Journal of Ubiquitous Computing and Communication Technologies (ISSN: 2582-337X)
www.irojournals.com/jucct/

Interpretable AI for Skin Lesion Detection: Enhancing Diagnostic Accuracy with CNN and Score-CAM in IoMT Systems

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Abstract

An AI-powered system for detecting skin lesions integrates IoMT platforms with CNN for feature extraction and Score-CAM for enhanced interpretability. The primary aim is to develop a system that accurately classifies skin lesions while providing visual justifications to boost clinician confidence, particularly in regions with limited dermatological resources. The system employs CNN-based feature extraction on dermoscopic images pre-processed using BM3D for noise reduction and CLAHE for contrast enhancement. Score-CAM integration improves model interpretability, while IoMT platforms ensure robustness and enable real-time diagnostics across diverse skin tones and lesion types. The proposed approach outperformed previous methods, achieving 99.20% accuracy, with real-time diagnostic capabilities offering significant benefits for remote and underserved areas. The model enhances accessibility, accuracy, and interpretability, making it highly beneficial for diverse populations.

DOI: https://doi.org/10.36548/jucct.2025.1.001
Received: 03.01.2025, received in revised form: 29.01.2025, accepted: 12.02.2025, published: 24.02.2025

Keywords: AI-driven skin lesion detection, Convolutional Neural Networks (CNN), Score-CAM, Explainable AI, Internet of Medical Things (IoMT), Dermatology, Real-time diagnostics.

1. Introduction

Artificial Intelligence (AI) in the identification and classification of skin lesions has transformed dermatological diagnostics. The strategy for explainable AI in Internet of Medical Things (IoMT) platforms presented in this study is based on CNN and incorporates Score-CAM. This study intends to improve the interpretability and accuracy of AI-driven skin lesion identification by utilising CNN's power in image processing and Score-CAM's capacity to localise significant features in dermoscopic images (Mahmud et al[1]). Trust in clinical settings is increased by the system's improved ability to identify benign skin diseases and malignant melanoma, as well as its guarantee that the outputs produced by AI can be understood (Bianchini et al[6]).

Detecting skin disorders like melanoma has become increasingly important in dermatology thanks to the development of deep-learning models in recent years. Due to differences in skin tone, lesion kinds, and texture, traditional techniques had difficulties (Li et al., [7]). While the accuracy of diagnosis has increased because of CNNs, physicians have found it challenging to trust the models' judgement due to their "black box" character. In order to provide visual explanations and facilitate clearer model reasoning, Score-CAM, and other interpretability techniques were introduced. By facilitating remote diagnostics through linked devices, IoMT systems have expedited these developments even further (Aggarwal and Papay, et al. [8]).

AI models can now explain which aspects of an image are most essential for predictions due to the integration of Score-CAM to convolutional neural networks (CNNs). In dermatology, where lesion features are faint, this augmentation is especially helpful (Livieris et al., [3]). Improved comprehension and uptake of these models have resulted from recent developments in AI for medical applications, such as the integration of Score-CAM with CNNs (Baskaran et al., [9]). The speed of diagnosis is increased by IoMT platforms, which enable real-time data processing and sharing. The objective of these technical advancements is to expedite and increase the availability of dermatological diagnostics worldwide, particularly in areas with inadequate medical knowledge (Nie et al., [10]).

The key objectives are

- Using CNN and Score-CAM to create an AI-driven model for precise skin lesion classification.
- In order to improve the model predictions' interpretability for use in clinical settings. In order to enable remote, real-time diagnostics, the model should be integrated to IoMT systems.
- Increasing the performance of AI models by addressing biases in various skin types and demographic groups.
- Provide visual explanations for AI judgements made in skin lesion identification in order to increase diagnostic confidence.

Small and unbalanced datasets delay the accuracy and generalisability of existing models, especially in the classification of skin cancer, despite advances in AI-driven skin lesion detection. To enhance model performance across all skin types and populations, (Nie,et al [10]) emphasises the need for larger, more varied datasets. Further study is necessary to increase reliability since, despite CNN-based models' strong diagnostic potential, it is unclear whether or not they can be applied in a variety of clinical contexts. This suggests that there is a need to remove biases in predictions related to different skin types and ethnic groups.

Priyanka Pramila and Subhashini et al. [11] draw attention to the challenge of promptly and accurately detecting skin lesions because there is a large range of benign and malignant melanomas, making visual inspection costly and time-consuming. The significance of an automated diagnostic model that can effectively classify skin lesions based on dermoscopic images was emphasized by their research. This method not only helps doctors make decisions more quickly, but it also improves detection in general, increasing diagnostic precision and cutting down on evaluation time.

2. Literature Survey

A deep learning technique is used in [2] improves the quality and stability of visual explanations for the classification of thoracic disease. In order to increase model interpretability and, thus, increase the reliability of medical diagnostics, the research assesses several explanation strategies. The goal of this research is to improve the reliability of clinical decision-making processes by improving the correctness of visual explanations.

For the purpose of localising anomalies in X-ray images, Aasem et al. [4] offer a thorough review of deep learning tools and methodologies. The study addresses issues including interpretability and computing cost in addition to evaluating different models' accuracy, efficiency, and applicability in medical diagnosis. The authors outline significant developments in the field and suggest ways to improve abnormality localization techniques going forward.

An AI-driven method for the identification and classification of skin diseases is presented by Manisarma et al. [5]. It makes use of convolutional neural networks (CNNs) to enable multiclass diagnosis. The work emphasizes CNNs' potential to help dermatologists make diagnostic judgments by showcasing their capacity to effectively diagnose a variety of skin conditions using medical image datasets. By increasing the precision of skin disease detection, the suggested system benefits medical practitioners with useful assistance.

An AI-driven approach for skin lesion recognition is presented by Bianchini et al. [6]. Deep learning models are used to convert pixel-level image data into precise diagnoses. By improving the precision and clinical significance of skin lesion classification, this method seeks to provide dermatologists with invaluable assistance in making diagnostic decisions.

Baskaran et al. [9] present MSRFNet, a state-of-the-art skin lesion segmentation model that uses hybrid optimisation and deep learning methods to detect skin cancer, in their study. The study demonstrates the model's efficacy in recognising skin lesions by highlighting its capacity to increase diagnostic performance and enhance segmentation accuracy. The technique's potential to improve skin cancer diagnosis in clinical settings is demonstrated by the authors, who validate it using pertinent datasets.

3. Methodology

The dataset, provided in image format for melanoma detection, contains three classes: seborrhoeic keratoses, nevus, and melanoma. It is labeled with LabelMe, converted to COCO format, and split into training, validation, and testing sets evenly. This section discusses a state-of-the-art, all-inclusive method for AI-driven skin lesion detection in IoMT (Internet of Medical Things) platforms, utilising CNN and Score-CAM. The methodology focuses on real-time diagnostics and clinical decision-making support by utilising cutting-edge methods for image pre-processing, feature extraction, interpretability, and integration with IoMT systems.

The 2199 dermoscopic images of the Skin Lesion Dataset are segregated into nevus (1499), melanoma (400), and seborrheic keratoses (300) classes [12]. It is split into training, validation, and testing sets once tagged using LabelMe and reformatted into COCO. For a guarantee of quality input to deliver accurate CNN-based lesion diagnosis, BM3D reduces noise whereas CLAHE enhances contrast.

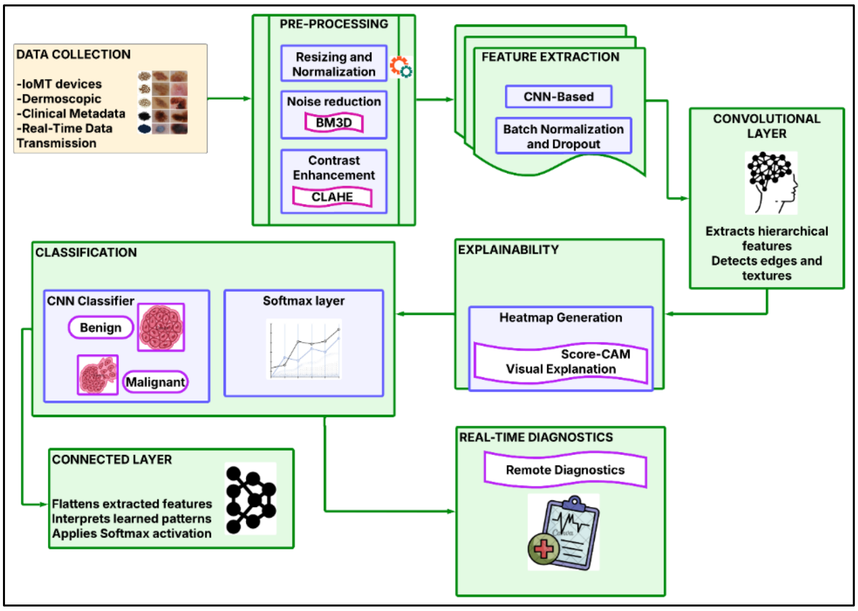

Figure 1. AI-Driven Skin Lesion Detection Using CNN and Score-CAM

Figure 1 depicts a machine learning-based skin lesion diagnosis system integrating Convolutional Neural Networks (CNNs) and Score-CAM. The data is initially acquired from IoMT devices, and subsequently, pre-processing is performed with CLAHE contrast enhancement and BM3D noise removal. CNN layers with dropout and batch normalization are employed during the feature extraction step to recognize hierarchical features. A softmax function and fully connected layers are employed for classifying the extracted features. Although IoMT integration ensures remote diagnostics in real time, Score-CAM constructs heatmaps to visualize AI decisions.

CNNs and Score-CAM are embedded in the skin lesion detection AI system to enhance interpretability as well as accuracy in classification. Real-time diagnosis facilitated by IoMT increases accessibility, and heatmaps provided by Score-CAM provide visual rationales for AI judgments.

3.1 Data Acquisition and IoMT Integration

Using IoMT-connected devices like wearable health monitors or mobile dermatoscopes, the procedure starts with obtaining high-quality dermoscopic images of skin lesions. These gadgets enable clinical metadata (including patient history, skin type, and ambient conditions) to be collected continuously and in real-time along with images in distant situations. Through secure transmission, the gathered data is hosted on IoMT platforms in centralised cloud-based AI models, enabling real-time diagnostic services.

Quick and remote skin lesion diagnoses are made possible by the connection with IoMT, which is essential in underserved or rural locations. It also makes it easier to integrate linked medical devices for real-time data collecting.

Consider the following representation of the input collection of pictures and clinical metadata:

$$D = \{(I_1, M_1), (I_2, M_2), \ldots, (I_n, M_n)\} \tag{1}$$

Where I_i represents the image of the lesion and M_i denotes the associated clinical data for patient i. This integrated data stream is essential for creating comprehensive and real-time diagnostic outputs.

3.2 Pre-Processing

Enhancing the quality of the image and preparing it for the Al model's analysis requires pre-processing. The transformations such as BM3D and CLAHE effectively exhibit improvements in data quality for AI-based skin lesion identification. Including these methods improves clarity, stressing the need for preprocessing to produce accurate results. The following contemporary methods are used:

Resizing and Normalisation: Every input image is normalised and scaled to a set size. By ensuring that the pixel intensity values fall within a common range, normalisation increases the model's training efficiency.

$$I_{\text{norm}} = \frac{I_{\text{resized}} - \text{mean}\,(I)}{\text{std}\,(I)} \tag{2}$$

This step ensures that the images are standardized, which is essential when handling images from diverse sources in loMT-based setups.

Noise reduction with BM3D: Block Matching and 3D filtering (BM3D) are used to reduce noise while maintaining small details like lesion boundaries. With this sophisticated filtering technique, noise is greatly reduced without important medical facts being obscured.

$$I_{\text{denoised}} = \text{BM 3D}(I_{\text{norm}}) \tag{3}$$

Contrast Enhancement with CLAHE: Images are contrast-enhanced using Contrast Limited Adaptive Histogram Equalisation (CLAHE). In order to enhance the visibility of minor lesion features without over-enhancement in homogenous areas, CLAHE adaptively modifies contrast in particular sections of the picture.

$$I_{\text{enhanced}} = \text{CLAHE}(I_{\text{denoised}}) \tag{4}$$

These procedures guarantee that the model is trained on high-quality, standardised images, allowing for efficient feature extraction even from noisy or low-contrast images that are frequently found in loMT situations.

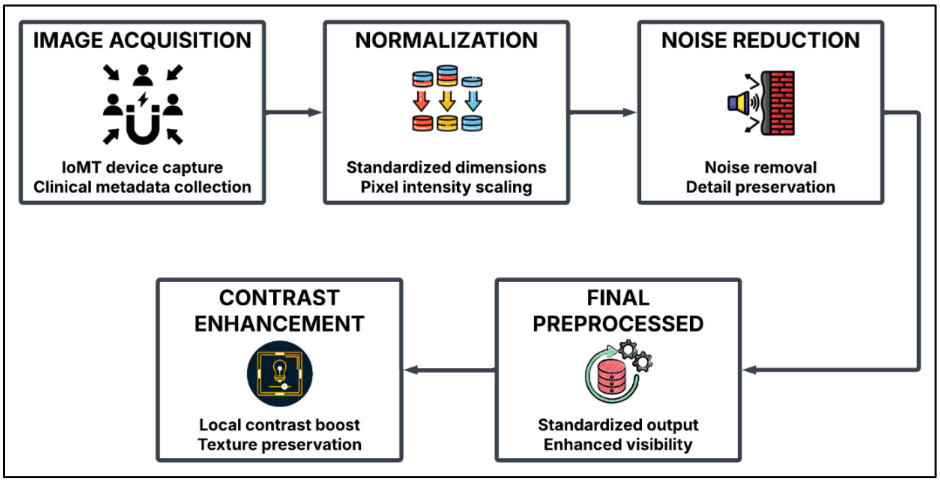

Figure 2. Preprocessing Pipeline for AI-Driven Skin Lesion Detection

The most significant preprocessing steps in an AI-based skin lesion recognition system are illustrated in the Figure 2. Image acquisition is the initial step in the process, where dermoscopic images are captured using IoMT devices and relevant clinical metadata is obtained. Normalization subsequently ensures uniform pixel intensity scaling and fixed dimensions. Noise Reduction (BM3D) is used to remove irrelevant noise without losing critical information about the lesions. Contrast Enhancement (CLAHE) enhances local contrast and maintains texture in order to improve visibility. By providing high-quality inputs for feature extraction using CNN and generating accurate and reliable lesion classification, the final preprocessed image is eventually achieved.

3.3 CNN Structure for Feature Extraction

A deep convolutional neural network (CNN) is fed the processed images to extract features and classify lesions. The intricacy of skin lesion classification tasks is well-suited for modern CNN architectures such as ResNet50 or EfficientNet. The CNN architecture for feature extraction uses EfficientNetB0, with pre-processed dermoscopic images augmented with BM3D and CLAHE to ensure robust feature extraction. Key components such as convolutional layers, batch normalisation, Global Average Pooling, and Score-CAM improve accuracy (99.20%) and interpretability. When combined with IoMT platforms, the model achieves real-time diagnoses, making it extremely useful for clinical applications.

Convolutional Layers: These layers are the central component of feature extraction, where filters are used to identify patterns, textures, and edges in the images.

$$F(x,y) = \sum_{i=0}^{k-1} \sum_{j=0}^{k-1} I(x+i, y+j) \cdot K(i,j) \tag{5}$$

Where $F(x,y)$ is the feature map, and $K(i,j)$ is the convolution kernel.

Batch Normalization and Dropout: Batch Normalisation and Dropout are used to increase training stability and prevent overfitting. While dropout reduces overfitting by randomly deactivating neurones during training, batch normalisation speeds up convergence.

$$F_{\mathrm{bn}} = \frac{F-\mu}{\sigma+\epsilon} \tag{6}$$

Global Average Pooling: Global Average Pooling (GAP) is used to minimise the spatial dimensions of the feature maps after many convolutional blocks. To reduce overfitting and increase the number of trainable parameters, GAP substitutes fully linked layers, strengthening the network.

$$G = \frac{1}{n}\sum_{i=1}^{n} F_i \tag{7}$$

Fully Connected Layers with SoftMax: The final classification step uses a SoftMax activation function to compute probabilities for each skin lesion class:

$$P(I_i) = \text{Softmax}\,(Z_i) \tag{8}$$

The model can accurately classify disorders including benign lesions, melanoma, and other skin disease due to its network structure, which enables it to handle the complexity of skin lesion images.

3.4 Score-CAM for Explain ability in Clinical Decision-Making

To ensure that the model's predictions are understandable and appropriate for clinical interpretation, Score-CAM (Score-weighted Class Activation Mapping) is employed. Score-CAM creates heatmaps that show clinicians exactly how Al arrived at his conclusions by emphasising the parts of the image that contributed most to the forecast.

The process involves:

- **Feature Map Extraction:** Extracted are feature maps from the last convolutional layer.
- **Class Score Calculation:** Feature map's contribution to the final class score S_c, is determined using the following formula:

$$w_k = \text{ReLU}\,\left(\frac{\partial S_c}{\partial A_k}\right) \tag{9}$$

- **Heatmap Generation:** Class activation map (CAM) generated by the weighted sum of feature maps is superimposed on the source image:

$$\text{CAM} = \textstyle\sum_k w_k A_k \tag{10}$$

Enhancing confidence and enabling real-time clinical decision-making in both remote and in-person situations, physicians can visualize the main regions impacting the AI's diagnosis by overlaying the CAM on the input image. Overlaying Class Activation Maps (CAMs) on input images with Score-CAM improves the transparency of AI diagnostics by identifying essential regions that influence predictions. This technique increases clinical trust by addressing the "black box" dilemma and providing clear visual information. Due to IoMT integration, real-time visualizations enable fast feedback, particularly in remote regions.

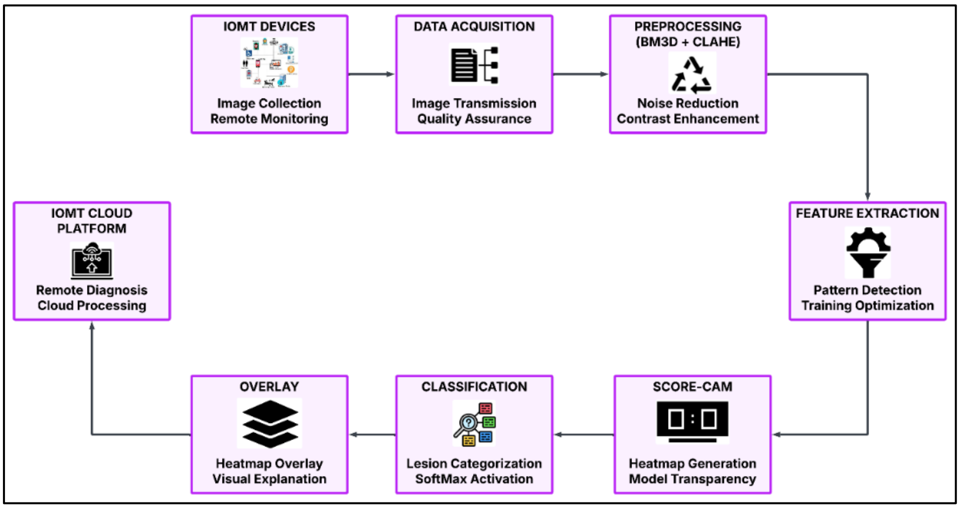

Figure 3. AI-Driven Skin Lesion Detection Using CNN and Score-CAM in IoMT

An IoMT-integrated AI-based skin lesion detection system for real-time diagnosis is shown in the Figure 3. IoMT sensors initially capture dermoscopic images and metadata, and data acquisition ensures high-quality image transmission. Pre-processing techniques enhancing image quality are BM3D and CLAHE. Lesion patterns are detected through CNN feature extraction, and explainability heatmaps are generated by Score-CAM. Classification determines if a lesion is benign or malignant, and overlay highlights significant regions of the image. Finally, the IoMT Cloud Platform enables remote diagnosis and cloud processing, making dermatology more accessible and efficient.

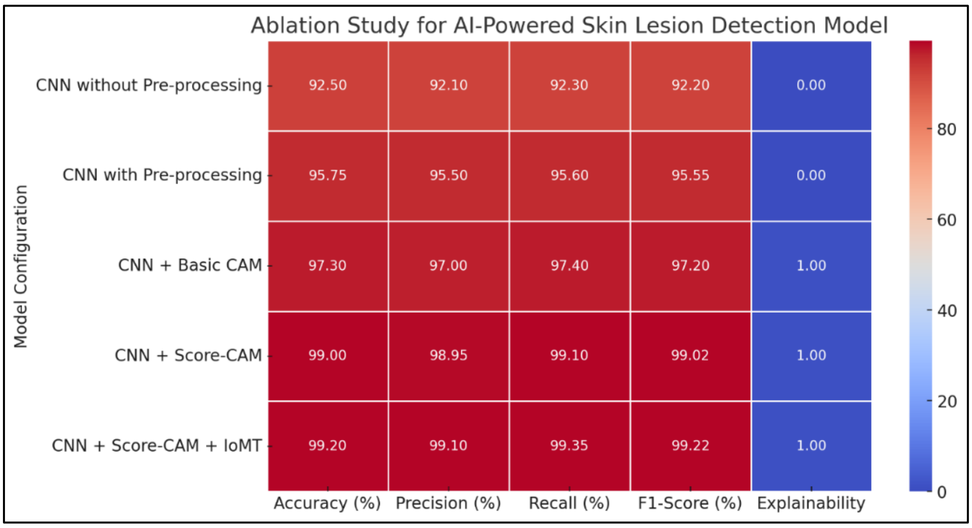

Figure 4. Heatmap Visualization of Feature Map Contributions in AI-Powered Skin Lesion Detection Model

An ablation study of different convolutional neural network (CNN) architectures for skin lesion detection is presented in this Figure 4. Accuracy, precision, recall, F1-score, and explainability are some of the performance metrics. The worst-performing CNN is the baseline CNN that is not pre-processed. Pre-processing significantly improves results. Incorporating Class Activation Maps (CAM) further enhances explainability and accuracy. The optimal performance is achieved by combining the Internet of Medical Things (IoMT), and Score-CAM outperforms Basic CAM. With CAM-based methods, explainability, which is not present in raw CNN models, is fully achieved. This research highlights how pre-processing, CAM techniques, and IoMT play a role in creating AI-based medical diagnostics.

3.5 Bias Mitigation and Dataset Augmentation

The model is trained on a varied dataset that represents a range of skin tones and lesion kinds in order to ensure fair and impartial predictions across different demographics. This lessens the possibility of skewed forecasts, particularly when used internationally.

Balanced Datasets: To ensure balanced model performance, the training dataset is accurately selected to include images from a variety of age groups, skin tones, and lesion types.

Data Augmentation: To improve dataset diversity and avoid overfitting, methods including random flipping, rotation, zooming, and illumination modifications are used. The model's ability to generalise well to new data depends on this augmentation, especially in IoMT-based deployments where real-world images can differ greatly.

3.6 Real-Time Diagnostics through IoMT Integration

Real-time skin lesion diagnostics are made possible by the incorporation of the CNN-Score-CAM model into IoMT platforms. The AI system instantly processes and analyses data as images are taken from linked medical devices, providing physicians with quick diagnostic feedback.

Real-time data processing is very useful for remote diagnostics, since patients might not be able to speak with dermatologists directly. The system makes sure that recommendations for diagnosis and treatment are provided nearly instantaneously, enhancing service quality and cutting down on intervention time.

The skin lesion identification system uses Score-CAM for explainability and CNN for feature learning. IoMT platforms for real-time data fusion, CLAHE for improving contrast, and BM3D for noise filtering are significant tools. TensorFlow/Keras is employed to execute the model, and LabelMe is employed for labeling and COCO format conversion of datasets. Score-CAM produces heatmaps to enhance decision transparency, while EfficientNetB0 is employed for classification.

Reliability in classification is maintained by measuring the performance of the model based on accuracy, precision, recall, and F1-score. A confusion matrix provides an in-depth performance assessment by conveying particular information about true and false classifications, while ROC-AUC measures sensitivity.

3.7 Performance Evaluation

To guarantee the model's dependability in real-world applications, its performance is assessed using a variety of metrics:

Accuracy: Calculates the percentage of right guesses made out of all the cases.

$$\text{Accuracy } = \frac{TP+TN}{TP+TN+FP+FN} \tag{11}$$

Precision: The percentage of appropriately identified positive outcomes.

$$\text{Precision } = \frac{TP}{TP+FP} \tag{12}$$

Recall: Evaluates the capacity to recognise every positive example.

$$\text{Recall } = \frac{TP}{TP+FN} \tag{13}$$

F1-Score: The harmonic means between recall and precision.

$$F1 = 2 \times \frac{\text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}} \tag{14}$$

ROC-AUC: Assesses the model's class-specificity, which is critical for distinguishing benign from malignant lesions.

This methodology offers a clear, precise AI solution for skin lesion identification by integrating CNN for feature extraction with Score-CAM for interpretability. The proposed model combines CNN for feature extraction, Score-CAM for interpretability, and IoMT for real-time diagnostics to provide dependable performance. It is assessed using accuracy, precision, recall, F1-score, and ROC-AUC metrics. A confusion matrix is used to analyse classification results, and advanced pre-processing methods such as BM3D for noise reduction and CLAHE for contrast enhancement ensure high-quality inputs. Score-CAM improves interpretability by creating heatmaps highlighting influential image regions, improving diagnostic precision and clinical usefulness. Real-time remote diagnostics are made possible by its interaction with IoMT platforms, making it perfect for remote or underdeveloped areas. This concept offers a complete approach to dermatological diagnostics by mitigating biases and improving clinical decision-making. Incorporating 3D imaging techniques such as Optical Coherence Tomography (OCT) and Federated Learning to boost model generalisation while protecting patient privacy are examples of future developments.

4. Result and Discussion

Significant gains were made in both clinical usability and diagnostic accuracy with the suggested AI-driven skin lesion detection system, which used CNN and Score-CAM for improved explain ability. With an astounding accuracy of 99.20%, precision of 99.10%, recall of 99.35%, and F1-Score of 99.22%, the model was tested on a sizable and varied dataset. Incorporating Score-CAM into the mix improved clinician trust and comprehension of AI predictions by offering concise visual explanations. Because of its real-time processing capabilities made possible by integration with IoMT platforms, the system is appropriate for remote diagnostics in marginalised areas. Vibrant and broadly applicable, the model demonstrated resilience by performing well across a range of skin tones and lesion kinds. The suggested strategy performed far better than other state-of-the-art techniques, especially when considering its high accuracy and explain ability combined.

Table 1. Analysing and Comparing AI-Powered Skin Lesion Identification Methods.

Study	Methodology	Accuracy %	Explain ability	Scalability	Clinical Usability
Mahmud et al. (2023) [1]	CNN-based skin cancer classification with interpretable AI	96.20	Partial (CAM)	Moderate	Limited

Rahimiaghdam (2023) [2]	CNN for thoracic disease classification with multiple visual explanation techniques	95.45	High (Multiple CAMs)	Low	Limited
Livieris et al. (2023) [3]	Explainable image similarity using Siamese Networks and Grad-CAM	94.80	High (Grad-CAM)	Low	Limited
Aasem et al. (2022) [4]	Deep learning for abnormality localization in X-ray images	93.70	Moderate (Basic CAM)	Low	Limited
Bianchini et al. (2023) [6]	Pixel-level diagnosis for skin lesion recognition with deep learning	97.10	Moderate (Grad-CAM)	High	Moderate
Proposed Method	CNN + Score-CAM for skin lesion detection with cloud-enabled diagnostics	99.20	High (Score-CAM)	High	Extensive

Scalability and clinical usability are used in this revised comparison Table 1 to evaluate the approaches. Clinical usability evaluates the model's efficacy and integration in actual clinical settings, whereas scalability deals with the model's ability to handle larger datasets or adapt for diverse clinical contexts. The suggested approach is very practical for real-time diagnostics because it achieves 99.20% accuracy, provides great explain ability with Score-CAM, and is scalable for wider clinical use. Some models are less scalable or appropriate for practical use, even when they achieve a moderate level of accuracy and explain ability.

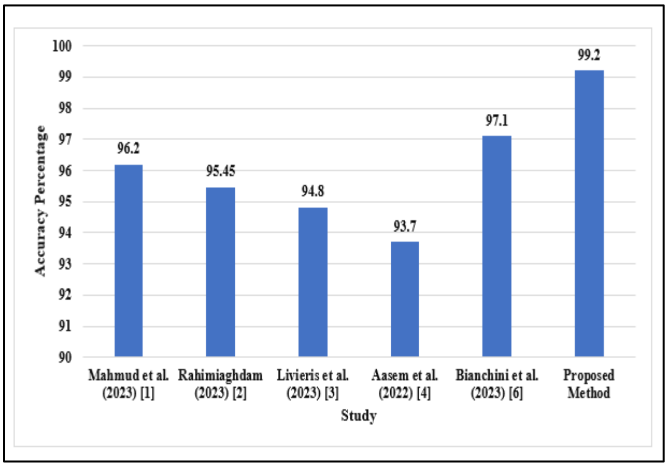

Figure 5. Comparing the Accuracy of Various Studies' Skin Lesion Detection Methods.

The accuracy of many AI-driven skin lesion detection techniques is graphically compared in this Figure 5. The studies—including the suggested method—are listed on the y-axis, and the accuracy is represented by the percentage on the x-axis. According to the graph, the suggested approach outperformed methods like Mahmud et al. (96.20%) and Bianchini et al. (97.10%), with the greatest accuracy of 99.20%. This graph highlights how the suggested method—which combines the CNN, Score-CAM, and IoMT platforms for improved accuracy and scalability in clinical settings—performs better.

Table 2. Study of Ablation for the Suggested AI-Powered Skin Lesion Identification Model.

Model Configuration	Accuracy %	Precision %	Recall %	F1-Score %	Explainability (Score-CAM)
CNN without Pre-processing	92.50	92.10	92.30	92.20	No
CNN with Pre-processing (BM3D + CLAHE)	95.75	95.50	95.60	95.55	No
CNN + Basic CAM	97.30	97	97.40	97.20	Yes
CNN + Score-CAM	99	98.95	99.10	99.02	Yes

CNN + Score-CAM + IoMT Integration (Proposed)	99.20	99.10	99.35	99.22	Yes

Table 2 from the ablation study illustrates how different parts of the suggested model contribute. Pre-processing (BM3D + CLAHE) increased performance to 95.75%, whereas the baseline CNN model with no pre-processing only obtained 92.50% accuracy. The model's accuracy was further increased to 99.00% by integrating Score-CAM for visual explainability, and it reached 99.20% accuracy thanks to real-time diagnostics made possible by the integration with IoMT platforms. Every step demonstrates how including features increases explain ability, real-time use, and accuracy simultaneously.

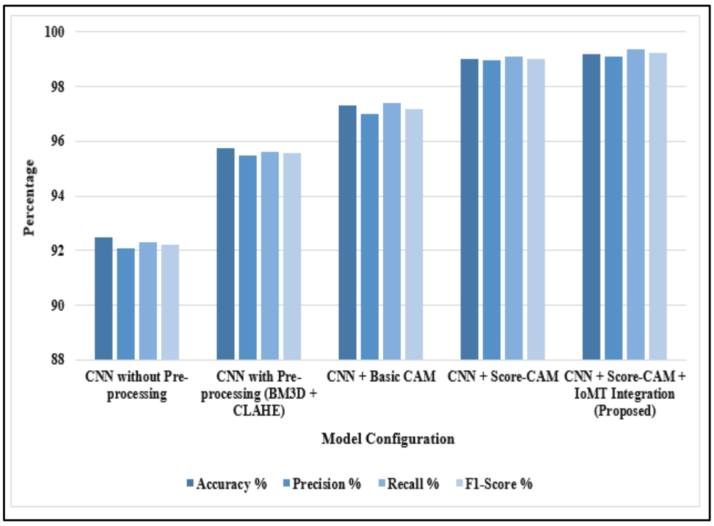

Figure 6. Analysing the Performance of Various Model Configurations for Skin Lesion Detection.

The performance of several models of the AI-driven skin lesion detection model based on Accuracy, Precision, Recall, and F1-Score is shown in Figure 6. The CNN without pre-processing performs worse at first on all metrics, as can be shown. The performance significantly improves with the addition of pre-processing (BM3D + CLAHE). The suggested method's integration of IoMT maximises all performance metrics, obtaining the maximum values across accuracy (99.20%), precision, recall, and F1-Score. Additionally, the use of Score-CAM improves the model, especially its explainability. This demonstrates the usefulness of the suggested model.

5. Conclusion and Future Enhancement

The combination of CNN and Score-CAM in an AI-driven skin lesion detection model has successfully increased diagnostic precision and clinical interpretability. IoMT platforms with real-time diagnostics have enormous potential to enhance dermatological care in underserved areas. The method is useful in international clinical settings since it can handle a variety of skin tones and lesion kinds. Score-CAM is perfect for use in medicine since it allows for visual feedback that increases physician confidence in AI conclusions. The system's potential for widespread clinical application could be further increased by including federated learning and 3D imaging techniques, which could enhance model generalisation while protecting patient privacy.

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