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A Smartphone Application for Skin Lesion Detection and Classification with Deep Learning Algorithms

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Abstract: The Skin Lesion (SL) classification has recently received a lot of attention. Because of the significant resemblance between these skin lesions, physicians spend a lot of time analyzing them. A Deep Learning (DL) based automated categorization system can help clinicians recognize the type of SL and improve the patient's health. In this research, DL approaches such as VGG-16, ResNet-50 and customized model are employed to detect the SL using a smartphone application. These models are trained on the SL classification dataset from the International Skin Imaging Collaboration (ISIC) 2019. The customized model over fits the other two models with a validation accuracy of 86.21%, whereas the validation accuracy of VGG-16 and ResNet-50 is 85.15% and 84.82%, respectively. Physicians will save time and have a higher precision rate in the automatic classification of SL utilizing DL.

Keywords: *Application development, Customized model, Deep models, Skin lesion classification, Tensor Flow Lite (TFL), Validation accuracy.*

1. Introduction

The World Health Organization (WHO) approximations that 2 to 3 million people are detected with SL each year around the world. [1]. The presence of SL is tightly connected to the prevalence of UV radiation caused by sunlight exposure [2]. About 60,000 people perished as a result of cancer caused by chronic sun exposure [3]. To improve a patient's prognosis, it is vital to detect cancer early. To address automated skin cancer diagnosis, several Computer-Aided Diagnostics (CAD) have been developed [4, 5]. Convolutional Neural Networks (CNN) that have been trained using dermoscopy image datasets are used in the majority of current techniques [6, 7]. However, there is a lack of dermatologists and dermatoscopes, particularly in rural areas limiting the adoption of a CAD system based on dermoscopy images [8].

In this circumstance, smartphones could be a beneficial tool for dealing with the problem. According to Mobile statistics report by Radicati Group the number of mobile users will be 7.1 billion worldwide and it also suggest to rise to 7.26 billion by 2022. In 2025, the number of mobile users worldwide is projected to reach 7.49 billion. According to a Deloitte study [10], India had 1.2 billion mobile consumers in 2021, with around 750 million of them using smartphones.

Harangi, B. suggested an approach that combines four CNN models: AlexNet, GoogLeNet, VGGNet, and ResNet [11]. The fusion approach presented in the study were used to identify seborrheic keratosis, melanoma, and nevus. Brinker, T.J. et al., used free source images of ISIC 2019 to train a ResNet-50 deep model [12]. Melanomas and atypical nevi are classified using trained model. Arik, A. et al. [13] and Demir, A. et al. [14] utilized dermoscopy images to train the standard CNNs such as ResNet and Inception-v3. Aggarwal, A. et al. presented an attention mechanism that aids CNNs in learning filters which selects significant pixel regions on a SL image to classify three forms of skin cancer [15].

Phillips, K. et al. developed an Android application (app) that discriminates between melanoma and non-melanoma SLs using a Support Vector Machine (SVM) trained on three categories of SLs with a dataset of 20 images [16]. Because it was trained with only a few samples, the

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model's performance is limited. Castro, P. B. C. et al. presented a solution which involves mutation operator of the Differential Evolution (DE) algorithm to address the data imbalance problem [17]. They also utilise an app to distinguish melanoma SLs from non-melanoma SLs.

Different deep models are trained and validated in this paper to differentiate between skin cancer and non-skin cancer. The best model is used in the smartphone app to assist professionals in diagnosing skin cancer during screening.

The following is the structure of the remainder of the article: The materials and methods are discussed in Section 2. The simulation results are discussed in Section 3. Section 4 focuses on the conclusions.

2. MATERIALS AND METHODS

Skin cancer diagnosis with a smartphone is becoming a prominent area of research. This section discusses the VGG-16, ResNet-50, and customized models. A general block diagram for early SL diagnosis is shown in Figure 1.

2.1. Data set understudy

Table 1 shows the ISIC 2019 dataset, which has a total of 3032 images. There are six types of skin cancer. The proposed study's sample images with subclasses are shown in Figure 2. The image is first scaled to 224 x 224 pixels. The three CNN models extract features of each disease via the convolution layer. Dropout strategies are used to avoid overfitting images. In this study, transfer learning is employed to fine-tune the weights. Optimizers have been most commonly used to fine-tune a model's weights, bias, and learning rate. The customized model uses the Adam optimizer, whereas ResNet-50 and VGG-16 employ the stochastic gradient descent (SGD) optimizer.

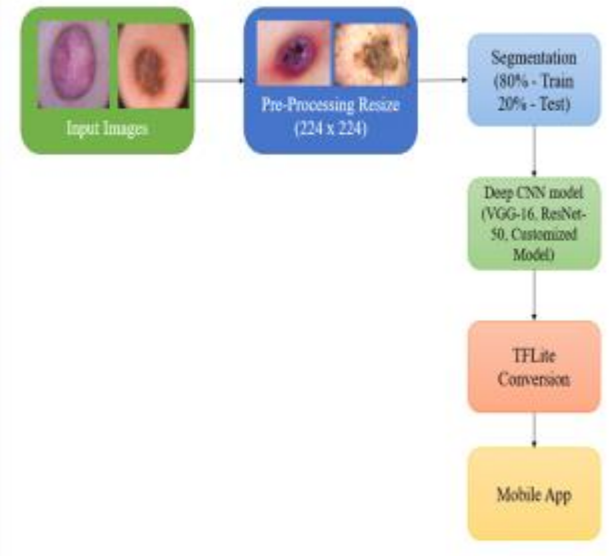

Fig.1. Block diagram for classification of SL

Table 1: Number of training and testing images in ISIC 2019 dataset

Classes	Images	Images in train dataset	Images in the test dataset
Actinic Keratosis (AK)	867	748	119
Basal Cell Carcinoma (BCC)	3323	2825	498
Benign Keratosis (BK)	2624	2267	357
Dermatofibroma (DF)	239	203	36
Melanocytic Nevi (NV)	8830	6850	1980
Vascular Skin Lesion (VSL)	253	211	42
Total	16136	13104	3032

2.2. VGG-16 model

The input to the network is a 224 x 224 image with RGB channels. The preprocessing is done only to normalize each pixel's RGB values. To accomplish so, each pixel's value is subtracted from the mean. The input image is transmitted through the first stack of two layers of convolution, with a receptive area of 3x3. Each of these 2 layers has filters with the count of 64. The activations are then routed via a second stack, with 128 filters. The size of the output at this stage is is 56 x 56 x128. Proceeding this is the layer of convolution and max pool layer, which forms the third stack. In total, there are 256 filters, yielding a stack output size of 28 x 28 x 256. There are two convolutional layer stacks after that, each having 512 filters. The final output of the stack will be 6 x 6 x 512. Following the stacks of convolutional layers is the 3 fully connected layers, with a flattening layer in between. The softmax activation layer is used for categorical categorization after the output layer. In this investigation, a Scaled Conjugate Gradient (SCG) optimizer with a learning rate of 1e-5 is used.

Fig.2. Different classes of SLs in the ISIC 2019 dataset

2.3 ResNet-50 Model

ResNet-50 is a residual CNN model with 177 layers. ResNet-50's architecture is divided into four stages. An image with a height and width that are multiples of 32 and a channel width of 3 can be accepted by the network. The image size given as input is 224 x 224 x 3. It is done as per the architecture. For initial convolutional and max pooling, each ResNet design uses the kernel size of 7 x 7 and 3 x 3 respectively. Three residual blocks with three levels make up stage 1. In all three layers, the kernels are employed to perform convolution operations. The channel width doubles as we progress through the steps, and the input size is halved.

2.3. Customized model

An image size with 224 × 224 pixels is used and it is fixed

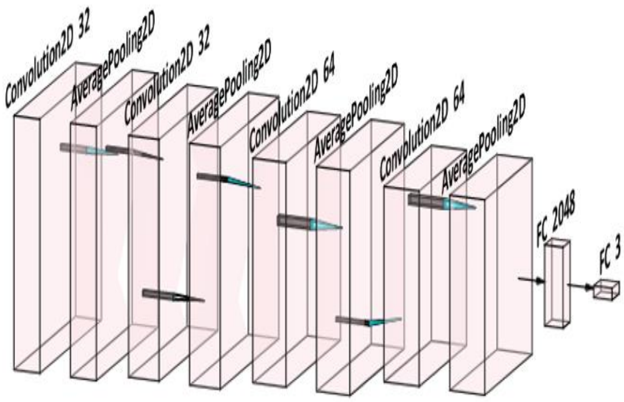

Fig.3. Architecture of customized model

The initial layer is a 2D convolution consisting of 32 3 x 3 filters with proper padding and Rectified Linear Unit (ReLu) activation. The 2D average pooling layer is the second layer, with pool size of 2 x 2 and strides of 2 x 2. After that, batch normalisation takes place. There are double stacks of 3 convolutional layers after that, with 64 filters having a 5 x 5 filter size. There is one fully connected layer with 2048 neurons and a 50% drop out. The output layer is a fully-connected layer with 6 neurons with softmax as the activation function. In this work, an Adam optimizer with a 0.0001 learning rate is used. The customised model architecture is shown in Figure 3.The initial layer is a 2D convolution consisting of 32 3 x 3 filters with proper padding and Rectified Linear Unit (ReLu) activation. The 2D average pooling layer is the second layer, with pool size of 2 x 2 and strides of 2 x 2. After that, batch normalisation takes place. There are double stacks of 3 convolutional layers after that, with 64 filters having a 5 x 5 filter size. There is one fully connected layer with 2048 neurons and a 50% drop out. The output layer is a fully-connected layer with 6 neurons with softmax as the activation function. In this work, an Adam optimizer with a 0.0001 learning rate is used. The customised model architecture is shown in Figure 3.

2.4. Mobile App development

To aid SL classification, a Tensor Flow Lite (TFL) tool is used. Teachable Machine is a web-based Graphical User Interface (GUI) application that allows users to create customised machine learning categorization models without needing a lot of technical knowledge. The developed app's main objective is to assist physicians with least or no experience with dermatology or with rare access to a dermatoscopy. Clinicians may use the app to identify individuals who may be suffering from skin cancer. The screenshot of the TFL app is shown in Figure 4.

Fig. 4. Screenshot of the TFL app

3. RESULTS AND DISCUSSIONS

The entire dataset is categorized into 80% training data and 20% testing data for cross-validation. A Colab-Pro environment is used to simulate the whole model. The confusion matrix for VGG-16, ResNet-50 and the customized model is presented in Figure 5, 6 & 7.

	AK	BCC	BK	DF	NV	VSL
AK	56	27	25	3	8	0
BCC	17	409	44	4	23	0
BK	12	21	242	9	73	0
DF	0	7	3	22	4	0
NV	9	39	95	11	1822	4
VSL	0	4	2	2	4	30

Fig.5. Confusion matrix of VGG-16

	AK	BCC	BK	DF	NV	VSL
AK	52	21	35	0	8	3
BCC	32	406	32	4	23	1
BK	25	19	251	4	64	0
DF	2	6	3	20	5	0
NV	7	44	96	8	1823	2
VSL	0	8	2	2	6	30

Fig.6. Confusion matrix of ResNet-50

	AK	BCC	BK	DF	NV	VSL
AK	61	23	25	0	10	0
BCC	12	437	14	1	33	1
BK	10	35	223	0	89	0
DF	0	10	1	20	4	1
NV	5	54	73	1	1844	3
VSL	1	6	2	1	3	29

Fig.7. Confusion matrix of customized model

It is observed that the customized model had the greatest validation accuracy of 86.21%, sensitivity of 79.53%, precision of 79.5%, specificity of 96.1%, and F1 score of 73.66%, whereas VGG-16 had the highest validation accuracy of 85.15%, sensitivity of 70.78%, precision of 70.16%, specificity of 90.78% and F1 score of 70%, and ResNet-50 had the highest validation accuracy of 84.82%, sensitivity of 69.1%, precision of 67.66%, specificity of 95.77% and F1 score of 67.83%. Figure 8 compares the performance of three models with various metrics.

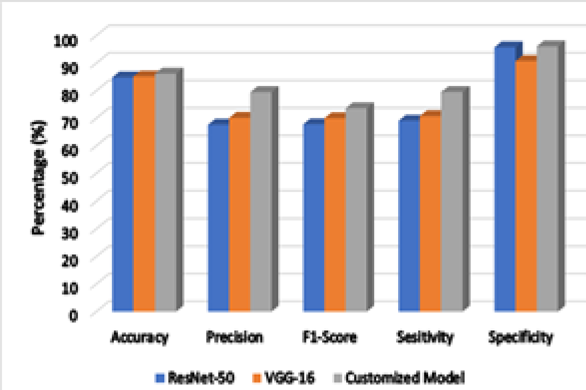

Fig.8. Comparison between three models with various metrics

Table 2 compares the proposed customized model to models that have already been published in the literature. The validation accuracy of the customized model is 86.1%, seems to be greater than the models considered for the study.

Table 2: Validation accuracy comparison of different models

Previous Study	Accuracy (%)
VGG-19 (Simonyan& Zisserman) [18]	80.17
ResNet-152 (He et al.)[19]	84.15
Efficent-B0 (Tan &Le)[20]	81.75
Efficent-B7 (Tan &Le)[20]	84.87
EW-FCM + Wide-ShuffleNet (Hoang et al)[21]	82.56
Proposed customized model	86.1

Customized TFL models along with labels are uploaded to TFL Classify mobile app. When the start button is clicked, the mobile camera will turn on, allowing real-time SL classification to be visualized with percentage accuracy. The screen shot of SL identification for vascular and dermatofibromia is shown in Figure 9.

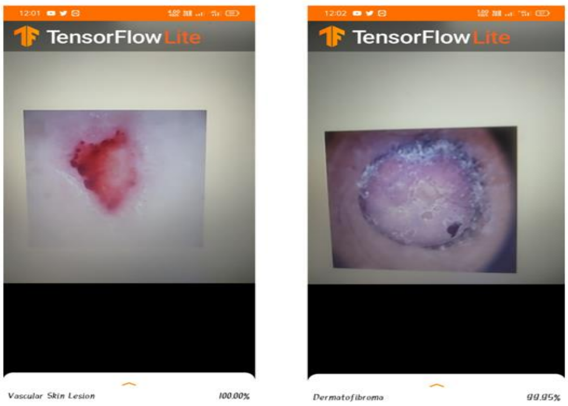

Fig.9. Sample screenshots of SL classification with TFL classifier

4. Conclusion

This study uses the ISIC 2019 dataset to develop a reliable approach for classifying SLs. By assisting in early detection, DL algorithms can help to minimize the risk of acquiring cancer. The customized model is compared to standard deep models like VGG-16 and ResNet-50 in this paper and found to outperform them. This customized model is further given to TFL classifier to detect real-time skin cancer. By including many preliminary data processing techniques, the work can be further progressed. It can be done using hybrid classification algorithms also. In addition to this, the proposed work can also be shared with relevant image processing techniques so that an autonomous decision system can be made on several medical issues as well.

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Author contributions

X.Anitha Mary: Writing-Original draft preparation, Software, Validation., Field study Conceptualization, **Peniel Winifred:** Data curation,Methodology, Software, Field study, **C. Suganthi Evangeline, Vinoth Babu Kumaravelu:** Visualization, Investigation**, C.Karthik, Subrata Chowdhury,** Khaled Rabie**:** Writing-Reviewing and Editing.

Conflicts of interest

The authors declare no conflicts of interest.

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