Grenze International Journal of Engineering and Technology, June Issue

Deep Learning based Skin Cancer Detection and Classification

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***Abstract*— Skin cancer is a serious and widespread type of cancer that requires early and precise detection for proper treatment and positive patient results. (CNNs) that comes under Deep Learning, has proven to be a powerful tool for automated skin cancer classification from medical images, but their lack of interpretability has hindered their adoption in clinical settings. In this report we have proposed integrating techniques like eXplainable Artificial Intelligence (XAI) like LIME and occlusion techniques with CNN models to address this challenge. The performance of the proposed framework will be assessed using various architectures of CNN, including ResNet50, InceptionV3, MobileNetV2, and VGG16, which will be fine-tuned to detect and classify skin cancer. We aim to yield higher accuracy for skin cancer diagnosis while also enhancing the interpretability and transparency of the decision-making process by proposing the combined excellence of deep learning and XAI. This approach aims to foster trust and facilitate the integration of automated systems into clinical practice, ultimately improving patient care.**

***Index Terms*— Convolution Neural Network, eXplainable AI, Occlusion Sensitivity, LIME, Resnet50, InceptionV3, VGG16, MobileNetV2.**

I. INTRODUCTION

Skin cancer is a serious health issue that requires urgent attention and cure. Early detection of skin cancer is beneficial and improves the recovery rate of patients. Traditional methods of skin cancer diagnosis involve visual inspection and have limitations in accuracy. With the advancements in Artificial Intelligence, the diagnosis of cancer has improved. Deep Learning techniques are widely being used to assess cancer lesions. These algorithms have excellent mechanisms in image analysis which further brings precision and quick assessments of cancer lesion images.

Through this paper, we have studied how different models interpret skin cancer images and diagnose cancer cells. The report explores deep learning techniques and covers techniques like image processing and AI model integration into the medical domain. Deep learning models can help improve patients through early detection and intervention for cancer treatments. We have developed and trained four deep leaning-based models to diagnose cancer lesions into 7 broad categories. Also, our focus is to enhance the interpretability of cancer diagnosis through Explainable Artificial Intelligence (XAI). Here we have used LIME and Occlusion Sensitivity to interpret our model results.

Grenze ID: 01.GIJET.11.2.546_1

II. RELATED WORK

In this literature survey, we have studied four relevant research studies which offered valuable insights into methodologies, advantages, limitations and results of previously implemented models for detecting and classifying skin cancer.

Dildar M,etal. [1] presented a methodology that uses a (CNN) for identifying skin cancer. A accuracy rate of 98.61% is achieved by this study. It utilized an augmentation and approach of transfer learning using the AlexNet architecture. This study mainly focuses on the requirement for a huge number of labeled dataset images for training and testing purpose, which can be difficult because of lack of availability of labelled skin cancer datasets.

Gouda W, etal. [2] proposed a two-phase approach for detecting and classifying skin lesion using deep learning. The first phase includes data collection, then preprocessing, and later on training/testing of a CNN model, while the next phase mainly focuses on real-time implementation and visualization of results. Their proposed system yields an overall accuracy of 70% and exhibits the power to classify melanoma types into classes like benign or malignant. The study highlights the requirement for data preprocessing to get accuracy.

Naqvi, et al. [3] presented a solution to detect melanoma using deep learning techniques. classifications. The proposed methodology implements image preprocessing using ESRGAN for improving the image quality which is then followed by segmentation and grouping using CNN. The system yields a precision of 86%. The study also depicts the inability to transfer knowledge to testing data, which eventually affects overall model performance in real-time.

Hermosilla, et al. [4] through their research have proposed a solution to diagnose skin cancer using deep learning methodologies such as ESRGAN, data augmentation, image resizing, image normalization, and deep learning models like ResNet50 and InceptionV3. An accuracy of 85.7% is gained using the InceptionV3 model, demonstrating the productiveness of the used approach in diagnosing benign and malignant forms of cancer. Despite that, the study shows the need for testing the model on large and complicated datasets.

All of the above-mentioned studies highlight the capability of DP techniques for detecting and classifying skin. While achieving high accuracy rates, the studies also note the challenges such as the need for extensive labelled datasets, preprocessing requirements, and limitations in generalizability. Further research and improvement are required in these areas to enhance the efficacy of DP -based approaches for skin cancer detection and classification.

III. SYSTEM ARCHITECTURE

A. Process

The pipeline for detecting and classifying skin cancer image using deep learning and XAI techniques includes of the following steps:

Data Preprocessing

The first step is Data gathering in which Skin cancer images are acquired from a dataset known as HAM10000.

Next step involves Data cleaning in which images are checked for missing data, or inconsistencies in format.

Further step includes Normalization of images in which they are resized, rescaled, or adjusted for colour variations to ensure consistency for the model.

Finally, Augmentation Techniques like cropping of images, flipping of images are used to increase total number of images in the dataset and improve model robustness.

Deep Learning Model Training:

Model Selection: A pre-trained CNN architecture like ResNet50 or VGG16 is chosen.

Fine-Tuning: The pre-trained CNN is optimized for classifying cancerous images. And then the model is trained on the labelled pre-processed skin cancer images.

Interpretability with XAI Techniques

Prediction: The trained CNN model takes a new skin cancer image as input and predicts its class.

XAI Explanation: Figure 3.1 depicts techniques such as LIME or occlusion sensitivity are applied to explain why the model made a specific prediction.

LIME: Identifies relevant image regions influencing the model's prediction.

Occlusion Sensitivity: Progressively blocks image regions and observes how the prediction changes, highlighting important areas.

Interpretable Output: The XAI techniques gives perception into the process of decision-making, highlighting areas in an image that contributed most to the classification.

Evaluation and Refinement
Performance Analysis: The model's outcome is analysed on a specific test dataset to assess the accuracy for classifying unseen skin cancer images.
Refinement: Based on the evaluation results and the interpretability insights from XAI techniques, the model or training process might be further refined to improve accuracy or interpretability.
By combining deep learning with XAI techniques, this pipeline motive is to give an accurate as well as interpretable model that can classify skin cancer lesion.

B. Algorithm

Data Preprocessing
Normalization:
The training set images, and the test set images are converted into NumPy arrays first. Next the mean and standard deviation of pixel values are calculated separately of both the sets. Normalization is done through formula:

$$x_{normalized} = \frac{x - mean}{std}$$

Finally, the normalized array values are reshaped with the shape: (samples, 75, 100, 3), where 75x100 is the dimension of the image and 3 refers to the number of colour channels that is (RGB).

Deep Learning Model Training (Convolutional Neural Network)
There are four pre-trained models which are customized and fine-tuned on the cancer images dataset. For instance, the RESNET50 model is considered as the base model first. Global average pooling is used with the input shape of (75,100,3).

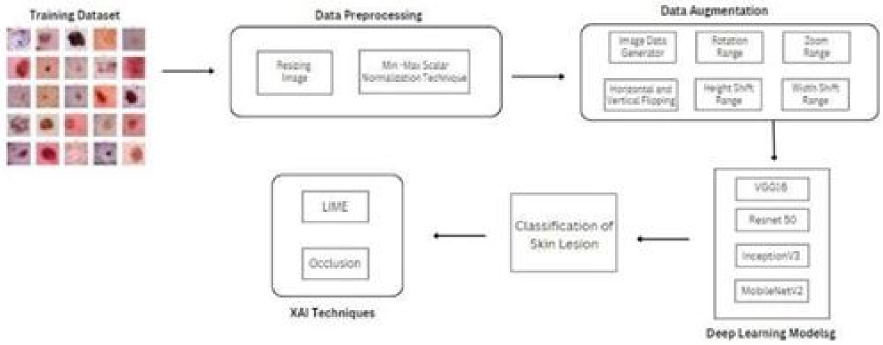

Figure. 1

The base model processes the input images as well as additional layers are added on top to customize the model for our dataset. Dropout layers (0.5) reduce overfitting, dense layers learn new patterns from the images. L2 regularization is used to avoid weight explosion and the ReLU activation function is used. Finally, the Softmax layer is used for multi-class classification.
The last few layers in the model are trainable to allow fine tuning.
The model uses a Stochastic Gradient Descent optimizer with a learning rate of 0.001. The categorial crossentropy loss function is used which is suitable of multi-class classification tasks. Model is trained for over 50 epochs with a batch size of 10. Validation is conducted at the end of each epoch using a separate validation set from the dataset.
The above steps are performed for each of the pre-trained models. Hence, 4 customized CNN models are obtained.

Interpretability with XAI Methodology
LIME refers to Local Interpretable Model-Agnostic Explanations.
For a specific image and its model prediction, LIME generates a set of slightly modified versions of the image (e.g., by applying small occlusions or colour changes in localized regions). It then queries the model to obtain predictions for these modified images.

LIME builds a simple interpretable model (often a linear model) that explains the relationship between the image features (presence or absence of modifications) and the model's predictions as shown in figure 4.1.
By analysing the coefficients of this interpretable model, LIME identifies the most important regions in the original image that influenced the model's decision.

Occlusion Sensitivity
The original image is divided into small grids.
For each grid cell, the corresponding region in the image is masked out (replaced with a constant value like black).
The occluded image is then passed through the model to obtain a new prediction.
The variation between the original prediction and the occlusion prediction is calculated.
Grid cells with a high difference in prediction scores indicate that the occluded region contained important features for the model's decision. Figure 4.2 pinpoints image areas crucial for classification.

IV. RESULTS

The performance of the model was evaluated using the categorical accuracy which is suitable for multi-class classification problems. The model's accuracy was tracked through both training as well as validation accuracy calculations. To refine the model, a learning rate annealing strategy was implemented known as the ReduceLROnPlateau callback. Whenever the validation accuracy plateaued for 3 consecutive epochs, the learning rate was reduced by a factor of 0.5. Instead of manually adjusting learning rates during training, this callback mechanism helps handle the learning rates automatically based on the model's performance. The minimum learning rate was set to 0.00001, so that it avoids learning rate to become excessively small, which can further hamper model performance.

A. Result Analysis

Table 4.1 states the performance metrics for various CNN architectures with highest accuracy of 99.91% achieved by VGG16 architecture.

TABLE I

Model	Accuracy
Resnet50	92.24%
InceptionV3	69.63%
MobileNetV2	87.66%
VGG16	99.91%

B. XAI Results

LIME

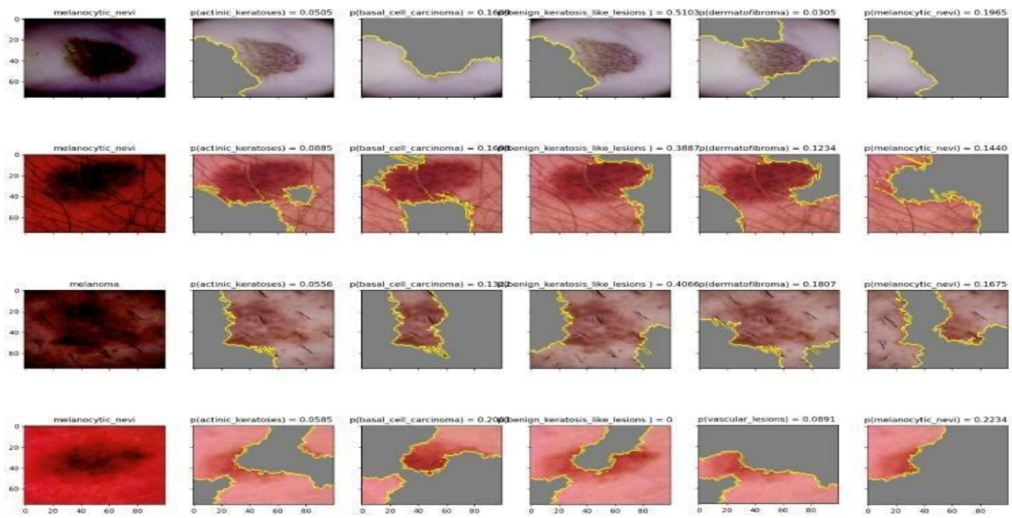

Figure 2

Occlusion Sensitivity

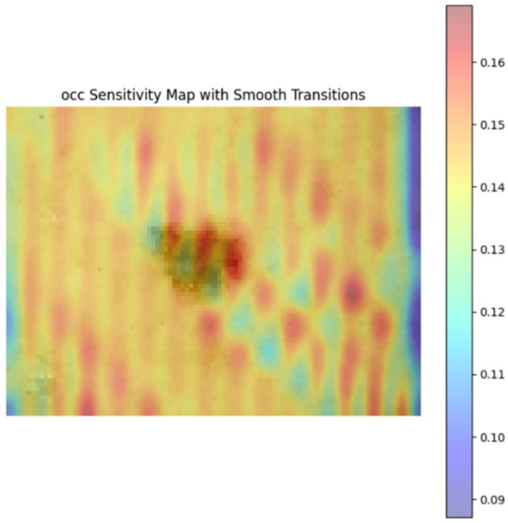

Figure 3

VI. Scope and Applications

The application of DL and XAI technique to the diagnosis and classification of skin has a lot of potential. Few uses and areas that require more research:

- Enhanced Diagnostic Accuracy: By combining XAI technique with present deep learning model development and refinement, diagnostic accuracy and dependability can be increased even further. Subsequent investigations could concentrate on creating ensemble models that integrate various techniques to enhance efficiency even more.
- Personalized medicine holds significant potential in customizing treatment strategies and diagnostics for skin cancer to individual patients based on their distinct characteristics, including skin type, genetic predisposition, and environmental factors. It is possible to develop deep learning algorithms to recognize minute differences in lesions and suggest tailored therapies.
- Remote Monitoring: Another application of this technology can be integration with smart wearables or even smartphones. This combination of deep learning-based models with wearable technology or smartphones can make remote monitoring of cancer lesions possible. This can be extremely beneficial in underserved or remote areas where the medical facilities are limited or unavailable. This will promote early diagnosis and intervention for cancer treatment. It enhances access to healthcare services in remote regions.
- Prognostication and Longitudinal Analysis: Deep learning models can also be used to identify the evolution of cancer lesions over time. The patterns and trends in cancer lesion evolution can help to determine the nature (malignant or benign) of the cancer lesions. The models can forecast the progression of the lesions, whether it is likely to worsen or not.
- Health system integration: The deep learning models can be integrated with electronic heath systems which will further improve diagnostic workflows and improve patient outcomes. This integration will help the adoption of AI-based tools in healthcare domain. Automation will reduce the manual intervention from doctors and improve physician productivity.

The research offers many opportunities for innovation and progression. There is scope for continued collaborations between researchers, clinicians, regulators and industry stakeholders to refine and fine-tune this technology-based cancer assessment to fully realize the potential of AI in the healthcare domain and enhance healthcare facilities.

VII. Conclusion

There is a great scope for combination of deep learning methods with XAI techniques. There has been a significant progress towards automating the identification of cancer lesions. This has improved the early diagnosis and detection of cancer among patients. The results of deep learning models are further understood and improved by the integration of XAI techniques. The comprehension of algorithmic decision-making process is improved. The combination has the power to completely transform the detection and categorization of skin cancer, leading to more precise, effective and easily available diagnostic instruments that eventually enhance patient outcomes and save lives.

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