Assessing Pretrained Model Through Transfer Multi-Task Learn For Melanoma Classification

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Abstract

Melanoma is a lethal skin cancer that is increasingly threatening the public health system due to increased incidence rates and mortality rates. Early detection of the disease is vital for improved outcomes and the reduction of mortality rates.Skin cancer classification remains a challenging task in the field of dermatology.While self-attention mechanisms and large language models have gained traction in skin cancer detection research, there is still insufficient evidence demonstrating their superior performance compared to CNNs. Thus, further exploration of this area is warranted.Where the quest for the optimal CNN pretrained model persists. In this study, we address this gap by assessing various pretrained models to determine the most effective one for skin cancer classification. Additionally, we introduce a novel approach that leverages transfer learning to develop a multi-task model capable of providing more comprehensive prediction information from dermatological images. Unlike conventional single output classification tasks that rely solely on label prediction, our proposed model utilizes transfer learning techniques to extract valuable features from pretrained models, enhancing its ability to predict multiple tasks simultaneously. This novel approach not only advances the field of dermatology by improving classification accuracy but also meets the growing demand for more informative predictions in clinical settings.

CCS Concepts

• :; • **Human-centered computing**;; • **Human computer interaction (HCI)**;; • **User models**;;

Keywords

Additional Key Words and Phrases: Skin Cancer,Deep Learning,Transfer Learning,Multi-Task Learn, Classification

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1 INTRODUCTION

Melanoma stands out as one of the most prevalent and deadliest forms of skin cancer, contributing significantly to skin cancer related fatalities worldwide. Its incidence is attributed to a myriad of factors including genetic predisposition, environmental exposures, and lifestyle choices. Notably, ultraviolet (UV) radiation remains a primary culprit, implicated in the majority of melanoma and non-melanoma skin cancer cases. Early detection of skin cancer is paramount for effective treatment, particularly before it progresses to advanced stages infiltrating deeper layers of the skin [1]. However, the task of detection is compounded by the diverse spectrum of melanoma variants, encompassing basal cell carcinoma, keratosis-like lesions, Bowen's disease, melanocytic nevi, and vascular lesions [2]. Moreover, the subtle manifestations of skin cancer in its nascent phases further exacerbate diagnostic challenges. In clinical practice, dermoscopy serves as a crucial tool for the early diagnosis of skin cancer. This non-invasive technique enables the evaluation of skin lesions that may elude detection by the unaided eye.

Nevertheless, the accuracy of skin cancer diagnosis may be compromised by the varying expertise levels among dermatologists, underscoring the imperative for precise and dependable diagnostic systems [3]. The complexity of skin cancer classification further compounds the diagnostic dilemma, necessitating sophisticated image analysis techniques capable of discerning salient features from lesion images. Extracting pertinent features such as shape, color, and texture from these images poses a formidable challenge, propelling researchers towards the development of advanced feature extraction systems [4]. In recent years, significant strides have been made in leveraging transfer learning methodologies and pretrained models for melanoma classification. Deep convolutional neural networks (CNNs) have emerged as powerful tools for image processing, offering unparalleled efficacy in the detection and classification of skin cancer [5]. These deep CNN architectures exhibit remarkable adaptability to the intricate and variable nature of fine grained images characteristic of skin cancer lesions [6]. Leveraging their capabilities, CNNs excel in extracting relevant features from skin lesion images, facilitating accurate classification [7]. Furthermore, transfer learning has garnered substantial attention, enabling the utilization of pretrained models trained on diverse datasets. By harnessing the initialized weights from pretrained networks, researchers can fine-tune models to suit the requirements of specific classification tasks, thus streamlining the development process [8–12]. This amalgamation of transfer learning and deep learning frameworks holds immense promise in advancing the field of skin cancer classification, offering a pathway towards more robust and accurate diagnostic solutions. In pursuit of a more comprehensive and interpretable approach to skin cancer classification, our aim is to harness the synergistic potential of transfer learning and multitask learning, thereby advancing the state-of-the-art in dermatological diagnosis and paving the way for more accurate and clinically relevant predictive models.

2 RELATED WORK

In addressing the challenges of skin cancer classification, researchers have predominantly relied on convolutional neural networks (CNNs) to extract salient features from dermatological images. Various methodologies rooted in machine learning, deep learning, and image processing have been proposed for segmenting, detecting, and classifying skin cancer lesions. Notable approaches include CNN-based methods such as those presented by Esteva et al. [13] and Dorj et al. [14], as well as techniques leveraging k-means clustering [15], multi-tract CNN architectures [16], and support vector machines [17]. While CNN-based methods have demonstrated high applicability in skin cancer classification, their effectiveness often hinges on the availability of extensive training data. However, the scarcity of high-quality datasets, exacerbated by a dearth of labeled images for abnormal cases, presents a significant challenge [18]. To mitigate this issue, transfer learning emerges as a promising solution, allowing the utilization of pretrained networks trained on diverse datasets. In recent years, there has been a growing interest in multitask classification approaches for skin cancer diagnosis. While existing research has primarily focused on single task classification, multi-task learning holds potential in simultaneously predicting multiple diagnostic outcomes from dermatological images. However, to date, there remains a gap in the literature regarding the application of multi-task learning specifically in the context of skin cancer classification. Thus, our research aims to address this gap by exploring the efficacy of transfer learning combined with multitask learning for enhancing the accuracy and interpretability of skin cancer diagnosis models. Through this endeavor, we seek to advance the state-of-the-art in dermatological diagnosis and contribute to the development of more robust and clinically relevant predictive models.

3 METHODOLOGY

In the domain of dermatological diagnosis, deep learning architectures, particularly CNNs, play a pivotal role in the detection and classification of skin cancers through automatic pattern recognition [19]. CNNs leverage artificial neural networks to analyze visual data, employing techniques such as backpropagation and feedforward propagation to learn features from training data and distinguish between different classes in test data [20][21] [22]. While CNN techniques offer superior performance compared to traditional machine learning methods, they often require substantial computational resources [23][24]. The computational demands of CNNs are contingent upon the architecture's complexity, including the number of layers utilized, such as convolutional, pooling, and fully connected layers [6].

To address the challenges in skin cancer classification, particularly the need for more comprehensive diag-nostic models, our methodology prioritizes the development of a multi-task learning framework. This framework aims to simultaneously tackle multiple tasks relevant to skin lesion analysis, thereby enhancing the overall diagnostic capability. Specifically, our approach extends beyond traditional class label prediction and includes the prediction of additional attributes such as age, gender, lesion location, and other clinically relevant information. By incorporating these multi-task predictions, our model provides a more holistic understanding of the dermato-logical condition, enabling clinicians to make more informed diagnostic and treatment decisions.

In addition to predicting skin cancer subtypes, our multi-task framework leverages advanced machine learning techniques to infer supplementary information from dermatological images. These predictions encompass a wide range of demographic and clinical characteristics, including patient age, gender, lesion location on the body, and potentially other pertinent factors such as lesion size and texture. By integrating these multi-task predictions into the diagnostic process, our framework empowers healthcare providers with a comprehensive view of the patient's condition, facilitating personalized treatment plans and improving overall patient care.

Furthermore, by jointly optimizing multiple tasks within a unified framework, our approach capitalizes on the synergies between different prediction tasks, enhancing the model's overall performance and interpretability. Through extensive experimentation and validation on diverse datasets, including standardized test sets annotated according to contemporary standards, we aim to demonstrate the efficacy and generalizability of our multi-task learning framework in real-world clinical settings. Ultimately, our methodology seeks to address the evolving needs of dermatological diagnosis by providing clinicians with a robust and versatile tool for skin cancer classifi-cation and comprehensive lesion analysis.

We propose a comprehensive methodology consisting of three main steps:

3.1 Benchmarking Pretrained CNN Models

We begin by benchmarking pretrained CNN models using zero training on the Bill's [25] balanced test set to evaluate their performance. Specifically, we utilize pretrained Torch version models to classify melanoma and non-melanoma lesions. The models are evaluated based on their accuracy in classifying melanoma lesions against other types of lesions. This process allows us to rank the pretrained models according to their classification accuracy.

3.2 Development of a Multi-Task Novel Model

Building upon the highest performing pretrained model identified in the benchmarking stage, we create a novel multi-task learning model: called M-MTL, architecture show 1. This model is designed to simultaneously perform multiple tasks relevant to skin lesion analysis, leveraging transfer learning techniques to fine-tune the pretrained model on our specific dataset. By incorporating transfer learning, we aim to capitalize on the knowledge learned from the pretrained model while adapting it to our target tasks.

3.3 Evaluation on Annotated Test Set

We further validate our multi-task model by reannotating the Bill's test set with metadata from the ISIS 2020 dataset, aligning it with

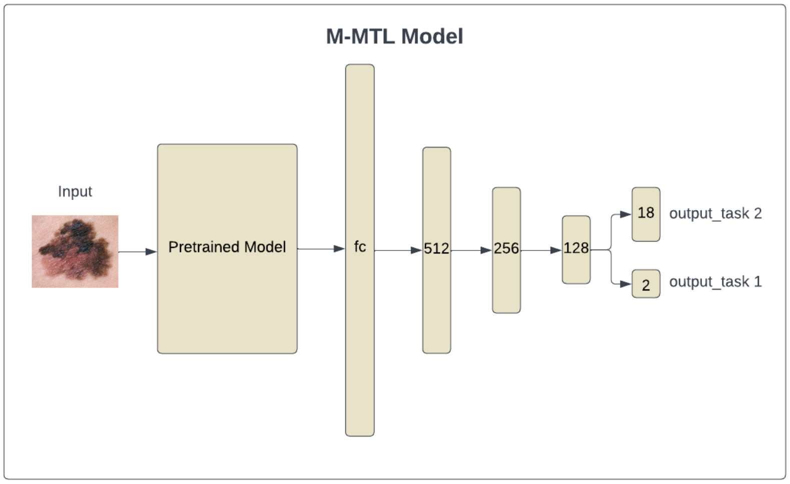

Figure 1: M-MTL Model

Table 1: Pretrained Family Models

Model Name	Citation
AlexNet	[21]
ConvNet	[8]
DenseNet	[16]
DeiT	[36]
EfficientNet	[35]
GoogleNet	[33]
Inception	[33]
MnasNet	[34]
MobileNet	[15]
RegNet	[27]
ResNet	[13]
ShuffleNet	[38]
SqueezeNet	[17]
Swin Transformer	[24]
VGG	[31]
Vision Transformer (ViT)	[11]
Xception	[7]

current standards. Subsequently, we test our model on this annotated test set to assess its performance in real-world scenarios. By using a standardized test set with updated metadata, we ensure the robustness and applicability of our model across different datasets and settings. This methodology enables us to systematically evaluate pretrained CNN models, develop a novel multi-task learning framework, and validate its performance using standardized test datasets. Through these steps, we aim to advance the state-of-the-art in skin cancer diagnosis and contribute to the development of more accurate and interpretable diagnostic models.

Table 2: Bill's Balanced dataset details

Dataset	benign	malignant	Total
Train	3924	3924	7848
Test	981	981	1962

4 EXPERIMENT AND RESULTS

4.1 The experiment setup

The hardware environment: CPU: Intel Core i7-6700K CPU@4.00GHz x 32, GPU: NVIDIA TITAN X (Pascal)PCIe / SSE2, HD: 2TB, Memory: 32GB. The software packages are: Python, PyTorch-gpu, batch size 32, early stop setup, schedule_lr.

4.2 Dataset

The International Skin Imaging Collaboration (ISIC) dataset is a leading repository for researchers in machine learning for medical image analysis, especially in the field of skin cancer detection and malignancy assessment. They contain tens of thousands of dermoscopic photographs together with gold-standard lesion diagnosis metadata. The associated yearly challenges have resulted in major contributions to the field.Bill's balanced dataset is balanced dataset.[25]. details table 2. For this study, First We choices Bill's balanced dataset for the initial evaluation the models, Then we used a publicly available ISIC2020 dataset [38],which typically refers to the International Skin Imaging Collaboration (ISIC) data set for 2020.

The ISIC datasets are widely used in the field of dermatology and computer vision for the development and evaluation of algorithms related to skin lesion analysis, including tasks like melanoma detection. The ISIC 2020 dataset includes a collection of skin images with associated metadata, including clinical information and lesion annotations. ISIC2020 dataset which contains 33,126 dermoscopic

Table 3: ISIC2020 dataset details

Diagnosis type	Total data
unknown	27124
nevus	5193
melanoma	584
seborrheic keratosis	135
lentigo NOS	44
lichenoid keratosis	37
solar lentigo	7
cafe-au-lait macule	1
atypical melanocytic proliferation	1

images from 2056 patients. The dataset is highly imbalanced with less than 2% malignant cases. As shown the dataset details table3.

4.2.1 Data Sample. In this sample Fig 2, we provide details about a single data sample, including an image of the skin lesion, the age of the patient,diagnosis. This information helps provide context for the dataset and demonstrates how different attributes are associated with each data sample.

4.3 Results of evaluation of Pretrained Models on Bill's Test Dataset

We evaluated a total of 86 pretrained models from the Torch library using the Bill's test dataset. The evaluation was conducted using the zero-train method, where the pretrained models were directly applied to the test dataset without further training. Highest Accuracy Model: RegNetX_16GF The RegNetX_16GF model achieved the highest accuracy among the evaluated models, with an accuracy of 59.84% on the Bill's test dataset. This indicates that the RegNetX_16GF model demonstrated superior performance in classifying skin lesions compared to other pretrained models. Lowest Accuracy Model: MnasNet0_75 Conversely, the MnasNet0_75 model exhibited the lowest accuracy among the evaluated models, achieving an accuracy of 35.58% on the test dataset. Despite its lower performance, this model provides valuable insights into the effectiveness of different pretrained models for skin lesion classification. Performance Comparison. The following figure 3 illustrates the accuracy achieved by each pretrained model on the Bill's test dataset: As depicted in the figure, there is considerable variation in the performance of pretrained models, with some models outperforming others significantly. This underscores the importance of selecting an appropriate pretrained model for skin lesion classification tasks.

4.4 Train loss figure

A consistent decrease in the training loss reflects the model's stable to learn and improve its predictive capabilities, which is a positive indication of successful training.

4.5 Test Results

The classification task achieved an accuracy of 86.25% and an F1 score of 0.6249. This indicates that the model performed well in correctly classifying skin lesions into their respective categories. For

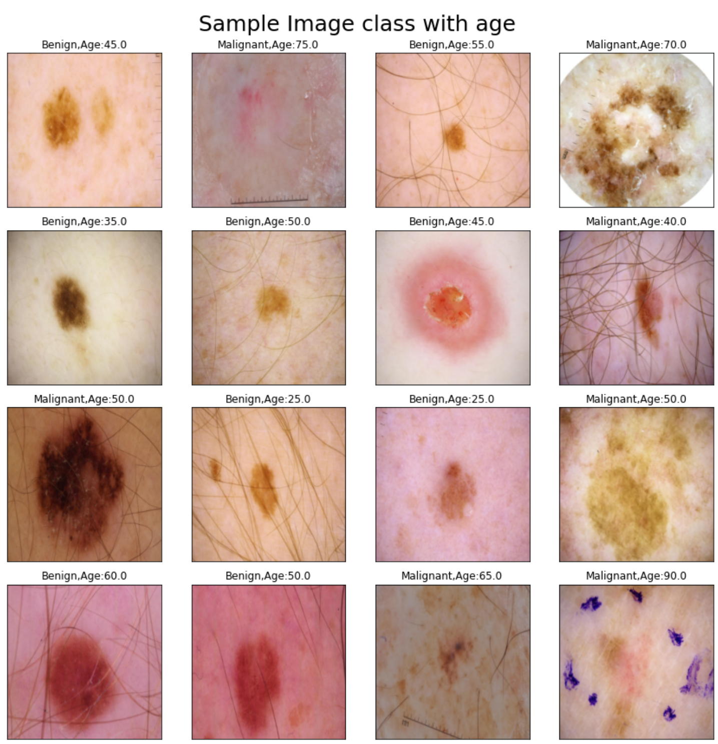

Figure 2: Sample Image

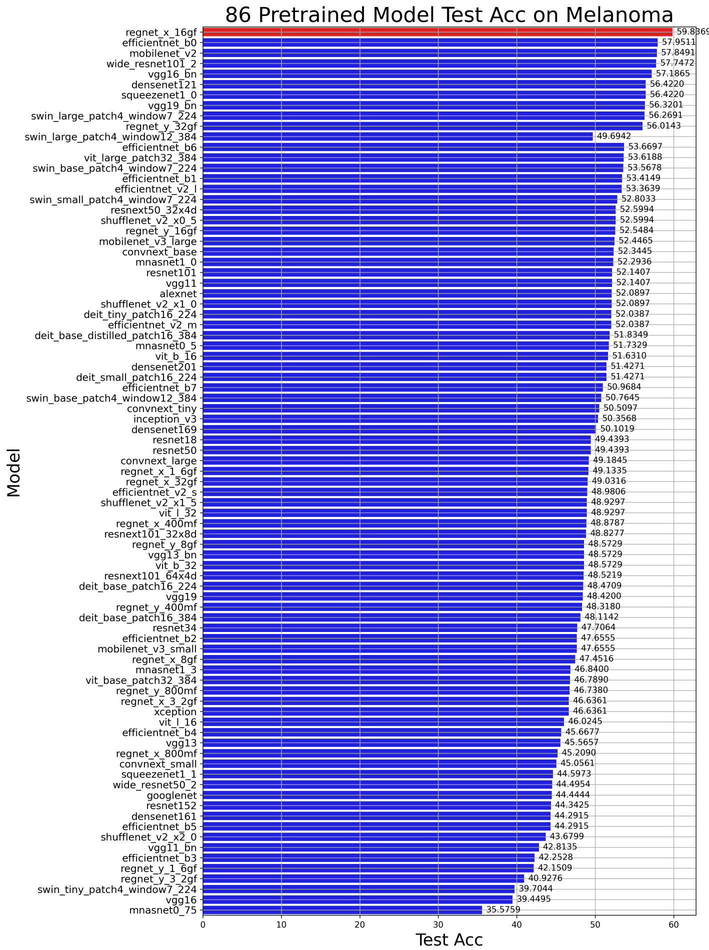

Figure 3: Test Results table of 86 model

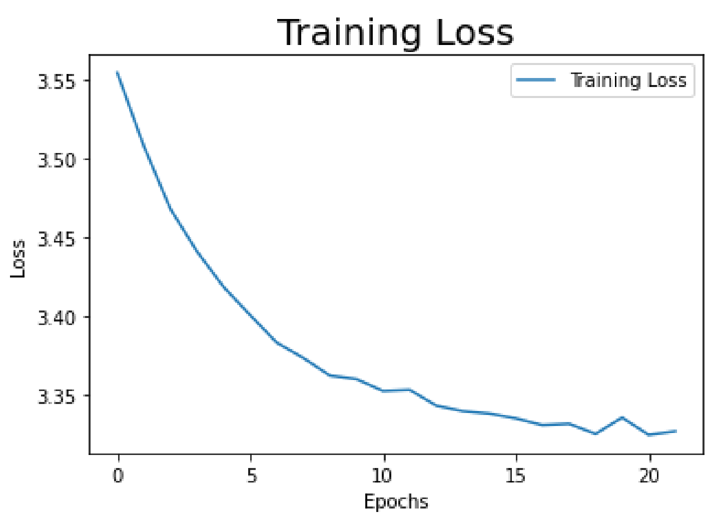

Figure 4: Train loss figure

Table 4: Test Results details

Model:	Class Acc	Class F1	Age Acc	Age F1
M-MTL	0.8625	0.6249	0.8253	0.6078

the age prediction task, the model achieved an accuracy of 82.53% and an F1 score of 0.6078. This suggests that the model's predictions for age were also reasonably accurate, considering the inherent challenges in predicting age from skin lesion images. Overall, the model demonstrated strong performance in both classification and age prediction tasks, with high accuracy scores indicating its effectiveness in analyzing skin lesion images for diagnostic purposes. However, further analysis and evaluation may be necessary to assess the model's generalization to unseen data and its robustness in real world scenarios.

5 CONCLUSION

This study represents an initial exploration into the realm of multi-task learning in the field of skin cancer diagnosis. The primary experiments conducted here have shown promising results, with our AI model successfully predicting both skin lesion classifications and patient age from images with commendable accuracy. However, this work is just the beginning of a broader research journey. There is a pressing need for further investigation and exploration into multi-task learning approaches within the domain of skin cancer analysis. By delving deeper into this area, we aim to develop more sophisticated AI models capable of providing comprehensive diagnostic information that aligns with the needs of dermatologists and clinical practitioners. Future research endeavors should focus on refining and enhancing multi-task learning frameworks tailored specifically to the intricacies of skin cancer diagnosis. This includes optimizing model architectures, exploring novel techniques for feature extraction, more out come task and representation, and leveraging larger and more diverse datasets to improve model generalization and robustness. Ultimately, the overarching goal of our research is to empower AI models to predict a broader range of clinically relevant information from skin lesion images, thereby facilitating more informed decision-making in dermatological practice. By continuing to push the boundaries of multi-task learning in this domain, we aspire to make significant strides towards improving patient care and outcomes in the field of skin cancer diagnosis and treatment.

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