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Detection of Melanoma in Skin Images using Convolutional Neural Networks

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INTRODUCTION

Skin cancer is one of the most common types of cancer, affecting millions throughout the world. It is primarily caused by overexposure to ultraviolet (UV) light from the sun or artificial sources. Melanoma is the most aggressive and life-threatening kind of cancer because of its high metastatic potential. Early identification is vital in lowering mortality rates. Traditional diagnostic approaches, such as eye examination and biopsy, are time-consuming and subjective. Recent advances in deep learning and computer vision show promise for automated skin cancer screening. Specifically, Convolutional Neural Networks (CNNs) have demonstrated high accuracy in classifying skin lesions from dermoscopic images. CNNs leverage hierarchical feature extraction, making them well-suited for recognizing complex patterns in medical images.

Keywords: Skin cancer, CNN

Skin Cancer: Types

In general, skin cancer falls into one of two categories:

Non-Melanoma Skin Cancer (NMSC): comprises the less aggressive but more common Squamous Cell Carcinoma (SCC) and Basal Cell Carcinoma (BCC).

Melanoma: A highly malignant form that arises from melanocytes and has a high mortality rate if not detected early.

Accurate diagnosis is crucial since a number of benign and precancerous lesions, including vascular lesions, pigmented benign keratosis (PBK), actinic keratoses, and seborrheic keratoses, can similarly resemble melanoma.

Motivation

Due to delayed detection, melanoma is the primary cause of skin cancer-related mortality. and misclassification of lesions. The primary motivations for this research include:

High Mortality Rates: Late-stage melanoma has poor survival rates, necessitating early detection.

Need for Automated Diagnosis: Current diagnostic methods are time-consuming and require expert dermatologists.

Advancements in Deep Learning: CNNs have revolutionized image-based classification tasks, offering a potential solution for automated melanoma detection.

Reducing Healthcare Burden: Early detection can reduce treatment costs and alleviate the strain on healthcare systems.

Problem Statement

Despite advancements in skin cancer detection, challenges remain:

Distinguishing Benign from Malignant Lesions: Many benign conditions resemble melanoma, leading to false positives.

Dataset Imbalance: Medical image datasets often contain fewer melanoma samples, affecting model performance.

Generalizability: The trained CNN models on particular datasets may not perform well across different skin tones cancers and imaging conditions.

The proposed CNN-based melanoma detection model aims to address these challenges by improving classification accuracy, reducing false positives, and ensuring adaptability across diverse datasets.

Skin Structure and Cancer Development

The human skin has three major primary layers:

Epidermis: The outermost layer, containing melanocytes is mainly responsible for skin pigmentation.

Dermis: It has blood vessels, connective tissue points, and nerve endings.

Hypodermis: The deepest layer, mainly composed of fat and connecting many tissue points.

Skin cancer originates in different layers, with melanoma developing from melanocytes which is present in basal layer of the epidermis. Prolonged UV exposure and genetic mutations trigger abnormal cell growth, leading to malignancy.

Applications of CNN-Based Skin Cancer Detection

The integration of CNNs in dermatology has multiple applications, including:

Clinical Diagnosis: Assists dermatologists in identifying malignant lesions with high precision.

Telemedicine and Remote Screening: Enables early detection in remote areas via smartphone-based applications.

Treatment Monitoring: Tracks lesion progression over time, aiding personalized treatment plans.

Research and Epidemiology: Facilitates large-scale studies on skin cancer trends and risk factors.

LITERATURE SURVEY

The literature survey provides a structured review of existing research on melanoma detection using CNNs. This section outlines key contributions, methodologies, and advancements that have improved diagnostic accuracy and efficiency.

CNN-Based Approaches for Melanoma Detection

Esteva et al. [1] engaged a deep CNN to categorize skin cancer types from different dermoscopic images, provided training on over 129,000 clinical images. Their proposed trained model demonstrated dermatologist-level accuracy, emphasizing the power of transfer learning with Inception v3.

Haenssle et al. [2] compared CNN diagnostic accuracy with dermatologists, training on over 100,000 dermoscopic images. The CNN achieved superior sensitivity (95%) and specificity (82.5%), highlighting its clinical applicability.

Transfer Learning and Pretrained Models

Codella et al. [3] implemented ResNet for melanoma classification, leveraging data augmentation and preprocessing techniques. Their approach achieved an AUC of 0.89, demonstrating the importance of dataset diversity.

Brinker et al. [4] employed EfficientNet with transfer learning, reducing dataset dependency. Their method improved melanoma detection sensitivity to 93% on a test set of dermoscopic images.

Dataset Augmentation and Imbalance Handling

Liu et al. [5] addressed dataset limitations using Generative Adversarial Networks (GANs) to synthesize dermoscopic images. This augmentation enhanced CNN sensitivity in melanoma detection.

Cui et al. [6] tackled class imbalance by integrating clinical metadata (e.g., patient age, lesion location) and class-balancing techniques, improving model robustness.

Advanced CNN Architectures and Techniques

Tschandl et al. [7] demonstrated that lesion segmentation and color balancing significantly enhance CNN accuracy in melanoma classification.

Gessert et al. [8] introduced an ensemble learning approach combining ResNet, DenseNet, and EfficientNet, achieving a balanced precision of 89% on the HAM10000 dataset.

Xie et al. [9] incorporated attention-based CNNs to differentiate melanoma from visually similar benign lesions, improving classification accuracy by 4%.

METHODOLOGY

This division tells the methodology used for detecting melanoma skin cancer using Convolutional Neural Networks (CNNs). The proposed system follows a structured workflow, including dataset collection, preprocessing, model training, and evaluation.

Dataset Collection

The selected dataset used for training and evaluation includes 10,015 dermoscopic images of skin lesions from seven dissimilar classes. These images are sourced from wellknown databases such as HAM10000 and ISIC (International Skin Imaging Collaboration). This dataset includes a variety of skin lesions which are pigmented such as:

- Actinic keratoses and intraepithelial carcinoma (akiec)
- Basal cell carcinoma (bcc)
- Benign keratosis-like lesions (solar lentigines, seborrheic keratoses)
- Melanoma
- Other benign, malignant condition

Data Pre Processing

This step transforms raw dermoscopic images into a clean and structured dataset suitable for CNN-based classification. The key preprocessing techniques include:

Resizing Images: Standardizing the input size to 128×128 pixels for uniformity.

Normalization: It is used to normalize the pixel values in between the range of 0 to 1 to imove the stability of the training.

Data Augmentation: Increasing dataset variability using rotation, flipping, scaling, and brightness adjustment to enhance model generalization.

Hair Removal: Using the Dull Razor Algorithm to eradicate the artifacts in hair from skin images, which could interfere with lesion detection.

Model Architecture

The CNN model comprises many convolutional layers followed by pooling layers, dense layers, activation functions, and fully connected layers. The architecture used is a modified ResNet model optimized for skin cancer detection

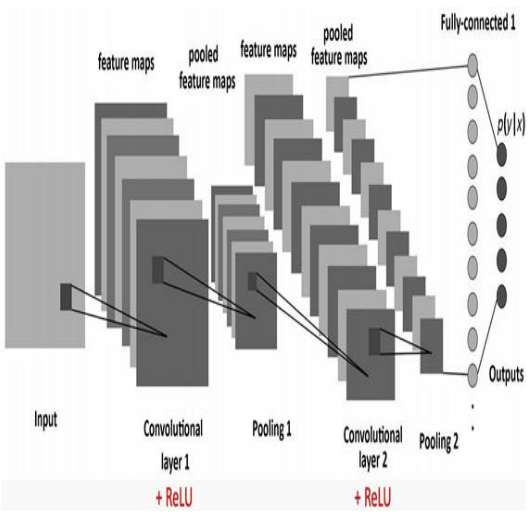

Fig 1 CNN Architecture

The projected CNN model has:

Convolutional Layers: Take out the hierarchical features from the given skin images.

Pooling Layers: Decrease the spatial dimensions while preserving significant features.

Fully Connected Layers: Classify the proper extracted features into melanoma and non-melanoma.

Activation Functions: ReLU and Softmax for non-linearity and classification.

Block Diagram

The following is the block diagram of proposed method and their step by step processing methods

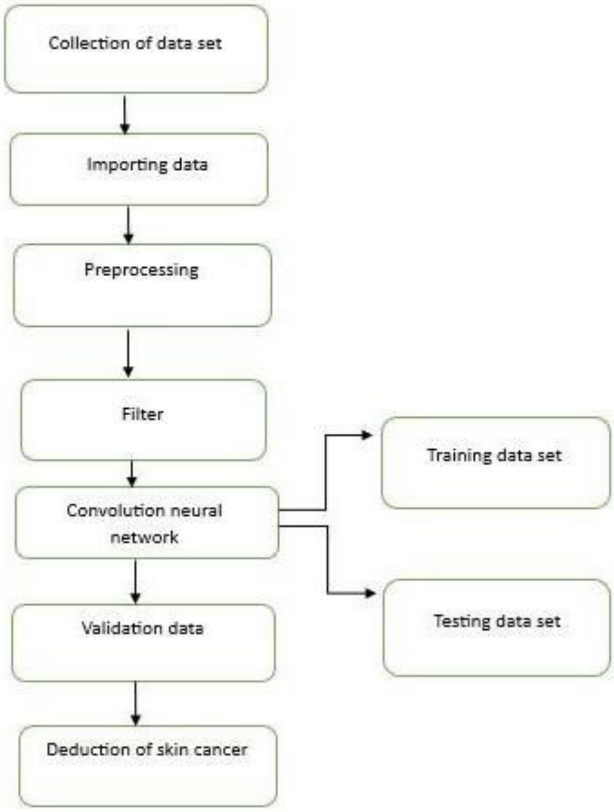

Fig 2 Block diagram of CNN model based early prediction of Skin cancer

Dataset Collection

The initial step in building a skin cancer detection method is collecting a robust and diverse dataset. Datasets are widely used in research because they contain thousands of images of various skin lesions, including cancerous (e.g., melanoma, basal cell carcinoma) and non-cancerous conditions. The trained dataset must represent different lighting conditions, skin tones, with lesion types to ensure the model can generalize across demographics and varied imaging conditions, helping to make it more applicable to real-world scenarios.

Importing Data

Once the dataset is collected, the images are imported into the working environment using libraries like TensorFlow or PyTorch, which are equipped for handling large volumes of image data. These libraries provide data loaders with batch processing capabilities, which help in managing memory and speeding up training. Organizing the dataset into labeled folders (such as "benign" and "malignant") also aids in efficient data loading and processing, while data generators or custom data pipelines handle the loading dynamically.

Preprocessing

Preprocessing prepares the raw images for training and analysis. Images are resized to a fixed dimension, such as 128x128 or 256x256 pixels, because CNNs require a consistent input size. Normalization then improves training stability by scaling pixel values to a predetermined range (for example, [0, 1] or [-1, 1]).

Data augmentation techniques, including rotation, scaling, flipping, and brightness adjustment, introduce variability in the data and help prevent overfitting by training the model to recognize lesions under diverse conditions. Noise removal methods, such as Gaussian blurring or median filtering, reduce background distractions, allowing the proposed trained CNN model is used to focus on appropriate features.

Filter

Filtering applies specific image processing techniques to enhance characteristics essential for to differentiate between benign and malignant lesions. For example, Gaussian blurring smoothens the image and helps the model focus on large patterns instead of minute details. Edge detection methods, like the Sobel or Canny filter, outline lesion borders and make it easier for the model to detect irregular shapes or asymmetry, which can be an indicator of malignancy. Additionally, transformations to different color spaces (such as HSV or LAB) may highlight certain color characteristics of cancerous lesions, improving model interpretability.

Training and Evaluation

Almost 80% of the dataset was used for training, and 20% was used for testing. The Evaluation metrics were F1-score, recall, accuracy, and precision. To avoid overfitting, early halting and dropout layers were used.

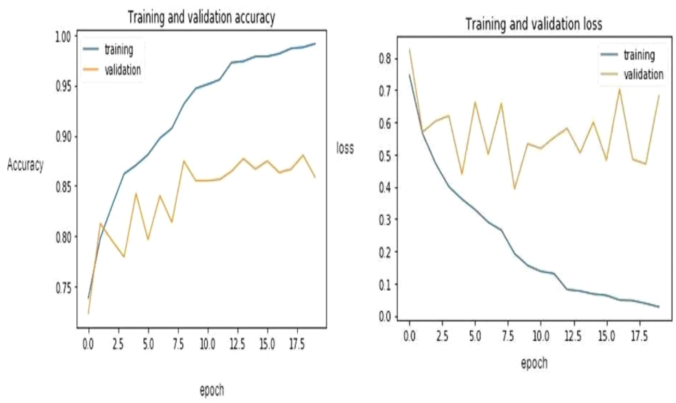

Fig 3 Training and validation Accuracy and loss

The two graphs show the training and validation loss and accuracy of a machine learning model over time. Both graphs indicate that the model is overfitting, as the training loss decreases significantly while the validation loss and accuracy plateau. This suggests that the model is becoming too specialized to the training data and performing poorly on new, unseen data. To improve the model's performance, techniques like early stopping, regularization, hyperparameter tuning, or data augmentation can be considered.

PROPOSED SYSTEM

The proposed CNN model is designed to enhance early melanoma detection by leveraging CNNs to examine the dermoscopic images. The methodology consists of several stages: data collection, preprocessing, feature extraction, training, and classification. High-quality datasets such as HAM10000 and ISIC Archive are used to ensure diversity in lesion types of skin. Preprocessing techniques like resizing, normalization, and hair removal improve image quality, while data augmentation (rotation, flipping, brightness adjustment) enhances model generalization.

The CNN architecture consists of fully connected layers for classification, pooling layers for dimensionality reduction, and convolutional layers for feature extraction. Activation functions like ReLU improve learning efficiency. The proposed model is trained on labelled skin lesion images and assessed using performance metrics such as accuracy, precision, recall, and F1-score. The system provides automated diagnosis assistance, generating probability scores and heatmap visualizations (Grad-CAM) to help dermatologists make informed decisions.

System Overview

The proposed system follows a structured workflow, incorporating image preprocessing, feature extraction, training, classification, and diagnosis assistance. The methodology consists of the following key stages:

Data Collection: Acquiring labeled datasets of skin lesions.
Preprocessing and Augmentation: Enhancing image quality and dataset diversity.
Feature Extraction using CNN: Identifying patterns in dermoscopic images.
Model Training and Validation: Learning classification patterns from labeled data.
Prediction and Classification: Distinguishing between malignant and benign lesions.

Pre processing and Augmentation

To improve model accuracy, raw images undergo pre processing steps:
Resizing: Standardizing image dimensions (e.g., 128×128 pixels).
Normalization: Scaling the pixel values lies in the range of 0 to1 for uniformity.
Hair Removal: Using Dull Razor Algorithm to eliminate noise from skin hair.
Augmentation: Enhancing dataset diversity through:
Rotation (0°-360°)
Flipping (in horizontal/vertical directions)
Adjustment in Brightness
Zoom and Cropping

Convolutional Neural Network (CNN) Architecture

The central part of the proposed method is a deep learning model based on CNNs, which is automatically, learns and extracts hierarchical features from images. The architecture consists of Convolutional Layers: Extracting features using small filters (kernels).

RESULTS AND DISCUSSION

The experimental outcomes and their analysis, highlighting the effectiveness of the proposed CNN of melanoma detection system. The model's effectiveness is evaluated based upon different metrics such as accuracy, precision, recall, and loss. The final results include training progress, validation results, and final predictions on test images.

Table 1 Proposed Model Validation Results

S. No.	Batch size	Number of epochs	Validation accuracy	Training accuracy	Training loss	Validation loss
1	35	20	74.59	87.68	34.86	73.45
2	35	30	48.79	90.96	23.13	33.85
3	35	40	62.88	62.89	91.81	1.00
4	35	42	46.3	93.3	12.85	36.59
5	35	50	47	91.21	22.57	83.37
6	35	70	58.95	62.02	94.49	1.10

Table 1 shows the model's performance over different epoch settings with a constant batch size of 35. At 20 epochs (Serial 1), both the training accuracy (87.68%) and validation accuracy (74.59%) are low, indicating the model is underfitting. At 30 epochs (Serial 2), the training accuracy jumps to 90.96%, but validation accuracy decreases to 48.19%, suggesting overfitting. By 40 epochs (Serial 3), the model achieves balanced performance with 62.89% validation accuracy and 91.81% training accuracy, indicating improved generalization. However, at 42 epochs (Serial 4), validation accuracy drops to 46.3%, though training accuracy is high (93.3%), indicating increased overfitting. The situation worsens at 50 epochs (Serial 5), where the validation accuracy remains low (47%) despite a high training accuracy (91.21%). At 70 epochs (Serial 6), validation accuracy rises to 58.95%, with training accuracy at 94.49%, suggesting slight improvement but continued overfitting. Validation loss correlates with this trend, increasing significantly as epochs rise, reflecting overfitting as the model focuses too much on training data and fails to generalize.

It provides comprehensive information about each and every layer of the model, including the type of layer, its output shape, and the various parameters (trainable and non-trainable) involved. displaying the structure of the model layer by layer. Each row in the table corresponds to a specific layer, detailing the type of layer, its output shape after processing the input, and the different parameters (trainable weights and biases). The training and validation accuracy graph fig. 4 illustrates the model's learning progression over multiple epochs. Initially, both training and validation accuracies start low but improve steadily as the model learns.

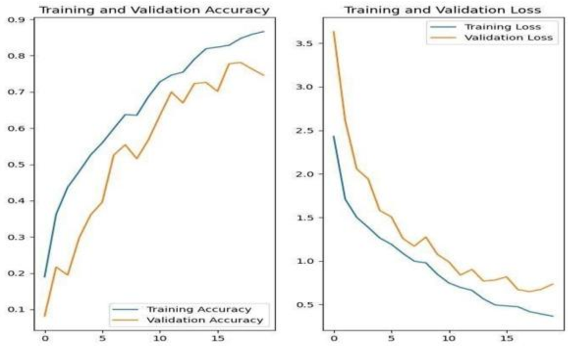

Fig 4 Proposed CNN model Training & validation accuracy (left). Training &validation loss (Right)

The accuracy of training increases smoothly, getting above 85%, while the validation accuracy follows a same trend, peaking around 75% with little fluctuations. The gap between training and validation accuracy remains moderate, indicating that the model generalizes well to unseen data. However, minor variations in validation accuracy suggest potential variability in performance, which could be addressed by further hyper parameter tuning or increasing the dataset size.

The training and validation losses in in Fig. 4 graph shows a consistent decline in both curves, representing that the proposed model is efficiently minimizing error. Training loss steadily decreases, while validation loss follows a similar trend, stabilizing towards the later epochs. This point gives suggestions about that the proposed CNN model is converging well without significant overfitting. However, if the gap between training and validation loss widens in later epochs, regularization techniques such as dropout, early stopping, or data augmentation could be implemented to enhance generalization. Finally, the results indicate that the CNN model effectively learns to differentiate between malignant and benign lesions, with room for further optimization.

CONCLUSION

The use CNNs for skin cancer detection has demonstrated significant potential in enhancing early diagnosis and improving classification accuracy, particularly in identifying melanoma, is one of the most lethal forms in skin cancer. CNNs are capable of analyzing dermoscopic images with remarkable precision, often surpassing the diagnostic capabilities of dermatologists in detecting cancerous lesions. It is not only minimizes human error but also provides a scalable, noninvasive diagnostic tool that can significantly improve healthcare delivery, particularly in areas with restricted access to specialized medical professionals. By automating the skin cancer screening process, CNNs facilitate detection in early stage, which is crucial for achieving successful treatment outcomes. Overall, the combination of CNNs into dermatological practices points out a promising advancement in the fight against skin cancer.

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