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Deep Learning -Based Automated Skin Lesion Detection And Classification

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Peer Review Information	Abstract
Submission: 20 Jan 2025 Revision: 24 Feb 2025 Acceptance: 27 March 2025 Keywords Deep Learning Skin Lesion Diagnosis Dermatology Medical Imaging Early Detection	Skin cancer is a prevalent and potentially life-threatening condition, emphasizing the need for accurate and timely diagnosis. Leveraging advancements in deep learning, particularly convolutional neural networks (CNNs), this study presents an automated approach for the diagnosis of skin lesions to aid in early detection. A diverse dataset comprising various skin lesion types, encompassing different skin tones and image qualities, is collected and preprocessed. Transfer learning from pre-trained models is employed to leverage feature representations learned on large-scale datasets. The model is fine-tuned on the skin lesion dataset, and hyperparameter tuning is performed to optimize performance. Validation and testing on separate datasets confirm the model's generalization capability. Post-processing techniques and interpretability measures enhance the reliability of model predictions. The developed system demonstrates promising results, providing a valuable tool for dermatologists in clinical settings. The study emphasizes the importance of continuous collaboration with medical professionals, ethical considerations, and adherence to regulatory standards in the deployment of deep learning-based diagnostic tools in healthcare.

INTRODUCTION

Skin cancer is one of the most prevalent forms of cancer worldwide, with early detection playing a crucial role in improving survival rates. Traditional methods of diagnosing skin lesions rely on dermatological examinations and biopsies, which can be time-consuming, expensive, and subject to human error. With advancements in artificial intelligence (AI), deep learning-based techniques have emerged as a powerful tool for automated skin lesion detection and classification.

Deep learning, a subset of machine learning, utilizes convolutional neural networks (CNNs) and other architectures to analyze medical images and differentiate between benign and malignant lesions. These models are trained on large datasets of dermoscope images, enabling them to learn complex patterns and features that might be imperceptible to the human eye. Automated skin lesion detection and classification systems aim to assist dermatologists by improving diagnostic accuracy, reducing workload, and ensuring timely medical intervention.

This paper explores deep learning-based approaches for skin lesion detection, highlighting key methodologies, datasets, and challenges in developing robust and reliable AI-driven diagnostic tools. By leveraging AI, the healthcare industry can significantly enhance early detection and treatment of skin cancer, ultimately improving patient outcomes.

Problem Statement

The current challenge in skin cancer diagnosis lies in the need for robust, interpretable, and clinically applicable automated systems that can effectively distinguish diverse skin lesions, and ethical considerations.

LITERATURE REVIEW

Skin cancer is a prevalent and potentially deadly disease, making early and accurate diagnosis crucial. Traditional methods of visual inspection and biopsy can be subjective and time-consuming. In recent years, deep learning (DL) has emerged as a promising tool for automated skin lesion detection and classification, offering the potential to improve diagnostic accuracy and efficiency. This literature review explores the advancements and challenges in this field.

Early Approaches and the Rise of Deep Learning: Early computer-aided diagnosis (CAD) systems for skin cancer detection relied on traditional image processing techniques and machine learning algorithms. However, these methods often struggled with the variability in lesion appearance and the complexity of dermatological images. The advent of deep learning, particularly Convolutional Neural Networks (CNNs), revolutionized the field due to their ability to automatically learn complex features from large datasets.

Key Contributions of Deep Learning: -Automated Feature Extraction: CNNs can automatically learn relevant features from skin lesion images, eliminating the need for manual feature engineering. This has led to significant improvements in diagnostic accuracy.

Improved Segmentation: Deep learning models can accurately segment skin lesions from surrounding skin, enabling precise measurement of lesion characteristics.

Enhanced Classification: CNNs can classify skin lesions into different categories (e.g., benign, malignant, melanoma) with high accuracy, aiding in diagnosis and treatment planning.

Popular Deep Learning Architectures: -Several CNN architectures have been employed for skin lesion analysis, including:

Res Net: Known for its ability to train very deep networks, Res Net has shown excellent performance in skin lesion classification.

Inception: This architecture uses multiple convolutional filters of different sizes to capture diverse features, improving accuracy.

Efficient Net: Focuses on optimizing network efficiency, making it suitable for deployment in resource-constrained environments.

Datasets and Challenges: The availability of large and diverse datasets, such as ISIC and HAM10000, has been crucial for training effective DL models. However, challenges remain:

Data Imbalance: Skin cancer datasets often have an imbalance in the number of benign and malignant lesions, which can affect model performance.

Inter-observer Variability: Dermatologist diagnoses can vary, which can impact the ground truth labels used for training.

Explainability: Understanding how DL models make decisions is important for clinical acceptance but can be challenging.

Recent Advancements: Ensemble Methods: Combining multiple DL models can improve overall performance and robustness.

Attention Mechanisms: Incorporating attention mechanisms allows models to focus on relevant regions of the image, enhancing accuracy.

Transfer Learning: Using pre-trained models on large image datasets can accelerate training and improve performance, especially when dealing with limited medical data.

Future Directions: Improving Explainability: Research is ongoing to develop methods for explaining DL model decisions, increasing trust and acceptance in clinical settings.

Multimodal Analysis: Combining dermo scope images with other clinical data, such as patient history and genetic information, could further enhance diagnostic accuracy.

Real-time Diagnosis: Developing DL models that can provide real-time diagnosis during dermatological examinations has the potential to transform clinical practice.

PROPOSED METHODOLOGY

Dataset

International Skin Imaging Collaboration (ISIC) created the ISIC Archive, a global library of dermoscopic pictures, with the dual goals of assisting clinical training and advancing technological research that would ultimately result in automated algorithmic analysis. The ISIC expands its collection every year and challenges participants to use automated skin cancer detection. There are 25,331 dermoscopy photos for ISIC 2019 that may be used for training in 8 distinct categories. The new systems must be able to recognise an extra outlier class that is not represented in the training data in the test dataset, which is made up of 8,239 photos. The majority of the photographs in the collection also include information in addition to the actual images. The patient's age, sex, and the area in which

the skin lesion is present are all included in the meta-data. The BCN 20000 (Department of Dermatology, Hospital Clinic de Barcelona) (7), HAM10000 (VI DIR Group, Department of Dermatology, Medical University of Vienna) (8), and an unidentified resource are where all of these data were obtained (9). Some examples of skin conditions from the ISIC 2019 dataset are displayed in Fig. 2

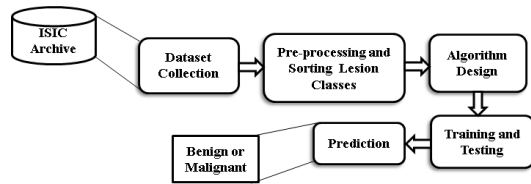


Fig. 1. Workflow of System

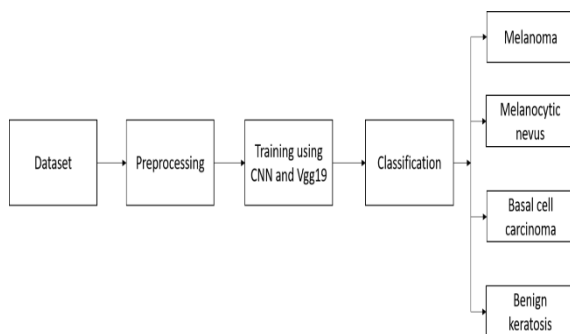


Fig. 2. Proposed System Architecture

Preprocessing

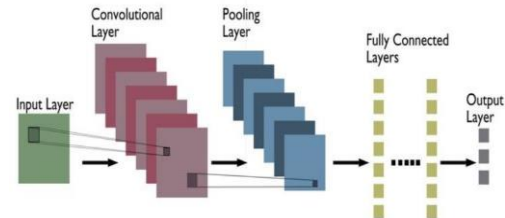
The collection is publicly available, and the information is disseminated in a way that makes it

possible to create enough textual input to enable comparisons to each picture. All files are shrunk to 224×224 pixels since scaling is one of the key steps in data preparation.

Training using CNN and Vgg19 algorithm

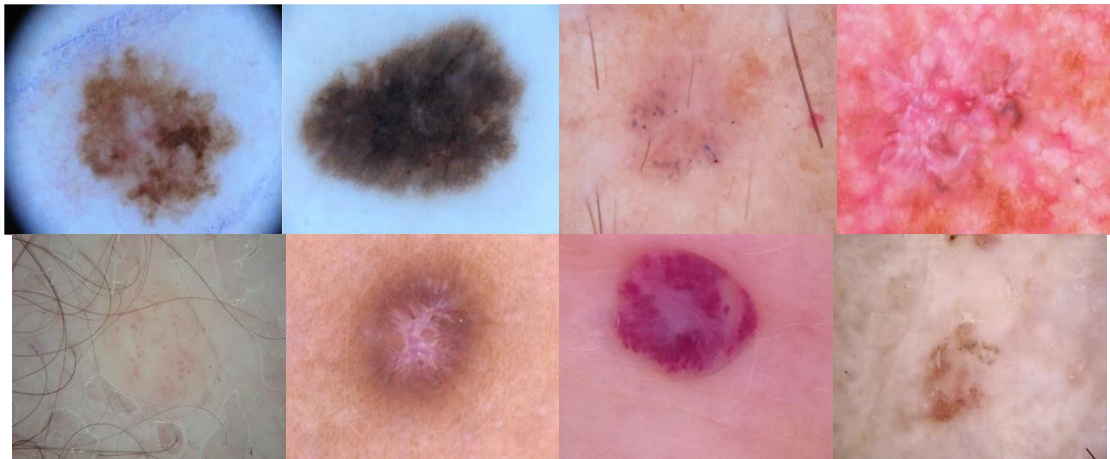
The proposed system uses CNN and Vgg19 algorithm for classification of skin lesion image into four different classes. Each algorithm is explained below.

CNN



CNN is a very effective algorithm for classification strategies. It is a feed-forward neural network including convolutional, pooling, flattening, and dense layers. The filter and kernels are used to process the image. Before beginning the training process, it is necessary to learn the fundamentals of CNN, which are shown in Fig.3. CNNs are a type of Neural Network

that is exceptionally effective at image recognition and categorization CNNs, or large-layer feed-forward neural networks, are one type of large-layer feed-forward neural network.



Convolutional Layer

A Convolutional Network's core component is the CL. CL's primary goal is to extract characteristics from the data it receives. Convolution preserves the spatial relationship between pixels by learning information from the input image's small kernel. A group of learnable neurons is used to hide the input image.

$G[m, n] = (f * h)[m, n] = \sum \sum h[j, k] f[m - j, n - k] k j$
 (1) Where f is the input image, h is the feature

detector kernel and $G[m, n]$ is the convolution output

ReLU Layer

ReLU stands for rectified Linear units in a non-linear process. All non-positive feature map values are replaced with zero apixel-by-pixel way. To understand how the ReLU works, we'll assume the neuron input is x , and therectifier is given. $f(x) = \max(0, x)$ (2)

Pooling Layer

The pooling layer keeps the most relevant information while reducing the complexity of each activation. A sequence of non-overlapping rectangles is created from the supplied images. A non-linear technique, such as average or maximum, is used to downsample each region. This layer, frequently placed between CLs, improves generalization and convergence speed while also being resistant to translation and distortion.

Flattening Layer

High-resolution data is efficiently resolved into representations of objects using a convolutional neural network. Therefore, it is possible to see the fully connected layer as adding a conventional classifier to the network's information-rich output to "understand" the findings and ultimately provide a classification result. Linking this fully connected layer to

the network requires flattening the convolutional neural network dimensions output.

Fully Connected Layer

Using these attributes, the FCL is used to divide the input image into several groups depending on the training dataset. The final pooling layer, or FCL, provides characteristics to the Softmax activation function classifier. The FCL's output probabilities add up to 1. Using Softmax as the activation function ensures this. With the help of the Softmax function, every

real-valued score may be reduced to a vector of summable values between zero and one.

Vgg19

The 16 convolutional layers, 3 fully connected layers, 5 max-pooling layers, and 1 softmax layer make up the 19 layers that make up Vgg19. There are 19.6 billion FLOPs in VGG19. The training of CNN VGG-19 used the many images in ImageNet. Simply defined, VGG is a deep CNN that is used to categorise picture

FUTURE SCOPE

Integrating information from diverse imaging modalities, such as dermoscopy and standard digital camera images, to enhance the accuracy and reliability of skin lesion classification.

Conducting real-world validation studies in collaboration with healthcare professionals to ensure the practical applicability and effectiveness of the developed system in clinical settings.

Incorporating interpretable models and methods to provide insights into the decision-making processes of the automated system, fostering trust among healthcare practitioners.

CONCLUSION

The development of a skin cancer classification system using Convolutional Neural Network (CNN) technology represents a promising avenue for improving early detection and diagnosis in dermatology. Leveraging advanced deep learning techniques, this system has the potential to significantly enhance the accuracy and efficiency of skin lesion classification, providing valuable support to healthcare professionals. Through the integration of interpretability features, the system aims to bridge the gap between the powerful but often opaque nature of CNNs and the need for transparent decision-making in clinical settings. However, it is crucial to navigate challenges such as data diversity, model interpretability, and ethical considerations to ensure the system's effectiveness, reliability, and ethical deployment. Ongoing collaboration with dermatologists.

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