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Review on Skin Lesions Diagnosis and Classification Using Deep Neural Architecture

*[1]Singasani Durga Nitish Krishna, [2]Vadlamudi Nishaanth and [3]J Shiva Sai

*[1, 2]Student, Department of Computer Science and Engineering, Chaitanya Bharathi Institute of Technology, Hyderabad, Telangana, India.

[3]Assistant Professor, Department of Computer Science and Engineering, Chaitanya Bharathi Institute of Technology, Hyderabad, Telangana, India.

Abstract

Session – Skin lesion this is the fiction and slang for changes or oddities on the skin stands for anything that may be deemed normal and ranges from trivial issues to severe ones such as cancer. Identification and staging of such lesions are well noticed, so that patients can be diagnosed and treated early since there is a drastic improvement in patients' results. Therefore, the project was intended to employ deep learning advanced methods in the detection as well as differentiation of skin lesions. Especially, the convolutional neural network is chosen to analyze a rather large and diverse set of skin images. The designed CNN was capable of learning and distinguish these features and patterns characteristic to many types of skin lesions.

Keywords: Skin lesions, deep neural architecture, skin cancer.

1. Introduction

Recent trends in skin cancer and interpretation intricacies explain why dermatology requires sophisticated diagnosis systems. Conventional approaches herein used the visually assisted identification, dermoscopy, and biopsies, which are expensive, time-consuming, and subject to human error. These limitations as well as the increasing rates of skin cancer around the globe has led to the quest for accurate and efficient computational models for diagnosis.

AI and DL have become the emerging tools in medical imaging because systems can process big data sets with high accuracy. Of these, convolutional neural networks CNNs have shown high promise in extracting hierarchical and non- linear features from dermoscopic images; thus, being instrumental in skin lesion classification tasks. Nevertheless, these models have their drawbacks, including the problems with data distributions, non-interpretable, andhigh computational cost in clinical applications.

The work builds on the advantages of pre-trained models, such as Xception, VGG16, and ResNet50; with the focus being made on achieving the highest possible accuracy in skin lesion classification. ALSO, Use of transfer learning significantly enhances model performance and data augmentation increases model applicability in different populations. Incorporation of the distinct representations also enhances the item representations so that the model captures more differentiation in the lesions. Adaptive features weighting is another factor that estimates the features' safeness in real-time, thus addressing the current requirements in dermatological analysis.

Such theoretical exploration and research on benchmark datasets further affirm the utility of this proposed approach, which outperforms basic models including SR-GNN, NARM, and TAGNN. The results underscore the possibility of using adaptive weighting and disentangled representation learning in deep learning models for skin lesion classification. This research also does not only bring about new knowledge in dermatological AI but also provides the foundation for improved, effective and explainable systems for skin cancer detection.

Specifically, how the suggested model enhanced the transfer learning techniques of Xception, VGG16, andResNet50 on classifying dermoscopic images enhances this study. Furthermore, data augmentation helps the model in improving it's generalization capability from training data especial in handling of few samples of categories in a data set. Disentangled representations are used additional to refine feature embeddings to further isolate the latent factors related to lesion characteristics. This approach does not only improve the degree of detailed analyses of the forecast but also helpful for constructing the effective and explainable system.

2. Literature Survey

a) Skin Cancer Diagnosis using Deep Learning, Transfer Learning, and Hybrid Model

Authors: Ravi Prakash, Trilok Nath Pandey, Bibhuti Bhusan

*Corresponding Author: Singasani Durga Nitish Krishna

Dash, Sudhansu Shekhar Patra, Utpal Chandra De, Abinash Tripathy

This paper is concerned with enhancing the diagnostic capability of skin cancer through developing a hybrid of transfer learning and deep learning networks. The hybrid model incorporates pre-trained networks including ResNet152V2, VGG19 and MobileNetV3Large because of the features they possess of extracting Hiarchical features from images. With learning such general-purpose feature extraction capabilities combined within the proposed framework and adapted to the dermoscopic image field, which is specially focused on skin lesion categorization and detection purposes, the main hypothesis is confirmed.

The paper also provides information about HAM10000 dataset of dermoscopic images, which are quite diverse and contains different types of skin lesions including melanoma, basal cell carcinoma and keratosis. The characteristics of dermoscopic images are learned by fine-tuning the parameter space of the models, acquired by transfer learning, to more locally optimum values. The hybrid model goes further in that besides merging the different networks, it combines the features extracted into one vector in order to capture fine details of the skin lesion such as surface texture or colors. Due to multi-model feature fusion, this work is able to distinguish between closely related lesion types with enhanced diagnostic accuracy.

Table 1: Analysis of Different Models.

Technique/Method	Accuracy	Precision	Recall	AUC
Fine Tuned CNN	0.7591	0.7411	0.7514	0.7421
VGG19	0.9529	0.9544	0.9503	0.9949
ResNet152V2	0.9748	0.9757	0.9748	0.9943
Mobile Net V3 Large	0.9605	0.9630	0.9780	0.9933
Hybrid Model	0.9752	0.9762	0.9746	0.9924

The disadvantages of using this method are many.

i). **High Computational Cost:** Because the hybrid approach used in this study incorporates several pre- trained models, the computational demands soar and this is problematic for the system especially when implemented in conditions of limited resources or where real-time sentiment analysis is desired. Training such architectures involve usage of high- end hardware which may not always be available.

ii). **Data Dependency:** The model highly depends on datasets carefully labelled such as the HAM10000 model. Feat selection may have a weakness such that the model trained on such data may not be as effective for other skin tones, age range or lesions' type. The study is also prone to bias which makes it a less generalizable tool to use in various clinical environment.

iii). **Overfitting Risk:** Since deploying multiple deep learning models is a somewhat complex process, there is a higher likelihood of overfitting on the data especially where the data is imbalanced or lacks enough training data. Even in cases when used with unseen data or real cases it is possible to experience decreased performance.

b) A Deep Learning Approach Based on Explainable Artificial Intelligence for Skin Lesion Classification

Authors: Natasha Nigar, Muhammad Umar, Muhammad Kashif Shahzad, Shahid Islam, Douhadji Abalo

This paper addresses to present a research problem that is central to AI-based skin lesion classification systems, that of interpretability. The developed model combines ResNet18 and XAI to introduce explanation to the model's predictions for more accurate clinical applications. For visualization, the system calls an explanation technique known as Local Interpretable Model-Agnostic Explanations (LIME). Here, the authors use the ISIC 2019 dataset consisting of more than 25,000 dermoscopic images of different lesion types to train the model for the classification of eight skin lesions: melanoma, basal cell carcinoma, and vascular lesions and other.

The study focuses on the "black box" characteristic of ordinary deep learning models not becoming accredited in clinic settings because of their lack of interpretability. LIME corrects for this problem by providing localized explanation specific to a given image that reveals the areas of the image that the model is most sensitive to. This is crucial because it brings together the views of the system with the views of a dermatologist, thus, closing the loop between Artificial Intelligence, and practice. Besides, there are possibilities of enhanced image preprocessing options applied to the model and fine-tuning algorithms to increase the robustness of the classification results.

Disadvantages and Challenges:

i). **Computational Overhead:** This is especially the case with features such as Explainable AI that in this case is implemented by the LIME technique, which increases computational overhead. This leads to a slower time for making predictions and explanations which makes the model less effective in the clinical diagnostic where quick diagnosis is needed.

ii). **Incomplete Explanations:** However, LIME offers localized explanations of the model's predictions but does not describe an overarching conclusion. These can result in partial conclusions specifically with dermatologists who would need more justification for their diagnosis.

iii). **Dataset Generalization Limitations:** The model is trained only on the ISIC 2019 dataset which does not embrace other datasets and diverse populations partially. Consequently, when used in other population or different demographic or lesion makeup, the system's performance can be reduced.

iv). **Limited Generalization of Explanations across Lesion Types:** The LIME-based explanations are informative locally and can possibly explain a wide variety of lesions including melanoma and benign keratosis. This inconsistency as depriving such explanations of reliability when it comes to explaining complex cases. As a result, clinicians can feel limited when relying on the system to make recommendations about all types of skin lesions.

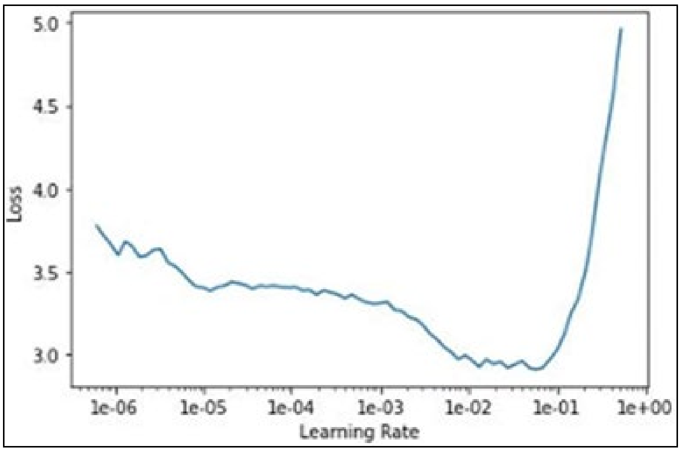

Fig 1: Model learning rate vs loss.

c) Multiple Skin Lesions Diagnostics Using Cascaded Deep Convolutional Networks

Author: Mainul Islam, Md. Ariful Islam Khandaker, Mohiuddin Ahmad

The current study presents an architecture of cascaded deep convolutional network for skin lesion classification and segmentation. For lesion classification, ResNet152V2 is used along with InceptionV3 and a modified Deep Res U- Net is incorporated to segment lesion boundaries accurately. Using transfer learning and fine-tuning approaches, the system applies pre-trained models to domains peculiar to dermoscopic imaging.

The proposed cascaded approach caters for the dual requirements of accurate lesion localization that is a precursor to accurate classification., which is an essential element in early stages of skin cancer diagnosis and therapy planning. It is also able to model both local and global characteristics of lesions well and equipped to distinguish benign from malignant categories of lesion with high accuracy. Moreover, the segmentation component also improves the model's capability to distinguish lesion outlines, which significantly determine the extent of pathological skin conditions. The performance of the proposed system on the ISIC 2016 and ISIC 2017 datasets from the experiments reveal that the system outperforms the standalone classification models. High segmentation accuracy and robust classification are obtained by adopting the cascaded architecture, which is why the proposed solution can be useful for dermatological diagnostics. However, the use of computationally intensive networks has its limitations that make implementation in the real world difficult.

However, there are a few disadvantages to it:

Cold-Start Problem: They also proved that the model fails to identify new or rare lesion types due to a lack of training information on the same. This lessens its capacity, to generalize nicely and limits of self-diagnosis when it is in such conditions.

- **i). High Computational Complexity:** The cascaded architecture that implements the classification and segmentation requires large amounts of computations and memory. This makes the system less usable in environments which does not have or cannot accommodate elaborate computer systems.
- **ii). Data Imbalance Issues:** Since the training and validation datasets contain a large proportion of large lesion examples, the model performed worse for underrepresented lesion types. This decreases the ability of the model in the detection of such occasional but very vital diseases like the melanoma at a tender stage.

Table 2: Models Performance on the training set

Metrics	Inception V3	VGG16	Resnet152V2
Accuracy (%)	72	91	91
Precision (%)	52	92	91
Recall (%)	72	91	91
F1-Score (%)	61	91	90

d) Skin Cancer Detection and Classification using Deep Learning

Author: Sweta Jain, Prathamesh Rajbhoj, Srushti Dhakate, Utkarsh Sathawane, Prathamesh Gujar

In this paper, authors describe the skin lesion classification using the CNN framework with the goal of malignant and benign skin lesions differentiation. The system is trained on ISIC 2018 dataset with the use of techniques such as rotation flipping and scaling in an attempt to handle data imbalance. The proposed CNN architecture aims at getting good features from dermoscopic images and correctly categorizing skin lesions.

This way, the procedure is aimed at achieving a reasonable trade-off between model complexity and possible errors, allowing to implement the model on computers available in clinical practice. Using data augmentation in this system aids in generalization as well as overcoming disadvantages brought by underrepresented lesion categories. The proposed framework shows efficiency according to experimental outcomes that report high precision, recall, and F1-score. However, in relation to contextual understanding and scalability there are certain limitations inherent in the model due to the previous use of image-based features and augmented data.

Table 4: Precision, Recall, F1 Score of class benign and malignant

Class Label	Evaluation Metrics		
	Precision	Recall	F1 Score
Benign	0.90	0.84	0.87
Malignant	0.81	0.88	0.85

However, there are a few disadvantages to it.

- **i). Lack of Contextual Features:** In the model, no other information about the patient's condition, including the demographic background, history of lesions, or family history, are taken into account. This in a way restricts it from offering a diagnosis that involves more precision and indeed that which will suit the client better.
- **ii). Synthetic Data Dependency:** Although some techniques such as flipping and rotation enhance model performance, the variations they provide may not capture those observed in clinical practice settings. This could only decrease the reliability of prognosis in various situations.

3. Proposed Method

To overcome the difficulties associated with skin lesion diagnosis and classification, we put forward a complex deep neural structure based on several pre-trained CNNs and utilizing methods as XAI and transfer learning. The implementation of the solution is sectioned in the following manner:

- **i). Multi-Network Integration and Feature Extraction:**
  - **a) Model Ensemble:** The proposed method comprises an assembly of Xception, VGG16 and ResNet50 pre-

stored models for performing classification. These architectures are gradually optimized for dermoscopic images and perform feature hierarchy like texture, color and structural patterns to distinguish between benign and malignant lesions.

b) **Layer Fine-Tuning:** Unlike the pre-trained models where all earlier layers undergo freezing to allow the later layers to adapt to the new environment, all layers of the pre-trained models are fine-tuned for the aspect of domain specific feature adaptation. This approach increases the models' discriminative power with regard to the extent of the changes in the skin lesion characteristics used for classification of skin lesion.

ii). Explainable AI for Interpretability:

a) **Localized Explanations with Grad-CAM:** Grad-CAM is used to obtain visual explanations based on areas in dermoscopic images that lead to classifiers' decisions. They enhance the trust that dermatologists have in the system by enabling them to have access to explicit information about the functionality of the system decision making process.

b) **LIME for Global Insights:** In the spirit of global interpretability, LIME framework identifies the features and patterns that are used by models to make classification across different lesion categories.

iii). Adaptive Feature Enhancement and Transfer Learning:

a) **Attribute-Based Transfer Learning:** The novelty of the specific project is that by training on the models pre-trained on the ImageNet, the system is transferred to the dermoscopic image domain. This step brings training time forward while making certain discriminative features particular to skin lesions are extracted.

b) **Data Augmentation:** What is more, three methods including rotation, flipping, and scaling are used in order to widen the training dataset and to increase the class separation while at the same time decreasing the class imbalance problem by increasing the model's ability to generalize unseen cases.

iv). Segmentation and Localization of Lesion Boundaries:

a) **Deep Res U-Net Integration:** To provide an optimal boundary segmentation, there is a modified deeper Res high-precision U-net. This component helps to define the margins of the lesion and its subsystem serves to better define the critical areas of an image to produce better results.

b) **Jaccard Distance Loss Function:** The segmentation model is learned using the Jaccard distance as a measure of the loss function to capture the best set of masks for detecting lesion boundaries.

v). Training, Scoring, and Diagnostic Accuracy

a) **Weighted Loss Function:** Data imbalance is combined using a weighted loss function, making it possible to highlight the issue of underrepresentation of some lesions, for example, melanoma..

b) **Multi-Metric Evaluation:** Safeguard and optimization of the diagnostic system is done analytically by accuracy, F1-score, precision, recall, and AUC metrics.

vi). Iterative Improvement and Scalability:

a) **Continuous Feedback Mechanism:** There is also an iterative cycle to modify the model depending to user feedback and newly obtained data to reflect changes in clinical needs.

b) **Scalability across Large Datasets:** Firstly the architecture is built to work with big amount of data interactively, namely millions of dermoscopic images will be processed with the same level of efficiency.

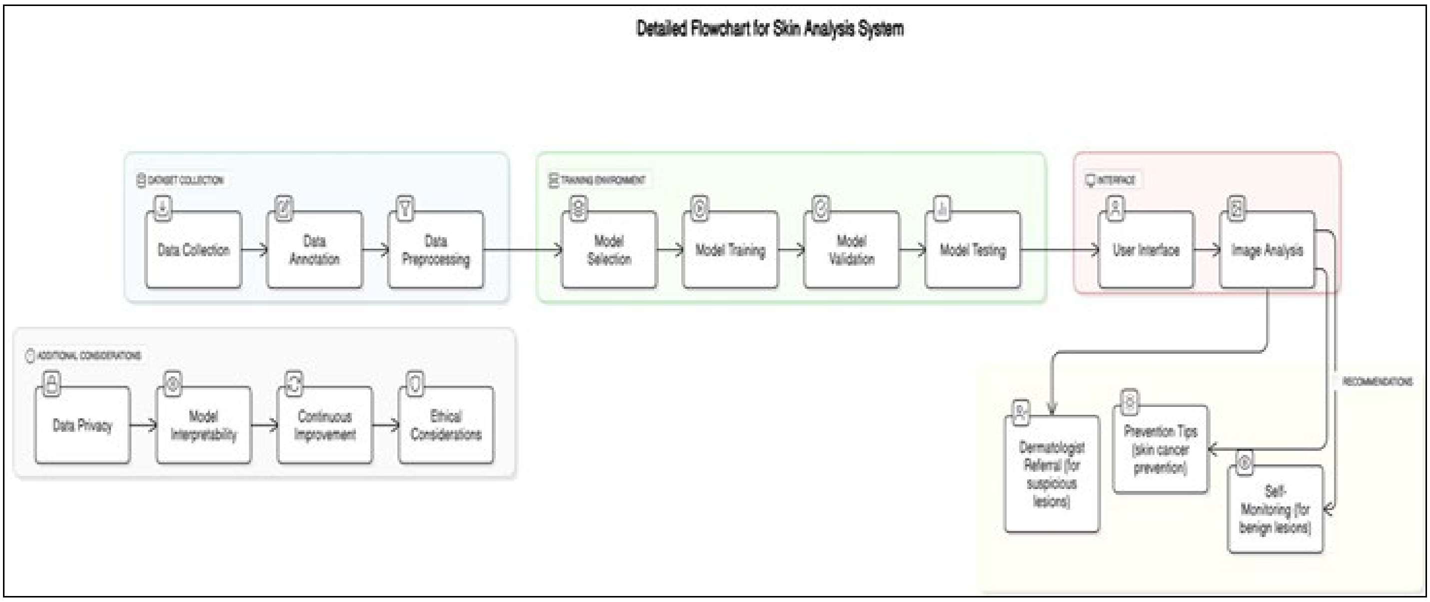

Fig 2: The overview of the proposed system

4. Datasets

a) HAM10000 Dataset

The HAM10000 dataset is alternatively called 'Human against Machine with 10,000 Training Images' datasetis one of the vast dataset that contains dermoscopic images to be used for skin lesion classification. It consists of 10015 dermoscopic images of which 7 terminates skin lesion type which includes melanoma, basal cell carcinoma, benign

keratosis, and vascular impressions. Diversity of the dataset and its high-quality annotation makes it an excellent product for deep learning applications in dermatology.
In addition to the directions in the raw scans, the contour map of each lesion in this dataset holds metadata like lesion identifiers, age, gender, and anatomical area, which help enrich model training. It is marked by dermatologists, which will make it suitable for supervised learning in general. The images are in common formats and in sizes widely used in the current CNN networks of computer vision. This dataset has rich metadata like lesion identifiers as well as age, gender, and the anatomical location of the lesion in case a model requires that information for training. The images are tagged manually by dermatologists which makes the data set suitable specifically for supervised learning problems. The images are in formats and resolution that are accessible by modern convolutional neural networks (CNNs). HAM10000 is primarily used in both research settings and clinical investigation by a vast number of users. This has been crucial in training convolutional neural networks (CNNs) for skin lesion analysis including classification, segmentation and even the explainability work. It is suitable for multi-class classification problem thus enabling models to learn differences of the lesions of different type and intensity. The data is stored in JPEG image format and the labels are in structured and well formatted CSV format, which is convenient for state of the art deep learning frameworks such as TensorFlow and PyTorch.

b) ISIC Dataset

The ISIC dataset which is offered by the International Skin Imaging Collaboration is an enormous source of skin lesion images with more than 25000 dermoscopic images with their labels. H It is one of the largest datasets in to dermatology, often being used for international competitions such as ISIC Skin and Lesion Analysis Challenges from 2018-2021. This dataset is made of images of different kinds of lesions, which are melanoma, nevus, keratosis, etc. It also contains both classifications and segmentation data.
What makes ISIC dataset unique is that it contains pixel level segmentation masks which enable the researchers not only for the predictive models but also to draw the boundaries of regions of interest, i.e., lesions. These types of masks are necessary to define the degree of a lesion, more specifically – in melanoma cases when boundary violations are diagnostically essential. Furthermore, the data set is given with the divided training, validation and testing sets for the benchmarks of dataset to machine learning algorithms. Another, more general, aspect of ISIC is that it focuses on standardization which makes it especially suitable for research in automated diagnosis, xAI, and multi-modal systems. In order to compare dermoscopic images, we pre-process the images to maintain uniformity to the samples being used. Also, the dataset has demographic metadata about the patient, for instance, age, gender, and the position of the lesion making a good dataset for building personalized diagnostic systems.

c) PH2 Dataset

The PH2 dataset is another anatomic oriented dataset of dermoscopic images of 200 images of pigmented skin lesion. It contains three distinct categories of lesions: synch, desmoplastic, common nevi, atypical nevi and melanoma. All the images come with pixel-wise segmentation masks and annotations, and the annotations were further audited and validated by three dermatologists. This makes the dataset highly robust for use in tasks cutting across boundary delineation and classification of lesions.
The images in the PH2 dataset are obtained employing dermoscopy under specific directed conditions of image acquisition to generate more uniform data. This reduces sources of variability like; exposure to light, focus or even magnification, unlike other datasets, that contain variations in the mentioned factors. The images are taken in RGB colour mode and the actual picture size is 768×560 pixels, is high resolution because images to show details of texture, color and the structure of the lesion. Nearly all the images in the dataset are associated with segmentation masks indicating the precise boundaries of the lesions. These masks are highly accurate that it is possible to get pixel level analysis and better training of segmentation models. Segmentation information is accompanied by annotations that describe important aspects of the lesion such as its asymmetry, margin characteristics, color distribution, and size, which are measurable attributes consistent with diagnostic measures taken in practice. This paper underlines a significant role of small but very rich datasets in the development of the algorithms intended for the early detection of melanoma, in particular, and medical imaging, in general. That is why integrating PH2 with other sources can be helpful in reaching both high scalability and high precision and ultimately improving the analysis of skin lesion images.

5. Conclusion

This project marks a milestone in the development of the automated skin lesion classification using deep learning tool. To overcome the basic issues of dermatology, the proposed system insulate pre-trained CNN models, including Xception, VGG16, and ResNet50 and hematologic techniques, including explainable AI and transfer learning. The key points include: transfer learning is applied to extract features from dermoscopic images efficiently, Grad-CAM and LIME explainability facilitates clinicians' trust and validation of the model's predictions.
The proposed architecture is much more accurate for diagnosis as well as significantly faster and therefore ideal for use in a realistic environment. This is due to the usage of data augmentation and fine-tuning which make the model capture the variability of lesion types such as melanoma and benign keratosis. Also, segmentation tasks help to integrate necessary lesion boundary in the final maps, thereby providing accurate information to clinicians. Its weight loss function also makes the system more capable of handling discrepancies in dataset distribution by preserving more underrepresented lesion types categories. Altogether, the work advances the field of AI-based dermatological diagnosis and supports extending the gained knowledge in this direction. The proposed solution proves not only the precision in the lesion classification but the feasibility of the approach for real-time applications as well for the future shift in the skin cancer care with the early diagnosis.

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