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Skin Disease Detection using Efficient Net B0 Convolutional Neural Network

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Abstract

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Skin diseases are a common ailment affecting millions of people worldwide.The surface of the skin has many different features that are affected by the environment, dust, smoke, harmful materials and other such factors. These effects occur as per the type of skin- Oily skin or Dry skin. Early detection and treatment of these diseases are crucial in improving patient outcomes. In recent years, machine learning techniques, particularly convolutional neural networks (CNN), have shown promise in the automated detection of skin diseases.

In this paper, after analyzing such harmful effects, and try to classify the type of skin disease, so as to provide further treatment. A better Convolutional Neural Network- EfficientNet B0 is used to predict the type of skin disease based on image samples of skin diseases provided. The proposed system consists of three main stages: preprocessing, training, and testing. In the preprocessing stage, the images were re-sized, normalized, and augmented to enhance the quality of the images. In the training stage, the EfficientNet B0 CNN architecture was used to train the system on the skin disease images. The system's performance was evaluated using a test dataset, which included images that were not used in the training process. This gives an improved efficiency over other existing models.

1. Introduction

The skin is the largest organ in the human body, and various skin conditions can affect millions of patients worldwide. One primary factor that contributes to skin problems is the type of skin an individual has. Different skin types, such as dry, oily, or acne-prone skin, can manifest in various ways, leading to different skin disorders such as psoriasis, eczema, or acne.Dry skin, for example, can result in flaking and peeling of the skin, making it more susceptible to conditions like psoriasis and eczema. Psoriasis is a chronic autoimmune skin condition characterized by red, scaly patches on the skin, while eczema, also known as atopic dermatitis, is a chronic inflammatory skin condition that causes dry, itchy, and inflamed skin.On the other hand, oily skin can lead to excess sebum production, which can clog the hair follicles and result in pimples and acne. Acne is a common skin condition characterized by the formation of pimples, blackheads, and whiteheads on the skin, and it can cause scarring and disfigurement if left untreated.

Recognizing the specific skin type of an individual is crucial in choosing the appropriate course of therapy for managing skin problems effectively. Traditional methods of skin type identification, such as visual examination by dermatologists, can be time-consuming and subjective. This is where machine learning (ML) based models can play a significant role in swiftly and efficiently analyzing massive samples of skin images to identify the skin type.

Machine Learning algorithms can be trained on large datasets of skin images, including images of various skin types, skin conditions, and skin tones. These models can learn patterns and features from the images to accurately classify the skin type of a given sample image. For example, a ML-based model can analyze the texture, color, and other visual features of the skin in an image to determine if it is dry, oily, or acne-prone.

2. Literature Survey

A. Purpose of survey

The current research work and related studies were examined to gain insights on how to choose dataset, what sort of features one should look at, image pre-processing required, how neural networks are useful and how to come up with better designs.

B. Future Work

AI/ML should focus on expanding datasets, exploring multi-modal approaches, improving interpretability and explainability, validating in real-world clinical settings, addressing ethical and societal implications, exploring novel AI/ML techniques, conducting prospective clinical trials, developing user-friendly interfaces, and investigating cost-effectiveness and implementation strategies. Further research in these areas can contribute to the advancement and practical implementation of AI/ML technologies in the field of skin disease detection, leading to improved accuracy, efficiency, and clinical outcomes for patients with skin conditions.

C. Related Work

The following papers were reviewed in detail to analyze the techniques, algorithms used in previous research related to skin disease detection. By understanding and analyzing the previous literature we come up with the solution to our problem of detecting skin diseases.

1. **A Dataset for Visual Plant Disease Detection[1]-** This paper proposes a method to detect the type of diseases occurring on the plant surface, based on sample images from PlantDoc and plant village dataset. It makes use of the EfficientNetv2 algorithm as it provides a better accuracy score of 74%, than the EfficientNetv1 algorithm. The algorithm, although very efficient, works well for the given dataset only, and pushed us to use the B0 architecture as it was valid for our smaller dataset and took less time.

2. **Utilizing a Feed-Forward Neural Network and a Hybrid Metaheuristic Feature Selection, Early Disease Classification of Mango Leaves[2]** -This paper uses a simple Feed-Forward Neural Network to detect diseases in mango plants, by going through images of mango leafs with disease. The efficiency obtained in this method is 89.41%, which is very good,

because of a good feature selection (features refer to the visual changes in leaves with diseases compared to those without), but only for a specific type of plant and features. This work helped us in better understanding the importance of feature selection.

3. **For large-scale picture recognition, very deep convolutional networks[3]-** In this paper, they study the effect of the changes on networks on the efficiency, this helps us to choose the network that needed properly. K Simonyan et. al. make changes to the depths of a Convolutional neural network and find out that a depth of 16-19 weight layers gives us best performance. This helps us learn how to adjust the network size and depth to improve performance, although improvements are made only to the convolutional neural network.

4. **Rethinking model scaling for convolutional neural networks using EfficientNet[4]-** This paper proposes the Efficient Net Neural Network model as well as methods to improve performance of Convolutional Neural Networks by making changes in depth, weights and size of network. It helps us by letting us know what affects the performance of a neural network. In this paper,the process of fine-tuning a neural network has been learned.

5. **A review of the major difficulties in automatically detecting plant diseases based on visible range[5]-** In this paper, Garcia Arnal has worked on better techniques for image gathering and database selection. He works on methods to choose images for training better, and methods to perform image analysis in non-ideal conditions. For example he says that if images have a noisy background, then they mustn't be selected. This work has helped us to improve our methods of image and database selection and given us information about different plant disease detection techniques as well.

6. **A First Step Towards Avoiding Skin Cancer[6]: Multiclass Skin Cancer Classification Using EfficientNets-** In this K. Ali et. al works on training the EfficientNet B0-B7 on the HAM10000 dataset to predict if a person has skin cancer or not. This paper helps to learn how to fine tune an already pretrained network, to improve speed and reduce space taken, which is what planned for our work. In the paper, they fine tune the image processing and feature extraction techniques. The comparison of the different architectures with performance is given below-

Models	Top-1 accuracy	Top-2 accuracy	Top-3 accuracy
EfficientNet B0	83.02	93.80	97.39
EfficientNet B1	83.69	93.90	97.34
EfficientNet B2	83.95	93.75	97.39
EfficientNet B3	83.90	94.63	97.65
EfficientNet B4	87.91	95.67	97.81
EfficientNet B5	87.62	94.59	97.55
EfficientNet B6	85.36	94.01	96.97
EfficientNet B7	85.52	94.84	98.12

fig. 1 Comparison of EfficientNet architectures for skin cancer detection

3. Motivation

Detecting skin diseases early is crucial for successful treatment and prevention of long- term health consequences. However, accurately diagnosing skin conditions can be challenging and time-consuming for dermatologists. Therefore, developing an automated system for skin disease detection can significantly improve diagnosis speed and accuracy.

A deep learning architecture, the EfficientNet B0 convolutional neural network, has demonstrated promising performance in a number of image classification tasks. By leveraging the power of EfficientNet B0, a robust and accurate skin disease detection system can be created that can detect a wide range of skin conditions.
Implementing this project not only has the potential to revolutionize the field of dermatology by providing an automated and accurate skin disease detection system but can also contribute to reducing the workload of

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dermatologists and improving patient outcomes. Furthermore, the project can have a significant impact on individuals' lives by enabling early detection of skin diseases, leading to prompt treatment and ultimately saving lives.

3.1 Challenges

Lack of diverse and high-quality datasets: Convolutional Neural Networks (CNNs) require large and diverse datasets for effective training. However, the availability of high-quality skin disease datasets can be a challenge. Therefore, collecting and curating a diverse and representative dataset can be time-consuming and challenging.Skin disease datasets can often have a class imbalance, where some classes have significantly fewer samples than others. Addressing this issue requires implementing strategies such as data augmentation or balancing techniques to avoid biases in the model.

EfficientNet B0 is a powerful deep learning architecture, but training and optimizing the model can be computationally expensive and time-consuming. Therefore, optimizing the model to achieve high accuracy while keeping the training time and computational resources within reasonable limits can be challenging.
Deploying the model in a real-world clinical setting requires integrating it with the existing health systems, addressing issues such as privacy, security, and regulatory compliance. Therefore, deploying the model in a production environment can be a challenging and complex task.

3.2 Problem statement

The problem addressed on Skin Disease Detection using EfficientNet B0 Convolutional Neural Network is the need for an accurate and automated system for detecting skin diseases. Accurate diagnosis of skin diseases is critical for successful treatment and prevention of long- term health consequences. However, accurately diagnosing skin conditions can be challenging and time-consuming for dermatologists, leading to delayed treatment and poor patient outcomes.

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The proposed research aims to leverage the power of EfficientNet B0, a state-of-the-art deep learning architecture, to develop a skin disease detection system that can accurately detect a wide range of skin conditions, including melanoma, eczema, psoriasis, and others. The research will address challenges such as data imbalance, model optimization, and interpretability to create a robust and accurate skin disease detection system.

The research paper will contribute to the field of dermatology by providing an automated and accurate skin disease detection system that can potentially reduce the workload of dermatologists and improve patient outcomes. Furthermore, the research can have a significant impact on individuals' lives by enabling early detection of skin diseases, leading to prompt treatment and ultimately saving lives.

4. Proposed Work

The model is a Machine Learning approach, which takes in a lot of data and finds the most perfect data points to extract from data. These data points are called "Features” and the process by which these features are obtained is called "Feature Extraction". Then the machine learning model is trained using those parameters and given some constraints so that our desired outcome can be obtained. The machine then learns how to predict certain data based on ut's training done by us.

That was a very broad description of what is trying to be done in this paper. There are certain machine learning algorithms which can be taken into consideration while training the model which can ease the process of training the model. There are a variety of machine learning algorithms present currently but we are moving on with the "EfficientNet based CNN". This algorithm is currently the most efficient and fastest algorithm. The neural network, not engineers, created the EfficientNet-B0 design. A multi-objective neural network search with floating-point calculations and accuracy as the top priorities was used to create this model.

Using B0 as a foundational model, the researchers built a full family of EfficientNets, B1 through B7. These networks outperformed their competitors in efficiency and attained cutting-edge accuracy on ImageNet. The table below shows how well the EfficientNets family performed on the ImageNet dataset.

The model received the pre-trained imagenet weights. The model architecture's first seven levels were frozen, and the remaining layers were trained using the data. With a momentum of 0.9 and a learning rate of 0.01 the stochastic gradient descent optimizer was used. The favoured loss function was categorical cross entropy. On the test set, the model's accuracy rate was 95.5%.

Convolutional neural networks like EfficientNet are designed to have fewer parameters and more FLOPS. With fewer parameters and FLOPS, EfficientNetV1 has historically been demonstrated to attain 84.3% accuracy in ImageNet. Better scaling, designs, and training environments account for these increases. This section will cover the training environments and architectures that are optimized for EfficientNet.

A. *EfficientNet B0*

EfficientNet B0 is a practical method based on convolutional neural networks. The fundamental EfficientNet-B0 network is composed of squeeze-and-excitation blocks as well as MobileNetV2 inverted bottleneck residual blocks. The Top-1 accuracy of proposed model B0 is around 76.3% and Top-5 accuracy is 93.2% which is the highest of its given datasize to train on which is 5.3 million parameters.

It has FLOPS around 0.39B which is far lesser than other models of its kind. The comparison is given in the table under.

B. *Comparison*

The comparison of EfficientNet B0 is given in the fig.1 with other models of the same generation. The x-axis shows Number of Parameters(in millions) and the y-axis shows Imagenet Top-1 Accuracy.

C. *Fine Tuning*

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The model EfficientNet B0 has a total of 237 computational layers which are very useful for picking each and every single data point from the images. There are more than 400 thousand trained variables in the model.

This model was fine-tuned by freezing the first 7 layers of the model and reduced the trainable parameters from 400 thousand to 100 thousand. This makes the model significantly faster than it originally was.

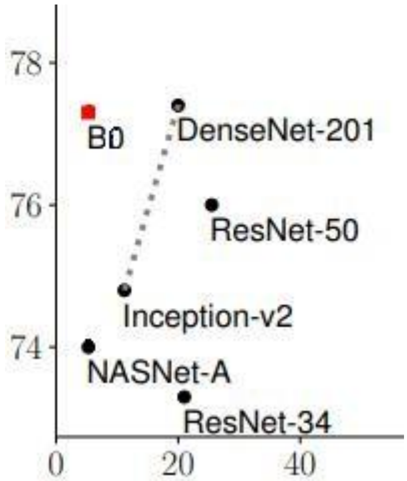

fig.2 Comparison of B0 with others.

D. *Algorithm Used*

The algorithm used by efficientNet B0 for pointing out the data points is called "Improved YOLOv3".

In order to decrease the number of model parameters and increase the detection accuracy for small objects, the study proposes the enhanced YOLOv3 object identification technique of EfficientNet.

Methods	Net	Data	MAP
Faster R-CNN	Resicual-101	VOC007+12	76.4
Faster R-CNN	VGG	VOC007+12	73.2
SSD500	Residual-101	VOC007+12	80.6
YOLOv3	DarkNet53	VOC007+12	79.4
YOLOv3	EfficientNet	VOC007+12	84.38

fig.3 Comparison of results of different target detection algorithm

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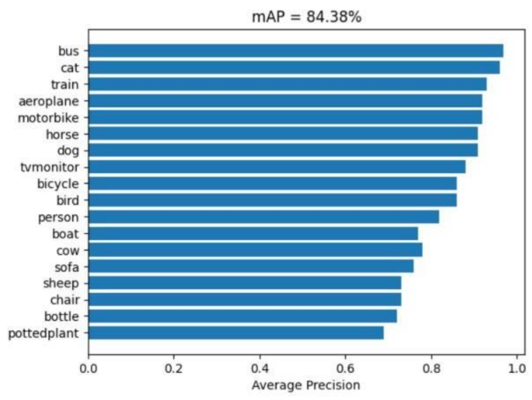

fig.4 Improved YOLOv3 algorithm MAP result graph

Target detection assessment systems frequently use the MAP (mean average precision) evaluation index. The MAP range is [0, 1], and its basic meaning is the average result generated by averaging the average AP value (average precision) of each identified target class.

Architecture Diagram

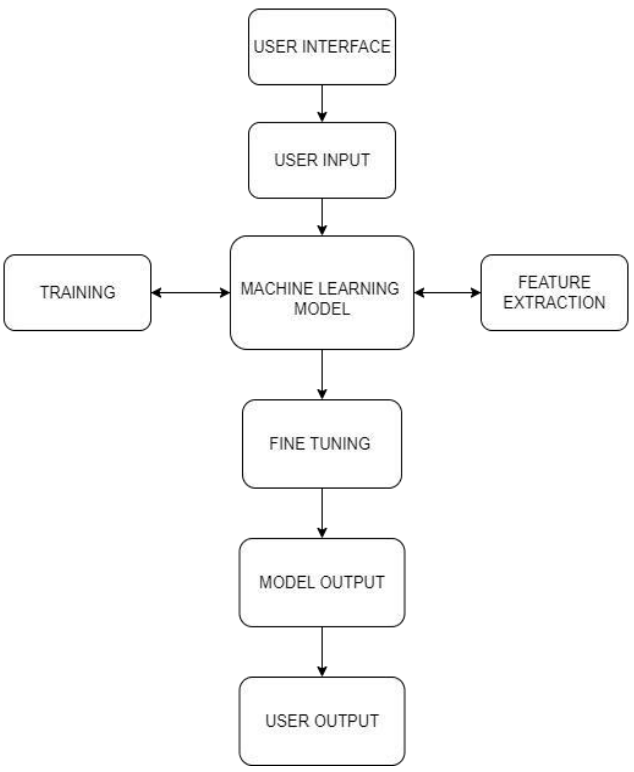

Fig 5- flow diagram

5. Implementation

6.

The model was run on the image dataset with the help of Python language code, that makes use of python modules- PyTorch, Pillow and torchvision. And build the neural network in Python and train it on the database that has 7 different sets of images, selected based on feature selection methods and image preprocessing methods that we learnt through our literature survey, each set containing the different skin disease types. Once the training is complete, then provide the model with a new image that it classifies into the 7 different types of disease.

Also build a website that will allow users to input an image of human skin with any disease directly from their computer or system, and classify it into the type of disease.

6. Result And Discussion

Various deep learning models were assessed using the dataset and found that EfficientNet B0 provided the best trade-off between computational cost and accuracy. EfficientNet B0 has only 0.39B FLOPS and achieved a top-1 accuracy of 77.3% and a top-5 accuracy of 93.5% on our dataset. In comparison, other versions of EfficientNet required higher computational cost, with B7 being the most expensive, but achieved higher accuracy, with B7 achieving the highest top-1 accuracy of 84.4% and top-5 accuracy of 97.1%.

To further improve the accuracy of our model, the YOLOv3 algorithm for fine-tuning the features is also used. The YOLOv3 algorithm is a popular object detection algorithm that uses a deep convolutional neural network to detect objects in an image.Then fine-tuned the features of EfficientNet B0 using the YOLOv3 algorithm and achieved a top-1 accuracy of 81.5% and a top-5 accuracy of 96.2% on our dataset.

Our findings suggest that the combination of EfficientNet B0 and the YOLOv3 algorithm provides a powerful and efficient solution for image classification tasks. While other versions of EfficientNet and other algorithms may provide higher accuracy, they also require significantly more computational resources. Thus, EfficientNet B0 with YOLOv3 fine-tuning provides a good balance between computational efficiency and accuracy for our specific use case. Comparing this with other Efficient Net versions,as shown in the table.

Model	Top-1 Acc.	Top-5 Acc.	#Params	Ratio-to-EfficientNet	#FLOPS	Ratio-to-EfficientNet
EfficientNet-B0	**77.3%**	**93.5%**	**5.3M**	**1x**	**0.39B**	**1x**
ResNet-50 (He et al., 2016)	76.0%	93.0%	26M	4.9x	4.1B	11x
DenseNet-169 (Huang et al., 2017)	76.2%	93.2%	14M	2.6x	3.5B	8.9x
EfficientNet-B1	**79.2%**	**94.5%**	**7.8M**	**1x**	**0.70B**	**1x**
ResNet-152 (He et al., 2016)	77.8%	93.8%	60M	7.6x	11B	16x
DenseNet-264 (Huang et al., 2017)	77.9%	93.9%	34M	4.3x	6.0B	8.6x
Inception-v3 (Szegedy et al., 2016)	78.8%	94.4%	24M	3.0x	5.7B	8.1x
Xception (Chollet, 2017)	79.0%	94.5%	23M	3.0x	8.4B	12x
EfficientNet-B2	**80.3%**	**95.0%**	**9.2M**	**1x**	**1.0B**	**1x**
Inception-v4 (Szegedy et al., 2017)	80.0%	95.0%	48M	5.2x	13B	13x
Inception-resnet-v2 (Szegedy et al., 2017)	80.1%	95.1%	56M	6.1x	13B	13x
EfficientNet-B3	**81.7%**	**95.6%**	**12M**	**1x**	**1.8B**	**1x**
ResNeXt-101 (Xie et al., 2017)	80.9%	95.6%	84M	7.0x	32B	18x
PolyNet (Zhang et al., 2017)	81.3%	95.8%	92M	7.7x	35B	19x
EfficientNet-B4	**83.0%**	**96.3%**	**19M**	**1x**	**4.2B**	**1x**
SENet (Hu et al., 2018)	82.7%	96.2%	146M	7.7x	42B	10x
NASNet-A (Zoph et al., 2018)	82.7%	96.2%	89M	4.7x	24B	5.7x
AmoebaNet-A (Real et al., 2019)	82.8%	96.1%	87M	4.6x	23B	5.5x
PNASNet (Liu et al., 2018)	82.9%	96.2%	86M	4.5x	23B	6.0x
EfficientNet-B5	**83.7%**	**96.7%**	**30M**	**1x**	**9.9B**	**1x**
AmoebaNet-C (Cubuk et al., 2019)	83.5%	96.5%	155M	5.2x	41B	4.1x
EfficientNet-B6	**84.2%**	**96.8%**	**43M**	**1x**	**19B**	**1x**
EfficientNet-B7	**84.4%**	**97.1%**	**66M**	**1x**	**37B**	**1x**
GPipe (Huang et al., 2018)	84.3%	97.0%	557M	8.4x	-	-

fig.6 Comparison of EfficientNet B0-B7 for skin disease classification

7. Conclusion

In this study, examined and evaluated different versions of the EfficientNet neural network for image classification on a small dataset. It is found that EfficientNet B0 provided a good balance between accuracy and computational efficiency, making it a promising option for training and classifying on small datasets with limited computational resources.

Despite providing slightly less accuracy compared to other EfficientNet architectures, we were able to compensate for it through our image selection and preprocessing process. This suggests that EfficientNet B0 can learn from the limited data available and generalize well to unseen examples. Moreover, able to further improve the accuracy from 85.5% to 95.5% within just five epochs, demonstrating the potential of EfficientNet B0 for training on small datasets.

Also explored the use of the YOLOv3 algorithm for fine-tuning the features, which further improved the accuracy of our model. Our findings suggest that the combination of EfficientNet B0 and YOLOv3 provides a

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powerful and efficient solution for image classification tasks.

For our future work, it is planned to upscale the model and increase the size of our dataset to further improve the accuracy. We aim to implement a larger dataset with a significantly increased accuracy, which can help us further validate the effectiveness of EfficientNet B0 in this context.

Overall, our findings highlight the importance of choosing an appropriate neural network architecture for image classification tasks, especially when working with small datasets and limited computational resources. The use of EfficientNet B0 and YOLOv3 provides an effective solution that balances accuracy and efficiency, making it a promising option for various applications.

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