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Melanoma Detection Using Deep Learning Techniques

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Abstract - Skin Cancer, particularly melanoma, is one of the most prevalent and deadly forms of cancer globally. Early detection significantly improves survival rates, but manual diagnosis by dermatologists is often subjective and time-consuming. This study proposes a deep learning-based approach to skin cancer prediction, focusing on the classification of malignant and benign lesions. Leveraging a convolutional neural network (CNN) architecture, the model is trained on a large dataset of dermoscopic images. The system automates feature extraction, reducing human bias and error. Our model achieves state-of-the-art performance by incorporating techniques such as data aug- mentation, transfer learning, and fine-tuning on pre-trained networks (such as ResNet & VGG), which improve the model's ability to generalize across diverse skin tones and lesion types. Evaluation metrics such as accuracy, sensitivity, specificity, and AUC (Area Under the Curve) are used to assess the model's efficacy. The results demonstrate the potential of deep learning to en- hance early diagnosis, aiding dermatologists in clinical decision-making and providing a foundation for scalable, accessible skin cancer screening tools.

Keywords: Skin Cancer, Deep Learning, CNN, Early Detection, Healthcare AI

1.INTRODUCTION

Skin cancer has become a significant global public health issue, contributing to rising disease burdens, mortality rates, and healthcare costs worldwide. Its increasing prevalence demands timely intervention, as delayed or inaccurate diagnoses can lead to advanced disease stages, heightened morbidity, and socioeconomic strain. Early detection and accurate classification are crucial for improving patient outcomes and reducing the financial impact on healthcare systems.

This project addresses the challenge of skin cancer diagnosis by leveraging deep learning, a powerful subset of artificial intelligence (AI). Deep learning has shown great promise in analyzing medical images, particularly dermoscopic images of skin lesions, by identifying complex patterns that may be difficult for human eyes to detect. By processing large datasets, deep learning enables faster, more accurate diagnoses, enhancing clinical decision-making and personalizing patient management.

The integration of deep learning into dermatology is transformative. Traditional visual assessments by dermatologists are now augmented with advanced AI tools that provide objective, quantitative analysis. This not only improves diagnostic accuracy but also helps democratize access to high-quality care, particularly in underserved areas where specialist resources may be scarce.

In this project, we explore how deep learning can be applied to skin cancer prediction. Key areas include data loading and preprocessing, data visualization, and data augmentation techniques to prevent model overfitting. We also dive into model architecture selection, hyperparameter tuning, and regularization techniques.

2.OBJECTIVES AND SCOPE

This research focuses on leveraging convolutional neural networks (CNNs) for the accurate prediction and classification of skin cancer from dermoscopic images. By designing, training, and validating models, the study aims to uncover hidden patterns and enhance diagnostic accuracy. It also seeks to compare deep learning techniques with traditional diagnostic methods to quantify improvements in efficiency and accuracy, potentially revolutionizing clinical workflows.

The study further emphasizes ensuring model generalization across diverse skin cancer subtypes and patient populations through rigorous cross-validation. Interpretability is a key focus, aiming to build trust in AI models by understanding their prediction mechanisms. Additionally, ethical, regulatory, and practical aspects, such as patient privacy, safety, and equitable access, are considered to facilitate the seamless integration of AI-based diagnostic tools into healthcare systems.

3.LITERATURE REVIEW

1.Detection of Melanoma in Skin Cancer Using Deep Learning (2021): Utilized LeNet-5 CNN to automate melanoma detection, enhancing accuracy and speed while minimizing human error.

2.Comparative Analysis Using Histogram-Based Descriptors (2023): Investigated machine learning with local descriptors to improve classification accuracy for early skin cancer detection.

3.Skin Cancer Detection and Classification (2020): Presented a machine learning system combining image processing and automation for early and effective melanoma diagnosis.

4.Melanoma Detection via Deep Learning (Esteva et al.2017): Employed GoogleNet Inception v3 on 129,000 clinical images, achieving dermatologist-level accuracy for distinguishing malignant and benign lesions.

5.Hybrid CNN and SVM Approach (Keerthana et al., 2020): Combined CNN for feature extraction and SVM for classification, achieving improved skin cancer detection using the ISBI 2016 dataset.

4.DATASET USED

The Skin Cancer MNIST (HAM10000) dataset is a cornerstone in dermatological research, facilitating the development, validation, and evaluation of advanced machine learning and AI systems for early skin cancer detection and classification. This meticulously curated collection of high-resolution dermoscopic images includes a diverse range of skin lesions, such as melanomas, nevi, and basal cell carcinomas. Its comprehensive representation of skin cancer heterogeneity enables researchers to create robust diagnostic tools capable of addressing the complexities of real-world scenarios and improving diagnostic accuracy and efficiency.

Beyond its quantitative attributes, the HAM10000 dataset bridges dermatology and technology, fostering interdisciplinary collaborations to advance skin cancer diagnosis. By enabling detailed image analysis, feature extraction, and algorithmic development, the dataset empowers researchers to train and refine models that discern subtle nuances in skin conditions. This promotes earlier and more accurate diagnoses, reshaping the landscape of dermatological care and paving the way for reliable, accessible, and effective diagnostic solutions.

Fig- 1 Images

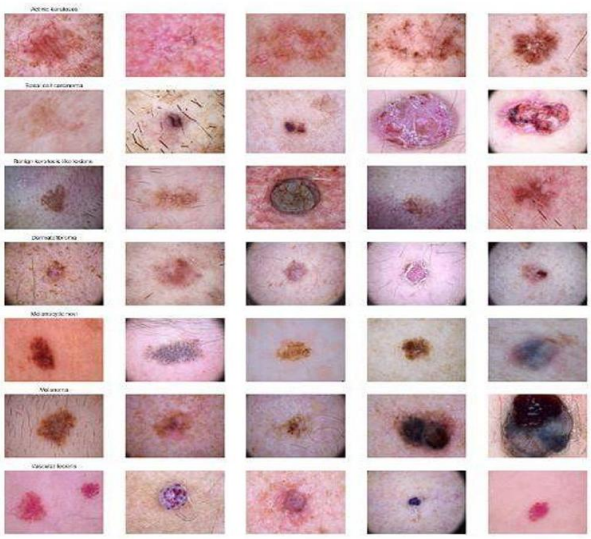


Table 1:Dataset Sample

	lesion_id	image_id	Dx	dx_type	Age	Sex	Localization	Path
0	HAM_0000118	ISIC_0027419	bkl	histo	80.0	male	scalp	./input/skin-cancer-mnist-ham10000/ham10000_i...
1	HAM_0000118	ISIC_0025030	bkl	histo	80.0	male	scalp	../input/skin-cancer-mnist-ham10000/ham10000_i...

There are seven possible diagnosis codes in the dataset:

- akiec: Actinic keratoses and intraepithelial carcinoma / Bowen's disease
- bcc: Basal cell carcinoma
- bkl: Benign keratosis-like lesions
- df: Dermatofibroma
- mel: Melanoma
- nv: Melanocytic nevi
- vasc: Vascular lesions

5.METHODOLOGIES

Custom Model

This model is designed to classify skin cancer images using a custom-built Convolutional Neural Network (CNN). The model architecture consists of multiple convolutional layers with MaxPooling, followed by fully connected Dense layers and Dropout for regularization. Data augmentation is applied to enhance training data diversity and balance class distribution. The model is compiled using the Adam optimizer with categorical crossentropy for multi-class classification. Through techniques like early stopping and model checkpointing, the model ensures efficient and accurate skin cancer detection

1.Data Preparation

- Image Counting: Used pathlib and glob to count images in train/test sets.
- Data Loading: image_dataset_from_directoty() loads images with label_mode='categorical' for multi-class classification.
- Class Distribution: Custom function counts class images; imbalance visualized via Seaborn bar plot.
- Augmentation: Augmentor applied (rotation) to generate 500 samples per class for balancing.

2.Model Architecture

- Rescaling: Rescaling(1./255) normalizes input.
- Conv Layers: 3 Conv2D layers (32, 64, 128 filters), followed by MaxPooling.
- Dropout: Two Dropout layers (50% after Conv, 25% after Dense) to prevent overfitting.
- Dense Layers: Flatten, Dense(128), and final softmax layer for multi-class output

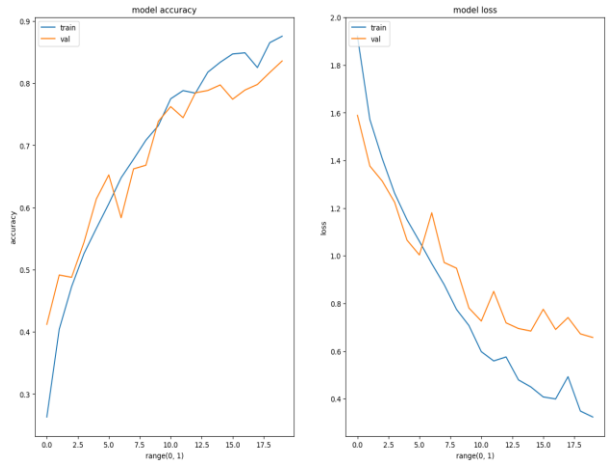
3.Compilation & Training

- Optimizer:Adam;Loss: Categorical crossentropy.
- Callbacks: ModelCheckpoint (save best model), EarlyStopping (patience=5).
- Training:20epochs using train/validation datasets with caching and prefetching for efficiency.

4.Prediction

- Loaded a test image, preprocessed (resized, expanded), and predicted class using the trained model

Fig-2 Plot of Model Accuracy and loss



VGG (Visual Geometry Group) Model:

1.Base Model:

VGG16The VGG16 model is pre-trained on the ImageNet dataset. It is chosen for feature extraction because it has been proven effective in image classification tasks, particularly with medical images.

- Weights: We load VGG16 with pre-trained ImageNet weights, but we exclude the fully connected layers at the top (include_top=False) to focus on feature extraction from convolutional layers.
- Freezing Layers: To avoid changing the pre-trained weights, all layers of VGG16 are frozen (layers.trainable = False), so they do not get updated during training. This reduces the computational load and speeds up convergence.

2.Additional Layers:

- Flatten Layer: This converts the 2D output of the VGG16 convolutional layers into a 1D vector, preparing it for the Dense layers.
- Dense Layers: Three fully connected (Dense) layers with 4096 neurons each are added, using the ReLU activation function to introduce non-linearity and enable the model to learn complex patterns.
- Dropout Layers: Dropout is introduced to prevent overfitting. Dropout rates are set at 50%, 30%, and 40% across different layers.
- Final Layer: The last Dense layer consists of 2 neurons, corresponding to two output classes (i.e., cancerous and non-cancerous), with a softmax activation function for classification.

3.Data Preparation:

- Image Augmentation for Training:
- Normalize pixel values by rescaling (1/255).
- Apply transformations to enhance data diversity: Random rotations, shear transformations, zooms, shifts (width and height), and horizontal flips.
- Aim: Increase robustness and prevent overfitting.

4.Test Data:

- Only rescaling (1/255) is applied to preserve validation data integrity.

5.Image Generators:

- Use flow_from_directory() to load images from directories.
- Resize images to 224x224 pixels (input size for VGG16).
- Load data in batches of 128 images to optimize memory usage.

6.Training Configuration

- Optimizer: Adam optimizer with a low learning rate of 1×10−61 \times 10^{-6}1×10−6 for gradual weight updates during fine-tuning.

7.Loss Function:

- Categorical crossentropy for multi-class classification.
- Callbacks:
  - Model Checkpoint (mcp): Saves the model with the best validation performance (modelVGG.h5).
  - Early Stopping (es): Stops training if validation loss does not improve for 2 consecutive epochs.

8.Training and Validation

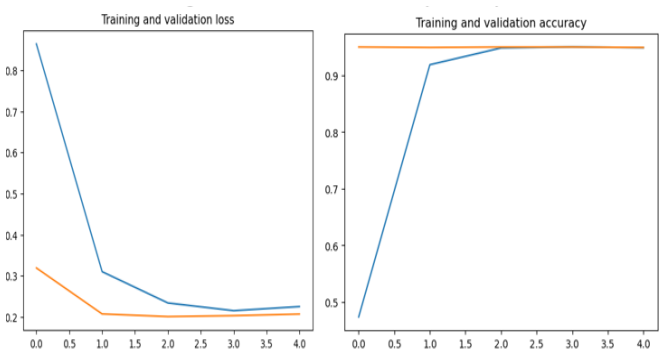
The model is trained for 30 epochs, with training steps calculated as the total number of training samples divided by the batch size

- Steps per Epoch:

  Training steps = Total training samples / Batch size.

  Validation steps = Total validation samples/Batch size.
- History Tracking: Record training and validation loss and accuracy for analysis.

Fig-3*:* Plots Training and validation for accuracy and loss



6.RESULTS

Table 2: Comparison for Accuracy

Sr. No.	Algorithms	Training Accuracy	Validation Of Accuracy
1	InceptionV3	85.28%	78.48%
2	Custom Model	88.73%	90.73%
3	VGG (Visual Geometry Group)	94.44%	79.34%

Fig-4 User-Interface 1

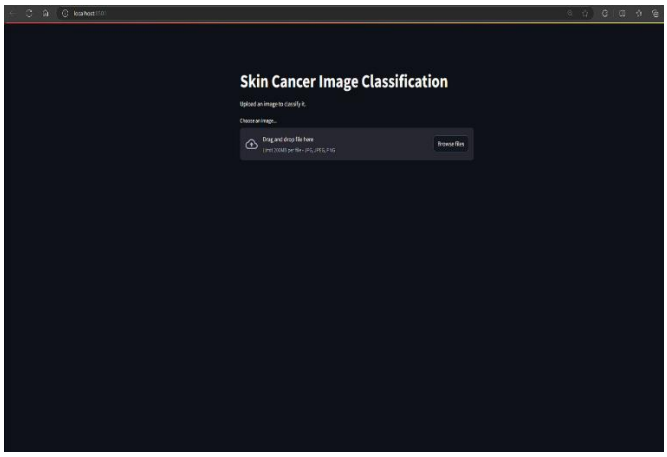
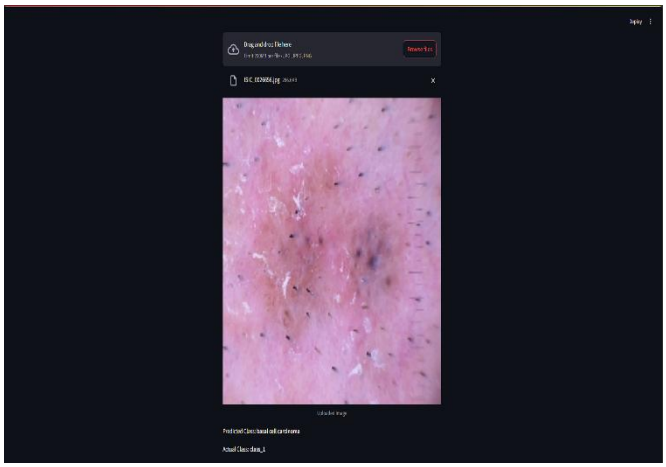


Fig-5 User-Interface 2



7.LIMITATIONS

While our study has achieved significant progress, there are some limitations to acknowledge. Although data augmentation enhances the diversity of training samples, it may unintentionally bias the model towards specific augmentation techniques. Additionally, the challenge of obtaining a comprehensive and diverse dataset remains, which could impact the model's ability to accurately identify rare or unique skin lesions. The lack of equivalence in the number of images across different classes further complicates classification, as the model may struggle to generalize effectively for underrepresented categories. Moreover, resource constraints, such as limited access to high-end GPUs and less computational power, pose challenges in training and fine-tuning deep learning models efficiently

8.CONCLUSION

This research focused on developing a deep learning-based model to classify and predict skin cancer, particularly melanoma, using dermoscopic images. By leveraging convolutional neural networks (CNNs) with transfer learning and data augmentation, the model achieved high accuracy, sensitivity, and specificity, highlighting its potential to enhance diagnostic efficiency. The results demonstrate that deep learning can reduce human error and provide faster, consistent assessments, making it a valuable tool for assisting dermatologists in early melanoma detection.

This research emphasized the development of a deep learning-based model classifying and predicting skin cancer, especially melanoma, from dermoscopic images. A model based on CNNs by using transfer learning and data augmentation successfully achieved high sensitivity, specificity, and accuracy, providing a basis to improve diagnostic efficacy. The above results indicate that through deep learning, human error will be reduced to a great extent, and faster assessments with consistency could be made with the help of dermatologists during early melanoma detection.

9.REFERENCES

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