Automated Dermatological Diagnosis Utilizing Convolutional Neural Networks: A Comparative Analysis

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ABSTRACT

The incidence of fatalities due to skin cancer is increasing, rendering it a significant public health concern. Computer-aided diagnosis tools are increasingly being utilized to enhance the accuracy of skin cancer diagnoses. This study seeks to establish a dependable approach for skin cancer detection employing machine learning algorithms to classify images using Convolutional Neural Networks (CNNs), a type of deep learning that is known for its efficiency and accuracy. This study identified skin cancer images with pre-trained DenseNet169, VGG16, MobileNetV2, and Xception architectures. The accuracy performance of these models was 91.2% for DenseNet169, 88.13% for VGG16, 77.86% for MobileNetV2, and 94% for Xception. These deep-learning algorithms can assist dermatologists in diagnosing skin cancer with more accuracy and mitigate errors attributable to human oversight.

Keywords-skin cancer; VGG16; deep learning; Xception

I. INTRODUCTION

Melanoma is the most lethal form of skin cancer. The probability of effectively treating specific skin malignancies increases with early identification [1]. Dermatologists primarily employ two methods to identify skin disorders. Dermoscopy, also called dermatoscopy, is used to identify issues with cutaneous growths such as nevi [2]. This inspection is extremely thorough, as it enlarges moles to reveal features that are invisible to the human eye. Dermoscopy can be performed with both manual instruments and automated systems, and is generally a preferred diagnostic procedure because it delivers early diagnosis without substantial unwanted effects [3]. In contrast, histopathology employs a series of methods based on the use of a microscope to evaluate alterations in organs, tissues, and cells [4]. Machine learning and image processing methods are employed to detect and categorize skin diseases from images, identifying important features [5]. Image quality and noise reduction are two areas where machine-learning classifiers really shine [6].

Skin diseases can affect people of any age. Diagnosis of a specific skin disease condition can be difficult and challenging because the symptoms can be similar to those of other conditions, particularly in cases where they occur in clusters [7]. The diagnosis of skin conditions is notoriously difficult for many reasons, such as the fact that hair, sweat, and other unpleasant artifacts hamper skin segmentation and examination. Due to the similarity in appearance, colored images can make it difficult to distinguish between different dermatological diseases. The main issues with large-scale biomedical image processing are data structure problems and crucial information extraction issues [8]. Digital images obtained from cameras might exacerbate skin issues due to their grainy quality, poor resolution, or inconsistent lighting. Dermatological conditions may present diagnostic challenges due to atypical lesion characteristics, such as variations in hair pigmentation [9].

II. RELATED WORK AND RESEARCH GAP

Table I summarizes prior research efforts focused on the diagnosis of skin cancer with deep learning algorithms. Many previous studies focused on well-known architectures such as DenseNet, VGG16, and MobileNetV2. However, many studies used limited or imbalanced datasets, limiting the generalizability of the findings. Furthermore, while transfer learning has been studied, comparisons of various pre-trained models on the same dataset remain limited. This work fills these gaps by comparing four pre-trained CNN models (DenseNet169, VGG16, MobileNetV2, and Xception) on large and heterogeneous datasets [10, 11].

TABLE I. DATASETS, TECHNIQUES, AND OUTCOMES FROM RECENT WORK ON SKIN CANCER DETECTION

Ref	Datasets used	Technique Used	Accuracy
[12]	ISBI 2016 dataset	DenseNet-201 and MobileNetv2	88.02%
[13]	HAM10000	XGBoost, MLP, SVM, and Random Forest	87.72%
[14]	MNIST HAM10000	MobileNetV2	80.4%
[15]	Kaggle datasets	AlexNet, MobileNet, ResNet, VGG16, and VGG19	84.94%
[16]	]ISIC 2019	EfficientNetB3	95.4%
[17]	ISIC 2019	GoogleNet and VGG19	GoogleNet-80.07%;l VGG19-85.57%
[18]	ISIC	Logistic Model Tree and ReliefF	79.39%
[19]	HAM10000	Differential Evolution-CNN	91%
[20]	HAM10000	CNN and a pre-trained InceptionV3 model	CNN: 91%, Pre-trained InceptionV3: 95.72%
[21]	ISIC	VGG16 architecture	86.67%.
[22]	HAM10000	Modified ResNet-50	86%
[23]	ISIC 2015, ISIC 2019	CNN	88.83%
[24]	Kaggle	KNN, LR, RF, XGBoost, and SVM	91.6%
[25]	ISIC 2019	Attention-based Inception-Residual CNN (AIR-CNN)	91.63%

III. MATERIALS AND METHODS

This study used the CNNs DenseNet169, VGG16, MobileNetV2, and Xception to implement feature extraction and classification. These models were implemented using TensorFlow and Python 3 after the dataset was preprocessed and normalized.

- DenseNet169 is one of the models in the DenseNet group [26]. In this model, additional information obtained from previous layers is provided to all subsequent levels through feature maps.
- VGG16: The VGG16 model is widely utilized as a pre-trained model for cutaneous cancer classification [27]. The convolutional layers retrieve features from the input image, which are used by the fully connected layers to make predictions.
- MobileNetV2 is an architecture developed by Google, trained on 1.4 million images across 1000 classes. It is a sophisticated DCNN architecture that performs well on mobile devices. The architecture of MobileNetV2 is based on its predecessor, MobileNetV1, but introduces a novel structure known as the "inverted residual" to preserve information.
- XceptionNet is a pre-trained CNN architecture that, similar to other deep learning models such as Inception and ResNet, has been trained on an extensive dataset such as ImageNet for image classification tasks. Its name stems from "Extreme Inception", as it is an augmentation of the Inception architecture utilizing depth-wise separable convolutions for enhanced performance.

Figure 1 illustrates the melanoma classification technique followed in this study, using CNNs, DenseNet169, VGG16, MobileNetV2, and Xception, as well as important preprocessing for input images, to obtain the highest accuracy.

A. Dataset Description

The limited quantity and inadequate diversity of skin disease datasets greatly influence the training process of many neural networks employed for the autonomous diagnosis of skin conditions. The HAM10000 dataset, a subset of the ISIC repository, includes 10,015 images showing seven different skin diseases [10]. The "Skin Cancer: Malignant Vs Benign" test dataset [11], consisting of 1800 benign and 1497 malignant images, was used to train and test the VGG16 model.

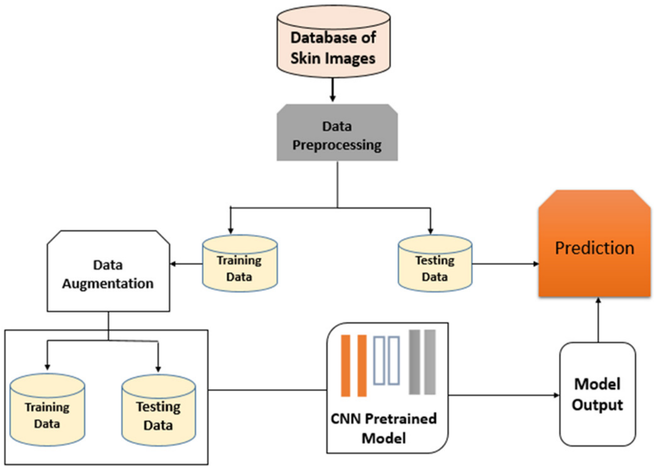

Fig. 1. Proposed methodology for this study.

Figure 2 shows some example images, namely: (a) an unprocessed skin image exhibiting anticipated cancer, (b) an image displaying less contrast, (c) an image containing random noise variations, and (d) an image featuring both hair and random noise variations.

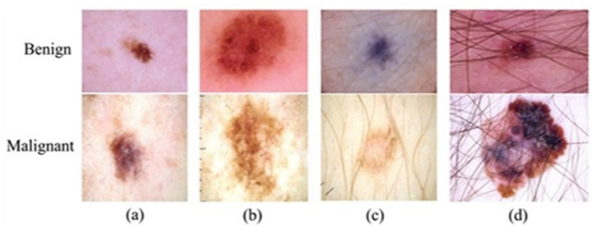

Fig. 2. Skin cancer malignant model sample images. (a) Clearly visible; (b) Less contrast ;(c) Noisy; and (d) Hair.

B. Data Visualization

Data visualization employed several graphical and statistical data representations [28]. Figure 3 shows a histogram of the seven types of skin disease that the HAM10000 dataset contains. The most common skin condition is melanocytic nevus or nevus (nv), while mel, bcc, vasc, df, and akiec are shorthands for melanoma, basal cell carcinoma, vasculoderma, dermatofibroma, and actinic keratosis, respectively. Figure 4 presents the disease distribution in the dataset according to gender.

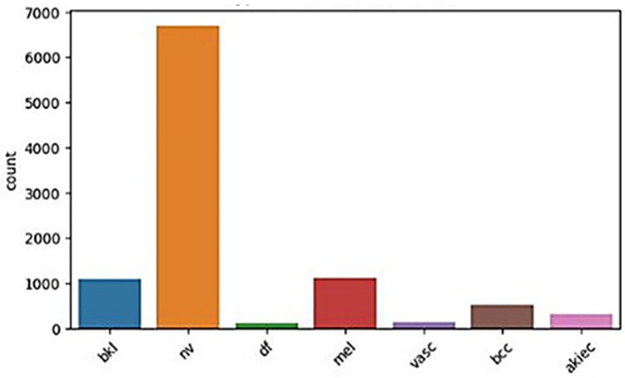

Fig. 3. Distribution of skin diseases.

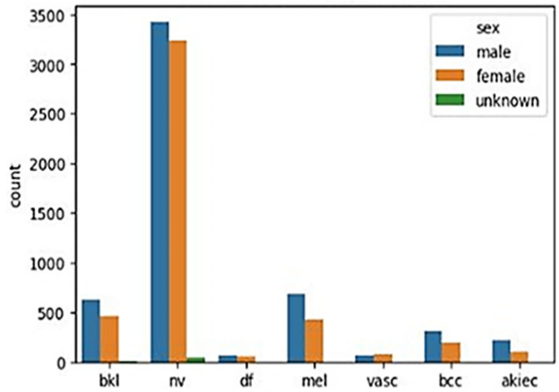

Fig. 4. Disease distribution according to patient gender.

The frequency distribution of the HAM10000 dataset shows an imbalance. The lack of training data could decrease the predictive capacity of the model for the underrepresented skin disease categories. Resampling techniques can be used to normalize the dataset, increasing the sample count.

C. Data Preprocessing

Each image has to be precisely the right size for the sequential CNN model to work. The 224×224 pixel size is the default for DenseNet-169 input. Data normalization was used to normalize the input data and decrease the total number of training iterations.

D. Augmenting Data

Data augmentation was used to artificially expand the dataset and improve the learning capacity of the models. There is a high risk of model overfitting in the HAM10000 dataset because most images are from melanocytic skin disease classes, and more data is needed to train the model to accurately predict the prevalence of other types of skin disease.

Oversampling was employed to reduce the imbalance in the dataset. Automatic data augmentation during model training is available through the deep learning Keras package. Data augmentation is a versatile approach that can support a wide variety of techniques. In this study, five different data augmentation techniques were used, namely scaling, cropping, flipping, padding, and rotation, each contributing to the model's robustness and adaptability.

IV. RESULTS AND DISCUSSION

CNN models employ several layers, including convolutional, pooling, nonlinear, and fully connected layers. In image processing, the higher-level layers of a CNN find general features for categorization, whereas the lower-level layers find edges [29]. The Adam optimizer was employed to adjust the learning rate during model training [9], which dictates how quickly model weights are adjusted. Although a lower learning rate yields more accurate weights, it increases computation time. The categorical cross-entropy loss function was used. Accuracy was used to measure the results of the training process. The CNN model was built on top of the multiclass classification model trained using the HAM10000 dataset.

A. Implementing DenseNet169

The optimal model was determined at epoch 19, attaining an accuracy of around 91.2% and an f-measure of 91.7%. The loss value decreased most significantly when the learning rate was around 1e-03, as shown in Figure 5.

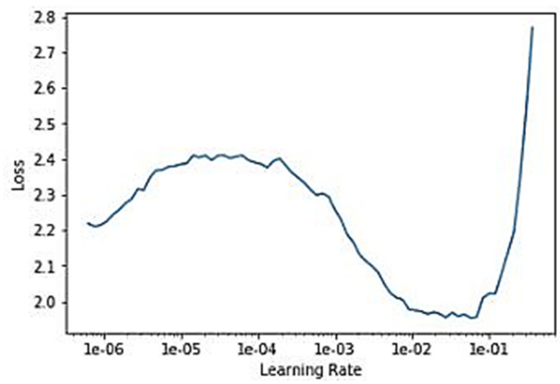

Fig. 5. Epoch and learning rate details of the DenseNet169 model.

B. Implementing VGG16

Pre-trained networks, such as VGG16, were used to facilitate classification because they have been trained on a large set of images from ImageNet. The network can be improved by adding layers and changing hyperparameters to fit needs. To finalize the weights of the layers in the VGG16 model, it was trained on 80% of the dataset images [11]. After training, the model was used to classify the test data images, achieving an accuracy of 88.13%.

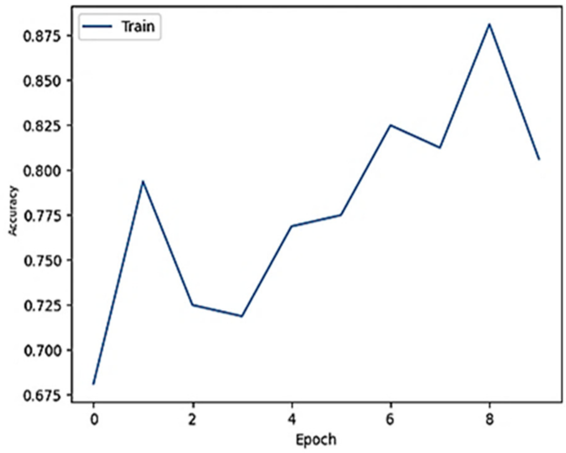

Fig. 6. Training accuracy of the VGG16 model.

C. Implementing MobileNetV2

Two common problems with training CNNs are that they can overfit and lose their gradient. Experimental data indicate that optimizers and learning rates configured with appropriate settings yield enhanced classification results for skin lesions. In this model, setting the learning rate scheduler to Adamax made it more likely to correctly classify skin lesions. The baseline learning rate was 0.0001. After training, MobileNetv2 achieved an accuracy rate of 77.86% on the test set.

D. Implementing Xception

The Xception-based model attained an accuracy of 0.94 on the test dataset (20%). The model's efficiency in recognizing various skin disorders fluctuated based on the disparity in the samples available for training and testing. Figure 7 illustrates the confusion matrix of the Xception model.

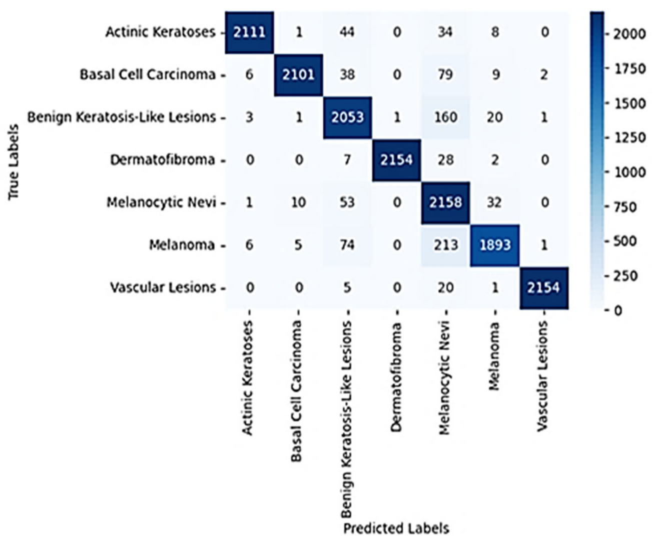

Fig. 7. Confusion matrix of the Xception model.

Figure 8 displays dermoscopic images of a range of skin lesions along with their actual and expected designations for diseases, demonstrating how well a machine-learning algorithm can diagnose skin disorders. This evaluation is crucial to evaluate the effectiveness of models in the classification of dermatological images. Table II displays a detailed comparison between the models used in this study and some previous ones. Utilizing a pre-trained model to extract distinct features from skin lesion images of skin lesions is the essence of transfer learning, which pertains to skin cancer classification utilizing models such as DensNet169, VGG16, MobileNetv2, and Xception. The next step is to train a new output layer to accurately identify whether a tumor is benign or malignant. By utilizing transfer learning in skin cancer classification models, the danger of overfitting can be mitigated, achieving remarkable results with sparse data.

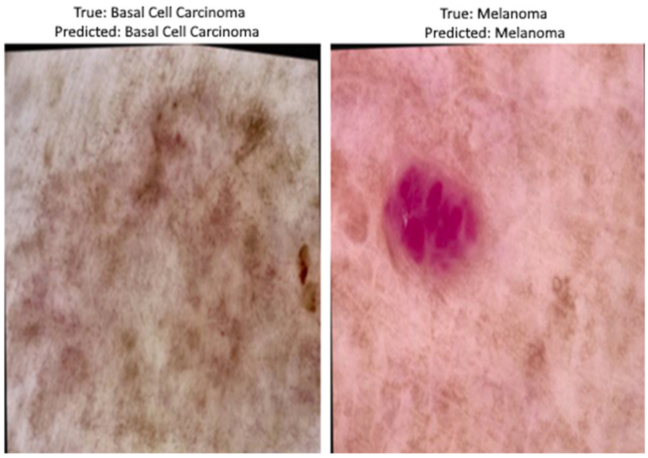

Fig. 8. True label prediction result of skin images.

TABLE II. COMPARATIVE ANALYSIS OF MODELS ON SKIN CANCER CLASSIFICATION

	Ref.	Dataset used	Techniques used	Accuracy (%)
Previous studies	[15]	Kaggle datasets	AlexNet, MobileNet, ResNet, VGG16, and VGG19	84.94%
	[30]	HAM10000	ResNet, InceptionV3, and ResNet Inception	85.7%,
	[31]	PH2, ISBI2016, and ISIC2017	Resnet50	86.5%
This study	DenseNet169	HAM10000	DenseNet169	91.20%
	VGG16	ISIC Archive	VGG16	88.13%
	MobileNetv2	HAM10000	MobileNetv2	77.86%
	Xception	**HAM10000**	**Xception**	**94%**

E. Real-World Implications

Artificial intelligence technologies provide dermatologists with assistance by pre-screening patients, prioritizing high-risk lesions, and decreasing diagnostic burdens. This allows dermatologists to focus on the most urgent cases. Pre-trained CNN algorithms can help eliminate human bias and unpredictability in diagnosis, resulting in evaluations that are standardized and objective across a variety of healthcare settings. The comparative results presented in this study can help in the development of more effective skin cancer detection and identification models.

V. CONCLUSIONS

This study used DensNet169, MobileNetV2, VGG16, and Xception CNN models to classify skin cancer from skin lesion images. The models were trained and evaluated using large and varied datasets. DesNet169, MobileNetV2, and Xception were trained and tested on the HAM10000 dataset, while VGG16 was trained and tested on a subset of the ISIC dataset. The comparative results demonstrate the feasibility of identifying skin cancer with deep learning algorithms. The datasets were divided into testing and training sets, with 80% allocated for testing and 20% for training. Xception achieved 94% accuracy; DenseNet169 achieved 91% accuracy, VGG16 achieved 88.13%, and MobileNetV2 achieved 77.86% on the test set.

VI. FUTURE DIRECTION

Although deep learning models such as Xception, DenseNet169, VGG16, and MobileNetV2 exhibit significant potential in the accurate diagnosis of skin cancer, several opportunities for future study and development persist. The integration of lightweight and efficient models into mobile applications or edge devices could allow dermatologists and general practitioners to perform immediate evaluations in resource-constrained environments. This would also improve access to early diagnostic tools in remote or underdeveloped regions. In the future, diagnostic tools for skin diseases may enable dermatologists to review the reports generated by the model after identifying the specific skin condition, enhancing model accuracy and proposing a therapy regimen for the dermatological condition.

DECLARATION OF COMPETING INTERESTS

The authors declare no conflicts of interest.

ACKNOWLEDGMENTS

Not applicable in this study.

DATA AVAILABILITY STATEMENT

The datasets used in this study are publicly available in [10] and [11].

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