Automated multi-class skin cancer classification through concatenated deep learning models

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ABSTRACT

Skin cancer is the most annoying type of cancer diagnosis according to its fast spread to various body areas, so it was necessary to establish computer-assisted diagnostic support systems. State-of-the-art classifiers based on convolutional neural networks (CNNs) are used to classify images of skin cancer. This paper tries to get the most accurate model to classify and detect skin cancer types from seven different classes using deep learning techniques; ResNet-50, VGG-16, and the merged model of these two techniques through the concatenate function. The performance of the proposed model was evaluated through a set of experiments on the HAM10000 database. The proposed system has succeeded in achieving a recognition accuracy of up to 94.14%.

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1. INTRODUCTION

Nowadays, computer technology and artificial intelligence have become a very important need for development and progress [1], in the field of medicine [2], commerce, industry [3], engineering [4], and many other applications. Many computer applications help people to obtain more services with less effort and impressive results [5]. Classification has become one of the major focuses of computer science [6].

Cancer is a harmful disease that has led to millions of human deaths [7]. One of the most common cancer types is skin cancer. The epidermis contains three types of cells: squamous cells, basal cells, and melanocytes; as shown in Figure 1 [8], squamous cells form the epidermis's external basal cells from the epidermis's lowermost layer. Melanocytes produce melanin, a brown pigment substance, which protects deeper layers of skin from sun exposure.

When human cells are exposed to too much ultraviolet (UV) radiation, the nature of the internal structure of the cell change, the resulting deoxyribonucleic acid (DNA) alterations have an impact on the skin cell's growth [9], and ultimate shapes of skin cancer [10]. According to the World Health Organization (WHO) estimates, skin cancer accounts for one-third of all cancer cases diagnosed worldwide [11]. Melanoma accounts for roughly three-fourths of all skin cancer-related deaths. Traditionally, skin cancer is diagnosed through an examination, medical examination, and biopsy, it is one of the most straightforward ways for diagnosing skin cancer, the procedure is time-consuming and uncertain.

Macroscopic and dermoscopic images have become the most prominent non-invasive instruments to aid dermatologists in skin cancer diagnosis in recent years [12]. Because macroscopic images are captured using cameras or cell phones, they are typical of poor quality and resolution. [13]. Dermoscopy images are high-resolution skin images created by visualizing deeper skin structures to improve skin cancer diagnosis. [14]. Dermatologists face difficulties making an accurate diagnosis of skin cancer, even with dermoscopy images, because multi-skin cancer types can appear comparable in their initial diagnosis. The average accuracy for the skin cancer diagnosis ranges between 62-80% [8]. However, dermatologists with experience greater than ten years can achieve 80% accuracy. The performance of dermatologists with less expertise fell even lower [15].

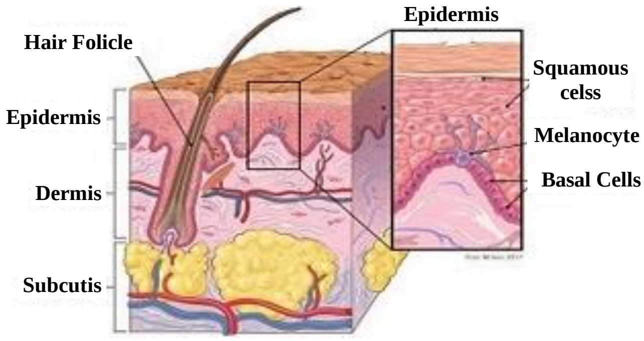


Figure 1. Anatomy of the skin layers [8]

Dermoscopy's biggest downside is the intensive training required. The development of computer-aided diagnostics tools to assist dermatologists in overcoming the obstacles they face has made tremendous progress in the research community. As more data becomes available, computer-aided diagnosis improves. It's easy to retrain the system with new data, The underlying model can be expanded to include a variety of different medical variables in its prediction pipeline. Deep learning's impressive performance in classifying images has resulted in its medical domains, such as skin cancer classification.

In this paper, an automated computer-aided diagnostic model with high accuracy for cancer classification is proposed. A study was conducted to compare the implementation of two pre-trained convolutional neural network (CNN) models and merge the two models' outputs to have a merged model with a higher performance on the HAM10000 dataset. Transfer learning is being used to gain a better understanding of the domain-specific characteristics of skin malignancies.

2. RELATED WORK

The use of image analysis to classify skin cancer has advanced dramatically throughout the years. Several different approaches have been tested. Researchers have attempted to progress diagnosis performance by employing various classification techniques and algorithms. When Fukushima in 1988 and later Le-Cunn in 1993 introduced the CNN structure; CNN is an artificial neural network using a grid-like structure designed for data processing such as images [16], image classification reached new heights in 1990; they used a convolution neural network for image classification. CNN's are the best state-of-the-art image categorization algorithms because they mimic the human visual cognition system. While many images classification literature is available, our survey analysis is limited to deep learning methods for images of skin cancer. The first development of a Google Net Inception V3 CNN model for skin cancer classification has been implemented by Esteva *et al.* [17]. Including about 3,374 dermatoscopic images, the classification accuracy recorded is 72.1. The study [18] used an improved ResNet50 model with a HAM10000 dataset with data augmentation. They performed a model with an accuracy of 90%.

In 2019, Qian Wang [19] Created a CNN for malignant melanoma cancer with over 50 layers for the International Symposium on Bioamedical Imaging dataset. The highest accuracy in the classification of this classification was 85.5%. A deep convolution neural network is used to classify a binary diagnosis group of melanocytic dermatoscopy. It registered a sensitivity and classification specificity of 86.6% in 2018 by Haenssle *et al.* [20]. Here, Dorj *et al.* [21] Established a multi-class classification using error-correcting output coding (ECOC) support vector machine (SVM) and CNN in-depth learning. The method consisted of the AlexNet deep learning CNN pre-trained with ECOC SVM and multi-class data classification. This work shows an average accuracy of 95.1%. In 2020, a model was developed by Gouda and Amudha [22] That can detect skin lesions automatically and help practitioners recognize disease spread early in time. They found that the best result was the ResNet34 model with an increase in data plan, expansion, and dropout of information. In this review, the best models have 92% accuracy.

3. RESEARCH METHOD

3.1. Dataset

Since dermoscopy has such a large influence over the world, this study focuses on dermoscopy images of skin cancer [23]. Training of neural networks for automated diagnosis of pigmented skin lesions is hampered by the small size and lack of diversity of available datasets of dermatoscopic images. This problem was tackled by releasing the human against machine with 10000 training images (HAM10000) [24] There are 10,015 dermatoscopic images in this dataset, which can be used as a training set for academic machine learning. All essential diagnostic categories in the field of pigmented lesions are represented in the cases: Actinic keratoses and intraepithelial carcinoma bowen's disease (AKIEC), basal cell carcinoma (BCC), benign keratosis-like lesions (BKL), dermatofibroma (DF), melanoma (MEL), melanocytic nevi (NV). and vascular lesions (VASC).

3.2. Deep learning for imbalanced data

Deep neural networks are made up of layers of shallow artificial neural network (ANNs) stacked one on top of the other, with the output of one layer feeding into the next. As a deep neural network develops, each layer learns something more complicated. CNNs are a form of image processing architecture that contain an input layer, output layer, and multiple hidden layers; a convolution layer, a full-connection layer, and a pooling layer are the three layers that make up a CNN.

The pooling layer and the convolution layer are frequently related. Before a neural network can be used, it must first be trained with data. During preparation, internal weights are adjusted to help the network learn a specific task. The dataset is the most critical aspect of practical training. One of the significant issues that affect the efficiency of deep learning models is an unbalanced dataset. A class disparity occurs when one class in a dataset, the minority group, has significantly fewer samples than the majority group. For better classification outcomes, the dataset should be balanced across groups.

3.2.1. Oversampling imbalanced datasets

Deep learning models require a decent amount of data to produce good results [25]. Random oversampling implies duplicating minority class examples at random and adding them to the training dataset. Replacement is used to choose examples from the training dataset randomly. As a result, samples from the minority class can be selected and added to the new more balanced training dataset numerous times.

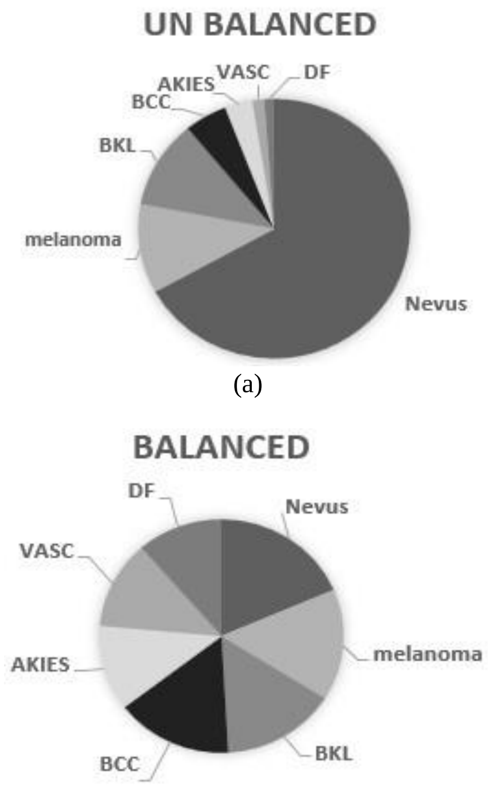
An increase in the number of samples for the minority class, especially if the class imbalance was high, may result in a considerable increase in the model fitting computing cost, especially when the model is repeatedly exposed to the same samples in the training dataset. Many machine learning algorithms might be influenced by this bias in the training dataset, leading some to completely overlook the minority class. This is an issue because predictions rely heavily on the minority class.

Resampling the training dataset randomly is one way to resolve the problem of class imbalance. Under-sampling, or deleting examples from the majority class, and oversampling, or duplicating examples from the minority class, are the two main ways to randomly resample an imbalanced dataset. In this paper, an oversampling technique was applied due to the unbalanced HAM10000 dataset; the class (nevus) has a high frequency than other classes, making the training process result with lousy accuracy.

The RandomOverSampler class can be used to implement random oversampling. First import required modules then define dataset, summarize class distribution, define oversampling strategy; the class can be defined and takes a sampling strategy argument that can be set to minority to automatically balance the minority class with the majority class or classes in the modified dataset. fit and apply the transform by calling the fit_sample () function. summarize class distribution. The result of oversampling is shown in Figure 2(a) shows the distribution before over sampling, Figure 2(b) shows the distribution after over sampling.

3.3. Functional API for deep learning

The Keras Python library allows you to quickly and easily create deep learning models. For most issues, you can build models layer by layer with the sequential API. It has limitations in that it does not allow you to design models with several layers of inputs and outputs. Keras' functional API is a different way of generating models that provide more freedom, including creating more complex models. The system proposed an image classification model that takes the image as an input. Feature extraction on a separate basis each is exposed to CNN models, which are then combined for interpretation and final prediction.



(a)

(b)

Figure 2. The imbalanced dataset before and after over-sampling (a) data before over-sampling and (b) data after over-sampling

3.4. Proposed model

The preprocessing steps for the proposed method have been minimized to ensure a more significant processing function. Since the dermoscopy images in the dataset have a resolution of 450×600 pixels, the image scaled down to 224×224 pixels to match the input image dimension for the models: ResNet50 and VGG16. ResNet stands for residual network, which is a network that promotes residual learning. ResNet50 refers to a 50-layer residual network. In general, deep convolutional networks have led to high accuracy classification in the medical field. The trend is to go deeper in the number of layers to solve complex tasks and increase classification and recognition accuracy. But going deeper with the neural networks, the accuracy starts saturating and then degrades also. Residual training tries to solve this problem [19]. Instead of attempting to learn some functions, residual learning aims to learn some residual. Residual can be clearly described as the subtraction of a function learned from a layer's input.

The first phase in the study was implementing the ResNet50 model on HAM10000. It achieved 85.2% accuracy. Second, a pre-trained Alex Net was executed and got 77.6%. Then, a VGG16 pre-trained model was applied; it got an accuracy 86.6%. Finally, a merge between the output of the best model and ResNet50 was done.

The proposed model is implemented using concatenate function; this function is proposed from the Keras library. It is a beneficial function when combining two pre-trained models is needed. The training of the model was implemented using Google Collaboratory in GPU run time. For the multi-classification model of skin cancer, the architecture of the proposed system is shown in Figure 3.

Initially, we oversample the dataset to make a balance between the dataset classes. On dermoscopic images of skin cancer, Preprocessing is utilized to align an image with the input dimensions of the architectures employed in this study. The images that have been processed are then fed to the architecture to complete the learning process. Finally, the output result should combine all the characteristics, including melanocytic Nevi, melanoma, keratose, actuic, vascular and dermatoplastic injuries, and basal cell carcinoma, categorized among the seven skin cancer groups. This method is used for two different architectures, ResNet50, VGG16, and its performance combined with concatenating outputs in a merged model.

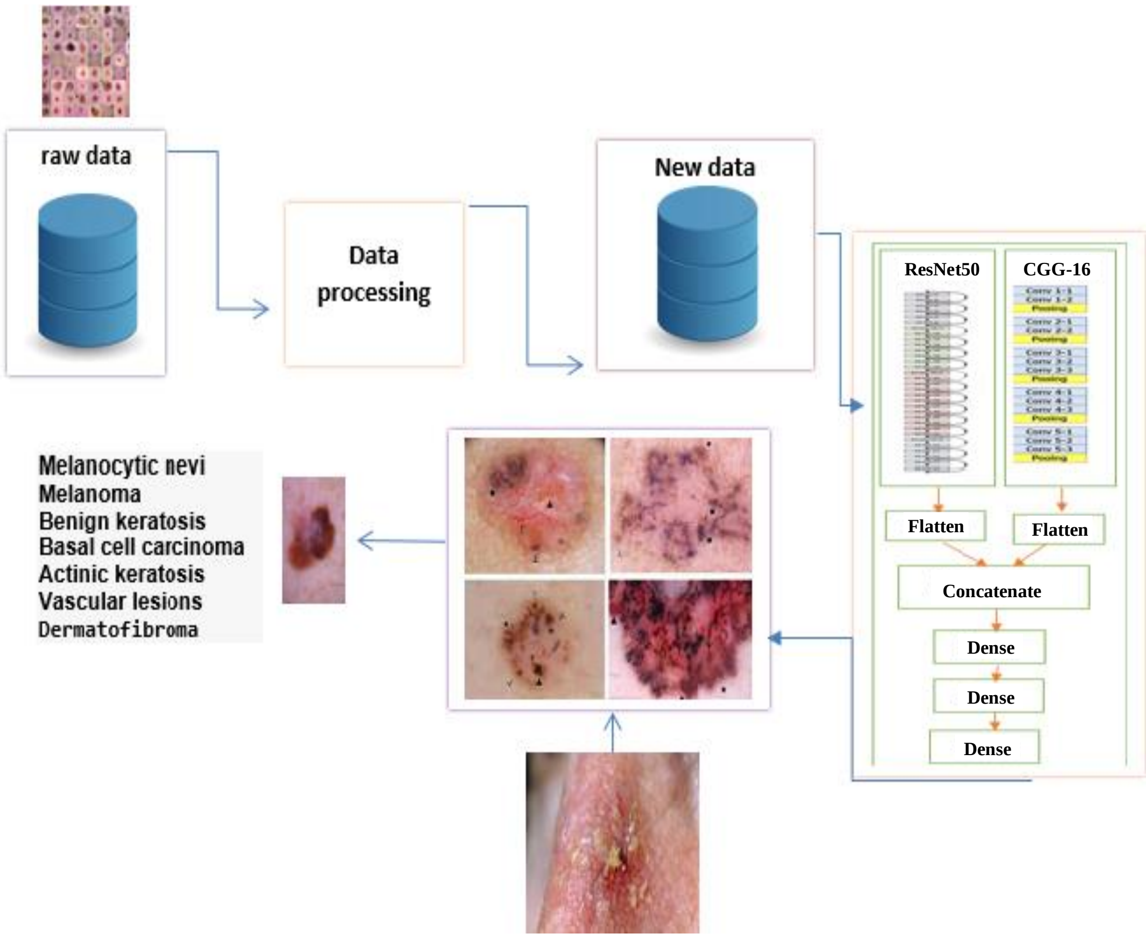


Figure 3. The architecture of the proposed model

4. RESULTS AND DISCUSSION

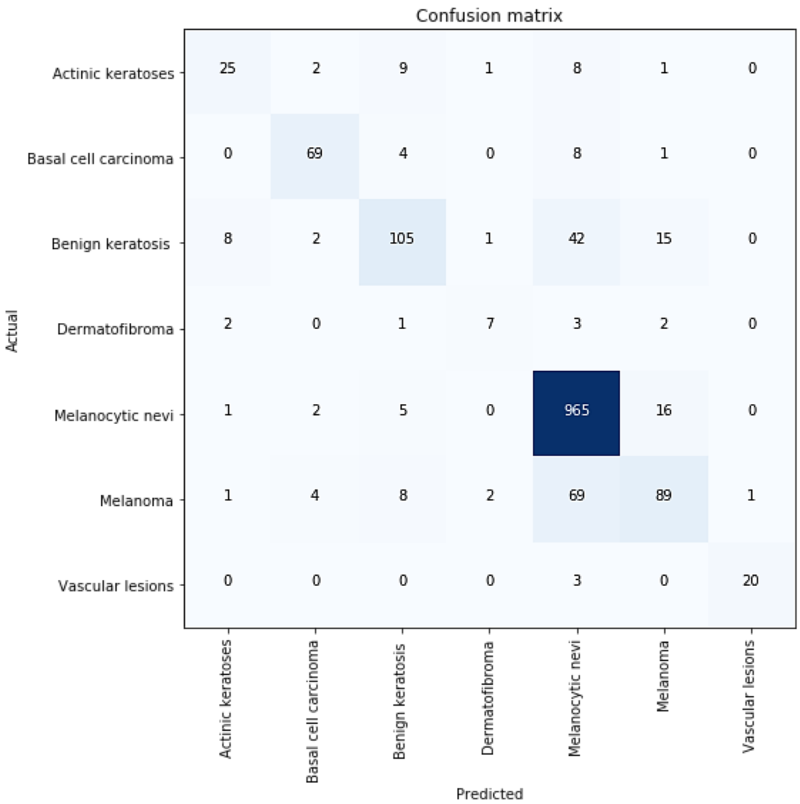
In general, the result is based on the testing data, which consists of 30% of the total images from the HAM10000 dataset representing seven different types of skin cancer. The deep model used in this study was implemented using the Keras library. Deep learning libraries, such as TensorFlow or Theano, can be used with Keras. The model is trained on Google Colaboratory, or colab for short, which lets you write and execute Python in your browser while also providing free GPU access.

The models' performance was evaluated, ResNet50, VGG16, and the merged outputs of the two models for the classification of skin cancer among seven classes: melanocytic nevi, melanoma, benign keratosis, basal cell carcinoma, actinic keratosis, vascular lesions, and dermatofibroma. The accuracy for ResNet50 was found to be 85.2%, VGG16 86.6%, and the merged model was found to be 94.14%. the best accuracy recorded for this merged model is shown in Table 1. The confusion matrices for ResNet50 as shown in Figure 4(a) and VGG16 models are represented in Figure 4(b) and the merged model has represented in Figure 5 dropout layers are disabled in keras during testing, allowing the network to conduct prediction and improve training accuracy for a few epochs while evaluating the model [26].

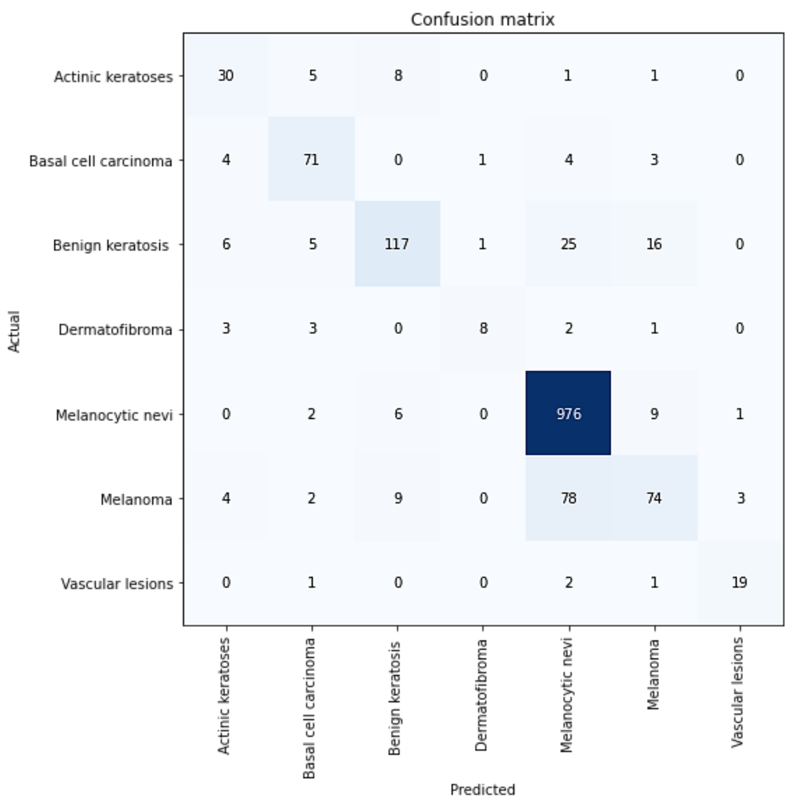
According to the literature, The model's efficiency decreases as the number of classification categories grows. Since the model must predict several groups, there is a higher chance that the prediction will be wrong. As a result, model output continues to deteriorate as the number of classification groups increases. In comparison to the proposed work in this paper, previous works [27]–[30] perform poorly.

Table 1.The accuracy and the time to run of the models

Model	Accuracy
ResNet50	85.2%
VGG16	86.6%
ResNet50+ VGG16	94.14%



(a)



(b)

Figure 4. Confusion matrices (a) confusion matrix of ResNet50 model and (b) confusion matrix of VGG16 model

Although [28]–[30] use 2 or 3 classes for classification, their classification accuracy ranges from 69.4 to 84.8%. In [29]–[31] classification is implemented on more than five classes and lacks precision. The accuracy is varying between 90.1%, 78.6% to 84.9%, and 80.0%. Table 2 shows the comparison of the proposed work with existing models. In multi-class skin cancer classification performed model outperformed both dermatologists and current deep learning approaches. Final Resnet50+VGG16 merged model emerges as an improved architecture for skin cancer classification that makes training easier and can improve accuracy.

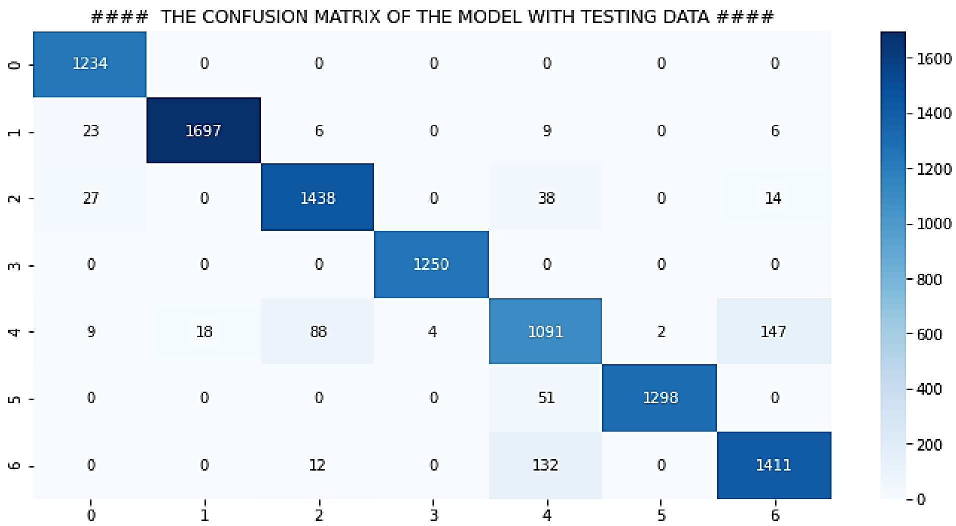


Figure 5. Confusion matrix of the proposed model

Table 2. Comparison between literature and proposed model

Reference	Technique	Number of classes	Accuracy
[28]	VGGNet	Two	81.3%
[27]	GoogleNet	Three	84.2%
	AlexNet		84.8%
	ResNet		82.8%
	VGGNet		81.3%
[32]	VGG16	Seven	80.1%
	GoogleNet		79.7%
[33]	Fully Convolutional Network	Five	85.8%
		Ten	81.8%
[30]	InceptionResnetV2	Seven	70.0%
	PNASNet-5-Large		76.0%
	SENet154		74.0%
	InceptionV4		67.0%
[29]	MobileNet	Seven	83.1%
[34]	CNN	Seven	77.0%
	CNN (one vs all)		92.90%
Proposed model	Resnet50	Seven	85.2%
	VGG16		86.6%
	Merged model		94.14%

5. CONCLUSION

As the prevalence of skin cancer has increased in the whole world, there is a pressing need to handle this global public health issue. Deep CNNs' outstanding success in medical image classification has led to their use in skin cancer classification. While previous studies for the skin cancer classification have been performed, they were unable to successfully broaden their investigation to include different types of skin cancer with good results. In this paper, we implement both dermatologists and current deep learning methods for skin cancer classification. The performance of two pre-trained CNNs is evaluated, and the combination of their outputs proposed the finest strategy for skin cancer classification on the HAM10000 dataset with accuracy 94.14%. We did a lot of research to find the best method to classify the medical image problem accurately. Future research could lead to more efficient deep learning computer-aided skin cancer diagnosis methods. By using new deep learning models with dermoscopy.

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