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Skin Cancer Detection Using 3D-TDP

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***Abstract*- Skin cancer, a critical health concern, is among the most common and potentially lethal cancers globally. Despite its prevalence, to increase survival chances, early identification is essential, like treatments are most effective when administered during the initial stages of the disease. Traditional diagnostic methods such as visual inspection or dermatoscopy, though widely used, can often lead to inconsistent and less accurate diagnoses due to the subjective nature of human assessment. The use of cutting-edge computational methods, especially deep learning, to improve the precision and effectiveness of skin cancer diagnosis has gained popularity as a means of overcoming these obstacles.**

This research presents a freshly developed technique for skin cancer recognition with the use of 3D-TDP (Three-Dimensional Texture and Depth Perception) technology. The 3D-TDP method integrates spatial and textural features from skin lesion images to provide a more detailed and comprehensive analysis compared to traditional 2D methods. By capturing the depth and texture variations in the skin, the proposed system can differentiate between malignant and benign lesions with higher precision. Furthermore, the 3D-TDP model employs a deep-learning-based framework that is constructed on a sizable collection of photos of skin lesions, enabling it to automatically recognise intricate patterns linked to various forms of skin cancer.

The key advantage of the 3D-TDP approach is its ability to reduce false positives and negatives, enhancing the reliability of early-stage skin cancer detection. This system is designed to assist dermatologists by providing an automated and accurate tool that supports decision-making, especially in ambiguous cases. The results of this study demonstrate that the 3D-TDP method can significantly improve diagnostic accuracy, potentially leading to better patient outcomes and reducing the global burden of skin cancer-related deaths.

Introduction

With rising incidence rates linked to variables including extended exposure to ultraviolet (UV) radiation and shifting climatic circumstances, skin cancer is a developing worldwide health concern. If not identified early, the most prevalent forms of skin cancer, such as melanoma, basal cell carcinoma, and squamous cell carcinoma, can frequently be lethal. For effective treatment and improved survival rates, early diagnosis is crucial. However, because human evaluation is subjective, traditional diagnostic techniques that mainly rely on visual inspection and dermatoscopy are prone to errors. These techniques frequently lead to incorrect diagnoses, which affect patient outcomes by delaying therapies or requiring needless biopsies.

To address these limitations, technological advancements in medical imaging and machine learning have paved paving the path for diagnostic instruments that are more precise and effective. In this regard, there has been a lot of interest in using deep learning to identify skin cancer. However, most existing models operate on 2D images, which limits their ability to capture the full spectrum of spatial and textural information from skin lesions.

This project introduces a new approach for skin cancer detection using 3D-TDP (Three-Dimensional Texture and Depth Perception) technology. The 3D-TDP system enhances the traditional image analysis process by integrating depth and texture data from skin lesions, providing a more comprehensive view of the lesion's structure. By leveraging deep learning algorithms trained on a diverse dataset of skin lesions, the 3D-TDP model can automatically learn and detect patterns associated with various skin cancers, resulting in improved diagnostic accuracy.

This approach aims to minimize the subjectivity and variability inherent in manual inspections, offering dermatologists an advanced tool that supports early and accurate diagnosis. By reducing false positives and negatives, the 3D-TDP model holds the potential to revolutionize skin cancer detection and significantly improve patient outcomes through early intervention. The introduction of 3D imaging and deep learning in dermatological diagnostics represents a critical step toward more reliable and accessible healthcare solutions. In the model development, we focused on four phase which includes,

1. Literature Review
2. Architecture
3. Methodology
4. Experimental Result

Literature Review :

Author(s)	Method	Limitations
Inthiyaz et al. [23]	Used softmax for classification and an already trained model for extracting features.	Small dataset, not generalizable to large datasets; high computational cost using ResNet-50.
Gajera et al. [24]	Examined eight CNN-based models that had already been trained for the sorting of dermoscopy images.	Small datasets (PH2, ISIC 2016, ISIC 2017); risk of overfitting on small datasets.
Alenezi et al. [31]	Employed a deep residual network based on wavelet-transform for classification.	Poor performance on photos of different sizes and colours, limited generalisability.
Shinde et al. [32]	Proposed a lightweight model for classification tailored for IoT devices.	Lower sensitivity and specificity than baseline models; more parameters and training time than MobileNetV2.
Bassel et al. [44]	Pre-trained models for feature	Small dataset (2637 training images, 660 test images); limited

	extraction; stacked CV classifiers.	generalizability to large datasets..
Abbas and Gul [38]	Suggested a NASNet architecture for the classification of skin cancer.	None specified.
Gouda et al. [40]	Pre-trained models and ESRGAN for data augmentation.	Small dataset (3533 ISIC 2018 images); accuracy still low compared to dermoscopy images.
Bian et al. [64]	Proposed YoDyCK (YOLOv3 with dynamic convolution kernel) with WGAN for data augmentation.	Addressed data bias using Asian images, but may lack global diversity.
Demir et al. [65]	Used Inception-v3 and ResNet-101 for classification.	Limited to 2437 images, affecting generalization.
Jain et al. [66]	Applied transfer learning models (e.g., Xception, MobileNet) for classification	Xception had best accuracy but high computation time; MobileNet was faster but less accurate.
Bechelli and Delhommelle [69]	Evaluated deep learning and machine learning methods using datasets related to skin cancer..	Deep learning models on HAM10000 dataset had low F1-score (0.70) and precision (0.68) on smaller datasets.

Architecture

This workflow for skin cancer detection using a 3D-TDP architecture begins by importing essential libraries and mounting Google Drive for data access. After setting dataset paths, the class distribution is optionally displayed and plotted to understand dataset balance. Data generators are configured, and an InceptionV3 model is built and compiled for training. Optional callbacks are set up to manage training, followed by calculating class weights to address any class imbalance. The model is then trained using the configured settings, including callbacks and class weights, ensuring optimal learning. After training, the model is evaluated, and results, including a classification report and relevant metrics, are displayed if desired. The workflow further allows for predicting labels on new images before the trained model is saved and downloaded, providing a complete pipeline for skin cancer classification. The workflow as follow :-

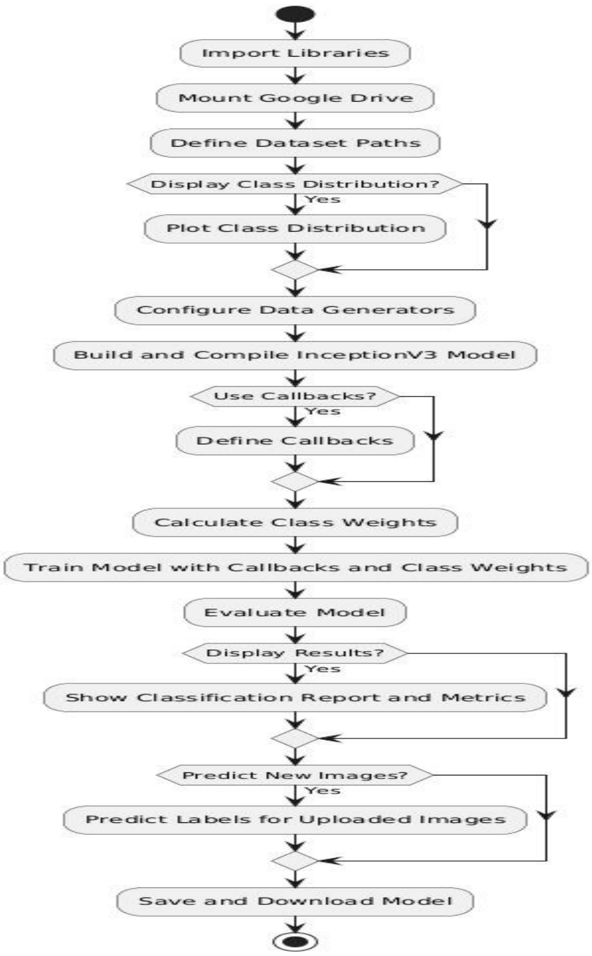

Fig No.1 – Architecture

Methodology

Transfer Learning:

A machine learning technique called transfer learning uses a previously learnt model developed for a particular task as a foundation for a new, related model. This method improves learning effectiveness and performance on the new assignment by utilising the knowledge from the original model, especially when the new dataset is limited in size. It significantly reduces training time and computational resources by allowing models to converge faster. Transfer learning is particularly effective in deep learning, where Convolutional Neural Networks (CNNs) and other models are trained on massive datasets. This technique is frequently used in several fields, such as natural language processing and picture recognition.

A pre-trained Inception V3 model that has been trained on a sizable dataset, such as ImageNet, is modified for particular tasks, like skin cancer diagnosis, in order to apply transfer learning in the context of Inception Net. A smaller, domain-specific dataset is used to fine-tune the pre-trained weights rather than starting from scratch when training the model. This involves replacing the final classification layer to align with the new task and training the model with a lower learning rate, allowing it to adjust the pre-existing feature extraction layers while learning to recognize new patterns relevant to the specific application. This process enhances the model's performance while saving time and resources, making Inception Net a powerful tool in transfer learning scenarios.

InceptionV3 Model:

A deep learning model called Inception V3 was created specifically for picture classification, renowned for its efficiency in handling complex visual tasks. It employs a novel architecture that utilizes multiple filter sizes at each layer, enabling it to capture a variety of features from input images. In skin cancer detection, Inception V3 is particularly beneficial due to its ability to accurately identify and classify skin lesions based on their visual characteristics. By training the Early diagnosis is made easier by the model's ability to distinguish between benign and malignant lesions after being trained on a big collection of dermatological photos. This model's performance is improved and training time is decreased when combined with transfer learning, which refines pre-trained weights on massive datasets for particular skin cancer detection tasks. Its high accuracy and efficiency make it a valuable tool in telemedicine and dermatology, providing clinicians with a reliable means to support their diagnostic decisions.

Callbacks :

callbacks play a crucial role in optimizing the training process by providing mechanisms to manage and enhance model performance. Callbacks are functions that can be invoked at specific stages of training, allowing for real-time adjustments based on the model's performance.

Callbacks used in model are :-

Early Stopping :

serves as a callback that terminates training when the model's performance on the validation dataset stops getting better after a predetermined amount of epochs. This keeps overfitting from happening and saves computing power. After a specified patience period, it examines a selected measure, like validation loss or accuracy, and ceases training if no improvement is seen (for example, if the validation loss does not decrease for three consecutive epochs).

Model Checkpoint :

is a callback that saves the model at specified intervals during training, enabling the recovery of the best-performing model based on a chosen metric. It allows users to set criteria for saving, such as when validation accuracy improves or validation loss decreases, ensuring that the most effective model version is retained for future inference or further training.

Reduce LROn Plateau:

When the model's performance on the validation set reaches a plateau, a callback lowers the learning rate, aiding in fine-tuning the learning process and helping to escape local minima. It monitors a specified metric and, if no improvement is observed over a defined number of epochs, decreases the learning rate by a specified factor, facilitating better convergence of the model as training continues.

Experimental Result

Accuracy Of Model :

The categorisation report for the skin cancer detection model shows that the three forms of skin cancer perform differently. The model has good accuracy in recognising this class, with the maximum precision (0.89) and recall (1.00) for melanoma. Squamous cell cancer has the lowest recall at 0.50, while basal cell carcinoma and squamous cell carcinoma have poorer precision and recall. The model's overall accuracy is 0.75, and its precision, recall, and F1-score weighted and macro averages are also between 0.74 and 0.75, reflecting a balanced performance.

Class	Precision	Recall	F1-Score
Basal Cell Carcinoma	0.67	0.75	0.71
Melanoma	0.89	1.00	0.94
Squamous Cell Carcinoma	0.67	0.50	0.57
Accuracy			0.75
Macro Avg	0.74	0.75	0.74
Weighted Avg	0.74	0.75	0.74

Table No.1 – Comparison of cell in terms of Precision, Recall and F1-Score

Prediction of class :

1) Melanoma :

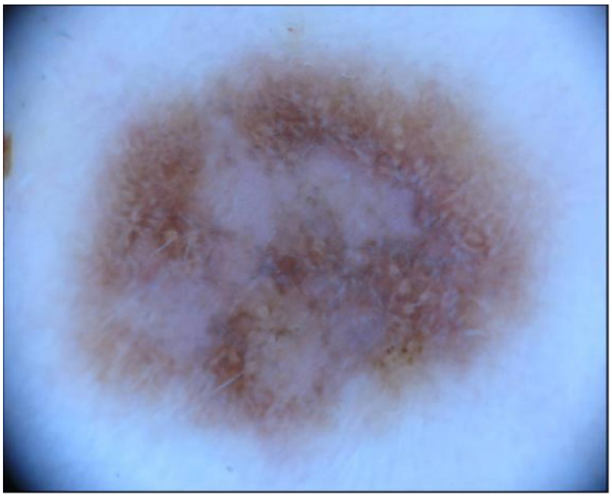

Fig No.2- prediction of Melanoma

2) Squamous Cell Carcinoma :

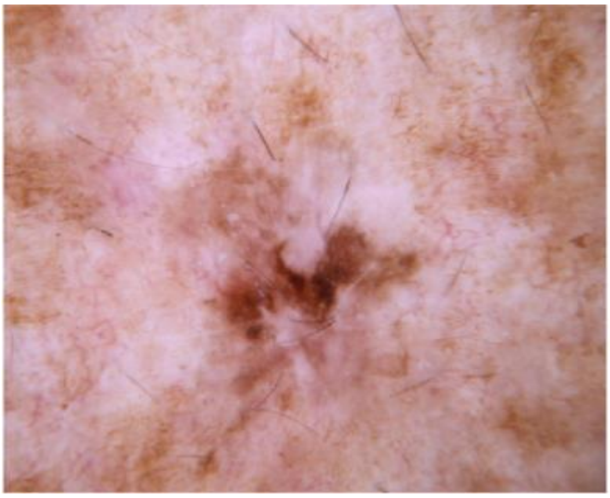

Fig No.3- prediction of Squamous cell carcinoma

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3) Basel Cell Carcinoma :

Fig No.4- prediction of Melanoma

Future Scope

Particularly for squamous cell carcinoma, increasing model generality through methods like data augmentation, cross-validation, and hyperparameter tuning can help lower validation variability and improve accuracy. Adding more varied samples to the dataset would increase its resilience and adaptability in practical situations.

Conclusion

In conclusion, this study effectively classified the three types of skin cancer cells—melanoma, squamous cell carcinoma, and basal cell carcinoma—using the Inception Net model with encouraging accuracy. Particularly in melanoma identification, the model's high precision, recall, and F1-scores demonstrate Inception Net’s potent feature extraction capabilities, which enable it to pick up on minute differences between cell types. The model's resilience and generalization are further supported by the steady decline in training and validation losses. These findings highlight Inception Net’s potential as a trustworthy instrument to aid in early diagnosis and improve clinical judgment in dermatology, which will improve the course of treatment for skin cancer.

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