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Artificial Intelligence for Sustainable Dermatology in Smart Green Cities: Exploring Deep Learning Models for Accurate Skin Lesion Recognition

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Abstract

Smart and sustainable dermatology takes on a new dimension within Green Smart Cities with the integration of artificial intelligence (AI) into dermatological diagnosis. This study explores the success of deep learning models in accurately recognizing skin lesions, focusing on the use of the HAM10000 dataset. Our comparative analysis highlights the crucial impact of network architecture choices, data augmentation, and preprocessing on model performance.

The results reveal that models leveraging transfer learning and fine-tuning on pre-trained networks excel in precision, underscoring their relevance in the context of smart green health. We also address opportunities for improvement in model generalization across diverse datasets and skin types. These findings provide a foundation for the development of more accurate skin lesion recognition models aligned with the principles of Green Smart Health, contributing to faster diagnostics, improved patient care, and ultimately, healthier Green Smart Cities.

This work opens avenues for future research, such as exploring of the effectiveness of deep learning techniques in diverse health contexts and the integration of clinical data for more personalized dermatological diagnostics within Green Smart Cities.

Keywords: Artificial intelligence, Medical Diagnostics, Skin cancer, Convolutional neural networks, Smart Healthcare;

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1. INTRODUCTION

Dermatology specialists have traditionally relied on visual examination or histological analysis of skin lesion samples collected through biopsy to diagnose skin cancer [1][2]. However, these methods have significant drawbacks, as they can be time-consuming, error-prone, and subjective, leading to divergent diagnostic conclusions even among highly trained professionals [3]. In contrast, dermoscopy can provide an enlarged and illuminated image of a specific patch of skin to improve diagnostic accuracy, but distinguishing melanoma from non-melanoma lesions remains challenging due to significant intra-class diversity in color, shape, size, and position [4].

Recognizing the critical importance of accurate skin lesion diagnosis, particularly in the context of urban health challenges, the dermatology field is turning to innovative solutions. Artificial intelligence (AI) emerges as a powerful tool to revolutionize dermatological practices, especially in the era of smart and green cities [5].

Recent advancements in artificial intelligence and deep learning algorithms have enabled the development of reliable and cost-effective tools for automated melanoma detection [6]. Studies have demonstrated the autonomous identification of malignant melanoma from dermoscopic images with high accuracy using deep learning algorithms [7][8]. Our research contributes to this evolving landscape, focusing on the application of deep learning models for skin lesion recognition, utilizing the HAM10000 dataset as a benchmark—a dataset that aligns with the quality and scale required for advancing medical practices in smart cities [9][10].

In this comparative study, we evaluate the performances of different deep learning models for skin lesion recognition, considering the unique challenges posed by urban healthcare environments. We explore the impact of factors such as transfer learning techniques, data augmentation, and image preprocessing on model performances [11]. By combining the results of these studies, our aim is to provide a comprehensive comparative analysis that not only guides the development of AI models for skin lesion recognition but also addresses the specific needs of healthcare in smart and green urban settings.

The following sections are structured accordingly. Section 1 introduces the subject and context of the study. In Section 2, we review related work and motivate our study. Section 3 describes the hardware and methods used in our research, including details of the dataset, the machine learning techniques (which include deep learning and transfer learning), data augmentation, image preprocessing and evaluation metrics. In Section 4, we present the results and provide a discussion of our findings. More specifically, section 4.1 summarizes the results and section 4.2 analyzes them. Finally, in Section 5, we conclude by offering suggestions for future research, given the unique challenges and opportunities presented by smart and green cities.

2. RELATED WORKS

In Ref [9] Bansal et al. (2022) presented an approach to enhance melanoma detection. Their method involved a combination of machine learning models that utilized features extracted through both manual (handcrafted) techniques. The authors employed manual feature extraction methods, encompassing color, texture, and shape-based features, along with two convolutional neural network architectures, for automated feature extraction. High performance was achieved, with an accuracy of 94.9%, a precision of 97.6%, 92% recall and 94% F1 score for melanoma detection. The authors also compared their approach with other feature-based and deep learning-based models, demonstrating that their proposed approach had better performance.

In their investigation, Bhatt et al. [12] introduced a computer-assisted diagnosis (CAD) system grounded on a deep learning approach. The system initiates by preprocessing dermoscopic images using a decorrelation and performing lesion segmentation through a MASK-RCNN model trained on RGB images derived from ISBI2016 and ISIC2017 datasets. Subsequently, segmentation images undergo feature extraction using a DenseNet deep model, and the resulting vector undergoes a feature selection process employing entropy-controlled least square SVM (LS-SVM). The efficacy of the system achieving 88.5% accuracy on the HAM10000 dataset.

In their research, Suiçmez et al. [13] presented a system employing advanced image processing techniques to remove obstacles like air bubbles, hairs, and other noises from dermoscopic images, aiming to improve the visibility of lesions during diagnosis. The system adopts an innovative hybrid model combining deep learning and the GradientBoost Classifier (GBC) for melanoma detection, a novel approach in the field. The system underwent assessment in the HAM10000 dataset, attained the highest accuracy rate reported in the literature, at an unprecedented

99.44%. The authors posit that AI-based systems, such as this one, hold the potential to alleviate the workload of healthcare professionals and enhance early diagnosis and treatment for patients.

The researchers introduced an integrated computer-aided diagnosis (CAD) framework to segment and classify cutaneous lesions within a deep learning [14]. Their proposed approach incorporates an altered bio-inspired multiple exposure fusion pre-processing step, a customized 26-layered CNN dedicated for segmentation of lesions, in addition four pre-trained CNN models are used during feature extraction and classification. The deep feature vectors extracted are merged using convolutional sparse image decomposition, and optimal features are selected employing a univariate metrics and a Poisson distribution feature select methodology. Compared to previous state-of-the-art methods, the suggested approach demonstrated superior accuracy rates across the HAM10000, ISIC2018, ISIC2019, and PH2 datasets. Notably, the proposed approach achieved 98.57% accuracy on the HAM10000 dataset.

The researchers proposed an Xception-ResNet50 (X-R50) concatenated model, designed for highly accurate classification into seven distinct skin classes [15]. The model demonstrated an impressive predictive capability of 97.8% when evaluated on a HAM10000 dataset. The X-R50 model, characterized by computational simplicity and efficiency, harnesses the combined features of the Xception and ResNet50 networks. The model's performance underwent validation through analysis of variance (ANOVA), revealing its superiority compared with other advanced transfer learning techniques.

Research work detailed in Ref [16] introduces a deep learning model named SC-DeLeNet, specifically designed for automated recognition of cutaneous anomalies, diseases, and cancer. The proposed model incorporates a 'Feature Coalescing Module' and a '3D-Layer Residuals' block to amalgamate dimensional features. A mean segmentation score of 0.9494 and an average classification accuracy of 0.9103 surpassing the performance of conventional and widely acknowledged classifiers.

The work presented in Ref [17] introduces a system utilizing digital hair removal and diverse filtering techniques. The authors propose an automatic Grabcut segmentation technique grounded in the clustering technique k-means and the color space Hue Saturation Value for image segmentation. In the classification, three machine learning algorithms are employed. The outcomes reveal that Support Vector Machine (SVM) slightly outperforms the other two classifiers, achieving 91.3% accuracy over the ISIC 2019 dataset in addition to 91.1% over the HAM10000, along with the highest F1-score. The proposed system outperforms state-of-the-art existing diagnostic methods with respect to accuracy, sensitivity, and specificity, underscoring its efficacy in skin disease diagnosis.

3. MATERIAL AND METHODS

3.1. Dataset

HAM10000 is a dataset comprising 10,015 high-quality dermoscopic images of skin lesions, as outlined in [18]. Each image in this collection has undergone manual labeling, categorizing it in one of seven distinct diagnostic classes. This extensive multi-class dataset serves as a prevalent resource for the exploration and advancement of computer-aided diagnosis systems and deep learning models dedicated to classifying skin lesions. Additionally, the dataset provides accompanying clinical metadata for each image, including the patient's age and gender, as well as location of the lesion.

3.2. Deep Learning Techniques

Deep learning, an important part of machine learning, employs multi-layer neural networks to model and solve complex problems by discerning intricate patterns in data. In the field of image analysis, deep learning models are based on convolutional neural networks (CNNs), specially designed to autonomously extract meaningful features from images. One of the notable advantages offered by deep learning lies in its ability to extract features automatically directly to the image from data, thus eliminating the need to manually process feature extraction. The domain of computer vision has witnessed the development of various pre-trained deep learning architectures, including renowned models like VGG ResNet [19], and DenseNet [20]. These architectures showcase remarkable performance across a spectrum of image analysis tasks, spanning image classification, segmentation, and object detection.

Pre-trained deep learning networks, in particular, exhibit promising outcomes in accurately detecting skin lesions from images, presenting potential utility in clinical contexts for skin cancer diagnosis and treatment. Trained on extensive datasets such as ImageNet, housing millions of labeled images, these networks achieve state-of-the-art performance across diverse tasks. They can be fine-tuned for specific objectives or employed as feature extractors for new datasets sharing similar characteristics. Harnessing the capabilities of pre-trained deep learning networks enhances the accuracy and efficiency of skin lesion recognition, with significant implications for healthcare outcomes.

A common machine learning method, transfer learning capitalizes on the knowledge acquired in one task or domain to process another, correlated task or domain. Instead of starting to train a new model from scratch for each task, it uses a pre-trained model, equipped with knowledge of relevant features and patterns from a large dataset [21]. By refining this pre-trained model over a new training data, it can be rapidly adapted to achieve optimal performance on a new task, even with limited training data.

In conjunction with fine-tuning, data augmentation emerges as a crucial technique in transfer learning. The combined application of transfer learning and data augmentation is advantageous in enhancing the performance of deep learning models when confronted with small datasets. While deep learning models typically demand substantial data volumes for optimal performance, challenges may arise in certain scenarios, such as medical diagnosis, where obtaining extensive datasets proves challenging. Transfer learning mitigates this challenge by enabling the utilization of pre-trained models with learned features from large datasets, and data augmentation contributes by expanding the effective size of smaller datasets through the generation of new examples

In the context of COVID-19 diagnosis, transfer learning and data augmentation have been used together to build accurate classification models using small datasets. By starting with a pre-trained model that has learned relevant features from a large dataset of medical images, for example, and then applying data augmentation techniques to generate new training examples, we can quickly adapt it to classify COVID-19 images with high accuracy, even with a limited number of COVID-19 images available for training [22,23,24,25]. This approach has proved successful in many investigations and could improve the accuracy and speed of COVID-19 diagnosis. For a comprehensive overview of techniques in this field, please refer to my recent review article [26].

3.3. Image pre-processing

While deep learning models have demonstrated significant promise in accurately identifying skin lesions, the efficacy of these models is strongly influenced by the quality of the input images. Various pre-processing techniques, including contrast enhancement, histogram equalization, and noise reduction, can be employed for this purpose. The aim of these techniques in particular helps to mitigate noise impact and deal with any patterns of imbalance within the dataset. In addition, it is imperative to eliminate unskinned background elements like hairs, as well as disturbing elements like uneven lighting, reflections and poor-quality backgrounds. By judiciously applying appropriate pre-processing techniques to mitigate these factors, we can significantly improve the ability to accurately detect skin lesions using deep learning models.

3.4. Evaluation metrics

We used various established evaluation measures, including precision, sensitivity, accuracy and F1 score, to assess the effectiveness of CNN architectures in predicting skin lesions. The true positives (TP) denote the correctly diagnosed cases, while the false negatives (FN) represent the incorrectly predicted cases. Correctly predicted negative instances are referred to as true negatives (TN), while inaccurately diagnosed negative instances are referred to as false positives (FP).

In the medical domain, sensitivity reflecting the percentage of accurately classified skin lesion. It is formulated as:

$$Sensitivity = \frac{TP}{(TP+FN)} \tag{1}$$

$$Precision = \frac{TP}{(TP+FP)} \tag{2}$$

$$F1\ score\ = 2 \times \frac{(Precision \times recall)}{(Precision+Recall.)} \tag{3}$$

4. RESULTS AND DISCUSSION

4.1. RESULTS

This section presents the results of our investigation into the effectiveness in skin lesion recognition using deep learning methods for HAM10000. Through a comprehensive comparison of contemporary studies, we evaluated each model's performance using established measures such as accuracy, precision, recall and F1 score. Our analysis involved identifying the strong and weak points of the different methods, discerning the key factors influencing model performance, such as data augmentation, preprocessing techniques, and network architecture. In the following tables, we present an overview of the results of our comparative analysis of skin lesion recognition models. Table 1 encapsulates each approach's performance measures. Table 2 delineates the feature extraction and classification techniques employed by each model. Tables 3 and 4 outlines whether each model incorporated segmentation, data augmentation, and preprocessing techniques. These tables furnish valuable insights into the merits and constraints of each approach, elucidating the pivotal factors influencing model performance.

Table 1. Performance Metrics for Binary and Multiclass Classifications

Classification Type	Accuracy	Precision	Recall	F1-score
Binary [9]	94.9%	92.6%	97.6%	94.8%
Multiclass [12]	88.5%	96.44%	88.54%	94.90%
Binary [13]	99.4%	99.4%	99.4%	99.4%
Multiclass [14]	98.57%	96.37%	93.89%	94.98%
Multiclass [15]	97.8%	97.9%	97.7%	97.8%
Multiclass [16]	90.58%	84.44%	83.36%	83.90%
Multiclass [17]	97%	97.71%	97.57%	95.14%

Table 2. Skin Lesions Skin lesion feature extraction and classification techniques

Technique of Feature Extraction	Technique of classification	Accuracy
ResNet50V2 and EfficientNet-B0 [9]	ANN	94.9%
DenseNet-201 [12]	Extreme learning machine (ELM)	88.5%
CNN architecture [13]	Gradient Boost Classifier	99.4%
ResNet-101, ResNet-50, Xception, VGG16 [14]	Multi-class SVM (MC-SVM)	98.57%
Concatenated Xception-ResNet50 (X-R50) [15]	SoftMax	97.79%
EfficientNet-B4 [16]	-	90.58%
Statistical techniques and GLCM [17]	SVM	97%

Table 3. Overview of studies of Skin Lesion Recognition with and without Segmentation Techniques.

Model Reference	Segmentation	Segmentation Technique
Bansal et al.[9]	No	-
Bhatt et al. [12]	Yes	MASK-RCNN model
Suiçmez, Çaı, et al [13]	No	-
Maqsood, S. and R. [14]	Yes	proposed a 26-layered CNN model
Panthakkan, A., et al[15]	No	-
Alam, M. J., et al [16]	Yes	Encoder and decoder side
Ahammed, M., et al [17]	Yes	k-means clustering & Hue Saturation Value color space

Table 4. Overview of studies using data augmentation and pre-processing techniques in skin lesion recognition and their accuracy.

Model Ref	Data augmentation	Pre-processing	Accuracy
Bansal et al.[9]	Yes	Yes	94.9%
Bhatt et al. [12]	Yes	Yes	88.5%
Suiçmez, Çağrı, et al [13]	No	Yes	99.4%
Maqsood, S. and R.D [14]	No	Yes	98.57%
Panthakkan, A., et al[15]	Yes	Yes	97.79%
Alam, M. J., et al [16]	Yes	No	90.58%
Ahammed, M., et al [17]	No	Yes	97%

4.2. DISCUSSION

These results in Table 1, 2, and Figure 1 highlight the efficacy of deep learning models in skin lesion recognition, achieving high accuracies on the HAM10000 dataset. The models utilized diverse techniques for feature extraction and classification, including pre-trained convolutional neural networks (ResNet50V2, DenseNet-201, Xception, ResNet-50, ResNet-101, and VGG16), alongside statistical feature extraction techniques (GLCM). The classification methods also varied, encompassing support vector machines (SVM), extreme learning machines (ELM), and gradient boost classifiers. Interestingly, the highest accuracy (99.4%) was achieved using a CNN architecture combined with a gradient boost classifier. Furthermore, transfer learning techniques, such as fine-tuning pre-trained CNNs, were shown to improve model performance, as demonstrated by the high accuracy achieved by the concatenated Xception-ResNet50 model (97.79%). Finally, the use of data augmentation and preprocessing techniques, such as contrast stretching and histogram equalization, also contributed to improved model performance, as evidenced by the high accuracy achieved by the GLCM and statistical features technique combined with SVM (97%). These findings highlight the potential of AI-assisted skin lesion recognition to improve accuracy and reduce the risk of misdiagnosis in dermatology.

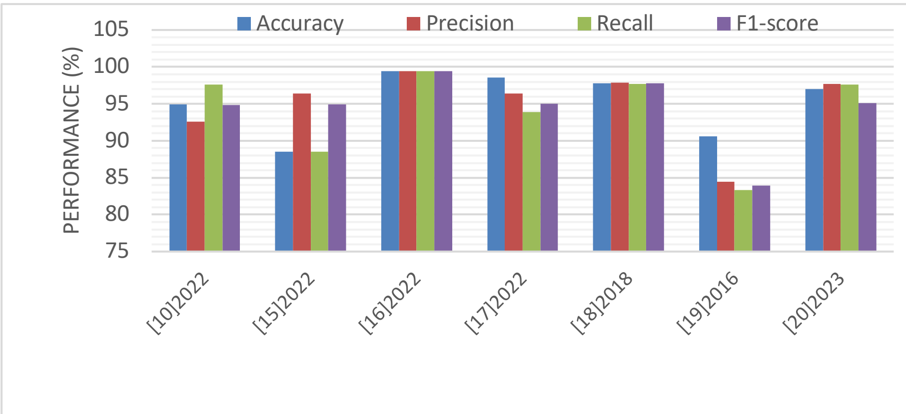

Fig 1. Performance graph of comparison of the approach in terms of accuracy, precision, recall, and F1-score on HAM10000 dataset.

Based on the table 2, it can be seen that all approaches achieved high accuracy, ranging from 88.5% to 99.4%. Approach [13] achieved the highest accuracy of 99.4% using a CNN architecture and Gradient Boost Classifier. Moreover, all approaches achieved high precision, recall, and F1-score values, indicating the effectiveness of the proposed methods in accurately classifying skin lesions. It should be noted that approaches [9], [13], [14], [15], and [17] used multiclass classification while approach [15] used binary classification. Multiclass classification is generally more challenging than binary classification due to the higher number of classes to be distinguished. However, approaches [9], [14], [15], [16], and [17] achieved high accuracy values in multiclass classification, demonstrating the effectiveness of these methods in distinguishing between different skin lesion types. It is also worth noting that some approaches utilized specific techniques, such as GLCM and statistical features techniques in approach [17], to extract features from the images, while others, such as approach [13], utilized more complex classifiers like Gradient Boost Classifier. Overall, these results indicate that various approaches can achieve high accuracy and performance in classifying skin lesions, which can have important applications in the diagnosis and treatment of skin diseases.

From the table 3, we can see that out of the six studies, four have used segmentation techniques, while two have not. Among the studies that used segmentation techniques, the techniques used were MASK-RCNN, a 26-layered CNN model, and encoder-decoder side methods. On the other hand, the studies that did not use segmentation techniques did not specify any particular techniques. Regarding the accuracy of classification, we can see that the study that achieved the highest accuracy of 99.4% did not use any segmentation techniques. However, among the studies that used segmentation techniques, the highest accuracy was achieved by the study that used a 26-layered CNN model with a segmentation technique, achieving an accuracy of 98.57%. It is also worth noting that the study that achieved the lowest accuracy of 88.5% used a segmentation technique, specifically the MASK-RCNN model. We can see that the use of segmentation techniques did not necessarily lead to higher accuracy in classification. However, the specific segmentation technique used may be a crucial factor in determining the effectiveness of the approach.

A comprehensive overview of the data augmentation and pre-processing techniques used in various models, and their corresponding accuracy, is given in Table 4. Data augmentation, which artificially enlarges the data set through various transforms applied to the original images (e.g., rotation, scaling, and flipping), and pre-processing, involving transformations applied to input images before feeding them into the model (e.g., resizing or normalizing), play crucial roles in enhancing model performance. Table 4 shows that most models employed the techniques of data augmentation, which improved classification accuracy. Pre-processing techniques were also used in most models, except for Model [16]. The accuracy of the models varied from 88.5% to 99.4%, with Model [13] achieving the highest accuracy. It's worth noting that Model [13] did not use any data augmentation techniques, but did use pre-processing techniques. Overall, the data augmentation and pre-processing techniques could have a significant impact on boosting the accuracy of classification models for medical image analysis. The effectiveness of such techniques depends on both the type of dataset and the architecture of the model applied.

Tables 1, 2, 3, and 4 collectively offer a thorough overview of diverse approaches, techniques, and models applied in skin lesion recognition. They underscore the efficacy and potential of deep learning in enhancing accuracy and mitigating the risk of misdiagnosis in dermatology. The studies reviewed used a range of convolutional neural network architectures, statistical feature extraction techniques, and classification methods, with high accuracy and performance achieved across the board. The use of segmentation techniques was not found to necessarily lead to higher accuracy, but the specific technique used may be a crucial factor in determining effectiveness. Data augmentation and pre-processing techniques were also found to play an important role in improving model accuracy.

5. CONCLUSION

In conclusion, in the context of green smart health within green smart cities, our benchmarking of recent models of deep learning for skin lesion recognition on the HAM10000 dataset is particularly significant. Our findings offer crucial insights, demonstrating the significant impact of network architecture choice, data augmentation, preprocessing techniques, and feature extraction methods on model performance. Models employing transfer learning with fine-tuning on pre-trained networks have notably excelled in terms of precision and performance metrics, emphasizing their relevance for green and smart health initiatives.

Within the framework of Green Smart Health, where sustainability and efficiency are central concerns, our study provides a solid foundation to guide future efforts to develop higher-accuracy and more efficient skin lesion recognition models. These models, aligned with Green Smart Health principles, offer real opportunities to improve not only diagnostic precision and speed, but also patient care, thus contributing to healthier and more sustainable communities within green and smart cities.

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