# Explainable AI Framework for Precise and Trustworthy Skin Cancer Diagnosis

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Abstract: Skin cancer, most especially melanoma, is a recognized health issue across the world and its management depends on early and correct diagnosis.Conventional methods like biopsies are relatively precise and reliable but they are time consuming and invasive and may cause either an infection or an outbreak. Non-invasive procedures such as dermoscopy depend on the knowledge of the physician, which can cause variability and randomness. To address these challenges, we propose an explainable AI (XAI) framework for precise and trustworthy skin cancer diagnosis. Our model integrates VGG16, InceptionV3, Inception-ResNet V2 and DenseNet-201 deep learning architectures fine-tuned on the HAM10000 benchmark dataset to distinguish skin lesions as benign or malignant. To ensure transparency and trust in the model's predictions, we incorporate cutting-edge explainability techniques, including LIME (Local Interpretable Model-agnostic Explanations), SHAP (SHapley Additive exPlanations) and gradient-based methods like Grad-CAM. These tools highlight key image features and regions that influence model decisions. This proposed work deepens the knowledge in the field of using AI in the diagnosis of skin cancer and paves the way for integrating explainability into AI healthcare systems, improving accuracy and user trust.



## 1 INTRODUCTION

Skin Carcinoma is one of the most commonly diagnosed and eventually fatal types of cancer that continuously on the rise all over the world. Although deep learning models for more complex layers are, in fact, highly accurate for diagnosing skin cancer, clinicians often struggle to understand how models draw their conclusions, which is a major drawback of popular AI systems and existing approaches to skin cancer diagnosis (P. Linardatos and Kotsiantis, 2020),(Wang et al., 2021). To address this challenge, Explainable AI (XAI) approaches have been developed, which can be categorized as follows:

### 1.1 Function Based Approach

This approach focuses on understanding the inner workings of the model, such as its number of layers, parameters, and hyperparameters. Both saliency maps and feature importance are simple procedures that explain how features affect the output of a model. An example is **Grad-CAM** (Gradient-weighted Class Activation Mapping), which helps in visualizing which of the areas in an image contributes to a model's decision.

### 1.2 Result Based Approach

This approach gives explanations for specific predictions based on approximations of the complex model with models that are easier to understand. Techniques like **LIME** (Local Interpretable Model-agnostic Explanations) and **SHAP** (SHapley Additive exPlanations) are popular for breaking down individual predictions, offering insights into which features contributed to the outcome. For instance, **LIME** can be used to explain predictions in text classification tasks by generating interpretable models around a specific instance (K. Aas and Løland, 2021).

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### 1.3 Conceptual Based Approach

This approach looks forward to providing human interpretable representation based on high-level features or domain knowledge. For instance, the conceptual explanation in medical imaging can be best illustrated by the ability to depict images that contain ”tumor-like” structures or ”abnormal patterns”. This type of explanation is the most helpful in fields where domain knowledge is highly important.

### 1.4 Mixed Approach

The mixed approach combines elements from the above approaches to provide a comprehensive explanation. Using function-based, result-based, and conceptual explanations, this approach provides a better understanding of the choice of model decisions. For example, in complex tasks such as medical diagnosis, a mixed approach might combine **Grad-CAM** visualizations with **LIME**-based feature importance scores, making the behavior of the model more comprehensible and understandable to the human audience (Lundberg, 2017). Such approaches assist in explaining and verifying mainly used AI solutions in such critical areas such as medicine and self autonomous systems. The proposed work aims to expand the horizons of health care, utilizing current standard methodologies such as SHAP, LIME, and Grad-CAM while performing layer-wise analysis to assess and interpret CNN model decisions for skin cancer diagnosis. The goal is to make the decision process clearer to understand and easier to control since it provides quantitative and qualitative data of how each pixel or region impacts the decision making of the developed model.

### 1.5 Objectives

The schematic diagram of the proposed approach is shown in figure 1 with various objectives as follows.

i. Perform an exploration of diverse interpretability techniques and compare and contrast them according to their suitability to explain CNN decisions.

ii. Incorporate layer-wise analysis in the propagation of information through the network in an effort to isolate the level of participation of every layer in the final result of the model.

iii. Promote the interpretation of mammography diagnostic results in order to improve the level of trust of physicians and patients.

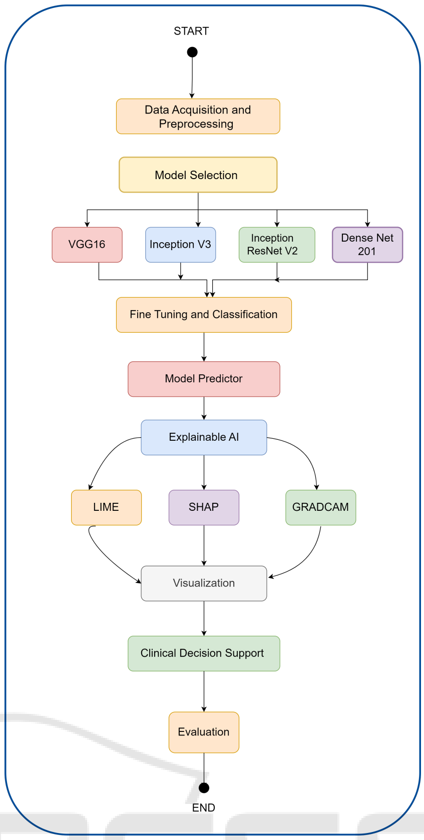



Figure 1: Schematic Diagram of the Proposed Model

## 2 RELATED WORKS OF XAI ON DIFFERENT APPLICATION DOMAINS

Partial Dependence (PD) plots are criticized for failing when it comes to interpreting black-box models with correlated predictors, which is why (Apley and Zhu, 2020) presented the Accumulated Local Effects (ALE) plots as more robust and less time- consuming. ALE plots do not exhibit extrapolation problems and are suggested as a standard tool for interpretability in supervised learning.

Machine learning models including SVM, DNN, and Random Forest were used by (P. Jain and Jain, 2024) to predict PCOS with 97% accuracy and used the two XAI strategies, namely LIME and SHAP to analyze key determinants of the disorder.

A recent study conducted by (K. Wei and Chen, 2022) implemented XAI in agricultural classification through the deep learning models of VGG, GoogLeNet, ResNet, in the fruit leaves dataset. During training the ResNet model, an accuracy of (99.11%, 99.4%, 99.89%) was achieved, and the attention module improved feature extraction from the input images and provided information about what as-

pect of the image the model is focusing on while classifying.
(H. Naeem and Ullah, 2022) proposed an AI-based explainable approach for malware detection using IoT devices using a fine-tuned Inception-v3 CNN model with transfer learning. By using color image malware display of Android Dalvik Executable File (DEX), the model achieved 98.5% accuracy in binary classification and 91% in multiclass prediction, surpassing other methods in various evaluation metrics.
(Molle et al., 2018) represented the dermatology case, where they observed that CNNs inspect features that are similar to those examined by dermatologists for skin lesions; however, more analysis is required for the interpretation of convolutional neural networks.
(J. M. Rozanec and Mladenic, 2022) proposed a Knowledge Graph-based XAI architecture that is used for demand forecasting with confidential high-level explanations and actions based on domain knowledge while preserving sensitive model details.
Four attribution methods were evaluated by (F. Eitel and the Alzheimer's Disease Neuroimaging Initiative (ADNI), 2019) for CNN-based Alzheimer's classification based on MRI data. It also clearly indicated that there are large fluctuations, while guided back-propagation and LRP yielded the most consistent values; so, it is necessary to use domain-specific criteria instead of a visual assessment of the maps.
(S. Pereira and Silva, 2018) introduced the idea of employing CNNs to detect the grade of glioma solely based on MRI data, thus avoiding the need for a biopsy. They assessed prognosis using whole brain and automatic tumor areas and used interpretability methods to guide the models to concentrate on the regions that are indicative of tumor grade.
(Mehta and Passi, 2022) used XAI for hate speech detection including pre-processing and exploratory analysis of datasets. LSTM achieved an accuracy of 97.6% on the Google Jigsaw dataset, while BERT variants (BERT + ANN: 93.55%, BERT + MLP: 93.67%) were evaluated for explainability using LIME and the ERASER (Evaluating Rationales and Saliency for Explanations in Reasoning) methods.
(S. Y. Lim and Lee, 2022) extended the XAI techniques of image classification to deepfake audio detection, providing an understanding of interpretability and explanation of model decisions involving variations of pitch and rhythm. The findings emphasized that the interpretability was consistent across environments and noted its divergence between human and model perceptions provided information to respond to the emerging problem of generative fake media.
(Kim and Joe, 2022) proposed an XAI approach for deep learning self-driving car models that maps image regions that have significant impacts on CNN decision making using sensitivity analysis. This increases reliability in conjunction with the application of the devices.
LSTM, Bi-LSTM, and Bi-GRU-LSTM-CNN models were employed by (A. Adak and Alamri, 2022) for sentiment analysis of FDS reviews with accuracy rates equal to 96.07%, 95.85%, and 96.33%, correspondingly. LSTM was chosen for false negatives as they are lower compared to the other. The two XAI methods that we used were SHAP and LIME; which provided explanations by isolating the words most influential to the sentiment of the models.

## 3 DATASET- SKIN CANCER MNIST (HAM10000)

The HAM10000 dataset (HAM, ) contains more than 10,000 dermatoscopic images of skin lesions, mainly melamonous to diagnose and categorize skin cancer. The dataset has seven different classes, namely: Melanocytic nevi, Melanoma, Benign keratosis similar lesions, Basal cell carcinoma, Actinic keratoses, Vascular lesions, and Dermatofibroma. This data set is relatively difficult in the development of models due to its applicability, especially due to the high imbalance of classes. In this regard, it plays a vital reference for a more accurate diagnosis of less common but potentially serious skin diseases.

## 4 DEEP CONVOLUTIONAL NEURAL NETWORKS (CNN) FOR IMAGE CLASSIFICATION

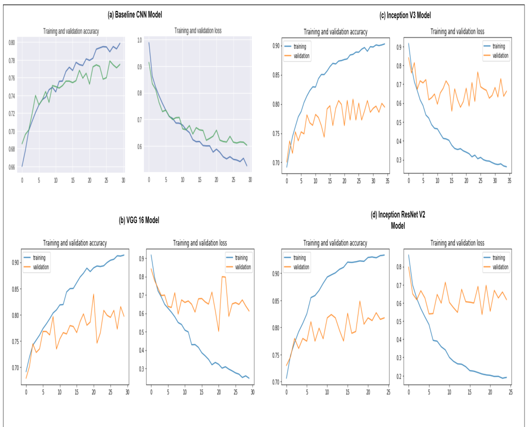
Deep CNNs are a well established deep learning architecture most applicable to image classification problems. Due to their capacity to learn about hierarchical features of items, Convolution Neural Networks are particularly useful in the skin cancer image classification task. In the initial layers model works with simple features or basic or low-level features such as edges or shapes, and as one passes through the network, the high-level or more abstract features are extracted in the latter layers and then the network is able to differentiate between the different types of skin cancer lesions.

### 4.1 Experimental Setup: Baseline and Pre-trained Models

The work proposed here incorporates both the baseline CNN and fine-tuned pre-trained deep models as described below:

1. **Baseline CNN:** This model acts as a benchmark for comparison. It uses only three convolution and pooling layers and has a basic structure in order to create a base for future models.
2. **Fine-tuned Pretrained Models:** Four pre-trained models – VGG16, Inception V3, Inception ResNet V2 and DenseNet 201, were applied to the HAM10000 skin cancer data set. These models were initially trained on a huge dataset like ImageNet, allowing them to extract/learn generic image features. The higher layers of these modnd.els were fine-tuned to the specialized task of skin lesion segmentation based on the HAM10000 dataset. This approach takes advantage of the existing knowledge of the pre-trained models but modifies them according to the classification problem at hand. Various models used are briefly described below-
   - **VGG16:** A well-known pre-trained deep model with a hierarchical convolutional pooling architecture. It is composed of five convolutional blocks, where third, fourth, and fifth blocks have four convolutional layers. This architecture enables the model to capture increasingly complicated features, making it highly effective for image classification tasks.
   - **Inception V3:** This top ImageNet model utilizes "Inception modules" to efficiently extract features. Specifically, it is a computationally efficient and effective framework for feature extraction.
   - **Inception ResNet V2:** The model is based on Inception V3 and combines residual connections to enable deeper networks training. Inception ResNet V2 also minimizes some possible issues of Batch Normalization.
   - **DenseNet 201:** This model comprises four "dense blocks", where each block generates feature maps through a series of operations (batch normalization, ReLU, and a 3x3 convolution). The layers between dense block are called transition layers which consist of convolution and pooling layers.

The figure 2 illustrates the training and validation accuracy and loss graphs for the above four models, providing a tabular summarization of various model performance during training.




| Model Training Observations Derived from above Accuracy and Loss Graphs | | | | | |
|---|---|---|---|---|---|
| **Model** | **Training Accuracy** | **Validation Accuracy** | **Training Loss** | **Validation Loss** | **Observations** |
| **Baseline** | High | < than Training | Decreasing | High | Overfitting, large gap between train and validation accuracy. |
| **VGG16** | High | < than Training | Decreasing | High | Similar to Baseline, indicating overfitting. |
| **Inception V3** | High | < than Training | Decreasing | Moderate | Moderate Performance, better than Baseline and VGG16. |
| **Inception ResNet V2** | High | < than Training | Decreasing | Low | Best performance among the models, with lower validation loss. |

Figure 2: Model Training Performance

## 5 EXPLAINABLE MACHINE LEARNING

Healthcare AI is still struggling mainly because it is hard to integrate something you cannot fully explain with AI-made decisions that require patient trust, model interpretability, and feedback for accurate and reliable results. In response to these challenges, most of the proposed works make use of CAM (Class Activation Mapping) methods that identify the areas in an image that a model uses to classify a given class, hence improving interactivity. Some CAM techniques (Zhou et al., 2015) also employ Global Average Pooling (GAP) or Global Max Pooling (GMP) to preserve spatial structures and detect discriminative areas, which improves decision-making and reliability in the healthcare domain. Although GMP analyzes the most significant section of an object, GAP can learn about and pinpoint the presence of a complete object. GAP helps better understand by including all discriminative factors in consideration. GAP considers all discriminative parts, ensuring a more comprehensive understanding. Therefore, GAP has higher accuracy than GMP in localization problems and is recommended for precise spatial localization in AI-based healthcare decision support systems.
Subsequent sections of this paper demonstrate the experiments performed with the help of explanatory methods such as LIME, SHAP, and Grad-CAM to analyze the outcomes provided by deep learning regarding the classification of skin cancer. These methods help to explain the model to justify the

kind of decision it made by pointing out features or regions in the input images that contribute mostly to the prediction and thus adds to reliability of the model.

## 6 LIME (LOCAL INTERPRETABLE MODEL-AGNOSTIC EXPLANATIONS) FOR EXPLAINING SKIN CANCER IMAGE INTERPRETATION

As experimented with skin cancer images, the LIME algorithm 1 offers a way to recognize which areas of an image are important for model decision. It does so by applying some transformations/perturbations to the input image (for example, deleting some superpixels) and comparing the changes to the output. LIME then fits a simple linear model – or Decision Tree – to mimic the behavior of the complicated deep model in the surroundings of the original image. Since this linear model involves learning coefficients, the super-pixels that have big contributions towards a prediction can be pinpointed, and how the model is making decisions can be revealed by overlaying the heat-map on the original image. Heatmap is a graphical data analysis tool in which data values are encoded as colors. It is popular for displaying the density of values on a matrix or a grid, where each cell will represent the value of the data point it contains.

**Algorithm 1** LIME Algorithm for Skin Cancer Image Predictions

Complex model $M$, skin lesion image $I$, predicted output class $y = \arg\max M(I)$. Feature importance and heatmap visualization.

**Step 1: Segment Image**
Divide $I$ into $k$ superpixels $\{S_1, S_2, \ldots, S_k\}$.
**Step 2: Generate Perturbed Images**
Create perturbed images by masking superpixels.
**Step 3: Get Predictions**
Pass each perturbed image through $M$ to obtain predictions.
**Step 4: Compute Weights**
Compute similarity between $I$ and perturbed images. Assign weights based on the similarity.
**Step 5: Train Model**
Fit a weighted linear regression model on the perturbed images.
**Step 6: Create Heatmap**
Assign model coefficients to superpixels. Visualize the heatmap highlighting regions influencing the prediction.

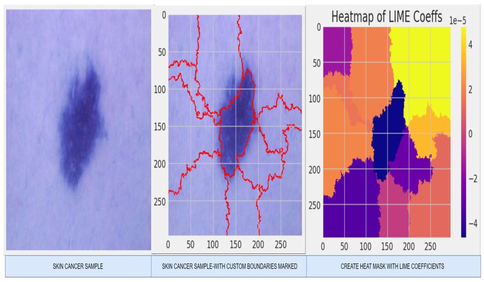



Figure 3: Visualizing Heatmaps for LIME

The image in figure 3 illustrates how different segments (superpixels) of an image contribute to the whole through the use of color. A positive coefficient value means that it has a direct proportional relationship with the prediction of the model, and regions that include brighter colors (like yellow) have a high positive coefficient. However, the negative coefficients are associated with the darker color, particularly the purple color to represent areas where it has a reducing impact on the confidence of the model. The right side of the figure presents a color bar that might help us to understand the values of the coefficients. Based on the intensity of the color depicted on the heatmap, the areas are delineated, which are most important for decision making in the chosen model with reference to the image.

## 7 SHAP ALGORITHM FOR SKIN CANCER IMAGE INTERPRETATION

SHAP (SHapley Additive exPlanations) values act as unified/global measure in that they provide a measure of how each feature contributes progressively to the model prediction across the given dataset. This theory comes from game theory, where there is an analysis of how each individual contributes differently to the team's outcome. Likewise, SHAP values explain how much each feature plays in the prediction of the model, giving an equal chance for each feature to contribute positively or negatively to the model across all permutations of features in a dataset as illustrated in algorithm 2. The color map on the right-hand side of figure 4 indicates the SHAP values. The blue regions correspond to negative SHAP values, while the red regions indicate positive SHAP values. The SHAP values are overlaid on the original image, highlighting the most important regions to make the prediction.

**Label: 1.0** corresponds to a malignant lesion with a probability of 56% malignancy. The SHAP visualization data reveal the fact that the model concen-

**Algorithm 2** SHAP Algorithm for Skin Cancer Image Predictions

Complex model $M$, skin lesion image $I$, background dataset $\mathcal{D}$. SHAP values for each pixel of $I$ and visualization.

**Step 1: Background Data**
Choose representative background images $\mathcal{D} = \{I_1, I_2, \ldots, I_m\}$.
**Step 2: Perturb Features**
Divide $I$ into $k$ superpixels $\{S_1, S_2, \ldots, S_k\}$.
Apply random binary masks to perturb the image.
**Step 3: Compute Predictions**
Generate samples by masking the background images and passing them through $M$.
**Step 4: Compute SHAP Values**
Calculate SHAP values for each superpixel. The formula calculates the average contribution of some feature $j$ by considering permutations of other features and measuring how adding $j$ changes the model's prediction
**Step 5: Aggregate SHAP Values**
Assign SHAP values to corresponding pixels in each superpixel.
**Step 6: Visualize SHAP**
Create a heatmap using SHAP values, with positive contributions in red and negative in blue.

trated on some peripheral regions illustrated by the red points to predict malignancy.

**Label: 0.0** corresponds to a benign lesion with 49% probability of malignancy. The SHAP visualization shows that the model considered multiple areas marked in blue (negative) and red (positive) across the lesion when making the prediction.

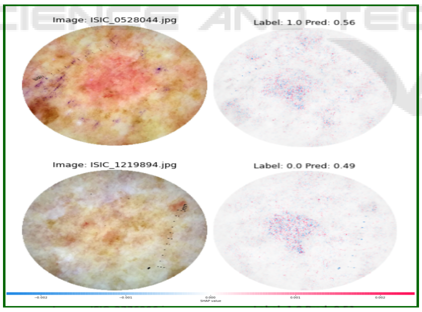



Figure 4: Visualizing Heatmaps for SHAP

## 8 GRAD-CAM ALGORITHM FOR SKIN CANCER IMAGE INTERPRETATION

Grad-CAM supports deep learning solutions in terms of interpretability, especially, in image classification problems that show tumor malignancy, as illustrated in the algorithm 3. It allows practitioners, such as radiologists or researchers, to:

- Ensure that the model targets areas that are of medical importance.
- Find any shortcut such that the model might pay a lot of attention to some part of the image which is of no importance.
- Understand the decision-making process, especially suitable in industries such as healthcare, where interpretability is essential.

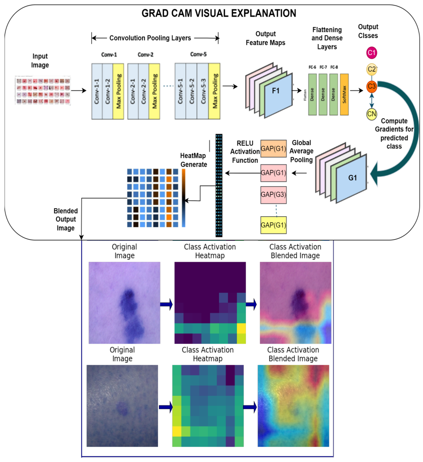



Figure 5: Visualizing Heatmaps for GRAD CAM

The figure 5 provides a step by step explanation of Grad-CAM applied to a skin cancer image as input, with overlaid heatmaps.

**Algorithm 3** Grad-CAM for Skin Cancer Image Predictions

Trained model $M$, image $I$, target class $c$, layer $L$. Grad-CAM heatmap.

**Step 1: Prediction**
Pass $I$ through $M$ to get the prediction $y_c = M(I)[c]$.
**Step 2: Gradients**
Compute $\frac{\partial y_c}{\partial A^k}$ for layer $L$.
**Step 3: Weight Feature Maps**
Calculate $\alpha^k = \frac{1}{Z}\sum_i \sum_j \frac{\partial y_c}{\partial A^k_{ij}}$.
**Step 4: Generate Heatmap**
Compute $H_{ij} = \text{ReLU}\left(\sum_k \alpha^k A^k_{ij}\right)$.
**Step 5: Rescale Heatmap**
Upsample $H_{ij}$ using bilinear interpolation to match the size of the input image $I$ . Scale $H_{ij}$ to the range $[0,1]$ for visualization.
**Step 6: Superimpose Heatmap** Overlay $H$ onto $I$ to visualize important regions.

## 9 RESULT

The graph in figure 6 represents the performance of the model on the Interpretation over Union (IoU) scale, which measures the overlap of the regions of importance highlighted by explainability methods and the actual areas of interest. X-axis shows the evaluated models and the Y-axis shows the IoU which reflects the accuracy to which the regions defined by the heatmaps correspond to the regions of interest. Values range from 0 to 1, where: 0: there is no overlap between predicted and true regions. 1: Perfect overlap. Grad-CAM, when compared to both LIME

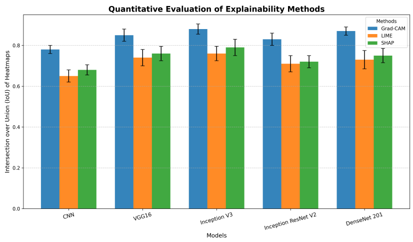



Figure 6: Comparison of IoU Scores for Explainable Methods: Grad-CAM, LIME, and SHAP

and SHAP, provides better results most of the time because of its capability to visualize model decisions. Some reasons for obtaining better results are:

1. Grad-CAM takes advantage of the overall channel-wise architecture of the CNN, which is designed to uncover spatial patterns at multiple levels of abstraction. Grad-CAM focuses particularly on the last layers of the convolutional neural network and explains what components of the input image are important for the model's prediction.

2. Grad-CAM emphasizes discriminative areas, such as lesions or patterns that are medicinally important.

3. Grad-CAM output consists of visual heatmaps that are easily understandable, as they indicate which areas influenced the model's decisions. These heatmaps provide excellent localization in certain parts of the image.

4. Unlike other models, Grad-CAM uses gradients of global feature maps, making it resistant to noise within the input image and resulting in accurate explanations.

5. LIME suffers from the limitation that it is effective at the local level but could be problematic when addressing the global context in image data.

6. SHAP is limited in that it can elicit the importance of features but does not provide spatial interpretations subsumed in the importance scores. Grad-CAM, however, demonstrates high accuracy in detecting spatial relevance.

## 10 SUMMARY OF USE CASES

By combining Grad-CAM, LIME, and SHAP, we achieve a comprehensive explainability framework:

- **Grad-CAM**are useful for achieving a more visual confirmation of the areas of .focus
- **LIME**could be used to explain generic decision-making behaviors.
- **SHAP** could be used to provide high-level pixel-level information and summarize important characteristics.

Such a combined strategy allows for the necessary balance between high-level interpretability and detailed analysis, which may be crucial in such fields as medical diagnostics, for example, skin cancer recognition.

## 11 CONCLUSION

The comparison of Grad-CAM with LIME and SHAP across models such as CNN, VGG16, Inception V3, Inception ResNet V2, and DenseNet 201 shows that Grad-CAM has better results in terms of IoU, demonstrating its ability to detect medically important zones. LIME and SHAP do not focus on regions similar to ground truths, while Grad-CAM concentrates on the class-discriminative areas and are useful for healthcare-related applications with high visual interpretability performance. Emerging architectures such as Vision Transformers (ViTs) and its evaluation on a more heterogeneous sample of medical imaging data could validate these findings. Applying domain knowledge and feedback from users also holds the prospect for enhancing usefulness of explainability methods in more important and significant applications.

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