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Skin Cancer Classification Using Convolutional Neural Network for a Smart Healthcare System: A Review

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ABSTRACT: Skin cancer is a life-threatening disease, and early detection is crucial for effective treatment. This study proposes an interpretable skin cancer classification system using an optimized Convolutional Neural Network (CNN). Image preprocessing and data augmentation techniques enhanced dataset diversity, improving model robustness. Using Adam and RMSprop optimizers with ReLU, Swish, and Tanh activations, the best-performing configuration achieved 82% accuracy with a 0.47 loss. The integration of XAI ensures transparency in model decision-making, helping dermatologists understand lesion classification visually. This system enables real-time and interpretable diagnosis through a smart healthcare application, reducing human error and supporting dermatologists with an automated, accurate, and explainable diagnostic tool.

KEYWORDS: Deep learning, CNN, Cancer detection, Data Analysis.

I. INTRODUCTION

Skin cancer is one of the most common and life-threatening forms of cancer, representing approximately one-third of all diagnosed cancers globally. The rising exposure to ultraviolet (UV) radiation due to ozone layer depletion, lifestyle changes, and environmental factors has drastically increased its occurrence. Early detection of skin cancer is crucial, as timely treatment can significantly improve patient survival rates. However, manual diagnosis by dermatologists often relies on visual inspection of skin lesions, which can be subjective, time-consuming, and prone to human error. Hence, there is a growing demand for automated, accurate, and interpretable diagnostic systems.

Recent advancements in Artificial Intelligence (AI) and Deep Learning (DL) have revolutionized medical image analysis, especially in dermatology. Convolutional Neural Networks (CNNs) have demonstrated remarkable capabilities in identifying patterns from dermoscopic images, enabling automated classification of skin lesions as benign or malignant. Despite their impressive accuracy, most deep learning models function as “black boxes,” providing little insight into their decision-making process. This lack of interpretability limits their acceptance in clinical practice, as medical professionals require transparent and explainable reasoning behind each prediction.

To address this challenge, this study introduces an interpretable CNN-based model for skin cancer detection integrated with Explainable Artificial Intelligence (XAI) frameworks such as Grad-CAM and Grad-CAM++. These visualization techniques help interpret the CNN’s predictions by highlighting the critical image regions influencing classification results. The system is trained using the HAM10000 dataset, containing diverse skin lesion categories, and optimized with activation and optimization functions for enhanced accuracy. The ultimate goal is to develop a smart healthcare system that not only provides reliable diagnosis but also justifies its decisions, supporting dermatologists with a transparent and trustworthy AI-assisted diagnostic platform.

II. LITERATURE SURVEY

Atlanta [1], Get an overview of melanoma skin cancer and the latest key statistics in the US. Melanoma accounts for only about 1% of skin cancers but causes a large majority of skin cancer deaths. If you have been diagnosed with melanoma skin cancer or are worried about it, you likely have a lot of questions. Learning some basics is a good place to start.

MUHAMMADUMAR [2], In this paper, an explainable artificial intelligence (XAI) based skin lesion classification system is proposed to improve the skin lesion classification accuracy. This will help the dermatologists to make rational diagnosis in the early stages of skin cancer. The proposed XAI model is validated using International Skin Imaging Collaboration (ISIC) 2019 dataset. The developed model correctly identifies the eight types of skin lesions (dermatofibroma, squamous cell carcinoma, benign keratosis, melanocytic nevus, vascular lesion, actinic keratosis, basal cell carcinoma and melanoma) with classification accuracy, precision, recall and F1 score as 94.47%, 93.57%, 94.01%, and 94.45% respectively.

Rebecca L. Siegel [3], Colorectal cancer (CRC) is the second most common cause of cancer death in the United States. Every 3 years, the American Cancer Society provides an update of CRC occurrence based on incidence data (available through 2016) from population-based cancer registries and mortality data (through 2017) from the National Center for Health Statistics. In 2020, approximately 147,950 individuals will be diagnosed with CRC and 53,200 will die from the disease, including 17,930 cases and 3,640 deaths in individuals aged younger than 50 years.

Mohammed Rakeibul Hasan [4], is research contains information about many CNN models and a comparison of their working processes for finding the best results. Pretrained models like VGG16, Support Vector Machine (SVM), ResNet50, and self-built models (sequential) are used to analyze the process of CNN models. ese models work differently as there are variations in their layer numbers. Depending on their layers and work processes, some models work better than others. An image dataset of benign and malignant data has been taken from Kaggle. In this dataset, there are 6594 images of benign and malignant skin cancer. Using different approaches, we have gained accurate results for VGG16 (93.18%), SVM (83.48%), ResNet50 (84.39%), Sequential_Model_1 (74.24%), Sequential_Model_2 (77.00%), and Sequential_Model_3 (84.09%).

Walaa Gouda [5], In this research, the deep learning method convolution neural network (CNN) was used to detect the two primary types of tumors, malignant and benign, using the ISIC2018 dataset. This dataset comprises 3533 skin lesions, including benign, malignant, non-melanocytic, and melanocytic tumors. Using ESRGAN, the photos were first retouched and improved. The photos were augmented, normalized, and resized during the preprocessing step.

Md. Al-MamunProvath [6], Cyclic learning rate is employed to increase the accuracy and maintain the computational efficiency of the proposed methods. This is both straightforward and effective which facilitates the model to converge faster. Several transfer learning models that have already been trained are also used, and they are compared to the proposed CNN from scratch. It is found that the proposed model provides better accuracy, reducing the impact of inter-class variations between Lung Adenocarcinoma and another class Lung Squamous Cell Carcinoma. Implementing the proposed method increased total accuracy to 97% and demonstrate computing efficiency in compare to other method.

Sunday AdeolaAjagbe [7], This study was aimed at advancing AD image classification with deep convolutional neural network (DCNN) involving convolutional neural network (CNN) and transfer learning (Visual Geometry Group (VGG)16 and VGG19) using magnetic resonance images (MRI) and extend the evaluation metrics since limitations and capacity of algorithms cannot be revealed by few metrics. The objectives of this research are to classify AD images into four known classes by neurologists and results of the finding are subjected to many evaluation metrics. This research used computer algorithms majorly DCNN and transfer learning to classify AD. Six metrics were used for the evaluation; accuracy, area under curve (AUC), F1- score, precision, recall and computational time.

Fawad Ahmed [8], In this paper, the pre-trained MobileNetV2 and DenseNet201 deep learning models are modified by

adding additional convolution layers to effectively detect skin cancer. Specifically, for both models, the modification includes stacking three convolutional layers at the end of both the models. A thorough comparison proves that the modified models show their superiority over the original pre-trained MobileNetV2 and DenseNet201 models. The proposed method can detect both benign and malignant classes. The results indicate that the proposed Modified DenseNet201 model achieves 95.50% accuracy and state-of-the-art performance when compared with other techniques present in the literature. In addition, the sensitivity and specificity of the Modified DenseNet201 model are 93.96% and 97.03%, respectively.

AND M. F. MRIDHA [9], The goal of this study was to develop reliable deep learning (DL) prediction models for skin cancer classification; (i) deal with a typical severe class imbalance problem, which arises because the skin-affected patients' class is significantly smaller than the healthy class; and (ii) interpret the model output to better understand the decision-making mechanism (iii) Propose an End-to-End smart healthcare system through an android application. In a comparison examination with six well-known classifiers, the effectiveness of the proposed DL technique was explored in terms of metrics relating to both generalization capability and classification accuracy

S. TALAYEH TABIBI [10], To develop a generalized ensemble classifier, we improved the level of diversity to make the classifier more robust and accurate. For this purpose, we have created diversity in both data and classifier levels. To train, validate, and test the model, the ISIC 2018 challenge dataset containing over 13,000 dermoscopic images was used. Based on the experiments, the proposed ensemble classifier achieved an accuracy of 90.15% which outperforms the base convolutional neural networks and other competing classifiers in terms of accuracy and robustness.

AKHILESH KUMAR SHARMA [11], The deep learning architectures such as recurrent networks and convolutional neural networks (ConvNets) are developed in the past, which are proven appropriate for non-handcrafted extraction of complex features. To additional expand the efficiency of the ConvNet models, a cascaded ensemble network that uses an integration of ConvNet and handcrafted features based multi-layer perceptron is proposed in this work. This offered model utilizes the convolutional neural network model to mine non-handcrafted image features and colour moments and texture features as handcrafted features. It is demonstrated that accuracy of ensemble deep learning model is improved to 98.3% from 85.3% of convolutional neural network model.

SUBHAJIT CHATTERJEE [12], This study aims to propose a transfer learning-based ensemble model for more accurate classification results. InceptionV3 and Xception are employed to build an ensemble model for classifying skin lesion images known as IncepX-Ensemble. A traditional data augmentation method was employed for the HAM10000 dataset to address the imbalanced data. This technique mitigates the class imbalance by incorporating data augmentation, enhancing model accuracy. At the experiment's outset, we utilized the original imbalanced data, and subsequently, balanced data were employed for the proposed model.

BELAL AHMAD [13], In the proposed framework, first, we learning the embedding from input images into Euclidean space by using deep CNN ResNet152 and InceptionResNet-V2 model. Second, we compute L-2 distance among corresponding images from euclidean space to learn discriminative features of skin disease images by using triplet loss function. Finally, classify the input images using these L-2 distances. Human face skin disease images used in the proposed framework are acquired from the Hospital in Wuhan China. Experiment results and their analysis shows the effectiveness of the proposed framework which achieve better accuracy than many existing works in skin disease tasks.

R. KARTHIK [14], A hybrid classification system is proposed, combining two tracks: the Swin Transformer and the Dense Group Shuffle Non-Local Attention (DGSNLA) Network, which integrates DenseNet169, Group Shuffle Depth-wise blocks (GSDW), and an enhanced non-local attention block (ENLA). This deep feature fusion approach effectively aggregates global and local features, resulting in more accurate feature representation and improved classification performance. To the best of our knowledge, this is the first study to combine a transformer with a custom CNN for skin cancer classification. The proposed network achieves an accuracy of 94.21%, an F1-score of 96.64%. a precision of 96.62%, and a recall of 96.25% on the HAM10000 dataset.

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M. A. RASEL [15], This critical mathematical mechanism influences the accuracy rate of the CNN. To obtain acceptable performance, CNN requires a large amount of training data. This research shows how fast and effective different types of nonlinear activation functions work on a CNN with limited image datasets. Experimental analysis reveals that the proposed CNN model with parameterized Leaky ReLU function outperforms (97.50% accuracy, 98.00% precision, and 98.00% sensitivity) the same network with distinct nonlinear activation functions for the problem of melanoma recognition by classifying skin lesion into three classes.

MUDASSIR SAEED [16], The dataset underwent rigorous preprocessing, which involves employing advanced Generative Artificial Intelligence (AI) techniques i.e., Generative Adversarial Networks (GANs) and Enhanced Super-Resolution Generative Adversarial Networks (ESRGAN), for augmentation. These generative techniques are carefully evaluated and compared for their effectiveness. Our CNN-based approach involves aggregating results from multiple transfer learning models, including VGG16, VGG19, SVM along with a hybrid model in combination of VGG19 and SVM.

ABDULRAHMAN DIRA KHALAF [17], This study explores the application of DL in skin cancer diagnosis, focusing on advances in image segmentation and classification. DL-based models are reviewed specifically by convolutional neural networks (CNNs), and evaluations on their effectiveness for skin lesion detection are provided. This study also examines the critical challenges of deploying DL models in clinical practice, covering issues including dataset diversity, model interpretability, and real-world implementation feasibility.

Table I : Comparison of Existing Literature

Paper Reference	Technology Used	Achievements	Limitation And Drawbacks
[1]	Clinical analysis.	Identifies melanoma risk.	Limited technical detail.
[2]	XAI-based deep learning.	High classification accuracy.	Limited generalization.
[3]	Statistical data analysis.	Tracks CRC trends.	Increasing young-age incidence.
[4]	CNN deep learning.	High detection accuracy.	Model-dependent performance.
[5]	CNN with ESRGAN.	Improved detection accuracy.	Limited accuracy gains.
[6]	CNN with cyclic learning rate.	High accuracy.	Dataset-specific.
[7]	DCNN with CNN and VGG16/VGG19.	Accurate multi-class AD classification.	High computational complexity.

[8]	Modified MobileNetV2 and DenseNet201.	High accuracy skin cancer detection.	Requires model modification and tuning.
[9]	CNN-based deep learning.	Improved detection accuracy.	Hard to deploy clinically.
[10]	Ensemble CNN deep learning.	90.15% classification accuracy.	High computational cost.
[11]	Ensemble CNN with handcrafted features.	98.3% accuracy.	High model complexity.
[12]	Transfer learning ensemble (InceptionV3 + Xception).	98% accuracy.	Sensitive to data imbalance.
[13]	ResNet152 & InceptionResNet-V2 with triplet loss.	High classification accuracy.	Needs large labeled datasets.
[14]	Swin Transformer + custom CNN.	94.21% accuracy.	High computational cost.
[16]	CNN with Leaky ReLU.	97.5% accuracy.	Needs large datasets.
[17]	CNN + VGG19+SVM with GAN augmentation.	96% accuracy.	High computation required.

III. PROPOSED ARCHITECTURE SYSTEM

The proposed system introduces an automated skin cancer detection approach using a **Convolutional Neural Network (CNN)** to classify dermoscopic images accurately. Users upload skin lesion images through the system interface, after which the images undergo preprocessing steps such as resizing, normalization, and enhancement to improve image quality. To address dataset imbalance and improve generalization, data augmentation techniques are applied during training. The

CNN model automatically extracts significant features like texture, color, and shape from the images without manual intervention. Based on the learned features, the system classifies the skin lesions into predefined categories and provides reliable diagnostic results. This CNN-based system reduces human dependency, improves diagnostic consistency, and supports early detection of skin cancer, making it suitable for smart healthcare applications.

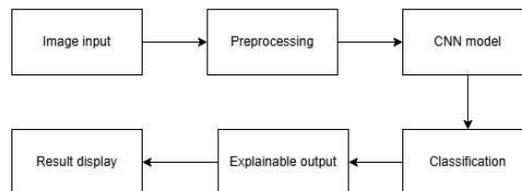


Fig: proposed system of architecture

IV. TOOLS AND TECHNIQUES

A. Deep Learning

Deep learning is a specialized branch of machine learning that utilizes artificial neural networks with multiple hidden layers to automatically learn complex patterns from large volumes of data. Unlike traditional machine learning approaches that rely on manually engineered features, deep learning models extract hierarchical features directly from raw input data. In image-based applications, deep learning enables systems to identify low-level features such as edges and textures in early layers and high-level semantic features such as shapes and object structures in deeper layers. This capability makes deep learning highly suitable for medical image analysis, object recognition, and image classification tasks. By leveraging large datasets and powerful computational resources, deep learning models achieve high accuracy and robustness, making them a core technology in modern intelligent systems.

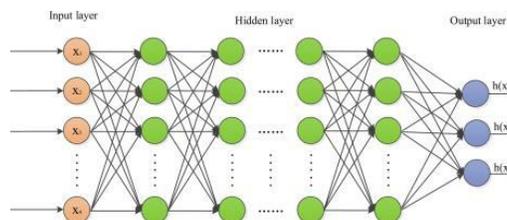


Fig 1.1 : Deep Learning

B. Python Libraries

Python provides a rich ecosystem of libraries that support the development and deployment of deep learning models efficiently. Libraries such as **TensorFlow** and **Keras** are widely used for building and training Convolutional Neural Networks due to their flexibility, scalability, and user-friendly APIs. **NumPy** is used for numerical operations and matrix computations, while **OpenCV** facilitates image processing tasks such as resizing, normalization, and enhancement. **Matplotlib** is employed for visualizing training performance, accuracy, loss curves, and model predictions. These Python libraries together form a powerful toolset that simplifies data preprocessing, model construction, training, evaluation, and visualization in deep learning-based image classification systems.

C. Convolutional Neural Network (CNN)

A Convolutional Neural Network is a deep learning architecture specifically designed to process and analyze visual data. CNNs consist of multiple layers, including convolutional layers, pooling layers, and fully connected layers, each serving a distinct purpose. Convolutional layers apply learnable filters to extract spatial features such as edges, corners, and textures from input images. Pooling layers reduce spatial dimensions, improving computational efficiency and reducing overfitting. Fully connected layers perform the final classification based on the extracted features. CNNs automatically learn discriminative features from images, eliminating the need for manual feature extraction. Due to their high accuracy and ability to capture spatial hierarchies, CNNs are extensively used in medical imaging, object detection, face recognition, and disease diagnosis systems.

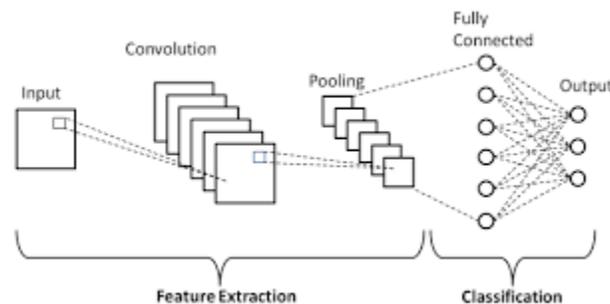


Fig 1.2 : CNN Architecture

D. Image Classification

Image classification is the process of assigning predefined labels or categories to images based on their visual content. In deep learning-based image classification systems, Convolutional Neural Networks play a crucial role by automatically extracting meaningful features and learning class-specific patterns from training data. The process typically involves image preprocessing, feature extraction through CNN layers, and classification using fully connected layers with activation functions such as Softmax or Sigmoid. Image classification using CNNs provides high precision and reliability, especially in complex and large-scale datasets. This approach is widely applied in healthcare for disease detection, agriculture for crop monitoring, security systems, and many other real-world applications where accurate visual recognition is essential.

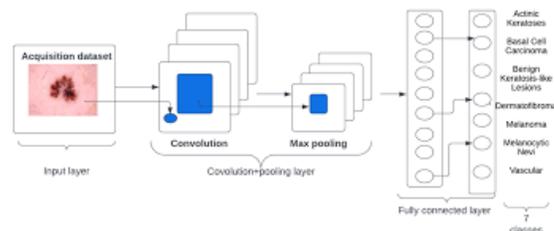


Fig 1.3 : Image Classification

V. DATASET USED

The project uses the **HAM10000 (Human Against Machine with 10,000 training images)** dataset, which is a publicly available dermoscopic image dataset. It contains **10,015 skin lesion images** categorized into **seven different classes**, including melanoma and non-melanoma lesions. To address class imbalance, data augmentation techniques were applied, increasing the dataset size and improving model generalization. The HAM10000 dataset is widely used in medical image

analysis research due to its diversity and reliability.

VI. MOTIVATION

Skin cancer has become a rapidly growing global health concern, affecting millions of people every year. Despite advancements in dermatology, early detection and accurate classification remain significant challenges due to the visual similarity between benign and malignant lesions. Manual diagnosis through dermoscopic examination largely depends on the dermatologist's expertise and subjective interpretation, which can lead to inconsistencies and delayed treatment. In many regions, especially where access to specialists is limited, this problem becomes more severe. The urgent need for a reliable, automated system that can identify skin cancer at an early stage with high precision has motivated researchers to explore artificial intelligence-based diagnostic solutions.

The development of Deep Learning (DL), particularly Convolutional Neural Networks (CNNs), has opened new possibilities in medical imaging by automating feature extraction and improving classification accuracy. However, the lack of interpretability in CNN models often raises concerns about their acceptance in clinical practice. Physicians need to understand not only what the AI predicts but also why it makes a particular decision. This research is motivated by the goal of combining high-performance CNN models with Explainable Artificial Intelligence (XAI) techniques such as Grad-CAM and Grad-CAM++, which provide visual explanations for each prediction. This approach enhances trust, transparency, and reliability, thereby supporting dermatologists in making faster and more confident diagnostic decisions while improving patient outcomes.

VII. GAP ANALYSIS

- Manual diagnosis is subjective and error-prone.
- Existing CNN models are “black boxes” with low interpretability.
- Limited datasets reduce generalization across diverse skin types.
- Poor integration with clinical workflow.
- Inconsistent performance under varied imaging conditions.

VIII. CONCLUSION

This project successfully presents an interpretable skin cancer classification system using an optimized Convolutional Neural Network (CNN). By integrating Explainable Artificial Intelligence techniques such as Grad-CAM and Grad-CAM++, the system not only achieves accurate predictions but also provides visual explanations for each decision. This improves transparency, trust, and usability in clinical environments. The model effectively handles class imbalance through data augmentation and demonstrates stable performance with improved accuracy. The proposed system can support dermatologists in early diagnosis, reduce human error, and contribute to smart healthcare solutions. Future enhancements may include advanced attention-based models and real-time mobile deployment.

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