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XAI-SKIN: An Approaches for the Diagnosis and Classification of Skin Diseases based on LIME Method

Alkeshkumar. B. Vaghela[1], Nileshkumar K. Patel[2], Reenaben K . Panchal[3] , Kishor H. Bamniya[4], Hemalkumar. R.Patel[5]
[1]Department of Electronics and Communication
Email : alkeshvaghela1@gmail.com
Institute : Government Engineering College Dahod -389151 gujarat india
[2]Department of Electronics and Communication
Email : nilesh06bec075@gmail.com
Institute : Government Engineering College College Godhra -389001 gujarat india
[3]Department of Electronics and Communication
Email : rkp.gec@gmail.com
Institute: L D college of Engineering , Ahmedabad, Gujarat, India
[4]Department of Electronics and Communication
Email : bamniya.kishor@gmail.com
Institute : Government Engineering College College Godhra -389001 Gujarat, India
[5]Department of Electronics and Communication
Email : hemal239803@gmail.com
Institute : Government Engineering College Dahod -389151 Gujarat,India

Abstract: Nowadays, it is challenging to make an accurate diagnosis of skin conditions. Precision in diagnosis is essential for improved prognosis and illness control. Skin cancer is one of the most prevalent cancers worldwide, and its rising incidence rates are posing a significant challenge to healthcare systems. Precise diagnosis and early detection are essential for both patient outcomes and effective therapy. Individuals and the healthcare system are severely impacted by the misdiagnoses. However, because skin illnesses are complicated and include a wide variety of symptoms and subjective interpretation, dermatologists have more challenges in identifying them. In order to prevent unnecessary procedures, provide appropriate care, and save healthcare resources, it becomes more challenging to precisely define critical attributes. Skin cancer may be successfully identified from a lesion picture using deep learning. its practical use is constrained by the lack of justification for its conclusions. Explainable AI (XAI) approaches specifically designed for skin disease diagnosis are used to train the AI models on skin disease data sets. In order to help physicians comprehend AI-driven diagnoses and foster confidence and collaboration with AI diagnostic tools, we provide them transparency and interpretability. ResNet50V2, VGG16, InceptionV3, and InceptionResNetV2 are the four pre-trained models that have been used. Due to the uncertainty of these models, this work also attempts to use Explainable Artificial Intelligence, which is based on Local Interpretable Model-Agnostic Explanation (LIME) , to explain the predictions of these models.

Keywords: Cancers, Explainable AI, Healthcare Systems, LIME, Melanoma, Skin cancer

INTRODUCTION:

As scientists and medical professionals work to comprehend the complexity of many skin disorders, dermatology has made tremendous strides in recent years. Millions of individuals worldwide suffer from skin disorders, which significantly influence their physical and overall well-being. The skin controls body temperature, acts as a sensory organ, and shields internal organs from germs [1]. Making deep learning models employed in decision-making systems interpretable is a major difficulty in vital situations such as medical diagnostics. To tackle this problem, Explainable Artificial Intelligence (XAI) research is under progress. However, a lot of XAI techniques are tested on generic classifiers and don't work well for difficult, practical problems like medical diagnosis. Because skin illnesses are so common, this helps with informed decision-making and enhances the diagnostic process overall [2]. Accurate diagnosis is essential. As a result, this work offers developments in ML and XAI to reduce mistakes and enhance the results of dermatological diagnostics. This partnership between technologists and dermatologists shows how important it is to improve the precision, efficacy, and efficiency of diagnosing skin diseases in order to improve patient outcomes and healthcare delivery [3].

Since saliency maps are a common way of providing explanation for image classifiers, the burgeoning area of Explainable AI (XAI) has attracted a lot of interest [4]. A pixel-by-pixel understanding of the decision-making process is provided by these maps, which graphically depict each pixel's contribution to the model's conclusion. Though saliency maps may be created in a variety of ways, their lack of clarity in urgent medical circumstances is a common criticism [5]. There are several different ways to provide explanations. They may be categorized as either global or local, denoting whether the explanation applies to the entire model or to particular predictions, or as model-specific or model-agnostic, depending on how much they rely on the inner workings of the AI model [6].

Literature Review: The field of disease detection has been significantly influenced by the blending of advanced deep learning techniques. which hold promise for significant improvements in diagnostic performance and accuracy. The table 1 provides the details regarding previous work done on AI-driven skin cancer detection. Chiu et al. (2025) proposed a novel two-stage AI ensemble methodology to improve the diagnostic precision of skin cancer detection, focusing on reducing false negatives for malignant lesions. The research utilized two datasets: the ISIC dataset and the CSMU Hospital (CSMUH) dataset. Eight pre-trained deep learning models were trained on these datasets, with the top three models selected to create an ensemble. The two-stage classification strategy was designed to first classify skin lesions broadly and then refine the classification to ensure more accurate detection of malignant cases. This approach effectively minimized the risk of false negatives, a critical factor in ensuring early and accurate melanoma diagnosis. The results demonstrated significant improvements in diagnostic accuracy. For the ISIC dataset, false negative classifications for malignant lesions were reduced from 124 to 45 cases, highlighting the robustness of the two-stage approach. The CSMUH dataset achieved an outstanding milestone of zero false negatives. The ensemble model also enhanced overall diagnostic precision for both melanoma and non-melanoma cases, demonstrating its clinical viability in diverse settings. Nguyen et al. (2025) conducted a comprehensive comparative study of machine learning (ML) models for automated skin cancer detection, emphasizing the performance of convolutional neural networks (CNNs). The research aimed to assess the effectiveness of various ML algorithms, including CNNs, Support Vector Machines (SVMs), and Random Forests, using preprocessing techniques and diverse datasets to ensure model robustness and generalizability. The study found that CNNs outperformed other models, achieving the highest accuracy (92.5%), sensitivity (91.8%), and specificity (93.1%). These results highlight CNNs' superior ability to extract complex features from dermoscopic images and differentiate between malignant and benign lesions. In comparison, SVMs and Random Forests delivered comparatively lower performance metrics, demonstrating their limitations in handling the complexities of image-based dermatological data. authors have also identified key challenges in automated skin cancer detection. Dataset diversity emerged as a limitation, as the models struggled with underrepresented skin tones and lesion types. Additionally, the study noted the need for improved model interpretability to foster trust and usability in clinical settings. Sajid et al. (2025) explored advanced convolutional neural network (CNN) approaches for improving melanoma detection, leveraging data augmentation techniques to address challenges in image diversity and model generalization. Using the HAM10000 dataset, the researchers applied augmentation strategies such as random flips, cropping, Gaussian blur, and other transformations to enhance training data variability and reduce overfitting. To refine the model's performance, ablation studies were conducted, systematically adjusting key parameters to identify optimal configurations. The study reported a remarkable improvement in melanoma detection, achieving an accuracy of 93.43%, sensitivity of 99.74%, and specificity of 88.53%. These metrics surpassed existing benchmarks, particularly in sensitivity, demonstrating the model's effectiveness in identifying malignant melanoma cases while minimizing false negatives. Oluwasegun et al. (2025) focused on enhancing skin cancer diagnostic systems by employing advanced image processing and classification techniques. To address challenges arising from imbalanced datasets, the researchers implemented data augmentation strategies, ensuring equitable representation across classes and improving the reliability of model training. The study utilized feature extraction methods, including Gray-Level Co-occurrence Matrix (GLCM) and

Color Histogram, to capture crucial textural and color attributes from dermoscopic images. These features were then classified using a Random Forest algorithm, chosen for its robustness and ability to handle complex datasets. The optimized approach achieved an impressive accuracy of 97%, highlighting the efficacy of balanced datasets and advanced feature extraction in artificial intelligence (AI)-based diagnostic systems. This work underscores the critical role of preprocessing and feature engineering in improving model performance and operational efficiency in healthcare. Oluwasegun et al.'s findings offer valuable insights for integrating AI into dermatological diagnostics, ultimately contributing to more accurate and accessible skin cancer detection. Shafik (2025) conducted a comprehensive review of machine learning (ML) techniques and their applications in early skin cancer diagnosis and automation. The study highlighted advancements in artificial intelligence (AI)-based diagnostic systems, showcasing their ability to enhance accuracy, reduce subjectivity, and streamline clinical workflows. The review emphasized the role of AI in addressing common diagnostic challenges, such as inter-observer variability and resource constraints, particularly in underserved regions. By automating key processes, AI has the potential to standardize diagnostics and improve accessibility to high-quality care. They have also identified ongoing challenges, including the need for diverse datasets, improved interpretability of ML models, and strategies for seamless integration into clinical settings. Despite these hurdles, the study underscored the transformative potential of AI in revolutionizing skin cancer care, paving the way for more accurate, efficient, and accessible diagnostic systems. Abou Ali et al. (2024) focused on achieving precise skin cancer classification across eight categories by leveraging advanced deep learning techniques and a novel data augmentation method, dubbed "Naturalize." The study utilized the ISIC2019 dataset, incorporating Naturalize augmentation, which involved the use of the Segment Anything Model and composite image generation to enhance dataset diversity and model robustness. The results were remarkable: the approach achieved perfect performance across all metrics, including 100% accuracy, precision, recall, and F1-score, when applied to the Naturalized 7.2K ISIC2019 dataset. The evaluation process involved confusion matrices and Score-CAM visualizations, which provided detailed insights into model predictions and decision-making processes. This work demonstrated the transformative potential of AI in dermatology, particularly in the context of skin cancer classification. The integration of innovative augmentation techniques alongside deep learning architectures highlights a significant leap toward achieving high-quality, automated diagnostic tools for dermatology.

Claret et al. (2024) study explores the integration of discrete wavelet transformation (DWT) with convolutional neural networks (CNNs) to improve skin cancer diagnosis. DWT was employed for feature extraction from lesion images, leveraging its ability to capture spatial and frequency domain information. The extracted features were fed into CNNs for classification. Comparative analysis was conducted against artificial neural networks (ANNs) and multilayer perceptron (MLP) models to assess performance. Using the HAM10000 dataset, the proposed approach achieved a sensitivity of 94% and a specificity of 91%, outperforming traditional methods. This research demonstrates the potential of combining advanced signal processing techniques with deep learning for enhanced diagnostic accuracy in dermatology. Kaushik et al. (2024) study presents a cutting-edge approach to achieving dermatologist-grade skin cancer classification by fine-tuning the GoogleNet Inception v3 CNN. Leveraging a large and diverse dataset of 135,550 images spanning 2,055 categories, the researchers introduced an innovative algorithm tailored for precise classification. The model's performance underscores its ability to deliver dermatologist-level accuracy in detecting skin cancer. The findings highlight the transformative potential of this approach in public health, particularly in regions with high skin cancer prevalence. By offering a reliable and scalable diagnostic solution, the study contributes to advancing AI's role in addressing global healthcare challenges. Ramoliya et al. (2024)proposed a novel Explainable AI (X-AI) framework designed for skin cancer detection in telesurgery applications. The system leverages advanced Convolutional Neural Network (CNN) architectures, combining ResNet and MobileNet for robust feature extraction. To address the critical need for interpretability in AI-driven healthcare, the study integrates X-AI techniques such as Local Interpretable Model-agnostic Explanations (LIME) and Integrated Gradient (IG). The X-CaD framework offers enhanced diagnostic precision by providing interpretable heatmap outputs, enabling clinicians to understand and trust the model's decision-making process. The system demonstrated reliable performance through observed loss and accuracy metrics, showcasing its potential to improve telesurgical outcomes for skin cancer diagnosis. Sudharson et al. study introduces Dermatec, an advanced AI-powered platform designed for monitoring chronic skin conditions and enhancing dermatologist recommendations. The platform integrates a state-of-the-art Convolutional Neural Network (CNN) for precise skin condition analysis and a novel Siamese neural network for efficient image comparison, enabling autonomous monitoring and recovery assessment. Dermatec achieved an impressive accuracy of 99.8%, significantly improving diagnostic precision and treatment recommendations. By empowering dermatology practices with advanced AI capabilities, the platform represents a transformative step in chronic skin condition management and research, highlighting its potential to revolutionize patient care and dermatology diagnostics. Reddy et al. (2024)study presents an innovative AI-based model for accurately differentiating benign and malignant skin lesions. Leveraging Google's collaboration platform, the model was trained on a representative dataset, emphasizing a cost-effective and environmentally sustainable approach. The AI model achieved notable performance metrics, including 92% accuracy, precision, recall, specificity, and F1 score. These results underscore the model's efficiency in skin lesion classification, demonstrating its potential as a reliable and accessible diagnostic tool. The research highlights the importance of scalable, eco-friendly AI solutions in advancing dermatopathology and improving patient outcomes. Manisarma et al. study emphasizes the critical importance of early detection in preventing the progression of skin cancer, particularly melanoma and benign cancers. The research provides an overview of current hardware and software developments, focusing on the application of Convolutional Neural Networks (CNNs) for accurate diagnosis. While quantitative results were not presented, the study underscores early detection's life-saving potential and highlights the growing role of CNNs in improving diagnostic accuracy. The findings advocate for continued advancements in AI-based tools to enhance clinical outcomes in dermatology. Ravindar et al. study presents a novel integration of Artificial Intelligence (AI) with Internet of Things (IoT)-connected dermascopes for real-time data collection and analysis. By leveraging AI-powered computer vision, the system demonstrated high diagnostic accuracy, reduced diagnostic times, and adaptability to diverse clinical scenarios. The findings underline the transformative potential of AI and IoT in revolutionizing early skin cancer detection and improving patient outcomes. Reddy et al. address challenges in melanoma detection using a comprehensive AI framework. The approach integrates Generative Adversarial Networks (GAN) for data augmentation, Bidirectional Long Short-Term Memory (Bi-LSTM) networks for sequence analysis, and the African Vulture Optimization Algorithm (AVOA) for optimal feature selection. This innovative methodology achieved 98.5% accuracy, effectively overcoming data imbalance and overfitting issues, marking a significant step forward in skin cancer diagnosis. Thepade et al. study evaluates various Deep Convolutional Neural Network (DCNN) models, including DenseNet121, VGG19, Xception, and ResNet50, for melanoma detection. DenseNet121 paired with the Random Forest classifier achieved the best performance metrics, although accuracy varied across models. The research highlights the model-specific advantages of DCNNs, underscoring the importance of tailored approaches in AI-based dermatological diagnostics.Mayanja et al. emphasize the importance of diagnostic accuracy and interpretability in dermatology. The study applies machine learning (ML) integrated with Explainable AI (XAI) techniques on diverse datasets to enhance model transparency. The results demonstrated improved diagnostic outcomes, reduced errors, and strengthened collaboration between clinicians and AI tools, showcasing XAI's role in building trust and reliability in AI-driven dermatology.

Table 1: Previous work done on AI-driven skin cancer detection

Reference	Objective	Methodology	Results
Chiu et al. (2025) [7]	Enhance skin cancer diagnosis using a two-stage AI ensemble approach.	Used ISIC and CSMU datasets, trained eight pre-trained models, and combined the top three in an ensemble. Implemented a two-stage classification strategy for reduced false negatives.	Reduced false negatives for malignant lesions: ISIC dataset dropped from 124 to 45 misclassifications; CSMUH dataset achieved zero false negatives. Enhanced diagnostic precision for melanoma and non-melanoma cases.
Nguyen et al. (2025) [8]	Compare ML models for automated skin cancer detection and highlight CNN performance.	Applied preprocessing techniques and diverse datasets for model robustness. Evaluated CNNs, SVMs, and Random Forest algorithms.	CNNs achieved the best results: 92.5% accuracy, 91.8% sensitivity, 93.1% specificity. Identified limitations like dataset diversity and model interpretability.
Sajid et al. (2025) [9]	Improve melanoma detection using CNNs with data augmentation techniques.	Used data augmentation (random flips, cropping, Gaussian blur, etc.) on the HAM10000 dataset. Conducted ablation studies to refine model parameters.	Achieved 93.43% accuracy, 99.74% sensitivity, and 88.53% specificity. Surpassed existing performance for melanoma detection.
Oluwasegun et al. (2025) [10]	Optimize healthcare operations by enhancing skin cancer diagnosis with advanced image processing and classification.	Applied data augmentation to balance datasets. Extracted features using GLCM and Color Histogram, classified using Random Forest.	Achieved 97% accuracy. Demonstrated the importance of balanced data and feature extraction in AI-based diagnosis.
Shafik (2025) [11]	Explore ML techniques for early skin cancer diagnosis and automation.	Reviewed advancements in AI-based diagnosis. Highlighted challenges and opportunities in automation.	Highlighted AI's role in reducing subjectivity and resource dependence in diagnostics. Emphasized the transformative potential of AI in skin cancer care.
Abou Ali et al. (2024) [12]	Achieve precise eight-class skin cancer classification using deep learning and "Naturalize" augmentation.	Used ISIC2019 dataset with Naturalize augmentation (Segment Anything Model and composite image generation). Evaluated using confusion matrices and Score-CAM visualizations.	Achieved 100% accuracy, precision, recall, and F1-score with the Naturalized 7.2K ISIC2019 dataset. Demonstrated transformative AI capabilities in dermatology.

Claret et al. (2024) [13]	Enhance skin cancer diagnosis by combining CNNs and discrete wavelet transformation (DWT).	Applied DWT for feature extraction from lesion images, trained CNNs, and compared performance with ANN and multilayer perceptron models.	Achieved sensitivity of 94% and specificity of 91% using the HAM10000 dataset. Demonstrated improved accuracy over traditional methods.
Kaushik et al. (2024) [14]	Achieve dermatologist-grade skin cancer classification using GoogleNet Inception v3 CNN.	Fine-tuned CNN with a large, diverse dataset (135,550 images) organized into 2,055 categories. Introduced an innovative algorithm for precise classification.	Achieved dermatologist-level accuracy in skin cancer detection. Highlighted potential public health impact, especially in regions with high skin cancer prevalence.
[15] Ramoliya et al., 2024	Develop X-CaD, an Explainable AI (X-AI) for skin cancer detection in telesurgery.	Combined ResNet and MobileNet for CNN-based feature extraction; X-AI techniques (LIME and IG) for model interpretability.	Enhanced skin cancer diagnosis with interpretable heatmap outputs, achieving reliable loss and accuracy metrics.
[16] Sudharson et al., 2024	Create Dermatec for monitoring chronic skin conditions and dermatologist recommendations.	Used CNN and a novel Siamese network for precise analysis and image comparison.	Achieved 99.8% accuracy, improving diagnostic accuracy and empowering dermatology practices.
[17] Reddy et al., 2024	Distinguish benign from malignant skin lesions using AI.	Trained AI model using Google's collaboration platform and a dataset of benign/malignant cases.	Model achieved 92% accuracy, precision, recall, specificity, and F1 score. Highlighted a cost-effective, carbon-neutral approach.
[18] Manisarma et al.	Diagnose skin cancer early to prevent progression.	Overview of hardware/software developments for melanoma and benign cancer diagnosis using CNNs.	Stressed early detection as crucial for saving lives but lacked quantitative results.
[19] Ravindar et al., 2023	Combine AI and IoT-connected dermascopes for early skin cancer detection.	Integrated real-time data collection with AI-powered computer vision.	Demonstrated high accuracy, shorter diagnostic times, and applicability in clinical scenarios.
[20] Reddy et al., 2023	Enhance skin cancer detection with AI.	Used GAN for data generation, Bi-LSTM for sequence analysis, and African Vulture Optimization Algorithm for feature selection.	Achieved 98.5% accuracy in detecting melanoma. Overcame data imbalance and overfitting issues.

[21] Thepade et al., 2023	Evaluate DCNN models for melanoma detection.	Compared DenseNet121, VGG19, Xception, and ResNet50 with ML classifiers.	DenseNet121 with Random Forest performed best; accuracy varied across models, emphasizing model-specific advantages.
[22] Mayanja et al., 2023	Enhance diagnostic accuracy and transparency in dermatology using Explainable AI.	Applied ML with XAI techniques to diverse datasets for better interpretability.	Improved diagnostic outcomes, reducing errors and enhancing clinician-AI collaboration.

Proposed work:

The proposed methodology for developing an Explainable AI (XAI) model for skin lesion classification is caried out in four different steps:

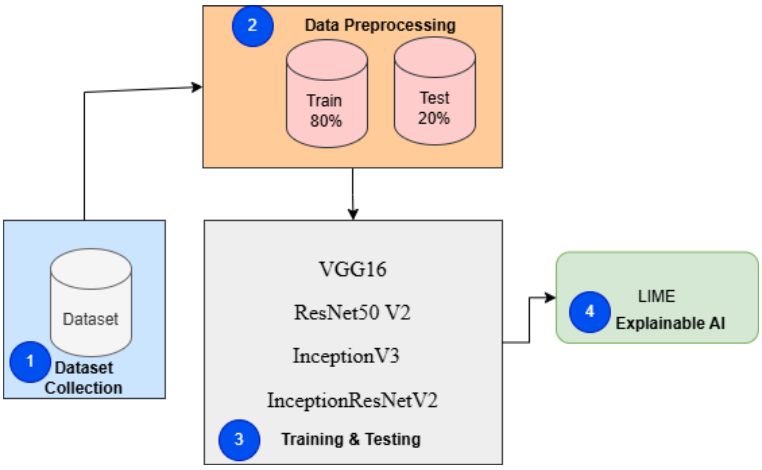

Figure 2: Block diagram of proposed methodology

1. **Dataset Collection:** The first step involves collecting a comprehensive dataset of skin lesion images. This dataset is crucial for training and evaluating the different models. Using the data set, a total of 646 skin lesion images were first gathered from seven separate sources. Of those pictures, 207 were from SJS, 250 were from EM, and the remaining 189 were from BP. The information gathered from the seven websites is displayed in Table 2. These originally gathered images underwent cropping and background removal, producing a hybrid dataset of 657 images. In addition, a JPEG format conversion was performed on every image in the collection. This dataset will be released to the public after the required processes are finished. It contain a diverse set of images representing various types of skin lesions, ensuring the model can generalize well across different cases.

Table 2: Detail description of Dataset collected from different websites

Site Name	SJS	EM	BP	Total
Dermnet NZ	116	28	47	191
DermIS	51	20	72	143
Global Skin Atlas	24	92	24	140
Dermatology Atlas	0	52	41	93
Dermnet	0	55	0	55
SJS Awareness UK	16	0	0	16
University of IOWA Health Care	0	3	5	8

2. Data Preprocessing: Once the dataset is collected, it undergoes preprocessing to prepare it for training and testing. This involves splitting the dataset into two subsets: 80% for training and 20% for testing.

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Preprocessing steps may include resizing images, normalization, augmentation, and other techniques to enhance the quality and diversity of the data, thereby improving the model's performance.

3. Training and Testing: The preprocessed data is then used to train multiple deep learning models are employed:

VGG16: VGG16, developed in 2014. VGG16's straightforward design, relying heavily on small convolution filters, makes it easy to implement and extend. Despite its relatively simple structure compared to more recent architectures, VGG16 achieves high accuracy on various image classification benchmarks. This model is widely used not only for image classification but also for feature extraction and transfer learning in various computer vision tasks. Its ability to learn intricate features and patterns from images has made VGG16 a foundational model in the development of more advanced deep learning architectures.

ResNet50 V2: ResNet50V2, developed by Microsoft Research in 2016, is an enhanced version of the original ResNet. ResNet50V2 consists of 50 layers, including convolutional and identity blocks, organized to enable deep learning without degradation in performance. The key innovation is the use of residual blocks, which incorporate skip connections allowing gradients to bypass certain layers, facilitating the training of much deeper networks.

The architecture of ResNet50V2 also includes bottleneck layers, which reduce the number of parameters while maintaining network depth by using a series of 1x1 convolutions followed by 3x3 convolutions. This design makes the model both deep and efficient. Batch normalization is another crucial element, applied after every convolutional layer and before activation functions, which improves convergence and stability during training. These features collectively enhance the model's ability to learn complex patterns from images.

ResNet50V2 is particularly effective for image recognition, object detection, and semantic segmentation, where deep and efficient models are required. Its robust architecture allows it to achieve high accuracy across various benchmarks and datasets. The residual learning framework not only enables the construction of very deep networks but also serves as a foundation for further advancements in network design, influencing subsequent deep learning models and research.

InceptionV3: InceptionV3, developed by Google in 2015. This model builds on the ideas introduced in earlier Inception models, enhancing both performance and efficiency. InceptionV3 features a complex architecture composed of various inception modules that apply multiple convolution filters of different sizes. This multi-scale approach granularity, making it highly effective at identifying diverse patterns within images.

One of the key innovations of InceptionV3 is the use of dimensionality reduction through 1x1 convolutions, which significantly reduces the computational cost without sacrificing model accuracy. Additionally, the model employs asymmetric convolutions, such as breaking down a 7x7 convolution into two smaller convolutions (e.g., 1x7 followed by 7x1), further enhancing computational efficiency. This approach not only reduces the number of parameters but also speeds up the training process.

Another important feature of InceptionV3 is the inclusion of auxiliary classifiers. These are smaller networks attached to intermediate layers of the main network. By providing additional gradient signals, auxiliary classifiers ensure that gradients propagate more effectively through the network, leading to better performance.

InceptionV3 has demonstrated remarkable results on various image classification benchmarks and is widely used for transfer learning and feature extraction in numerous computer vision tasks. Its sophisticated architecture, combining multiple convolutional filters and efficient design principles, has set a new standard in the field and continues to influence the development of subsequent deep learning models.

InceptionResNetV2: InceptionResNetV2, introduced by Google in 2016, represents a sophisticated blend of two powerful deep learning architectures: Inception and ResNet. This model combines the multi-scale feature extraction capabilities of Inception modules with the gradient-stabilizing benefits of residual connections. The result is a highly efficient and accurate architecture for image classification and other computer vision tasks. InceptionResNetV2 builds upon the inception modules, which apply multiple convolution filters of different sizes (e.g., 1x1, 3x3, 5x5) in parallel within the same layer. This approach captures a wide range of features from the input images at different scales, enhancing the model's ability to detect intricate patterns. By integrating residual connections, the model facilitates the flow of gradients through deeper layers, effectively addressing the vanishing gradient problem that can hinder the training of very deep networks. One of the critical aspects of InceptionResNetV2 is the use of inception-residual blocks. These blocks combine the inception module's multi-scale processing with shortcut connections from ResNet, allowing gradients to bypass certain layers and thus maintain robust gradient propagation. This hybrid design enables the model to achieve greater depth and complexity without the training difficulties typically associated with very deep networks. InceptionResNetV2 also employs techniques such as dimensionality reduction through 1x1 convolutions and the use of batch normalization. These techniques reduce the number of parameters and improve training stability and convergence. Additionally, asymmetric convolutions (e.g., breaking down a 7x7 convolution into 1x7 followed by 7x1) are utilized to enhance computational efficiency. The combination of these advanced techniques allows InceptionResNetV2 to excel in a variety of computer vision applications, from image classification to more complex tasks like object detection and segmentation. Its ability to learn and generalize from large datasets makes it a popular choice for both academic research and practical applications in industry. InceptionResNetV2's innovative architecture continues to influence the development of new models, underscoring its significance in the evolution of deep learning.

4. EXPLAINABLE AI WITH LIME

This step involves generating visual and textual explanations for the model's predictions, helping clinicians understand the rationale behind the decisions and increasing the transparency of the AI system. to improve confidence in deep learning models' predictions and overcome their opaque character. Utilizing an interpretable model to approximate the model locally, the XAI methodology LIME clarifies individual predictions.

The process of generating LIME explanations involves several steps:

Instance Selection: For each input image that we want to explain, LIME selects a single instance for detailed analysis.

Perturbation: LIME creates a dataset of perturbed samples by making slight modifications to the selected instance. These perturbations might include slight changes in pixel values or regions of the image.

Model Prediction: The deep learning model makes predictions on each of the perturbed samples. These predictions help in understanding how the model's output changes with variations in the input.

Local Model Training: LIME trains a simple, interpretable model on the perturbed samples and their corresponding predictions. The behavior of the complicated model close to the chosen instance is approximated by this local model.

Feature Importance: The weights or coefficients of the local model indicate the importance of different features (or regions of the image) in making the prediction.

Result Analysis:

The provided Figure 3 display the training and validation loss curves for four different deep learning models over 300 epochs. The models being evaluated are likely VGG16, ResNet50 V2, InceptionV3, and InceptionResNetV2, as mentioned in the proposed methodology. The analysis of these results helps to understand how well each model is performing and converging during training and validation.

(a) Training and Validation Loss for Model 1

The training and validation losses for the first model are displayed in graph (a). The model is successfully learning from the training data when the training loss continuously drops and stabilizes. Nonetheless, the validation loss exhibits considerable fluctuations and stays very high over the epochs, indicating a possibility of overfitting. This indicates that although the model works effectively with training data, it has trouble generalizing to new data.

(b) Training and Validation Loss for Model 2

Effective learning is seen in graph (b), where the training loss once more declines and stabilizes at a low value. Better generalization is shown by a smaller validation loss and reduced volatility when compared to model 1. In comparison to the first model, this one appears to be more resilient and less prone to overfitting.

(c) Training and Validation Loss for Model 3

The training and validation loss for the third model is shown in Graph (c). Like the earlier versions, the training loss drops and stabilizes. Though it is somewhat better than model 1, the validation loss is larger and more variable than in model 2. This points to a mild case of overfitting, in which the model functions OK but might need further regularization strategies or data.

(d) Training and Validation Loss for Model 4

The loss curves for the fourth model are displayed in Graph (d). Effective learning is indicated by a decreasing and steady training loss. With minor oscillations and a low validation loss, the validation capabilities are excellently shown. This model seems to strike a good mix between validation and training performance, which suggests it could be the best of the four models tested.

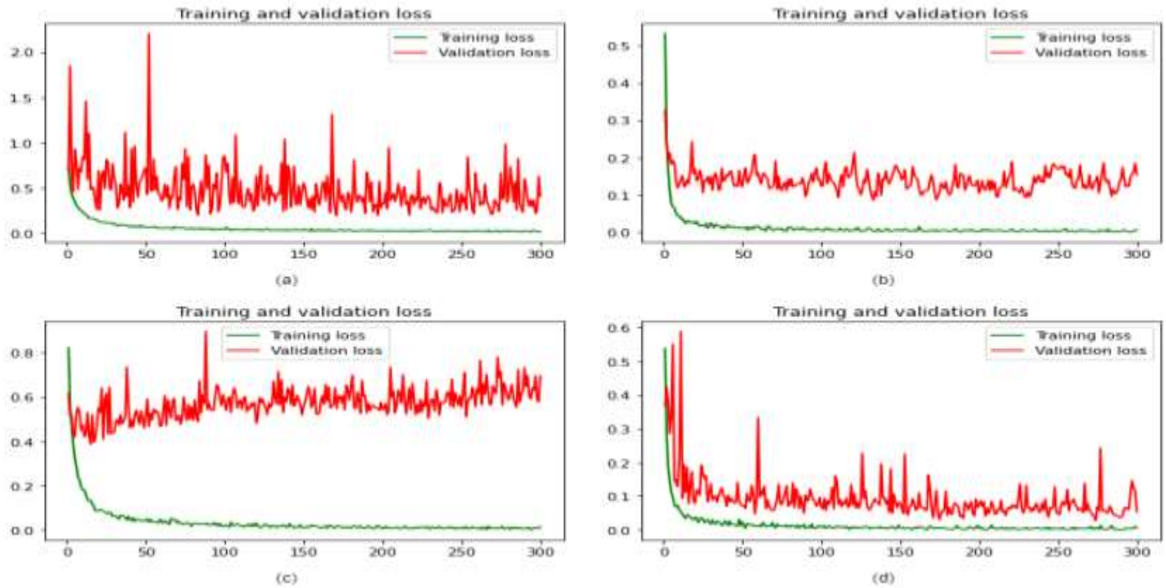

Figure 3: Training and Validation loss

Table 3 provides the performance of various feature extractors for skin lesion classification was evaluated using several key metrics: accuracy, precision, sensitivity (recall), specificity, and F1 score. Among the evaluated models, InceptionResNetV2 emerged as the top performer, achieving the highest scores across all metrics. Specifically, it attained an accuracy of 99.06%, precision of 99.09%, sensitivity of 99.05%, specificity of 99.52%, and an F1 score of 99.07%. This demonstrates its superior ability to correctly classify skin lesions with high reliability and balanced performance across different evaluation criteria. VGG16 also performed well, with an accuracy of 95.92%, precision of 96.13%, sensitivity of 95.74%, specificity of 97.88%, and an F1 score of 95.93%. ResNet50V2 showed robust results as well, achieving an accuracy of 98.26%, precision of 98.23%, sensitivity of 98.26%, specificity of 99.12%, and an F1 score of 98.24%. InceptionV3, while still providing reliable performance, lagged behind the other models with an accuracy of 90.27%, precision of 90.44%, sensitivity of 90.14%, specificity of 95.05%, and an F1 score of 90.29%. These results suggest that InceptionResNetV2 is the most effective model for skin lesion classification in this study, offering the highest accuracy and consistency. Its superior performance in all evaluated metrics makes it the preferred choice for applications requiring precise and reliable skin lesion classification.

Table 3: Result analysis of four different models

Feature Extractors	Accuracy (%)	Precision (%)	Sensitivity or Recall (%)	Specificity (%)	F1 Score (%)
VGG16	95.92	96.13	95.74	97.88	95.93
ResNet50V2	98.26	98.23	98.26	99.12	98.24
InceptionV3	90.27	90.44	90.14	95.05	90.29
InceptionResNetV2	**99.06**	**99.09**	**99.05**	**99.52**	**99.07**

InceptionResNetV2 is a promising model for clinical applications in skin lesion categorization since it seems to be the most successful model in terms of both accuracy and interpretability. Utilizing LIME for interpretability improves these models' reliability and practicality in real-world medical situations by providing insight into the decision-making process of these models.

The figure 4 showcases the performance of four deep learning models—InceptionResNetV2, VGG16, InceptionV3, and ResNet50 V2—in classifying skin lesions, with interpretability provided by the Local Interpretable Model-agnostic Explanations (LIME) framework. Each model was tested on three classes: Steven-Johnson Syndrome (SJS), Bullous Pemphigoid (BP), and Erythema Multiforme (EM). InceptionResNetV2 demonstrated the highest precision, with LIME interpretations consistently highlighting relevant areas in the input images, reflecting its reliable and focused decision-making process. VGG16 also performed well, with coherent LIME highlights, though the areas were slightly more dispersed compared to InceptionResNetV2. InceptionV3 and ResNet50 V2, while accurate in their predictions, exhibited broader and more scattered focus areas in their LIME interpretations, indicating a comprehensive but less pinpointed analysis of the input features. Overall, InceptionResNetV2 emerged as the most effective model, balancing accuracy and interpretability, thus making it a promising candidate for clinical use in skin lesion classification. The use of LIME enhances the transparency and trustworthiness of these models, crucial for their adoption in medical practice.

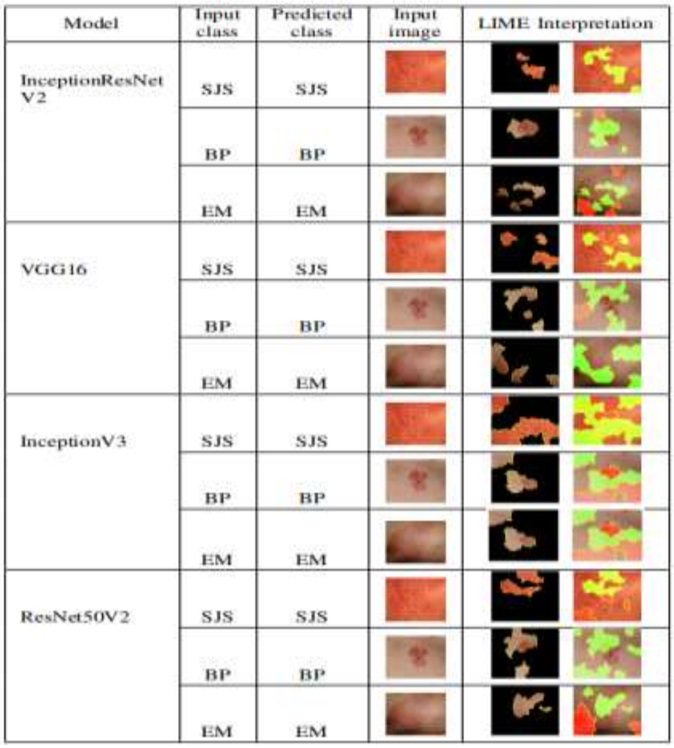

Figure 4:LIME performance of four deep learning models

CONCLUSION:

The field of disease detection has been significantly influenced by the blending of advanced deep learning techniques, which hold promise for significant improvements in diagnostic performance and accuracy. The current study emphasizes the difficulties in correctly detecting skin diseases. Skin diseases are complicated and have a wide variety of symptoms identifying them can be difficult for dermatologists and lead to subjective interpretation. Precisely identifying the essential characteristics is essential to prevent needless actions, provide appropriate care, and preserve medical resources. The comprehensive analysis of various deep learning models (VGG16, ResNet50V2, InceptionV3, and InceptionResNetV2) for skin lesion classification, enhanced by the interpretability provided by LIME (Local Interpretable Model-Agnostic Explanations). Among the models evaluated, InceptionResNetV2 demonstrated the highest performance with an accuracy of 99.06%, precision of 99.09%, sensitivity of 99.05%, specificity of 99.52%, and an F1 score of 99.07%. The use of LIME allowed us to generate visual explanations for the model predictions, significantly enhancing the transparency and trustworthiness of the AI system. These explanations were particularly useful in understanding which parts of the input images influenced the model's decisions, aligning well with clinically relevant features of the skin lesions.

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