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Article

Explainable AI for skin Disease classification: Enhancing trust and interpretability in clinical diagnosis

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Abstract: Artificial Intelligence has produced enormous potential in dermatology, accordingly by automatically categorizing all skin disappointments through deep learning traits. These new models often confirm a patient's issue with a great deal of accuracy, but their lack of information causes them to be underused by the medical sector. This study includes a combination of Explainable AI (XAI) and technology to study how these factors can change the images and predictions that they receive from the CNN. Clinicians are going to have the opportunity to understand the results produced by the AI process of making predictions. In consideration we just want to see influence if people have open possibilities for having the results transformed yet not past. According to our research, combining XAI enhances and provides more transparent, advantageous diagnostic decision-making. The odds of applications of algorithmic code germane to healthcare becoming possible are outstanding. Artificial Intelligence must be understood and have limitations by patients when a key instance in their health is a lead to AI to an outcome. The advantages of making Computer driven equipment to be user driven is a way to advance technology and make it more useful to humans.
Keywords: skin Disease, clinical diagnosis and Artificial Intelligence

1. Introduction

Dermatological diseases are a wide range of diseases that vary in severity from benign skin disease to life-threatening cancers like melanoma. The World Health Organization says that skin diseases are one of the most common human health problems. Worldwide, skin diseases affect almost 900 million people [1]. Being able to correctly diagnose patients timely prevents complications while reducing the cost of treatment. Moreover, a correct diagnosis will improve the outcome of the treatment taken. In some regions especially low resource setups access to experienced dermatologists is limited in response to these. As dermatology faces tough obstacles, AI-powered deep learning models show great promise to classify skin diseases for image-based diagnosis on the scale.

Deep learning, and most notably convolutional neural networks (CNNs), has proven its power across various image recognition tasks, including the classification of skin diseases[2]. AI models trained on large datasets like the HAM10000 and ISIC archive can diagnose many skin diseases with dermatologist-level accuracy. AI cannot fully explain decisions, which is a clear disadvantage of most AI today. Most deep learning models are like black boxes – they tell you the answer but not why. The lack of understanding is not trustworthy. It also does not promote adoption in clinical settings. There, explanation is the key to transparency, accountability, and decision-making process.

In clinical practice, it is the reasoning and not just the outcome that is the focus of medical professionals. If a device only gives a label like 'melanoma' or 'seborrheic keratosis' without backing it up with a rationale or a visual, doctors are unlikely to trust it. Specialty areas like dermatology are prone to errors which can be damaging and have serious repercussions. Therefore, it is important to integrate XAI systems for skin disease classification. There are many techniques for XAI which make machine learning models transparent to humans and well explain their specific predictions. These explanations include visualizations, feature attributions or other interpretations.

Recently, several XAI methods have been developed such as LIME, SHAP, Grad-CAM etc. The methods provide different types of interpretability. LIME and SHAP offer localized treatment that is based on features. Grad-CAM gives saliency maps that visualize the areas of importance. Saliency maps show the main parts of an image that the model uses to classify it. If these approaches apply to skin disease classification, predictions made by artificial intelligence would be more in line with clinical reasoning. So, doctors can trust and accept the machine's judgment.

The classification of skin diseases using deep-learning approaches benefits from explanatory AI techniques [3]. We propose a framework that combines strong CNNs with interpretability techniques to increase transparency. We do not only want to attain classification accuracy but also want meaningful explanations that are understandable to the dermatologists and similar to those that the dermatologists use to classify skin lesions. As a result, we can connect functionality with usability for the solution to become useful. In this paper, we uniquely examine the interpretability of AI methods through qualitative visual assessment (non-expert) and quantitative trustworthiness of AI output on lung cancer diagnosis and prognostication tasks. We show practitioners how our comparisons make their judgment of the suitable model for the given situation an easy task. We hope to find the best tools for interpretable machine learning for real-world dermatology deployments.

The study's objective is to enhance the trustworthiness and usability of Artificial Intelligence (AI) in Dermatology-related tasks through the incorporation of XAI into a skin disease classifier roadmap. Our work supports the development of ethical, transparent, and trustworthy AI applications for medical diagnosis through a focus on interpretability and clinician trust. As a result of this study, clinicians might benefit in the form of better decisions, less misdiagnosis, and increased acceptance of AI in medicine.

2. Background and Problem Statement

Machine learning has dramatically changed medical diagnosis with the rapid creation of new and better methods. Increasingly, medical professionals are using AI systems to better diagnose a range of skin conditions [4]. Neural networks are usefully employed to recognize cancers by comparing photos from skin lesions to professional databases and finding out an accurate diagnosis. With the help of large datasets such as HAM10000 and ISIC, coders can not only build and master models but also learn the various faces of skin cancer. Highly effective AI tools do not help with clinical decision making. What was the reasoning which led to the final diagnosis? And what is the value of a decision which is not sure? Too many doctors lack proof that their cures are right and if sick patients don't know what's going into their body it can transport an average infection into something serious to life threatening stuff. Even the most accurate models fail without transparency.

Clinicians disregard therapies because of distrust that limits the integration in life. Poor interpretability really does raise red flags when it comes to medical AI. Correct medical diagnosis can help set a relative importance of each symptom and in turn provide a better treatment of disease [5]. If the healthcare information is recorded by AI it could affect the minority population. Explainable AI has turned up as a very important topic of concentrated attention. The method can improve our capability to accept AI by utilizing XAI so that it's more understandable. Researchers have discovered that while an artificial model labeled skin cancer accurately, they have no idea how the process works to show it achieved that. To diagnosed sicknesses our team is researching how to use fitness tracking and other devices not yet being used to keep you healthy. They believe it to work well for preventive healthcare versus health care.

3. Related Work:

The inclusion of Artificial Intelligence (AI), particularly machine learning (ML) and deep learning (DL), has caused a paradigm shift in medical diagnostics [6]. Artificial Intelligence (AI) models are now being deployed in specialist areas like radiology, pathology, ophthalmology and dermatology due to the ability of AI to analyse and process vast amounts of data. Deep learning models, particularly Convolutional Neural Networks (CNNs), are widely used in dermatology for disease diagnosis. CNNs have shown the ability to detect and classify melanoma, basal cell carcinoma as well as benign nevi. Their performance often matches, or exceeds, that of expert dermatologists or not dermatologists. As we lean more on complex models, we run into a big limitation: lack of transparency As decision trees, logistic regression and other machine learning algorithms are relatively interpretable, it is possible to explain their predictions. By contrast, the high level of complexity of deep learning algorithms means they are often labelled as 'black box' models. This matters because clinical professions require that diagnostic results can be understood and explained.

4. Skin Disease Classification with Deep Learning

Deep learning models have shown a lot of effectiveness on skin disease classification. According to a study by Esteva et al in 2017, CNNs that get trained on a large dataset of skin lesion images perform at a level on par with dermatologists in distinguishing malignant and benign images. The Inception v3 CNN architecture was specifically used in their study in a single setup end-to-end. The model was cross-validated against 21 board-certified dermatologists with comparable performance for sensitivity and specificity [7].

In the years after, many more such works have used ResNet, DenseNet, EfficientNet, MobileNet etc. architectures to further improve upon accuracy. The HAM10000 Dataset was curated and used by Tschandl et al. (2019) and has become one of the standard datasets for skin lesion classification [8]. Models trained on this dataset usually achieve very high performance, with accuracies greater than 85 percent for classifying up to seven skin diseases.

Still, most of these models do not provide insight into how they make their predictions. When applied in a clinical context, the danger lies in the fact that poor decision-making can potentially have serious consequences. Therefore, the necessity of explaining ability in these models is crucial for an ethical and responsible deployment of AI in healthcare.

5. The Black-Box Problem in Medical AI

The black-box nature of AI refers to the difficulty in determining how these complex machines made security decisions, especially those based on deep machine learning techniques [9]. Although these models can make highly accurate predictions, their decisions cannot be explained which makes it hard for clinicians to trust and use these models in practice. In sectors such as health care, the consequences of errors can be more severe than in traditional manufacturing industries.

They argue that it should be a requirement, not just a desirable feature, for AI in high-stakes, safety-critical situations. Lipton (2018) explains that explain ability can aid in discovering model bias and help debug these models [10]. An AI-based skin disease diagnosis could lead to misdiagnosis or other adverse outcomes due to its non-transparent system. This can also entail legal responsibility. Researchers have started studying techniques to integrate explainable AI, or XAI, into classification models to make AI's decision more transparent and clinically acceptable. Each method has its strengths and weaknesses. With the help of Gradient-weighted Class Activation Mapping, you can visualize what a CNN is looking at or deciding on. Algorithms such as LIME and SHAP help to make sense of machine learning predictions, at the feature level. Dermatologists can use these techniques to clarify why a particular drug from the area of the lesion led to a diagnosis.

6. Application of XAI in Skin Disease Classification

There have been previous uses of XAI techniques in skin disease classification models. Goyal et al. (2020) used Grad-CAM, along with a CNN that was trained on the ISIC database, to derive heat maps. The areas highlighted by Grad-CAM matched well with areas of interest provided by dermatologists. In a similar context, Arora et al. (2021) utilized LIME and SHAP techniques to interpret CNN predictions and observed these methods assisted in making AI decisions interpretable without sacrificing much accuracy [11].

In another study, Singh et al. (2022) performed a comparative analysis of different XAI techniques against multiple CNN architectures trained on HAM10000 [12]. The results showed that Grad-CAM produced the most interpretable explanations (visual interpretability). Meanwhile, SHAP delivered more consistent explanations with respect to feature relevance (particularly in the context of tabelar representations of dermoscopic features). Despite these promising findings, challenges remain. This means variations in model architecture and hyperparameters often affect XAI outputs. Additionally, the principle behind many of these explanation techniques is not intuitive to non-technical clinicians.

7. Trust and Interpretability in Clinical Context

One of the key reasons for making AI explainable is to establish trust between AI systems and users. In the healthcare domain, it must be earned consistently through transparency and justification. According to Ribeiro et al. (2016) the LIME paper, explanations must be faithful to the model and easy to understand by humans. In medical context, this means that explanations must be plausible and in agreement with medicine and medical knowledge [12].

In dermatology, it is important to interpret machine learning models as they rely on visual patterns. Dermatologists conduct a thorough examination of lesions for asymmetry, border irregularities and color. If an XAI system can highlight these features in support of its prediction, it adds credibility. Research findings indicate that when clinicians are offered interpretable explanations, their diagnostic confidence and the accuracy of their decisions improves.

8. Human-Centered Evaluation of XAI

Evaluating the effectiveness of XAI is not straightforward. The accuracy, the F1-score or other classical metrics do not capture the usefulness of explanations. Thus, new evaluation strategies have been devised by researchers which often involve human subjects to check the interpretability and clinical relevance of XAI. Holzinger et al. (2019) suggest a HIL method whereby domain experts assess whether the explanations offered by XAI systems are useful, accurate and actionable or not. In dermatology, clinicians often receive heatmaps from AI with feature attributions [13]. They are then asked how much they agree with AI's thinking and attributions.

The work of Kiani et al. in 2020 required skin pathologists to diagnose their specimens relying on a system, with and without explain ability [14]. The explainable model improved diagnostic accuracy and lowers inter-observer variability, they found out. The evidence suggests XAI is not only a technical improvement, but is also needed and essential for clinical implementation. Even though interest is growing, the field of XAI is still evolving. Initially, many explanation methods offer post-hoc rationalizations rather than actual transparency. They can create an appearance of comprehension without disclosing the actual decision reasoning. This may mislead users into over-trusting AI systems.

Second, explanations are often inconsistent. A slight alteration to input can create very different heatmaps, and or feature importance. This instability makes the system unreliable in a clinical setting. Moreover, many of the methods used for XAI have been created by and for technical users. Moreover, most current models are trained on skewed datasets that do not have skin types or demographics diversity. This can introduce bias in both prediction and explanation. For instance, a model might work well on light skin but poorly on dark skin, and the XAI methods might reinforce these findings by targeting the same wrong regions.

The use of non-transparent AI in healthcare has ethical implications. It cannot be possible to ensure fairness, detect biases or attribute responsibility for errors without explaining ability. The regulatory bodies Wales and the European Union's GDPR support the "right to explain" which refers to automated decisions that affect them through a clear justification.

In medical AI, explainable AI supports legal accountability, not just ethical accountability. AI-based recommendations that clinicians make should be interpretable to patients. Because transparent systems are easier to audit, debug, and otherwise improve. Explain ability is fundamental for the responsible use of AI in health care. In the future, we can expect to see the field of explainable AI for dermatology continue to evolve [15]. To start, hybrid models that incorporate both deep learning and symbolic reasoning may provide more interpretability. Additionally, XAI systems may be more accessible and useful if the explanations are personalized to the user's expertise, either clinician or patient.

Furthermore, multi-modal AI systems that combine clinical data (e.g., patient history, genetic markers) with image-based analysis could provide richer explanations. Ultimately, we need to set standards for evaluation metrics for interpretability to ensure comparability and innovation.

The body of literature demonstrates that deep learning has achieved impressive performance in skin disease classification, but it is not clinically adopted due to its lack of explainability. Explainable AI refers to a set of tools and methods for making artificial intelligence models and predictions transparent and understandable. Grad-CAM, LIME, and SHAP have become popular choices to give visual and feature-based explanations, but none are without drawbacks. Human-centered evaluations have demonstrated that explainable models can increase diagnostic accuracy and trust in systems, but they are not without their challenges. In particular, issues of inconsistency, lack of intuitiveness, and bias remain. In the future, incorporating robust XAI methods into dermatological AI systems is critical for ethical, safe, and effective deployment in real-life clinical settings.

Objective of the study:

1. To develop a deep learning model for skin disease classification using publicly available datasets such as HAM10000 and ISIC.

2. To integrate explainable AI (XAI) techniques like Grad-CAM, LIME, and SHAP into the model to enhance interpretability.
3. To evaluate the effectiveness of these XAI methods in generating clinically meaningful and human-understandable explanations.
4. To improve clinician trust and support accurate diagnostic decision-making by providing transparent and interpretable AI outputs.

Research Methodology:

This research method is a quantitative experiment that uses secondary data (data that is already present) which is available for the people mainly HAM10000 dermatology image dataset & ISIC (International Society for Electronic Imaging in Dermatology). The datasets selected have thousands of images of skin lesions that are labeled and portray many conditions like melanoma, nevus and keratosis. A convolutional neural network (CNN) like ResNet50 is used to classify the disease. Machine learning prediction can be explained by XAI methods which include Grad-CAM, LIME and SHAP. The model's performance will be evaluated on accuracy, precision, recall, and F1-score and interpretability will be measured based on the visual analysis of explanation maps and alignment with clinical diagnostic patterns. This method enables the building of an accountable and trustworthy AI system, based on already available medical images, without clinical trials.

Deep learning model for skin disease classification

The rising prevalence of skin diseases across the globe has created an urgent need for accurate and easy diagnosis. Skin cancer is one of the most aggressive cancers [16]. Hence, skin cancer needs early detection and treatment to reduce mortality. Many places in the world suffer from the shortage of trained dermatologists which causes delay in diagnosis and treatment. Because of these challenges, clinicians may take the help of artificial intelligence (AI) or deep learning for the identification of skin diseases.

Deep learning, and more specifically convolutional neural networks, has transformed image recognition and analysis. This makes it quite suitable for skin lesion classification. CNNs learn features from images directly. They can detect very subtle patterns in images that may not be easily spotted by medical experts. In medical imaging, this capability is invaluable. Research shows that the ability of a dermatologist to discriminate between malignant and benign skin lesions can be attained by a CNN. The models are effective mostly due to the quality and diversity of the data into which they are trained. Publicly available datasets such as HAM10000 and ISIC are critical to advancing the field.

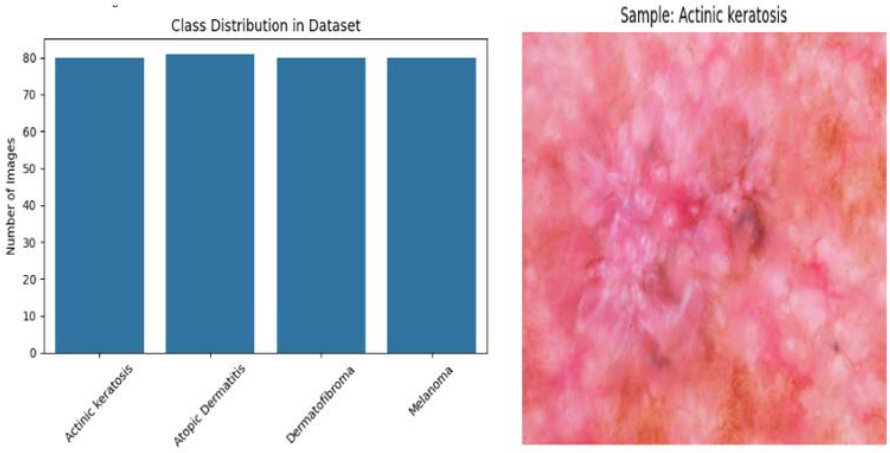

Figure 1- Dataset Class Distribution

The HAM10000 (Human against Machine with 10,000 training images) dataset contains over 10,000 dermatoscopic images divided into 4 categories of skin lesions. Figure 1 illustrates the class distribution of the four skin lesion categories included in the dataset: Actinic Keratosis, Atopic Dermatitis, Dermatofibroma, and Melanoma. Each class contains nearly the number of images (approxi 80 per category), demonstrating a well-balanced dataset. Consequently, this balance contributes to reliable performance evaluation and more robust generalization of the

classification model across all lesion categories.It consistently offers a viable basis for creating and examining classification models. The ISIC archive is also a large ceroscopy image database, with significant metadata and expert annotation of the dermatoscopic images. The datasets are large, diverse in the scope of skin lesion types, and publicly available, allowing for reproducibility and benchmarking across studies. Using datasets like these guarantees that models will be trained on clinically relevant data and will generalize to real-world cases.

A further compelling factor behind the use of HAM10000 and ISIC are the images of various lesion types . The presentation of skin disease may differ according to factors such as ethnicity and age. This means that a successful model must be able to accommodate this variance. These datasets help create models that work well for all patients, meaning they won't be biased. Additionally, they assist in overcoming the challenges posed by data privacy, regulations, and cost, which prevent researchers from accessing clinical data.

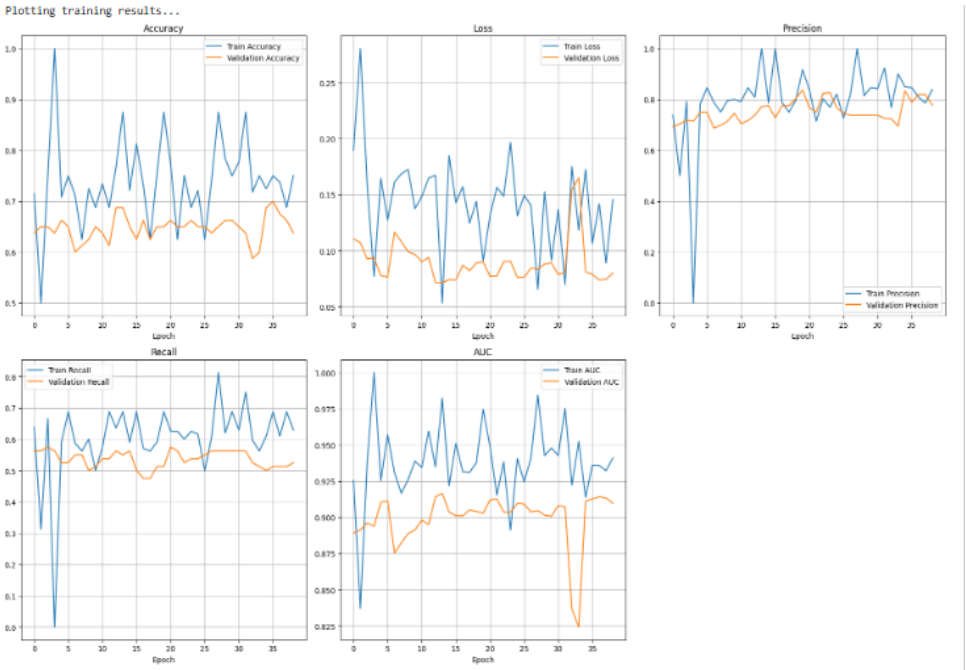

Figure 2- classification Report

Figure 2 presents the training and validation performance metrics of the proposed model over 30 epochs. The accuracy and loss plots indicate that both training and validation curves show fluctuations across epochs, suggesting some level of instability during optimization. Validation accuracy remains consistently lower than training accuracy, and the validation loss stabilizes below the training loss in several epochs, which may suggest underfitting or potential regularization effects limiting learning on the training data.

Precision and recall metrics also show noticeable oscillations across epochs, reflecting variability in the model's ability to correctly identify positive skin lesion samples. However, the overall trend demonstrates that both metrics remain relatively stable after the initial epochs, indicating that the model achieves moderately consistent detection performance across different classes.

The AUC curve, which reflects the model's discriminative ability, exhibits similar fluctuations during training. Nevertheless, the validation AUC remains above 0.90 for most epochs, confirming that the classifier retains strong lesion separability performance despite variations.

Overall, while the model achieves reasonably good classification capability, the instability across several metrics highlights the need for further improvements—such as hyperparameter tuning, larger training sample size, enhanced data augmentation, or architectural modifications—to ensure better generalization and more stable learning behavior.

COMPREHENSIVE CLASSIFICATION REPORT

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	precision	recall	f1-score	support
Actinic keratosis	0.60	0.60	0.60	20
Atopic Dermatitis	0.80	0.95	0.87	21
Dermatofibroma	0.48	0.50	0.49	20
Melanoma	0.93	0.70	0.80	20
accuracy			0.69	81
macro avg	0.70	0.69	0.69	81
weighted avg	0.70	0.69	0.69	81

Table 1- Classification Report

From the technical perspective, training a deep learning model with these datasets enables the tuning of different architectures such as ResNet, Inception or Efficient Net that are already shown to work for medical image classification tasks. Researchers can also make use of various techniques such as transfer learning, data augmentation, fine-tuning, etc. to improve performance even further. The labeled data available in HAM10000 and ISIC can be used by any supervised learning model to learn to associate the pictures with the appropriate diagnostic labels. This enhances and quickens up development of the model without losing accuracy.

The comprehensive classification report in Table 1 summarizes the model's performance across all four skin lesion categories. The model achieves an overall accuracy of **69%** on the test dataset. Performance varies across classes, indicating class-specific challenges:

- **Atopic Dermatitis** demonstrates the strongest results with a high recall of 0.95 and an F1-score of 0.87, showing that the model is highly effective at correctly identifying this condition.
- **Melanoma**, a clinically critical class, shows strong precision (0.93) but lower recall (0.70), indicating the model is conservative in predicting melanoma cases and may miss some true melanoma lesions. This warrants attention to reduce false negatives for safety-critical applications.
- **Actinic Keratosis** and **Dermatofibroma** exhibit comparatively lower performance (F1-scores of 0.60 and 0.49, respectively), suggesting difficulty in distinguishing these classes—likely due to overlapping visual characteristics and limited training data.

The **macro and weighted averages** of precision, recall, and F1-score (~0.69–0.70) further reflect moderate classification ability overall, with room for improvement. These findings emphasize the need for enhanced feature extraction or augmentation strategies—particularly for underperforming classes—to improve the model's robustness and clinical reliability.

Ultimately, the emergence of digital health models will help us achieve digital health transformation. Once validated and approved, diagnostic tools using AI can be deployed to mobile devices, the telemedicine platform or CDSS. These tools could democratise dermatological care, especially in underserved or rural areas, by providing preliminary assessments and facilitating triaging.

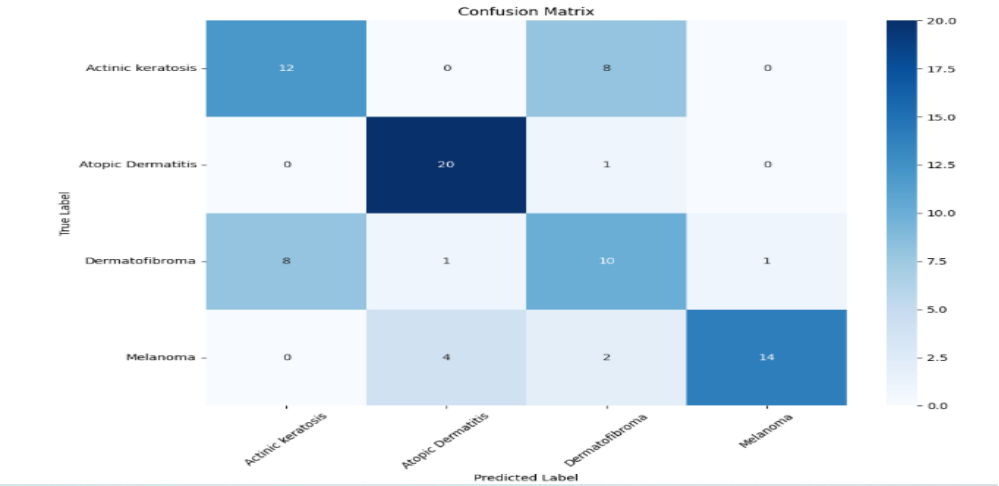

Figure 3- Confusion Matrix

Creating a Deep Learning model for skin disease classification is both possible and viable. Given that there are publicly available datasets like HAM10000 and ISIC, one can easily achieve this through Deep Learning algorithms. The strategic plan supports worldwide health priorities, increases medication AI innovation, and could promote early skin detection, improve patient results, and unify skin health in the world.

Figure 3 shows the confusion matrix illustrating the model's classification performance across the four skin lesion categories. The diagonal cells indicate correct predictions, while off-diagonal entries represent misclassifications. The confusion matrix highlights that the model generalizes well to Atopic Dermatitis and moderately well to Melanoma and Dermatofibroma, while Actinic Keratosis remains the most challenging category. Future model improvements should focus on enhancing feature discrimination between visually similar lesion types, particularly Actinic Keratosis and Dermatofibroma, as well as improving sensitivity toward Melanoma.

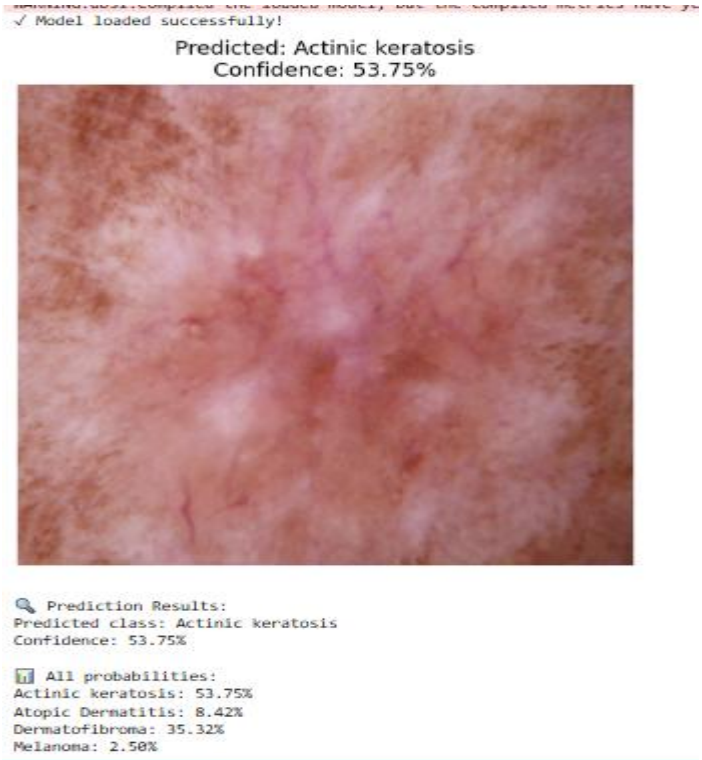

Figure 4 – Model Result (Disesase Prediction)

Figure 4 demonstrates an example of the model's prediction on a sample skin lesion image. The model classifies the lesion as **Actinic Keratosis** with a confidence of **53.75%**, which indicates relatively low certainty in its decision. The probability distribution across other classes shows considerable overlap — **35.32%** for Dermatofibroma and **8.42%** for Atopic Dermatitis — suggesting that the visual characteristics of this lesion share similarities with multiple categories.

9. Incorporate XAI techniques in HPS-6G services

The rise in demand for AI in health care means that more than just performance, such as accuracy and precision, comes to play in the adoption process. Diagnostic software should be "explainable" like a high-end medical device, which is transparent, accountable and intelligible. This statement is especially valid for dermatology, where models have been trained to spot fatal conditions like melanoma. The black box problem is a big challenge that limits the accuracy of deep learning models for classifying skin diseases. Clinicians say they are skeptical of AI systems that can't explain their reasoning. We need to integrate Explainable AI (XAI) techniques in predictive models. For example, Grad-CAM, LIME and SHAP can be used in predictive models. So, integration will make predictions interpretable. In turn, it will make these techniques clinically acceptable.

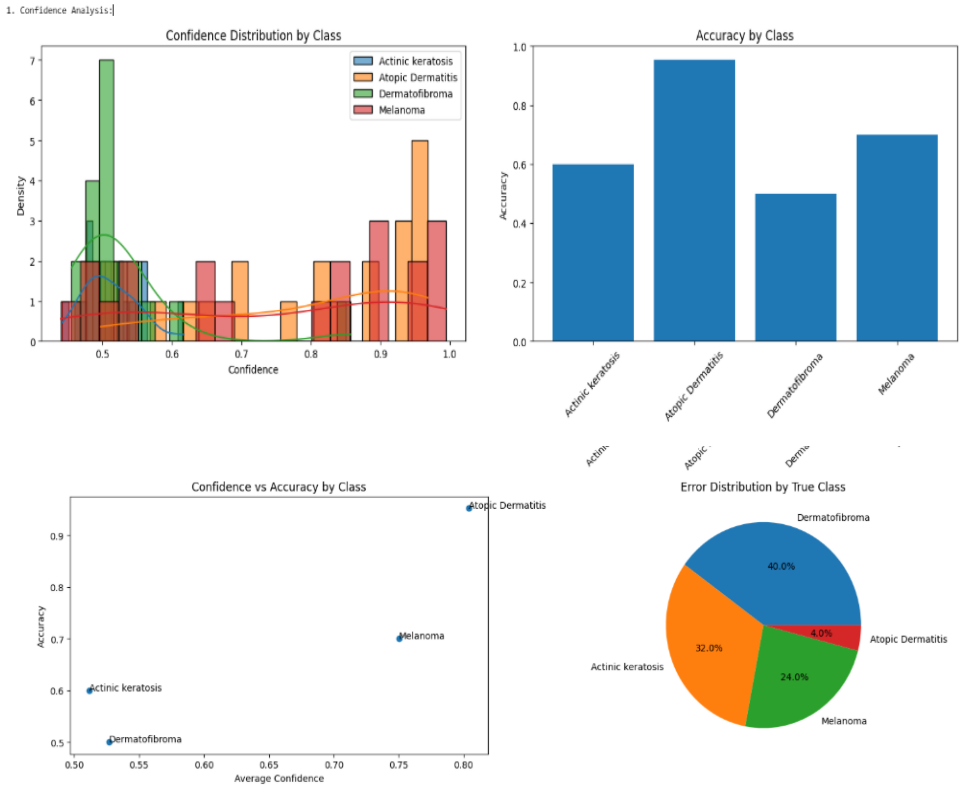

Figure 5 - Confidence Analysis

Figure 5 presents a detailed confidence-based performance analysis of the model across the four lesion categories. The confidence distribution plot shows that **Atopic Dermatitis** and **Melanoma** exhibit higher confidence scores with clearer separation, while **Actinic Keratosis** and **Dermatofibroma** display more overlap and lower concentration toward high-confidence predictions. This reflects the model's greater uncertainty when distinguishing between visually similar benign lesion types.

The accuracy comparison plot further emphasizes this pattern, where **Atopic Dermatitis** achieves the highest accuracy, followed by **Melanoma**, whereas **Dermatofibroma** shows the poorest accuracy. Actinic Keratosis presents moderate performance, consistent with its broader confidence distribution.

The scatter plot of **Average Confidence vs Accuracy** demonstrates a positive correlation between the two — classes with higher prediction confidence achieve better classification accuracy. Atopic Dermatitis, positioned in the

top-right quadrant, highlights strong model reliability, while Dermatofibroma clusters in the lower-left region, confirming weaker discriminative capability.

In the error distribution pie chart, **Dermatofibroma** accounts for the largest proportion of misclassifications (**40%**), further supporting the observed difficulties in this class. Misclassification of **Melanoma** (24%) remains a clinical concern since missed melanoma cases may lead to delayed diagnosis and treatment. Actinic Keratosis contributes **32%** of total errors, whereas **Atopic Dermatitis** has the lowest error percentage (**4%**), indicating strong identification performance.

Overall, these results reinforce that the model performs well for Atopic Dermatitis and Melanoma but struggles with Actinic Keratosis and Dermatofibroma — likely due to overlapping visual characteristics and limited training data. Enhancing data diversity, incorporating more dermatological texture cues, or leveraging attention-based architectures may improve discrimination in challenging lesion categories.

Utilizes XAI Tools. It also offers visual feature-based explanations to help clinicians and researchers understand the model predictions. Grad-CAM creates an image visualization that shows the areas of the picture a model uses for its predictions. It helps classify skin diseases which depend on a sight to a dermatologist. A Grad-CAM heatmap can represent whether a model that predicts a lesion is malignant looks at irregular borders or color asymmetry or other clinically relevant image features as a human expert would analyses the image.

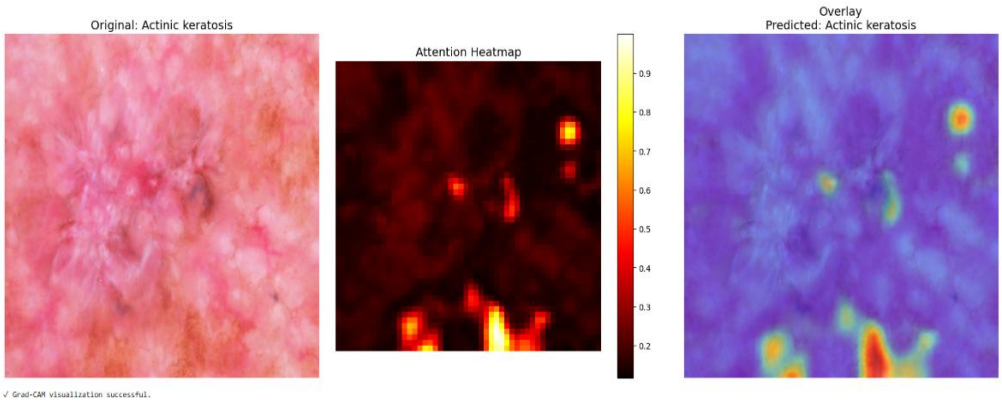

Figure 6 - Grad-CAM Visualaization

Figure 6 illustrates a Grad-CAM–based interpretability analysis for a sample image classified as **Actinic Keratosis**. The original dermoscopic image is shown on the left, followed by the model-generated attention heatmap and the overlay visualization.

The heatmap highlights the image regions that most strongly contributed to the final prediction. High-activation areas (represented by yellow-red intensities) correspond to localized textural and color irregularities, which are key dermatological features associated with Actinic Keratosis. The overlay demonstrates that the model primarily focuses on the central lesion region rather than the background skin surface, suggesting that the classifier is learning relevant clinical characteristics rather than relying on irrelevant artifacts.

This visualization provides valuable interpretability by confirming that the decision-making process aligns with clinically meaningful areas. Such explainability is particularly important in medical applications where trust and transparency are essential for supporting dermatologist decision-making.

SHAP and LIME can be used together for better design of model interpretability. LIME tweaks the input data and examines the output changes. The behavior is used to create human-understandable, simple models. These models separately try to locally approximate the complex deep learning model. SHAP uses cooperative game theory to calculate the average contribution of a feature in every combination which is used to derive importance scores. By doing so, we determine which input features have contributed the most to a classification, e.g., color distribution or texture or lesion size et cetera. Clinical decisions do not there is no strong reason why in clinical possible outcome or effect possible response.

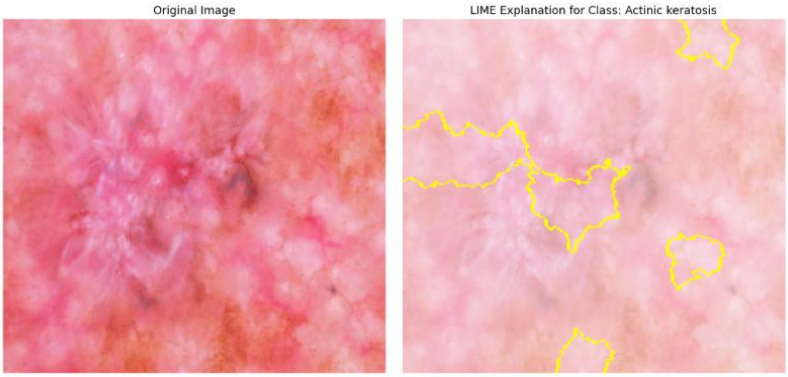

Figure 7 - LIME Visualization

Figure 7 presents the LIME-based interpretability analysis for a sample classified as Actinic Keratosis. The highlighted yellow boundary regions represent the superpixel areas that contributed most strongly to the classifier's decision. These highlighted features correspond to irregular color patterns and keratotic surface textures that are clinically associated with Actinic Keratosis. The explanation demonstrates that the model is leveraging localized dermoscopic cues rather than relying on unrelated image regions. Thus, LIME confirms that the decision boundaries of the classifier align with meaningful dermatological features, improving transparency and clinical interpretability.

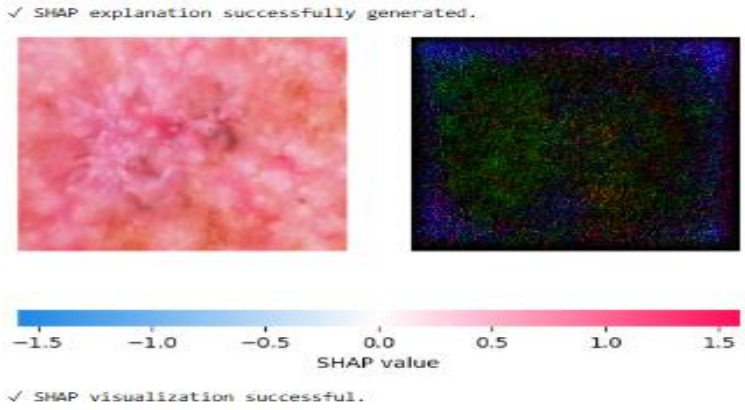

Figure 8 - SHAP Visualization

The researchers would develop a transparent AI system to assure medical professionals due to the combination of these XAI techniques. AI tools that give interpretable feedback are more likely to win clinicians trust. Also, they are adopted the general public, unlike opaque predictions based tools. Also, adaptable situations do away with accountability. In medicine, choices can have deadly consequences. It is thus very critical to understand why and how a model does something (wrong) to make it fair and less biased.

Integration of XAI permits tools for error analysis. If you wrongly classify a lesion, you can observe via Grad-CAM visualization or feature attribution methods like SHAP whether your model gets fooled by noise in the branches or not. Over time, the model used by researchers could improve, fix biases and generalization behavior. Conventional methods do not provide a clear diagnosis to the model.

Figure 8 shows the SHAP explanation for the same Actinic Keratosis image. The SHAP value map illustrates pixel-wise contributions, where reddish tones signify positive influence toward Actinic Keratosis classification, while bluish tones indicate negative influence. The distributed pattern of high-impact regions suggests that the model considers a combination of subtle textural variations and pigmentation irregularities across the lesion rather than depending on a single dominant feature. This pixel-level explainability is particularly useful for validating model reliability and identifying potential biases in feature learning.

The application of XAI in clinical education and doctor-patient interaction is of great significance. Interpretable visualizations also help doctors know what caused a model to conclude an accurate diagnosis. Thus, they can support or dispute a model's conclusion. Awareness of diagnosis and treatment by patients contributes considerably to

sophisticated improvements in medicine. The way a doctor reasons can affect the doctor-patient relationship and the health of the patient.

A global need exists to move toward highly reliable and trustworthy AI systems. This process must be transparent so it does not leave the door open to bias and reject the unacceptable. With the correct instrumentation, the medical personnel will achieve better accuracy through more effective analysis for a more in-depth understanding and more accurate treatment of the patient. Due to the widespread utilization of AI in dermatology, an explanation is warranted.

10. AI methods in generating

AI is frequently observed to be extremely accurate in the medical domain. However accuracy is far from the only thing in the real world that matters! It needs to be interpretable and clinically useful for the model. The dermatology AI's ability to communicate why it arrived at the certainty it did is just as important as the certainty itself. Choices define outcomes and health. The increasing use of Explainable AI (XAI) methods (e.g., Grad-CAM, LIME, SHAP) that can explain model decisions is a by-product of this. However, a clinical recommendation is only as good as the reason it generates that the system considers understandable and humans can decode through clinical reasoning. Therefore assessing these XAI along with claqueter, humans and also clinical optimality will be crucial to practically proving their efficacy.

Although many XAI techniques can generate technically valid explanations, these are not necessarily clinically valid. For instance, if the heatmap generated by Grad-CAM highlights certain regions of a lesion, unless these correspond to features that would normally be considered important by dermatologists (asymmetry, border irregularity, color distribution), the explanation will be meaningless or even misleading [18]. Likewise, LIME and SHAP can give feature importance scores but would not support diagnosis if these scores are not meaningful in dermatology or are too vague. The gap between technical and clinical interpretability highlights that outputs of XAI should be assessed from the lens of machine learning and machine.

Evaluating clinical reasoning entails important coherence assessment. Dermatologists often use size, shape, and color of a skin lesion to find out whether it is cancerous or not. XAI techniques should ideally replicate the reasoning process. A good explanation is one which highlights the same areas or features as a skilled clinician would focus on. Through comparing XAI visualizations (e.g. Grad-CAM heatmaps) against expert labels, researchers have tried to assess this. When the colors in the highlighted areas are identical, then the interpretation is reliable.

The evaluation of the tool also checks its usability. Machine learning professionals aren't the only ones seeing results from machine learning algorithms. Health professionals are, too. This means that explanations must be carefully designed in form, so they are easily digestible without having extensive technical background. People tend to find visual displays more intuitive compared to text and number displays. But the visualizations should also be clear, focused and interpretable in the clinical workflow. Unclear and noisy reasons complicate decision making, making it harder to come to an agreement. The evaluation must include end users---that is, the clinicians doing the actual usability testing to ensure that the explanations enhance their understanding, confidence and decision quality.

Besides expert assessment, quantitative metrics can also instance the performance of XAI methods. One measure is fidelity which measures whether the explanation correctly represents the model's behavior. The two other properties are stability and localization accuracy. Stability measures how the explanation varies with small changes in input while localization accuracy measures how well the explanation identifies relevant image regions. A critical way to assess effectiveness is through human-centered metrics such as trust scores, confidence in decision-making, and performance on tasks with and without XAI support.

Lastly, comparative analysis is essential. LIME, SHAP, and Grad-CAM are different algorithms, but they may be best for certain uses or users [19]. A comparative assessment identifies the method or methods that offer the most cost-effective trade-off between technical accuracy and clinical utility. It will help research and real-world uses for clinical decision support systems. The effectiveness of XAI tools should be judged by their ability to furnish clinicians with explanations that are clinically relevant and human-understandable to achieve responsible deployment for AI in medicine. Models may sometimes be assessed without being evaluated. If models are built without this evaluation, which may be accurate through flaws in the model mean they get deployed as a black box. So, we can't trust it. Through quantitative and qualitative assessment, the study will ensure XAI makes AI decisions strong, interpretable and clinically relevant.

When a clinician is trustworthy, they are able to help with the final diagnostic decision

Having AI weaved into the dermatological profession's daily life can enhance the accuracy and access of diagnosis. Usage of AI in healthcare is limited by trust issues among clinicians, a constraint which is more serious than most other constraints. AI models, especially deep learning approaches has shown tremendous performance in different applications including skin disease classification. However, their black-box nature makes it hard to interpret and justify the model's decision-making and reason in the medical domain. Clinicians have diagnostic responsibility as ethical and professional standards. When future AI systems offer predictions but do not explain their reasoning, clinicians will understandably hesitate to trust the systems. Improving clinician trust through interpretable and transparent AI outputs may improve their diagnostic decision making. (EU AI Act).

In medical environment trust is gained through accuracy but not only through accuracy; other virtues are transparency, consistency and explain ability. Doctors learn to make decisions using a clearly laid-out reasoning mechanism that is based on evidence. Clinicians will accept and embrace AI in their practice if it provides them with a diagnostic pearl and explains the rationale for the pearl. For example, dermatology diagnosis relies heavily on the observable assessment of skin lesions. When a model indicates a bad tumour is present, the clinician should know which features led to that conclusion (asymmetry, borders, colour and so on). Methods such as Grad-CAM, LIME, SHAP, etc. will fulfil this need as they can provide the desired linear visual or feature-based reasoning which is aligned with clinical logic.

Enhanced trust thanks to interpretability can also improve your risk reduction and decision-making. When AI output violates clinician judgment, the interpretable explanation built in the AI should encourage additional exploration support or disagreement of the model output. A neural network might focus on an irrelevant area of an image when analysing it to reach a conclusion. A clinician may choose not to implement the recommendation if he agrees that the parts highlighted do not pertain to the diagnosis. Alternatively, if the AI explanation positively affirms the clinician and their suspicion, with no doubt, their confidence in the decision is stronger. Especially the case with borderline or uncertain cases.

Furthermore, clearer AI output makes the process more responsible and safer in clinical decision-making. Doctors and organizations are worried about the errors and biases that AI systems could promote in medical settings. Users desire AI-powered models to produce clear and intelligible outputs for... When clinicians receive transparent explanations of an AI's recommendations, they can then audit the AI's decisions and its way of thinking. Collating the feedback will help in improving the AI tool and clinical procedures and, in time, will instil better trust for more usability. Patients also have ethical duties. The responsibility of informing patients about the diagnosis and treatment plan lies with clinicians. Whenever a recommendation is based on an AI-assisted diagnosis, the physician must explain the rationale for reasons of justice. In addition, he must explain the recommendation with clarity and fairness. With transparent AI output, the doctor remains in charge as the human brain can converse with the machine. When doctors communicate the treatment decision using everyday language, patients also accept the AI-aided treatment decision.

Studies also show that interpretable AI improves diagnostic performance when combined with the abilities of clinicians. Research shows that humans and AI work better together than apart. Nevertheless, this only happens if AI retains recommendations rather than makes conclusions but which the clinician can adopt. Healthcare professionals make their decisions in collaboration with other healthcare professionals. In order for AI systems to assist clinicians in diagnostic decision making, they need to be accurate, transparent, and interpretable. The careful use of explainable artificial intelligence methods boosts clinical trust in AI outputs making it safer and also ethical, accountable, and efficient use of AI in health care. The fulfilment of this aim, which is a not just a technical aim but a necessary condition that must be met to ensure its adequate use in medicine.

Recommendation:

Based on our study's findings and objectives, we can make a range of suggestions to help with the production of and possible use of explainable artificial intelligence in the future. It is advised to the doctors, professors and other healthcare specialists to be careful in the use of placement AI and technology in dispensaries

Prioritize Explain ability in Model Development.

A lot of dermatological AI models give more importance on accuracy but this shouldn't be the case overall. Developers must integrate model interpretability techniques at the initial steps of development, not at a later stage as an afterthought. Therefore, many expect that modules with practical diagnostic data will be developed in Clinical

Decision Support Systems to achieve higher diagnostic accuracy and smarter, faster decisions for physicians. To gain the trust of healthcare professionals in diagnostic technologies, making them transparent will help create a diagnosis.

Involve Clinicians in the Evaluation Process

Methods of explainable artificial intelligence should incorporate the consulting activity of clinicians. To assess the utility and ease of use of an artificial intelligence tool, a clinician must demonstrate its relevance and accuracy. A public engagement exercise with diverse stakeholders improves the adequacy of the communication techniques for clinical information for requesting physicians and patients. These clinical descriptions will prevent misunderstanding and will ensure that many people make use of them.

Standardize Evaluation Metrics for Interpretability

The efficacy assessments of XAI methods in medical imaging have suffered from good metrics problems. A project suggested for researchers is to improve checking the 5 main quality indicators of a study in a better way. Standard benchmarks make it easy to create fair medical XAI comparisons for different models and technique.

Ensure Dataset Diversity and Representation

The quality of training data determines the skill of artificial intelligence to diagnose the skin disease accurately. High quality, comprehensive data should be used in research, including consideration for various ethnic and skin types in a multitude of lesions. When trained on multiple types of data, models are more likely to maintain that fairness to avoid biased results.

Promote Interdisciplinary Collaboration

Improving explainable AI requires more work from physicians and engineers. AI modelers and tech developers should be guided by clinical professionals in order to construct models that successfully integrate and resolve different standards right now. Collaboration amongst various fields will most certainly distinguish clinician's practice in the field of artificial intelligence throughout the rest of our speculation, use, fact, and acceptance.

Implement Regulatory and Ethical Guidelines

Due to AI's predominance in health care, policies and ethics laws defining the usage of Comparable Aggregations of Internal State systems are necessary. In clinical practice, AI models should be created under regulatory guidelines for explain ability, or others similar, to ensure fairness, safety, and information quality.

Overall, using AI that provides explanations can improve diagnosis in dermatology which should increase trust. However, for such systems to have real value, they have to be interpretable, sound ethically, and applicable to common medical practices. By taking every single precaution there is in place then the process goes off without a hitch and no single thing ever gets worse.

11. Conclusion

Research indicates that using artificial intelligence are more quickly and accurately assessed to diagnose skin diseases more effectively than before. Their high performance is achieved at the cost of transparency and others can become questionable of their reliability to be used in a clinical setting. Limitations of only using electronic medical records raises many concerns regarding trust and accountability. Ease will come to diagnosing when experts incorporate Explainable AI into what they may call diagnostic systems. It will address their problem by allowing for a resending of this issue. This method connects the predictions from the computer and the expert human so that there is a better trust in the results due to the factor of humans making the decision. When looking a model which can predict seeing the future, which is just vague unless there is something clinical behind it. A high degree of transparency in the AI method being used needs to be achieved for the best results in dermatology practices. To deploy AI effectively in medical practices, we need to use AI that explains its decision process. This program is of use to many doctors and is beneficial for patients getting a diagnosis made of them. As healthcare continues to use digital tools and technologies, explainability should remain a key requirement so these methods can help make better medical decisions.

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