Accurate Skin Lesion Classification Using Multimodal Learning on the HAM10000 Dataset

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Abstract

Objectives: Our aim is to evaluate the performance of multimodal deep learning to classify skin lesions using both images and textual descriptions compared to learning only on images.

Materials and Methods: We used the HAM10000 dataset in our study containing 10,000 skin lesion images. We combined the images with patients' data (sex, age, and lesion location) for training and evaluating a multimodal deep learning model. The dataset was split into 70% for training the model, 20% for the validation set, and 10% for the testing set. We compared the multimodal model's performance to well-known deep learning models that only use images for classification.

Results: We used accuracy and area under the curve (AUC) receiver operating characteristic (ROC) as the metrics to compare the models' performance. Our multimodal model achieved the best accuracy (94.11%) and AUCROC (0.9426).

Conclusion: Our study showed that a multimodal deep learning model can outperform traditional deep learning models for skin lesion classification on the HAM10000 dataset. We believe our approach can enable primary care clinicians to screen for skin cancer in patients with higher accuracy and reliability.

Keywords: Multimodal Deep Learning, Skin Lesion Classification, Primary Care Physician, Skin Cancer Screening

Lay Summary

Skin cancer, which includes basal cell carcinoma, squamous cell carcinoma, melanoma, and less frequent lesions, is the most frequent type of cancer. Around 9,500 people in the United States are diagnosed with skin cancer every day. Recently, multimodal learning has gained a lot of traction for classification tasks. Many of the previous works used only images for skin lesion classification. In this work, we used the images and patient metadata (sex, age, and lesion location) in HAM10000, a publicly available dataset, for multimodal deep learning to classify skin lesions. We used the model ALBEF (Align before Fuse) for multimodal deep learning. We compared the performance of ALBEF to well-known deep learning models that only use images (e.g., Inception-v3, DenseNet121, ResNet50). The ALBEF model outperformed all other models achieving an accuracy of 94.11% and an AUROC score of 0.9426 on HAM10000. We believe our model can enable primary care clinicians to accurately screen for skin cancer in patients.

Background and Significance

Skin cancer is the most common type of cancer diagnosed worldwide[1]. It is estimated that approximately 9,500 people in the United States (US) are diagnosed with skin cancer each year[2]. It is predicted that around 20% of people in the US will develop skin cancer[2]. The two most common skin cancer types are basal cell cancer and squamous cell cancer, while melanoma is the third most common skin cancer[2]. However, melanoma has the highest mortality, with a long-term survival of less than 10%, despite recent decline in mortality attributed to better treatment[3].

There are geographical differences in the incidence and mortality of skin cancer[4]. The incidence and mortality of melanoma is higher for individuals living in rural and underserved areas, than their urban counterparts[4]. Many factors may contribute to this geographical disparity in melanoma incidence and death, including increased ultraviolet radiation exposure and lower adoption of sun protection strategies in rural compared to urban residents[5]. In addition, barriers to health care access and availability contributes to late detection and effective treatment of skin cancers. The lack of adequate number and distribution of dermatologists contributes to late detection of melanoma. Patients face considerable wait times ranging from 33.9 to 73.4 days to consult with a dermatologist regarding changing moles. Interestingly, even when medical care is offered at no cost, a significant number of patients decline it if the travel distance for their appointment exceeds 20 miles[6].

This situation is accentuated in isolated rural areas. Tele-dermatology has proven effective in mitigating geographic isolation, and various studies have affirmed its diagnostic and treatment accuracy and reliability through telemedicine. Nonetheless, numerous obstacles hinder its widespread adoption and implementation. Alongside privacy and liability concerns, dermatologists identify the absence of a consistent reimbursement system as the primary impediment for both store-and-forward and live-interactive tele-dermatology[7]. Karavan et al. discovered that 40% of patients diagnosed with melanoma in traditional clinics resided in areas where tele-dermatology services were underutilized[8].

Primary care clinicians based (PCCs) in the community often serve as the initial point of contact for patients and may assume a crucial role in offering screening and early diagnosis, particularly for individuals lacking sufficient access to dermatologists[7]. PCCs, while essential, face limitations compared to dermatologists in terms of early detection and have identified insufficient training during medical school and residency as hindrances to effective skin screening[9]. In primary care settings, the rapid and accurate diagnosis of skin conditions is of paramount importance for patient care[9]. However, distinguishing between various skin lesions can be a challenging task, and misdiagnosis can lead to serious consequences[10].

Prior work showed the effectiveness of deep learning models for skin lesion classification on dermascopy images[11]. With growing interest in multimodal deep learning models[12], it is now possible to combine skin lesion images and textual data (e.g., lesion location, patient age) for model training and inference. In this work, we investigate whether multimodal models can improve the accuracy of skin cancer diagnosis compared to models that only use images. Our approach, uses the Human Against Machine with 10000 training Images (HAM10000), a dataset comprising a diverse range of dermatological images [13] including basel cell cancer and melanoma.

Methods

Dataset

The skin cancer classification was carried out using the HAM10000 datasets[13]. The dataset has 7 variables. They are lesion id, image id, dx, dx_type, age, sex, and lesion location variables. The HAM10000 dataset has 7 classes. They are Actinic Keratoses(akiec), Basal Cell Carcinoma(bcc), Benign Keratosis(bkl), Dermatofibroma(df), Melanocytic Nevi (nv), Melanoma(mel), and Vascular Skin Lesions (vasc). Figure 1 and Table 1 below show more description on the dataset we used in this study (HAM10000 dataset). Figure I show the 7 classes of the HAM10000 dataset. Table 1 below shows the variables used in the dataset and a brief description of each variable

Table 1: Brief description of the variables

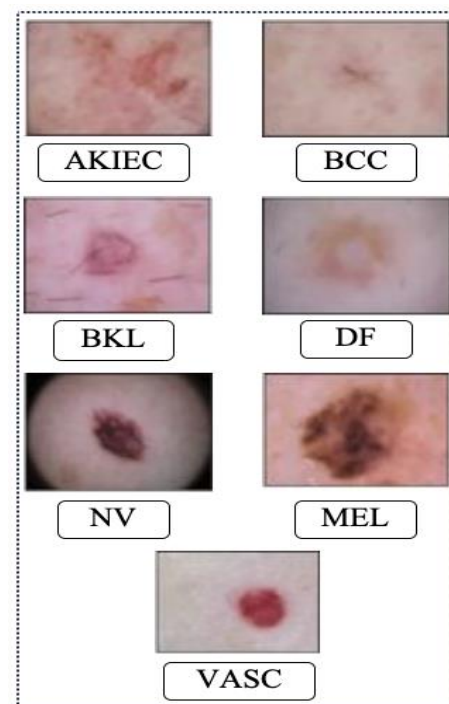| #	Variable	Brief Description
1	Lesion id	Patients associated with skin lesion
2	Image id	Image name in the HAM10000 folder
3	Dx	Lesion Class
4	Dx_type	How the Skin lesion was verified
5	Age	Age of patients
6	Sex	Sex of patients
7	Lesion Location	Location of the skin lesion

Figure 1 HAM10000 dataset classes

There are 327 lesions in the AKIEC, 514 of BCC, 1099 of BKL,115 of DF,6705 of NV,1113 of MEL, and 142 of VASC

Data Pre-processing

The images were resized to 224 by 224 pixels before passing them to the ResNet50, and DenseNet121 models. For the Inception-v3 model, the images were resized to 299*299 pixels. And for the ALBEF model, the images were resized to 256 by 256 pixels. The images were resized to this different size because they are the default image size in which the models were trained on. We also applied data augmentation such as colour jitter, random horizontal flip, random vertical flip, etc.

Deep Learning Models

In recent years, deep learning has gained a lot of traction in image understanding, image classification, language translation, speech recognition, and natural language processing. Convolutional neural networks (CNNs) have shown excellent performance in large-scale image classification and object detection competitions such as the ImageNet Large Scale Visual Recognition Challenge (ILSVRC)[14]. We present a few popular CNNs and the Multimodal that we used in our work.

Inception-V3: CNNs that are deep with many layers are prone to overfitting and consume a lot of computational resources. Inception-V3 was introduced by Szegedy et. al. in 2014[15] to solve these problems by using sparsely connected architectures. It uses the inception module that applies multiple convolutions (e.g., 1x1 convolution, 3x3 convolution, 5x5 convolution) and a maximum pooling layer. The outputs are concatenated to create the input for the next stage. A version of Inception-V3 called GoogLeNet with 22 layers won the ILSVRC 2014 competition[16]. Inception-V3 is an image recognition model that achieved around 78.1% accuracy on the ImageNet dataset. The model was first introduced and implemented in the paper "Rethinking the inception Architecture for Computer Vision"

ResNet: He et. al. introduced the deep residual neural network (ResNet) architecture, which won first place in the ILSVRC 2015 competition[17]. ResNet uses skip connections between layers to solve the vanishing gradient problem. Residual blocks reduced the total parameters by allowing the gradient to flow directly through the skipped connections backward from later layers to the initial filter. In our work, we use ResNet50 which has 50 layers.

DenseNet: Huang et. al. introduced the DenseNet[18] architecture where every layer in the model is connected to every other layer in a feed-forward manner. DenseNet was proposed to solve the

problem of vanishing gradient while being computationally efficient. It promotes feature reuse resulting in a more compact model. In our work, we use DenseNet121 which has 121 layers.

ALBEF: Junnan Li et al introduced ALBEF model[19].It is a state-of-the-art deep learning model that learns the joint representation of image and text data.The model combines the Vision Transformer (ViT-b/16) as the image encoder and BERT as the text encoder. We used the joint text-image encoder to encode both the text and images, and then add a linear fully connected layer to it. The Image encoder are initialized with weights pre-trained on ImageNet-1k[20]. The input image is encoded into a sequence of embeddings.

In our work, we used a joint text-image encoder which aligns the BERT text encoder's embeddings with the image encoder's (Vision Transformers). We then added a linearly fully connected layer and then predict the 7 output classes of AKIEC, BCC, BKL, DF, NV, MEL and VASC.

Skin Lesion Classification

We split our dataset into three sets randomly: training set (70% of the images), validation set (20% of the images), and testing set (10% of the images). The training and our validation set were used during the training process. We then used the testing set to evaluate our model. All the images were resized and zero-padded. The test set has the following class with these dataset numbers (akiec:38, bcc:49, bkl:110, df:11, mel:109, nv:667, vasc:18).

We used data augmentation to improve our overall performance when training our models because deep learning requires many images. Data augmentation helps to increase the number of images artificially to improve the performance of a model and prevent overfitting. We used horizontal flip, vertical flip, colour jitter, and random rotation.

Our system was implemented in Python using PyTorch[21], CUDA, Numpy[22], and OpenCV[23] libraries. We used existing implementations of the ALBEF model for our multimodal lesion
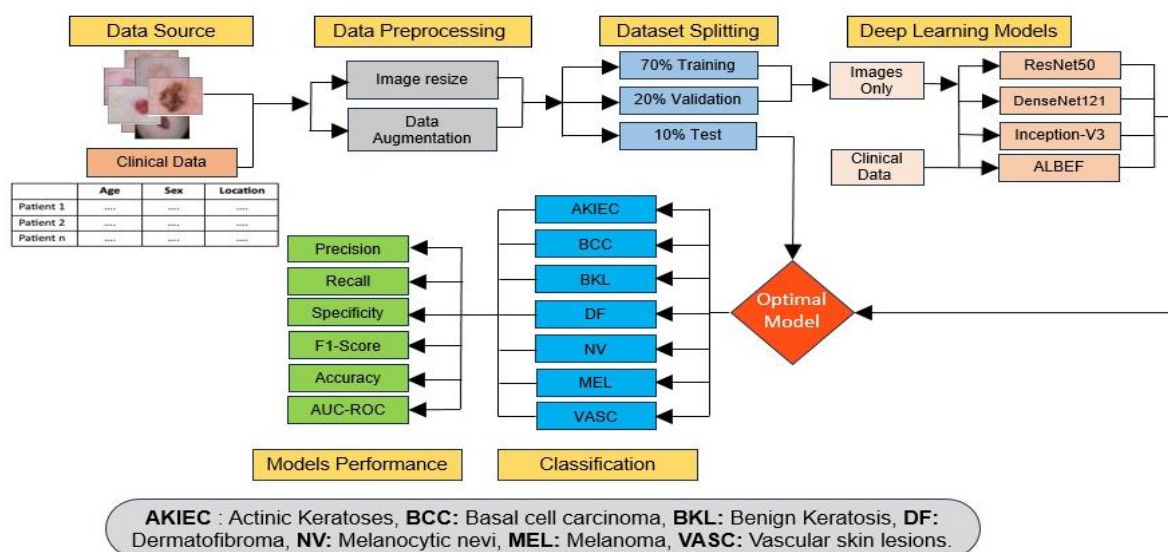

Figure 2 Skin Lesion Classification Approach

classification[24]. The models were trained and tested on a Dell Precision server with an Intel Xeon processor,96 GB RAM, 2 TB disk storage, and two NVIDIA Quadro RTX4000 (8GB) graphics processing units (GPUs).

Model Training Settings

The Inception-V3, ResNet50, and DenseNet121 models were trained with the same hyperparameters: (a) batch size of 16, (b) 200 epochs, and (c) learning rate of 1e-4. Also, each model used the Adam optimizer[25] and binary cross entropy loss function.

The ALBEF model was trained with the hyperparameters: (a) batch size of 16, (b) 200 epochs, (c) learning rate of 1e-4 (d) patch size of 16. The best model based on the highest validation accuracy was saved and used for classification on the test set.

For the Inception-V3, ResNet50, and DenseNet121 model, we performed data augmentation on our lesions using RandomHorizontalFlip, RandomverticalFlip, RandomRotation, ColorJitter and we then transformed it to tensor using the ToTensor method in Pytorch. We trained 70% of the data using a batch size of 16 in 200 epochs. We then picked our best model by using 20% of the dataset as the validation set. We used the ImageNet pre-trained model for fine-tuning the model.

In our ALBEF model, we resized the image to 256 pixels. We then transformed the lesions using RandomResizedCrop and RandomHorizontalFlip. Since ALBEF aligns the BERT and VisionTransformers features. The BERT was pretrained on 'bert-base-uncased'. Our other hyperparameters are patch size of 16, embed_dim of 768, depth of 12, num_heads of 12, mlp_ratio of 4, qkv_bias of True and eps of 1e-4. We trained 70% of the data using a batch size of 16 in 500 epochs. We then picked our best model by using 20% of the dataset as the validation set.

Results

In this section, we present the performance metrics of InceptionV3, ResNet50, DenseNet121, and the Multimodal fusion (ALBEF) on the HAM10000 dataset. On the ALBEF model, we performed two different experiments.

1) Using the text (age, sex, and lesion location) with the images for the training.
2) Using only the Images and passing blank as the text. We performed this experiment to show the effect of adding text on the overall performance of the model.

Performance Metrics

Next, we briefly describe the performance metrics that were used to evaluate our different models. The Classification models aim to classify the HAM10000 dataset into 7 classes. We applied the concept of true positives (Tp), true negatives (Tn), false positives (Fp), and false negatives (Fn). Below are the brief definitions of Tp, Fp, Fn, and Tn. Tp indicates the total number of HAM10000 Skin Lesions that were predicted correctly in the positive class, Tn denotes the lesions that are in the negative class and are classified correctly as the negative class. Fn denotes the total number of skin lesions that were in the positive class but were predicted incorrectly as the negative class and Fp are the lesions that are in the negative class but were predicted incorrectly as the positive class.

Table 2: Different metrics used in our evaluation

Metric	Formula
Precision (*P*)	$T_p/(T_p+F_p)$
Sensitivity/ Recall (*R*)	$T_p/(T_p+F_n)$
Specificity	$T_n/(T_n+F_p)$
Accuracy	$(T_p+T_n)/(T_p+T_n+F_p+F_n)$
F1-score	$2*P*R/(P+R)$

Table 3*: Comparison of the performance of the different models on the HAM10000 dataset (the best model is shown in **bold**)*

Models	Accuracy	Precision	Sensitivity/Recall	Specificity	F1-Score	AUCROC
InceptionV3	0.8653	0.8202	0.7608	0.9570	0.7838	0.8589
ResNet50	0.8503	0.7815	0.7129	0.9646	0.7292	0.8388
DenseNet121	0.8862	0.8505	0.8249	0.9685	0.8350	0.8967
ALBEF (Only Images)	0.9132	0.8959	0.8524	0.9748	0.8693	0.9136
ALBEF (Text and Images)	**0.9411**	**0.9073**	**0.9019**	**0.9833**	**0.9033**	**0.9426**

Table 3 shows the performance metrics of InceptionV3, ResNet50, DenseNet121, and ALBEF on the HAM10000 dataset. ALBEF outperformed all other models. ALBEF model has the best accuracy, precision, recall, specificity, and F1-Score.

Discussion and Conclusion

We implemented the multimodal deep learning models to classify the skin lesions in the HAM10000[13] dataset. The sensitivity, specificity, AUCROC, accuracy and precision of classification using the ALBEF model with the image dataset and the associated text was the highest among the five different experiments that we conducted and deemed applicable in a primary care setting.

Multimodal model is a new field of Artificial Intelligence that helps to replicate the ability to combine information from multiple models. Information from many sources like audio, text, image, and video assists in implementing more complex models that improve the performance of many applications[26].Multimodal learning includes fusion-based approaches, alignment-based approaches, and late fusion.

The ALBEF model (Align Before Fuse) enables us to fuse visual and clinical information, providing a holistic view of the skin lesions[19].This Multimodal approach has the potential to significantly enhance the diagnostic capabilities of primary care physicians and nurse practitioners[27]. The ALBEF model used BERT as text encoder and Vision Transformer model as the image encoder. We used the joint text-image encoder to encode both the text and images and added a linear fully connected layer to it. ALBEF model has been used in a wide array of domains such as Hateful detection, Image Retrieval etc[19]. ALBEF can learn joint representations; this has made it very useful in Image retrieval tasks such as in text queries, text-based on images e-commerce applications, etc. It has also been applied in natural language processing for generating text captions for images. It can be used in classification tasks too.[28]

Adebiyi et al used three different models (InceptionV3, ResNet50 and DenseNet121) for their skin lesion classification[11,29]. They used 770 de-identified dermoscopy images from the University of Missouri (MU) Healthcare. They then created three unique images that contained the original images and images after they applied a hair removal algorithm. DenseNet121 achieved the best accuracy of 80.52% and AUCROC score of 0.81 in their experiment.

Alam et al achieved an accuracy of 85% on the HAM10000 dataset by using the Inception-V3 model[30]. Akter et al achieved an accuracy of 0.82 on the HAM10000 dataset using the ResNet50 model. Our ALBEF model outperformed their works by achieving an accuracy of 0.9411[31].

Tschandi et al applied Multimodal learning for skin lesion classification[32].They employed two ResNet50 convolutional neural networks (CNN) followed by a late fusion technique to combine the features. Their result showed that combining the dermoscopic with macroscopic images and the metadata may improve network performance. Multimodal machine learning has been applied in Knee Osteoarthritis progression prediction from Plain Radiographs and Clinical Data by Tiulpin et al[33]. They utilized the raw radiographic data, clinical examination results, and previous medical history of the patient. They were able to achieve an area under the ROC curve (AUC) of 0.79.

We used the Inception-V3, ResNet50, DenseNet121 and ALBEF models. Our InceptionV3 model achieved an accuracy of 0.8653 and an AUCROC of 0.8589 on the HAM10000 dataset. The ResNet50 model achieved an accuracy of 0.8503 and an AUCROC of 0.8388. The DenseNet121 achieved an accuracy of 0.8862 and an AUCROC of 0.8967. We also implemented Multimodal models that combines the text features in the HAM10000 dataset and the Lesion for the Classification. The text we used in our experiments are the age, sex, and location of the lesion. The Multimodal model we used in this work is the well-known ALBEF (Align Before Fuse) model. We performed two experiments using the ALBEF model. In the first experiment, we used the lesion and passed the text as blank. This achieved an accuracy of 0.9132 and an AUCROC of 0.9136. In the second experiment on the ALBEF model, we used both image and the text. This achieved an accuracy of 0.9411 and an AUCROC of 0.9426. Overall, our Multimodal model outperformed all the other models. This shows that the addition of other patient's feature specifically text in this instance can improve the overall performance of the Skin Lesion Classification.

Our study has some limitations**.** We only used three metadata (Age, Sex, and Location) with the images in our multimodal classification. We believe having more metadata in the dataset may even increase our performance.

We recommend future studies utilize additional text features, as our study was limited to age, sex, and localization data.

Acknowledgments

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