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Deep Learning Framework for Identification of Skin Lesions

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Abstract

Skin ailments don't just affect the physical appearance of an individual but also lead to psychological issues. Vitiligo and discoloration patches are such conditions that can negatively impact one's self-assurance. Here, authors have designed 14 distinct models to classify skin lesions using the HAM10000 dataset which is sorted into 7 classes including Actinic Keratosis, Melanocytic nevi, Actinic keratoses, Melanoma, Benign keratosis-like lesions, Basal cell carcinoma, and Vascular lesions. Further, authors compared their model against other state-of-the-art models, and additional-ly employed various pre-trained models like Resnet50, InceptionV3, MobileNetV2, Densenet201, VGG16, VGG19, InceptionResnetv2, Xception, EfficientNetB0, EfficientNetB1, EfficientNetB2, EfficientNetB3, Effi-cientNetB4, EfficientNetB5 that were trained on image net datasets. Their primary aim was to develop a framework that can be implemented in real-world applications using Efficient Nets. Experimental evaluations have shown that their proposed models have outperformed traditional pre-trained models like ResNets and VGG16 in terms of accuracy, precision, re-call, and validation loss, despite being lightweight. Interestingly, this im-provement was achieved without any data augmentation techniques. The authors achieved accuracy above 90% for all the EfficientNet models (B0-B5), which was far better than the existing pre-trained models, thus establishing the supremacy of proposed model.

Keywords: Convolutional Neural Network, Grey Level Co-occurrence Matrix, Rectilinear Unit, Stochastic Gradient Descent

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1. Introduction

Recent reports from the World Health Organization (WHO) have confirmed a significant increase in the number of cases of skin cancer over the past decade. As of 2021, there have been approximately 2.3 million cases of non-melanoma skin cancer and 1.06 million cases of melanoma skin cancer reported worldwide. Shockingly, one out of every three cases is diagnosed as skin cancer. Non-melanoma and melanoma are the two most prevalent types of skin cancers, with basal cell carcinoma and squamous cell carcinoma being the most common types of non-melanoma tumors. However, these tumors have a high chance of being cured if detected early.

Skin cancer occurs when one of three types of cells, namely Langerhans cells, melanocytes, or keratinocytes, replicate irregularly, causing the skin to grow abnormally. As these cells continue to replicate, skin cancer can spread to other parts of the body through the lymphatic system.

Non-melanoma is the fifth most commonly occurring skin cancer in both genders and is more prevalent than melanoma, which is the 19th most commonly occurring cancer. Melanoma is a rare and aggressive form of skin cancer that develops in melanocytes, which are cells that produce the skin pigment melanin. It is primarily caused by prolonged

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exposure to ultraviolet (UV) light. When the skin's protection is com-promised through prolonged exposure to UV rays, the skin's DNA is damaged. Dam-aged DNA cannot control the cell's growth, which may lead to cancer. While some skin diseases are caused by environmental factors like dust, moisture, and sunlight, others are genetically inherited.

Moreover, melanoma has a nearly 100% chance of being cured if detected during the early stages. The first step in identifying malignant lesions is through visual inspection by a dermatologist. However, identifying melanoma lesions is challenging because they can often look similar to normal skin lesions. Currently, medical professionals can achieve an accuracy rate of 66% to 81% for identifying melanoma lesions due to the absence of an effective method.

Another challenge in identifying melanoma lesions is the requirement of high-quality images that require a magnifying lens. Integrating physical inspection with high-end image examination has the potential to improve diagnostic accuracy to 74% to 83%. Physical examinations are conducted by experienced medical experts, while automated systems using advanced technological advancements inspect high-end im-ages.

In the health sector, machine learning (ML) has shown its superiority. ML has also produced promising results in various sectors such as handwriting recognition, facial expression detection, and fingerprint identification. Researchers have proposed various established ML architectures for classifying skin diseases, evolving from conventional ML models to Convolutional Neural Networks (CNN) over the past few decades.

The shift to CNN models is due to their competency in image classification, yielding accuracy rates of 72% to 93%. This accuracy range can be a significant achievement in dermatology, given the minimal visual difference between interclass samples of skin lesions. Several traditional CNN architectures, such as DenseNet, ResNet, and Xception, have been trained on the ImageNet dataset, which contains over 1,000 dis-tinct classes, for different classification tasks. These models contain crucial perceptions for extracting the best features from images.

The research work is organized into various sections. Here, the requirement for carrying out this research is established in section 1. Similar kind of research work carried out by different researchers is discussed in section 2. The proposed methodology is elaborated in section 3. Results and discussion in section 4 and finally conclusion is presented in section 5.

2. Related Work

In recent decades, researchers have explored various approaches for identifying and classifying skin lesions, resulting in numerous proposed models. These models include SVM (Support Vector Machine), K-means, ANN (Artificial Neural Network), and CNN (Convolutional Neural Network) models, which are trained from scratch or using pre-trained models such as Resnet50, VGG16, and Inception. Each approach employs different techniques for feature extraction, image scaling, data augmentations, and feature-scaling to achieve improved results. A comparative analysis of re-cent work in this field is presented in Table 1.

A. Sagar in [10] carried out a research by by proposing a solution for Skin lesion classification that uses CNN with transfer learning. In the model proposed in [10], authors use 3 deep learning pre-trained models viz. Inceptionv3, InceptionResNetv2 and ResNet152. During experimental evaluation it is observed that the model achieves ROC- AUC and accuracy of 0.861 and 93.5% respectively. Further, Li-sheng Wei et al. proposed a model to categorize Herpes, Psoriasis and Dermatitis [11] that employs a novel detection methodology. As per the proposed method, skin images are initially preprocessed in order to remove noise and background details through filtering and transformation. GLCM is used for image segmentation to fetch the color and texture from different images. Further, classification is done using the SVM classifier that yields an accuracy of 85%,80% and 85% for ‘herpes’, ’Paederus’ and ‘Psoriasis’ respectively.

Md Ashraful Alam et al. also presented a model that uses InceptionV4, Inception-ResNetV2, PNASNet-5-Large, and SENet154 CNN models to classify Benign and malignant skin lesions [12]. The proposed model preprocesses the images and implements image augmentation in order to address imbalancing of the dataset. The model demonstrates a validation score of 0.76, 0.70, 0.74, and 0.67 for PNASNet5-Large, InceptionResNetV2, SENet154, and InceptionV4 respectively. Additionally, ensemble modelling yields a validation score of 0.73.

Authors in [13] also proposed a model that classifies 3 different Skin Diseases namely Herpes, Dermatitis, and Psoriasis. This model also performs preprocessing to remove noise using Filtration and transformation. Further, the classification is automated using CNN models and validated on HAM10000 datasets. Thereafter, authors in [14] also presented a model for Multi-Class Categorization of Skin lesions. It suggests independent CNN ensemble models and uses hyper parameters for 5 pre-trained models viz. NASNetLarge, InceptionV3, Xception, InceptionResNetV2 and Res-NetXt101. Further, ensemble models for ResNetXt101 + InceptionResNetV2 + Xcep-tion, InceptionResNetV2 + Xception, InceptionV3 + Xception, and InceptionRes-NetV2 + ResNetXt101 are also simulated. Here, the maximum accuracy for inde-pendent architectures and ensemble models is recorded 93.20% and 92.80% respectively.

Authors in [15] also proposed a model built on CNN based transfer learning technique i.e., GoogLeNet and VGG16 pre-trained models. The prime feature of the pro-posed model is image augmentation and preprocessing using color normalization. The model is validated towards Melanoma Detection using the official validation set for ISIC 2018 Task 3 competition. The proposed model demonstrates balanced accuracy of 0.801 for VGG16, 0.797 for the GoogLeNet architecture and 0.815 for ensemble modeling.

Table 1. Comparison chart of different state-of-art works on skin classification

Researcher	Dataset	Class	Methodology	Accuracy (%)	Precision (%)	Recall (%)
R. Yasir et al. (2014) [8]	-	Nine	ANN	90	-	-
H. Alquran (2017) [6]	-	Two	SVM	92.1	-	-
Li-sheng Wei et al. (2018) [11]	-	Three	SVM	83.3	-	-
AH Shahin (2018) [1]	HAM10000	Seven	Ensemble Learning	89.9	86.2	79.6
Milton et al. (2018) [12]	HAM10000	Seven	Ensemble learning			
K.T Hemsi et al. (2019) [9]	-	Seven	Transfer learning	93	-	-
M. A. Hilmy (2019) [4]	ISIC2018	Seven	Ensemble Learning	91.7	-	-
Hosny K.M et al. (2019) [3]	PH2 dataset	Three	Ensemble Learning	98.6	97.73	98.33
M. A. Albahar (2019) [2]	HAM10000	Two	Novel Regularizer	97.4	-	-
Kadampur, M.A. et al. (2020) [35]	HAM10000	Two	Deep Learning Studio (DLS)	99.7		
S.R.Hassan et al. (2020)[5]	ISIC2018	Seven	DenseNet model	92	91	91
Le, D. N. T et al. (2020) [7]	ISIC2018	Seven	CNN	93	88	85
S.S. Ch et al. (2020) [14]	ISIC2018	Two	Transfer learning	92.8	83	84
Wang et al. (2021) [18]	ISIC 2018	Seven	Self-supervised Topology Clustering Network	80.6	-	-
Zhao et al. (2021) [19]	Rosacea	Three	CNN(ResNet-50)	91.4	89.8	-
Dutta et al. (2021) [20]	ISBI 2017	Two	Deep CNN	87	73	76
Marta et al. (2021) [21]	ISIC 2018	Seven	CNN(ResNet-50)	80	-	-
Kumar et al. (2021) [22]	Interactive Atlas	Five	Multimodal Framework	73.6	71.34	68.93

During thorough analysis of the related literature, it has been noticed that there are some research gaps as follows:

- There is an imperative need for an automated system for skin lesion classification which can be deployed in the real-world at large.
- Lack of work using Efficient Nets applied on HAM10000 dataset.
- Most of the researchers have proposed models with 1 or 2 CNN models. Hence, it becomes improper to compare these models as each CNN model has different internal structure.
- Implementation of image augmentation leads to losing out the original essence of the dataset.

Authors in this research paper aim to address the research gaps by proposing a methodology in the following section.

3. Proposed Methodology

Authors in this paper have proposed a methodology as illustrated in Figure 1. In this study, the authors present a convolutional neural network-based paradigm that conducts categorization of 14 skin blemishes. The proposed prototype underwent experimentation with pre-trained Efficient Net models on the HAM10000 dataset and tested using a web application using the 'MobileNetV2' blueprint. The detailed configuration of the proposed system is elucidated in the ensuing subsections. The current research employs pre-trained models that were trained utilizing several dissimilar 'ImageNet' datasets, namely, Resnet50, InceptionV3, MobileNetV2, Densenet201, VGG16, VGG19, InceptionResnetv2, Xception, EfficientNetB0, EfficientNetB1, EfficientNetB2, EfficientNetB3, EfficientNetB4, and EfficientNetB5. In addition, the prototype underwent testing employing the HAM10000 corpus to classify seven distinct cutaneous lesions.

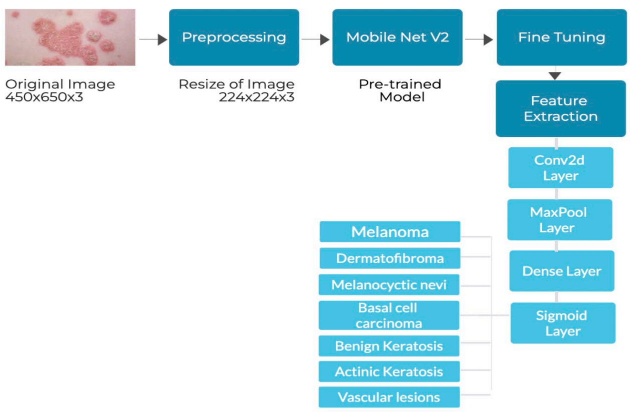

Figure 1. Illustration of Proposed Methodology

The presented framework employs MobileNetV2, with pre-existing weights fine-tuned on the HAM10000 dataset for 30 epochs. MobileNetV2 is a lightweight and high-speed model, optimized for mobile-based deep learning applications. It uses conventional down-sampling methods in the initial layers, utilizing depth-wise and point-wise separable convolutions, thereby enhancing its computational speed. The current study enhances performance through the use of Convolutional Layers, Max Pooling Layers, Dropout Layers, and a Dense Layer, with 'Relu' activation, followed by a Sigmoid Layer. The last layers of the pre-trained MobileNetV2 model undergo fine-tuning using an SGD optimizer with a learning rate of 0.01. The proposed model's overall workflow is demonstrated in Figure 1. Upon completion of the training process on the MobileNetV2 model, the weights are saved and forwarded to the Flask framework module, enabling recognition of any new image uploaded to the tool using the stored weights. The proposed web tool's workflow is depicted in Figure 2.

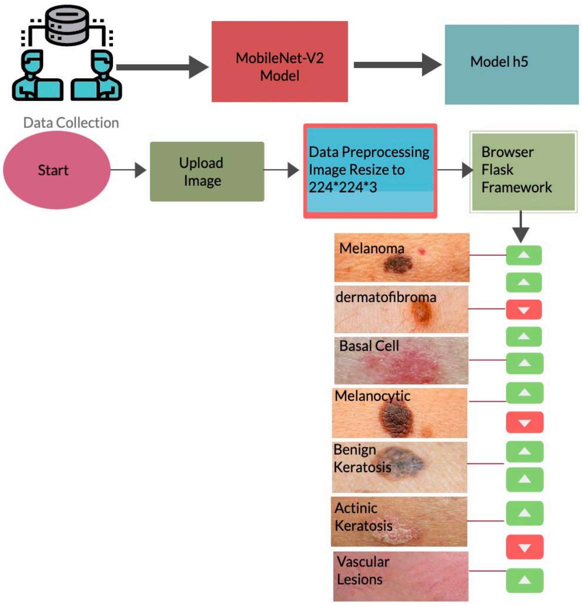

Figure 2. Flow of working of the web application tool.

4. Results and Discussion

Keras is a popular lightweight API in Python to implement deep learning. Keras is a lightweight API, which can easily run on many other deep learning libraries such as Theano, Tensorflow, Microsoft Cognitive Toolkit and PlaidML. Model is trained on Kaggle server using Tesla P100-PCIE-16GB and 6 minor GPUs. The performance of 14 models viz. Resnet50, InceptionV3, MobileNetV2, Densenet201, VGG16, VGG19, InceptionResnetv2, Xception, EfficientNetB0, EfficientNetB1, EfficientNetB2, EfficientNetB3, EfficientNetB4, EfficientNetB5 is checked to classify skin lesions among 7 different classes. The accuracy and other performance metrics achieved by different models are mentioned in Table 2. From the metrics, it is evident that Efficient Nets and Xception models outperforms other pretrained models.

The comparison of proposed approach and state-of-the-art models is discussed in Table 3 and Figure 6

5. Conclusion

The proposed research aimed to assess the performance of various Convolutional Neural Network (CNN) architectures in classifying 7 types of skin lesions using the HAM10000 dataset. The study utilized EfficientNets, which have been proven to outperform traditional architectures due to their lightweight design. These models achieved higher accuracy without requiring extensive preprocessing or data augmentation techniques. The research evaluated 6 Efficient Net models ranging from Efficient NetB0 to Efficient NetB5 and found that they outperformed pre-trained models like ResNets and VGG16 in terms of accuracy, precision, recall, and validation loss. These results were achieved despite the dataset being heavily unbalanced. The pro-posed models also achieved accuracy above 90% for all EfficientNet models, which is better than existing pre-trained models. Balancing the dataset and incorporating metadata could further improve model accuracy. The current work provides a model that is resource-efficient and can assist medical professionals in making effective and efficient predictions.

Table 2. Comparison chart of different state-of-art works on skin classification

Model	Accuracy	Precision	Recall	F1 Score	Training Accuracy	Training Loss	Validation Accuracy	Validation Loss
ResNet50	0.8545	81	82	81	0.9678	0.320	0.8545	0.6745
VGG16	0.8293	77	77	77	0.9283	0.2432	0.8293	0.6897
VGG19	0.8197	79	74	76	0.9021	0.4424	0.8197	0.7123
InceptionV3	0.8787	85	84	84	0.9697	0.5123	0.8787	0.6987

InceptionResNet V2	0.8685	83	82	82	0.9677	0.3232	0.8685	0.6970
Xception	0.914	89	89	89	0.9811	0.0324	0.914	0.6189
DenseNet201	0.906	88	88	88	0.9578	0.2423	0.906	0.6761
MobileNetV2	0.82	81	82	81	0.9456	0.2020	0.82	0.7980
EfficientNetB0	0.9078	88	88	88	0.9803	0.0599	0.9078	0.6054
EfficientNetB1	0.9134	89	88	88	0.9798	0.0559	0.9134	0.5688
EfficientNetB2	0.9212	89	88	88	0.9857	0.0445	0.9212	0.5815
EfficientNetB3	0.9211	89	89	89	0.9754	0.0835	0.9211	0.5172
EfficientNetB4	0.9232	88	89	88	0.9869	0.0464	0.9232	0.4879
EfficientNetB5	0.9252	89	88	88	0.9871	0.0431	0.9252	0.4334

Table 3. Comparison of the proposed work with other state-of-art works

Author	**Model Used**	**Data Augmentation**	**Accuracy**	**Precision**	**Recall**
Nyíri T et al. (2018)	VGG16	Yes	75.6	-	-
	InceptionV3		74.3		
	ResNet50		86.6		
	InceptionReNetV2		86.1		
	DenseNet121		89.2		
	Xception		90.1		
	DenseNet161		88.7		
Majtner, T (2018)	GoogleNet	No	79.7	-	-
	VGG16		80.1		
Shahin, AH (2018)	InceptionV3	Yes	89.7	84.9	80.0
	ResNet50		87.1	78.6	77.0
Chaturvedi, SS (2019)	MobileNet	Yes	83.1	89.0	83.0
Milton, MAA (2019)	InceptionV4	No	67.0		
	PNASNet-5-Large		76.0		
	InceptionRenetV2		70.0		
	SENet154		74.0		
Ratul AR et al. (2019)	VGG16	Yes	87.42	87.0	87.0
	InceptionV3		89.81	89.0	89.0
	VGG19		85.02	85.0	85.0
	MobileNet		88.22	89.0	88.0
Alom, MZ (2020)	IRRCNN	No	87.0		
Polat K (2020)	CNN	No	77.0		
Yao et al. (2021)	Deep CNN	Yes	86.2		86
Kumar et al. (2021)	Multimodal Framework	Yes	73.6	71.34	68.93

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