriate treatments can be given for immediate cure of patients [15][16].

3.1. Data preprocessing

The dataset's data was fairly heavily preprocessed before being used [17]. The dataset is created from this incomplete information once it has been digested. The data needs to be standardised in order to be

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used with the Python capabilities [18]. The information foundation for AI frequently uses the method of standardization. With no data loss or contrasts in the ranges of values, standardization aims to change the dataset's numeric segments' upsides to use a standard scale [19]. As a result, the data are normalized and fall between 0 and 1. The feature and label are separated, making them available for subsequent model processing [20][21].

3.2. Training and testing the model

Using a variety of libraries, including Pandas, Numpy, and Matplot, the model is created and trained in the Python programming environment [22]. Train and validation datasets are separated from the whole dataset. The validation dataset is used to provide a fair evaluation of a model fit on the preparation dataset while tuning model hyper parameters. The training dataset is used to fit the model [23].

3.3. Validating the model

The process of validating involves putting the dataset to the test using the training model [24]. The preparation set is derived from the equivalent dataset, which also contains the testing informational index [25]. The purpose of model approval is to evaluate the model's accuracy and execution in light of historical data for which we currently have actual [26]. Accuracy has been used to evaluate how the proposed framework is presented [27][28].

4. Results

4.1. Dataset

Our dataset consists of 1200 images of 10 types of scalp diseases, greater the dataset leads to better accuracy. It is separated into two which is the test and train dataset. The dataset consists of 10 scalp diseases like Alopecia Areata, Contact Dermatitis, Folliculitis, Head Lice, Lichen Planus, Male Pattern Baldness, Psoriasis, Seborrheic Dermatitis, Telogen Effluvium, Tinea Capitis. Some of the disease are explained below,

4.2. Performance evaluation

The interaction in which a prepared model is evaluated using a testing informational index is referred to as "model approval." The testing educational list is a different component of a comparable educational assortment that serves as the basis for the arranging set. The purpose of model approval is to evaluate the model's accuracy and execution in light of historical data for which we currently have actual. Accuracy is the measurement used for evaluation. Accuracy is a measurement for assessing arrangement models. Casually, accuracy is the small part of expectations that the model was correct. Officially, accuracy is the quantity of right expectations per complete number of expectations [29]. The Accuracy acquired is

$$\text{Accuracy}= (TP+TN)\ (TP+TN+FP+FN) \tag{1}$$

In the equation above, the letters TP, FN, TN, FP, and TN stand for the number of true positives, false negatives, and true positives, respectively. The models VGG16, MobileNetV2 and VGG19 are used in this study. Training and validation plot for VGG16, VGG19 and MobiNetV2 is shown in Fig 1, Fig 2 and Fig 3 respectively.

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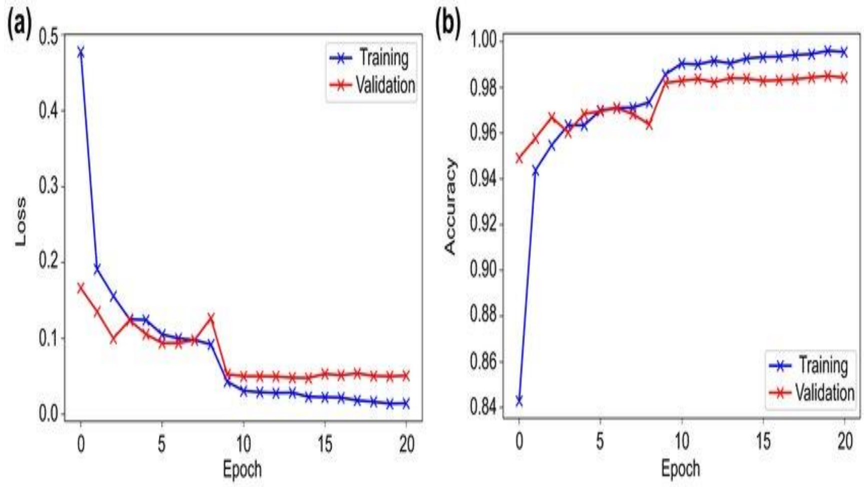

Figure 1. Training and validation a) Loss b) Accuracy graph of of VGG16.

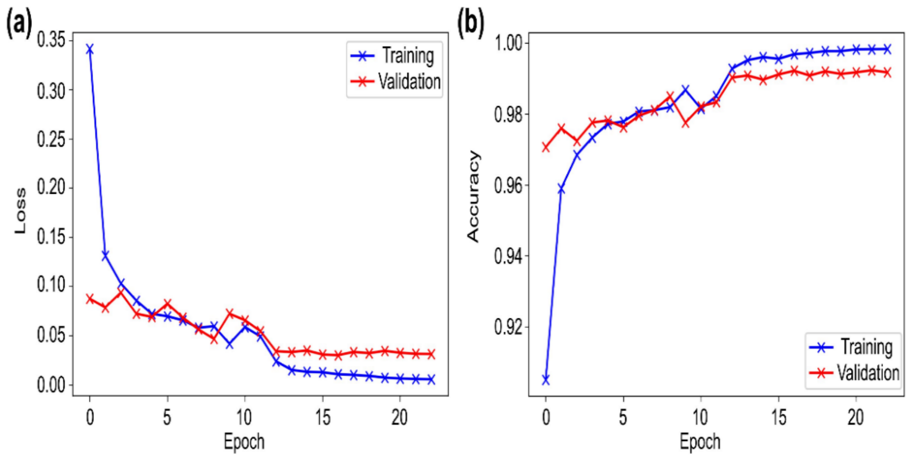

Figure 2. Training and validation a) Loss b) Accuracy graph of VGG19.

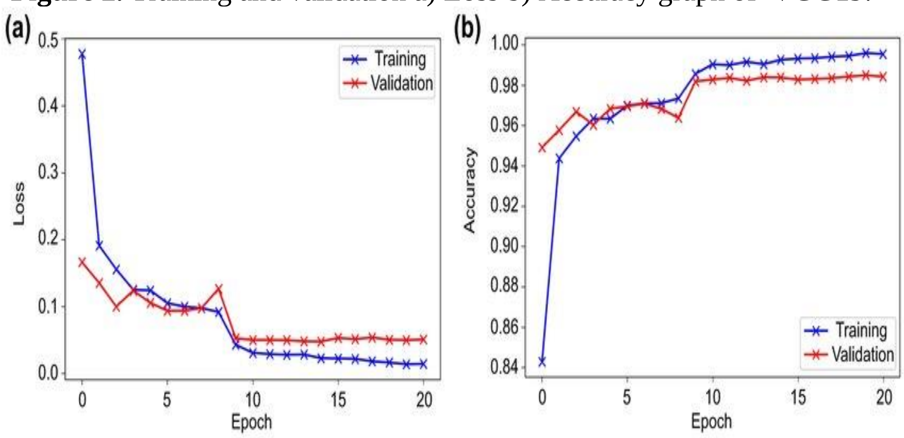

Figure 3. Training and validation a) Loss b) Accuracy graph of MobileNetV2.

5. Conclusion

Early diagnosis is important in terms of the successful treatment process in order to avoid severe baldness. Even with the significant advancement in technology, Baldness or hair fall cannot be cured because of improper identification at the initial stage. Treatment of hair-related illnesses requires prompt and precise action. Scalp Images is one of the most affordable and extensively used diagnostic tools for identifying hair problems. We've presented a new tool that can help increase diagnostic accuracy of hair-related disorders, thanks to recent breakthroughs in new deep learning algorithms. We used the most common deep learning approach known as VGG16,VGG19 and MobileNetV2 to implement computer aided diagnosis of hair-related disorders throughout this study. This model outperforms other mentioned models with accuracy of 99.08% in VGG16, 98.6% in VGG19 and 99.08% in MobileNetV2. Our proposed method outperforms existing state-of-the-arts. Therefore, it is concluded that the deep learning models VGG16,VGG19 and MobileNetV2 proposed above classify the hair diseases accurately. This is immensely helpful in the medical field for early and accurate diagnosis to avoid Baldness.

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