Deep Learning Approach to Identify Skin Cancer Diagnosis Using Decoding Predefined

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Abstract: **Skin cancer is one of the most rapidly spreading illnesses in the world and because of the limited resources available. Early detection of skin cancer is crucial accurate diagnosis of skin cancer identification for preventive approach in general. Detecting skin cancer at an early stage is challenging for dermatologists, as well in recent years, both supervised and unsupervised learning tasks have made extensive use of deep learning. Utilizing transfer learning on five cutting-edge convolutional neural networks, both plain and hierarchical classifiers were developed to distinguish seven mole types using the HAM10000 dataset of dermatoscopic images. Incorporating data augmentation techniques, the DenseNet201 network emerged as the most effective, boasting high accuracy and F-measure with minimized false negatives. Interestingly, the plain model outperformed the hierarchical one, particularly in binary classification distinguishing nevi from non-nevi. The research also outlines an extension employing a UNET segmentation model to precisely identify and segment affected areas, aiding doctors in assessing the extent of skin disease.**

Keywords: **Skin Cancer, UNET, Skin cancer, segmentation, deep learning**

INTRODUCTION

Skin alterations stem from various factors like sun exposure, allergies, and infections. While sunbathing is a popular pursuit for skin tanning, it can exacerbate skin lesions, a precursor to skin cancer. Melanoma and non-melanoma skin cancers, predominantly affecting Caucasians, saw over a million cases in 2018, ranking 5th in common cancers. Melanoma, less frequent but more fatal, accounted for around 300,000 new cases last year. Early detection is vital, as untreated melanomas can metastasize, becoming incurable. However, diagnosing melanoma remains challenging due to its resemblance to benign moles. Current diagnostic methods, like the ABCDE rule, though effective, rely heavily on physician experience and can be imprecise. Addressing this, the study aims to develop an accurate lesion classification system leveraging deep learning, offering reliable diagnosis support and paving the way for automated, accessible diagnostic tools.

LITERATURE SURVEY

Identification of melanoma in dermoscopy images using image processing algorithms Here, author aims to enhance early detection of skin cancer by segmenting lesions and identifying melanoma in dermoscopy images. Using 170 dermoscopy images, the study enhances input images for clarity and segments lesions using Otsu thresholding and morphological operations. Descriptive features are extracted from these segmented lesions. These features contribute to calculating the Total Dermatoscopy Score (TDS), a metric used to determine the presence or absence of melanoma. The proposed algorithm's performance is evaluated through classification accuracy, providing a reliable method for accurate melanoma identification in dermatological imagery.

An SVM framework for malignant melanoma detection based on optimized HOG features
As the author proposes an advanced Computer-Aided Diagnosis (CAD) system for early detection of melanoma skin cancer. This system utilizes a Support Vector Machine (SVM) model applied to optimized Histogram of Oriented Gradient (HOG) descriptors of skin lesions. Through experimentation on a sizable dataset of dermoscopy images, the framework exhibits exceptional performance. It achieves high levels of sensitivity (98.21%), specificity (96.43%), and accuracy (97.32%). Importantly, this accuracy is attained without compromising computational efficiency, positioning the proposed framework as a competitive and effective solution for state-of-the-art melanoma detection.
The impact of replacing complex hand-crafted features with standard features for melanoma classification using both hand-crafted and deep features

Since the author introduces an automatic melanoma detection system blending deep learning with hand-crafted features. Using a deep residual network (ResNet), the system extracts intricate features, while the scale invariant feature descriptor (SIFT) represents the hand- crafted feature. Contrary to expectations, incorporating SIFT didn't enhance accuracy. However, the deep-only solution surpassed state-of-the-art methods in accuracy. This research underscores the potency of solely relying on deep features, suggesting a more streamlined yet effective approach to melanoma detection without the complexity of additional hand-crafted features.

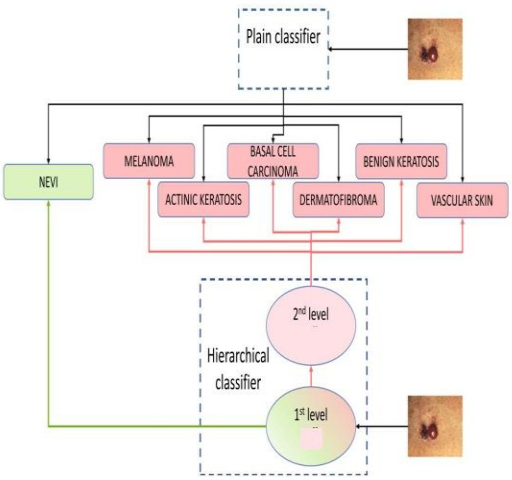
Problem Statement

Heave in skin diseases, extending beyond melanoma, underscores the urgency for advanced diagnostics. Visual similarities among conditions pose challenges, driving the need for a reliable automatic classification system. Hindered by limited datasets, the development is constrained, accentuating the necessity for robust methodologies. Addressing this, the project aims to enhance skin disease diagnostics, offering a potential breakthrough in accurate classification and timely interventions for improved patient outcomes in the face of diverse and complex skin pathologies

Proposed Method

Detecting skin cancer is a challenging task in medical profession due to very much similarity between different diseases and to overcome from this problem author of this paper employing various deep learning neural networks algorithms such as InceptionV2, InceptionV3, DenseNet, MobileNet and GoogleNet and among all algorithms DenseNet is giving more than 98% accuracy.

Architecture



Skin Cancer Detection Dataset:

All algorithms will get trained on above dataset

METHODOLOGY

Data Preparation and Preprocessing:

1.Data Collection: We initiate the project by sourcing dermatoscopic images from the HAM10000 dataset, a well-known repository for dermatological images. Data Normalization: To standardize the data and facilitate efficient model training, we normalize the pixel values of the images to the range [0, 1].

2. Dataset Shuffling: To ensure a balanced distribution and prevent any biases during training, the dataset undergoes shuffling, guaranteeing randomness.

Model Building and Training:

InceptionV2 Model:

1.Model Initialization: We first check for the availability of pre-trained weights for the InceptionV2 model. If available, we load them; otherwise, a new model is constructed from scratch.

2. Transfer Learning: Leveraging transfer learning, we employ the InceptionResNetV2 base model, a proven architecture in image classification tasks.

3.Layer Addition: Additional convolutional and pooling layers are integrated to capture intricate features from the images effectively.

4. Model Compilation: Using the Adam optimizer and categorical cross-entropy loss function, the model is compiled, setting the stage for effective learning.

5. Model Training: The model is trained on the prepared dataset, employing a batch size of 16 and undergoing 85 epochs to fine-tune the parameters.

6. Model Persistence: Post-training, the model's architecture and weights are saved, ensuring their availability for future endeavors.

InceptionV3 Model:

1. Reiteration: The process repeats, this time using the InceptionV3 architecture, allowing for comparative analysis between different Inception variants.

DenseNet Model:

1. Weight Consideration: Similar to earlier models, we check for pre-trained weights for the DenseNet model. If unavailable, a new model is constructed.

2. Transfer Learning Setup: We leverage DenseNet121, pre-trained on ImageNet, integrating its architecture into our model.

3. Layer Configuration: After the base layers, convolutional layers are added, followed by flattening before connecting to fully connected layers.
4. Model Compilation and Training: The model is compiled and trained on the dermatoscopic dataset, ensuring it learns to distinguish between different types of skin lesions.
MobileNet Model:
1. Iterative Process: Using the MobileNet architecture, we repeat the aforementioned steps, evaluating its efficacy and performance in skin cancer detection.
GoogleNet Model:
1. Weight Management: We start by checking for pre-existing weights for the GoogleNet model. In their absence, we craft a custom architecture inspired by GoogleNet.
2. Architecture Design: Designing a GoogleNet-like structure, convolutional and pooling layers are strategically placed to enhance feature extraction.
Model Compilation and Training: Similar to other models, the GoogleNet-inspired model is compiled and trained on the dataset, ensuring comprehensive learning.
Evaluation and Performance Analysis:
1. Metric Assessment: The performance of each model is rigorously assessed using key metrics like precision, recall, F1-score, and accuracy.
2. Visual Representation: Confusion matrices are employed to visually represent the performance metrics, aiding in understanding model strengths and weaknesses.
3. Comparative Analysis: Bar graphs are plotted, providing a side-by-side comparison of the performance of InceptionV2, InceptionV3, DenseNet, MobileNet, and GoogleNet models, offering insights into their relative strengths.
Skin Cancer Prediction and Segmentation:
1. Model Deployment: The trained models are deployed for predicting skin cancer types in unseen test images.
Image Preprocessing: Before prediction, test images undergo preprocessing steps, including resizing and normalization, ensuring consistency.
2. Prediction and Segmentation: The type of skin cancer is predicted using the deployed models. Additionally, a custom segmentation model based on the U-Net architecture is employed to offering a detailed view of the lesion.
4.Visualization: Finally, the original image is displayed alongside the segmented region, providing a clear visualization of the predicted skin cancer type and the precise affected area, aiding clinicians in diagnosis and treatment planning.

CONCLUSION

Skin cancer detection is crucial yet challenging due to the visual similarities among different diseases. In this project, various deep learning algorithms including InceptionV2, InceptionV3, DenseNet, MobileNet, and GoogleNet were employed to address this challenge. Among these algorithms, DenseNet exhibited exceptional performance with over 98% accuracy, outperforming others significantly. Training on the HAM10000 dataset facilitated accurate classification of seven types of skin cancer. Additionally, an extension was implemented using a UNet segmentation model to segment affected areas, enhancing the diagnostic process. This comprehensive framework offers promising prospects for accurate and efficient skin cancer detection in clinical settings.

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