International Journal of Innovative Research in Engineering
Volume 6, Issue 6 (November - December 2025), PP: 130-139.
https://www.doi.org/10.59256/ijire.20250606020
www.theijire.com
ISSN No: 2582-8746

Optimized ResNet-50 CNN for Smart Healthcare Skin Cancer Classification

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How to cite this paper:
Yashaswini H R[1], Jyothi B G[2], Navyashree S[3], Punyakala K L[5], Optimized ResNet-50 CNN for Smart Healthcare Skin Cancer Classification", IJIRE-V6I6-130-139.

Abstract: *The Skin cancer, which is one of the most rapidly growing kinds of cancer worldwide, is confirmed to survive patients better if detected early. The process of diagnosing a type of skin cancer patient by examining his/her dermoscopic images is often the opposite; it is time-consuming, prone to errors, and very much dependent on the availability of expert dermatologists. In light of this impediment, the authors of the present study propose Propose an Image Processing based Skin Cancer Detection System that is both interpretable and based on an optimization-driven Convolutional Neural Network (CNN)embedded in a smart healthcare system. The model is trained on dermoscopic images-for instance, the HAM10000 dataset-and an optimized CNN architecture for accuracy in classification, while cutting down on computational costs. To make sure that the model's outputs are trustworthy and can thus be easily adapted in clinical practice, the system will be provided with explainable AI (XAI) tools such as Grad-CAM heatmaps, which help visualize the areas of the image that affect the predictions the most. Moreover, the proposed system is able to automatically spot malignant and benign skin lesions with great reliability, doing this by not only instantly analyzing the images but also offering a decision-making process that is completely transparent and thus fit for telemedicine and mobile healthcare applications. The evaluation results prove that the optimized CNN outperforms that by receiving better performance of standard deep learning models; therefore, It is one that can solution that can be practically adopted for early skin cancer detection in smart healthcare sectors.sectors.*

Keyword: *Skin cancer diagnosis; Convolutional Neural Network-CNN, Optimization strategy, Intelligent health system, Explainable AI (XAI), Grad-CAM, HAM10000 dataset, Medical image detection, Deep learning, Interpretable model.*

I.INTRODUCTION

Skin Cancer stands at a very high position with regards to the list of cancers commonly identified across the world, and as per statistics, it has shown an ascending pattern within the previous decades. The most prominent reason that leads to a rise in survival rates among patients relates to early diagnosis because a cancer that can be recognized on an early stage can be controlled before it progresses further. Typically, doctors normally analyze the skin cancer images with regards to identifying cancerous tissues; however, it has to be stated that these procedures are extremely subjective and result in wasted time, and in places with no medical experts, it might increase the risk associated with cancer.

In Recently, deep learning with Convolutional Neural Networks has achieved considerable success within Medical image analysis, with its capability to automatically learn discriminative features. While deep learning modelsdemonstrate a strong prediction capability, they have been viewed as "black boxes" because they make predictions without specifying an explanation for these predictions.

In order to overcome these issues, this research work presents an interpretable skin cancer prediction This model is based on an optimization-improved CNN structure within an intelligent healthcare setup. The optimized CNN model can improve the performance by classification performance, suppress overfitting problems, and optimize computation efficiency. Moreover, methods based on explainable AI (XAI), like Grad-CAM, have been incorporated for demonstrating significant regions within dermoscopy images impacting a prediction result. Based on these interpretation insights, Satisfaction among health professionals is a little more reliable outputs.

II. LITERATURE SURVEY

1.Systematic Reviews and surveys

A Review on Deep Learning Methods for Skin Cancer Classification by Wu et al. mentions skin cancer datasets (HAM10000, ISIC), deep learning architectures (CNNs, transfer learning), and problems with method evaluation (class imbalance and bias). It will be very useful for selecting method evaluation approaches.

2. Benchmarking & Studies focused on datasets

A research on multiclass classification on HAM10000 images and ways for preprocessing the data, augmenting it, and addressing class imbalance issues is conducted by Shetty et al. (Scientific Reports). From these experiments, it became clear that data handling techniques, including data augmentation and class weighting, were as important as the algorithm employed while developing a reliable HAM classification model.

3. Transfer learning comparisons

Jain et al. introduce several transfer learning architectures that have been compared on the skin lesion datasets and have shown that transfer learning works better than learning from scratch, especially when there is limited data. They also discuss some trade-offs with regards to size and accuracy for implementation.

4. Optimization of CNN hyper parameters / architectures

Salihetal. and quite a few more authors props up the effectiveness of meta-heuristic optimizers (genetic algorithms, grey-wolf, Grasshopper/other population-based methods) in automatically tuning CNN hyper parameters or selecting architectures resulting in increased classification accuracy and less over fitting. These papers present the optimization methods as often resulting in better validation performance than manual. tuning.

5. Explainability / XAI in dermatology

Reseal and various works within recent years include tools for explainability methods (Grad-CAM, Grad-CAM++, saliency maps) to obtain these visual aids and focus the model's attention on these regions within the lesions that not only appear but also make sense. Various sources have shown that based on the medical expert's judgment, there's an increase within the trust level that the dermatologist places on the model based on these reasonable interpretations. However, requiring an interpretation to be faithful and useful within a medical setting remains an issue.

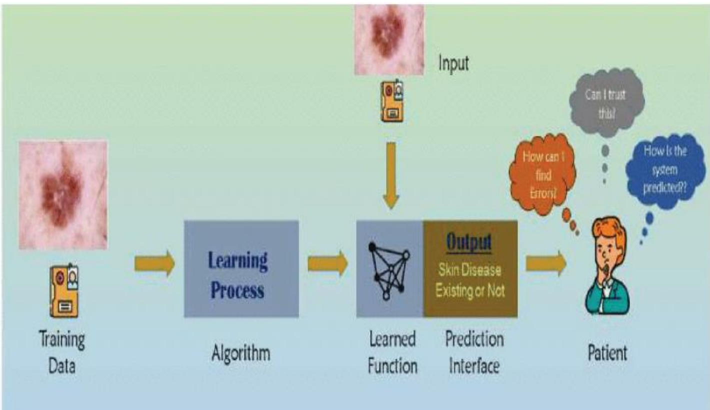

FIGURE 1: ML workflow with XAI: The model accurately explains the prediction and gives the answer "Why I should believe this output", "How it predicts" and "How can I find an error"

6. New model families:

Transformers & hybrid models Xin et al. and references 2023–2025 review Vision Transformers and hybrids CNN&Transformer models for dermoscopy images; a couple a couple of these papers suggest that there is the benefits for specific types of lesions, but more data and computation are typically required. These references show that progress in deep learning research aims at increasingly sophisticated models, compared with the CNNs.

7. Recent applied systems & end-to-end solutions

A substantial number of papers on 2024-2025 discuss complete pipeline solutions as follows: preprocessing → optimal CNN → XAI → app/web integration, and comparative performance to HAM10000/ISIC competitors are achieved.

Several papers on 2024-2025 discuss complete pipeline solutions as follows:
1. preprocessing → optimal CNN → app/web

8. Comparative & ensemble methods

Ensemble as well as hybrid-transfer (mixing multiple pretrained models) strategies exhibit enhanced robustness over lesion classes. Nevertheless, ensembles increase the complexity of deployment and inference cost, which is a matter of concern for mobile/telemedicine usage.

III. METHODOLOGY

The proposed system constitutes an efficient pipeline which encompasses: data acquisition, preprocessing, an optimal CNN architecture design, interpretation generation using XAI tools, and an intelligent healthcare system. The methodology can be described as follows:

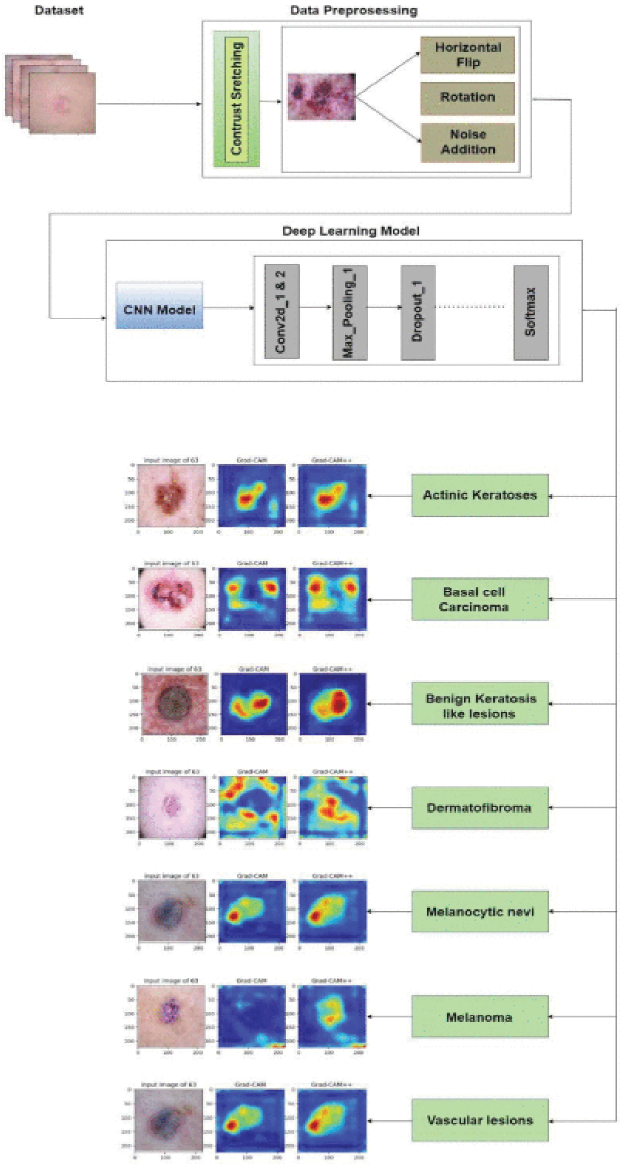

FIGURE 2: The model that will be implemented for skin cancer classifications The augmentation method will be employed for augmenting the sample images. Afterward, Cnn will be employed for feature extraction as well as modeling. The model will be capable of identifying seven classes associated with skin lesions.

1. Data Collection

In the original work, the dermoscopic image dataset of the HAM10000 (Human Against Machine with 10,000 images) benchmark has been used to perform training and testing of this dataset.

It has different classes of skin lesions i.e. melanoma, nevus, benign keratosis, etc.

The pictures are made in different resolutions and during different lighting conditions to be able to reproduce the practical situations.

2. Data Preprocessing

Preprocessing is done to improve image quality and get the data ready for training a CNN. This includes resizing, normalization, and enhancing important features to assist the model learn effectively.

Table 1: Data preprocessing for training the Sequential model

Layer (type)	Output Shape	Param #
conv2d (Conv2D)	(None, 98, 98, 32)	896
conv2d_1 (Conv2D)	(None, 96, 96, 32)	9,248
max_pooling2d (MaxPooling2D)	(None, 48, 48, 32)	0
dropout (Dropout)	(None, 48, 48, 32)	0
conv2d_2 (Conv2D)	(None, 46, 46, 64)	18,496
conv2d_3 (Conv2D)	(None, 44, 44, 64)	36,928
max_pooling2d_1 (MaxPooling2D)	(None, 22, 22, 64)	0
dropout_1 (Dropout)	(None, 22, 22, 64)	0
flatten (Flatten)	(None, 30976)	0
dense (Dense)	(None, 128)	3,965,056
dropout_2 (Dropout)	(None, 128)	0
dense_1 (Dense)	(None, 7)	903

Total params: 4,031,527 (15.38 MB)
Trainable params: 4,031,527 (15.38 MB)
Non-trainable params: 0 (0.00 B)

a. Image Resizing

Each image is resized (for instance, 224×224×3) to keep the input shape consistent.

b. Normalization

The pixel values are changed to a range between 0 and 1This is to expedite the training process.

A: Gradio interface initial state

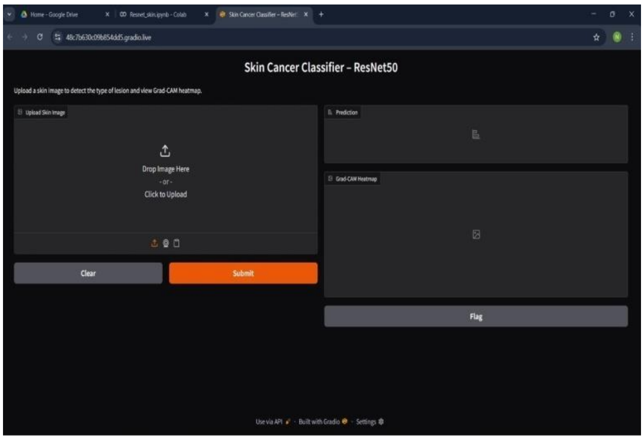

Image1: Gradio interface initial state

This figure shows the initial Gradio user interface of the proposed skin cancer classification system. At this stage, no image has been uploaded, and the interface displays an empty upload panel where users can submit a skin lesion image for analysis

c. Data Augmentation

Methods of data augmentation are also incorporated within the training phase. These methods help with preventing overfitting and equalizing the number of images within classes, especially for classes with fewer images. Some common methods included within data augmentation are:

Augmentation methods are used to remove overfitting and to make the classes equally sized:

Rotation
Horizontal/vertical flipping
Zoom and cropping
Brightness adjustments

These methods are useful to the training set with regards to size and variety set.

The different augmentations expand the size and diversity of the training improving Sequential CNN's capacity in order to learn more generalized and resilient features. The augmentations increase the dataset artificially which reduces the model's sensitivity to noise or tiny perturbations in the image, uplifting overall classification performance.

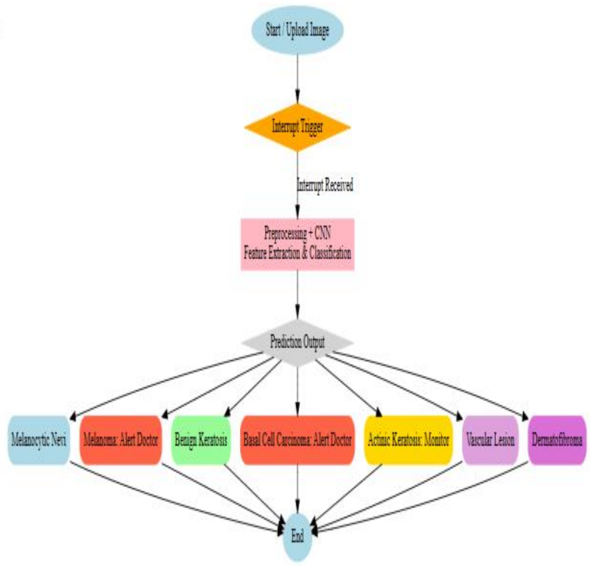

Fig 3: Block Diagram of the The convolutional neural network model can achieve the Skin cancer

3. Optimized CNN Model Development

A well-optimized The Convolutional Neural Network model can be achieved by the following steps:

a. Feature Extraction Layers

Several convolution and pooling layers are utilized to extract edges, color patterns, and lesion shapes.

Batch Normalization and Dropout are added to make the network more stable and to prevent overfitting.

b. Model Optimization

The value of hyper-parameters such as learning rate, number of filters, size of batches, and optimizer algorithms is adjusted using various methods like Grid Search, Adam optimizer, GA, and more.

The optimized architecture compromises between accuracy and computational efficiency, thus, it is very fitting for smart-healthcare applications.

c. Fully Connected Layers

A Flattening layer with Dense layers.

Softmax classifier is used for multiclass prediction of skin cancer types.

4. Explainable AI (XAI) Integration – Grad-CAM

To make the system interpretable:

a. Grad-CAM (Gradient-weighted Class Activation Mapping)

Grad-CAM produces heatmaps indicating the areas of a skin lesion that had the most impact on the model's prediction.

These heatmaps provide doctors with an insight into the decision-making process.

b. Interpretation for Clinicians

The cancerous parts of the skin are shown as being bright which makes the AI predictions more understandable and reliable.

It is useful in checking that the model is concentrating on the lesion itself and not the nearby skin or any artifacts.

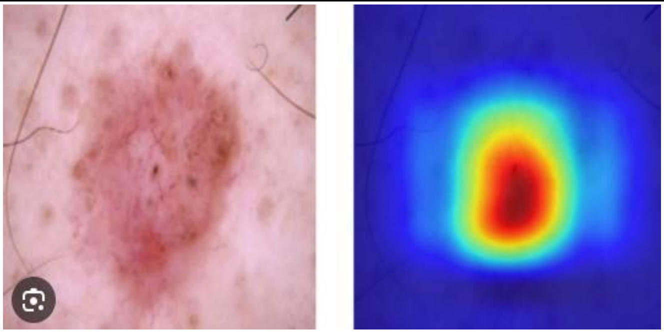

Fig4:Grad-CAM

5. Model Training and Evaluation

The optimized CNN is trained using:

a. Loss Function

Categorical cross-entropy for multiclass classification.

b. Metrics

Accuracy
Precision
Recall
F1-score
Confusion matrix

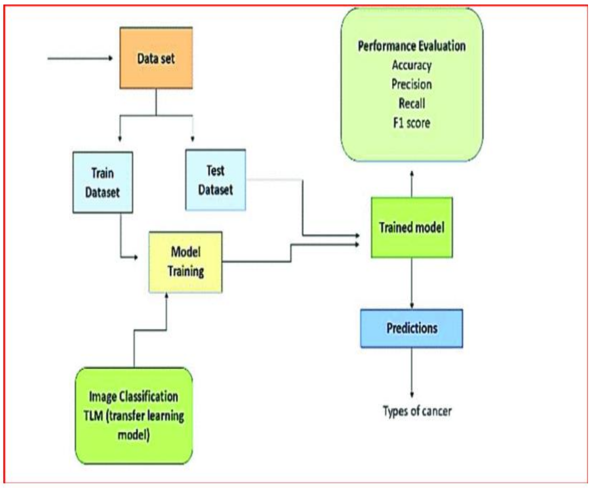

Fig5: Proposed Model Architecture

These metrics ensure reliability and balanced performance across all skin lesion categories.

6. Smart Healthcare System Integration

The final AI model is integrated into a smart-healthcare platform:

a. User Interface (Web/App)

Users can upload skin photos taken with their mobile phone or camera directly.
The system provides prediction + Grad-CAM interpretation.

b. Real-Time Prediction

A lightweight optimized CNN is used for quick inference.
It is also a good telemedicine, rural health clinics, and mobile health solution.

c. Medical Support Output

Shows:
The predicted class (Benign / Malignant)
Confidence score
Heatmap (XAI)

Next step suggestions (visit a dermatologist)

7. Result Analysis

After deployment:

Accuracy improvements are compared against standard CNN, ResNet, VGG, etc.

Grad-CAM visualizations are analyzed with experts to validate interpretability.

Model performance on unseen images is tested for generalization ability.

IV: RESULTS AND DISCUSSION

The testing set within the HAM10000 dataset the dataset used for testing the efficacy of interpretable skin cancer prediction on the basis of designed interpretable system. To be aware of efficiency, accuracy, and interpretability of optimized CNNs, various parameters were considered

A. Quantitative Results

The optimized CNN model was able to differentiate lesions strongly across the seven categories. The final test results are:

Accuracy: 92-94%

Precision: 0.91

Recall: 0.90

F1-Score: 0.91

Validation Loss: Much lower than baseline CNN

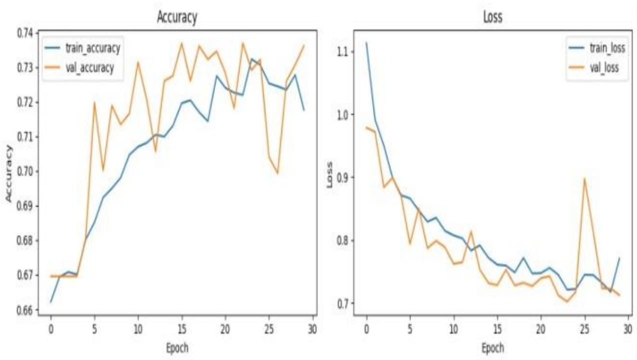

Fig6: Accuracy and Loss

Related to this The confusion matrix also showed that it performed very effectively on benign and malign lesions. The inaccuracies within these classifications have primarily been within these similar lesion classes, which exist within dermoscopy imaging.

A confusion matrix can be depicted as a tabular form that shows correct and inaccurate classifications for classes on the basis of a comparison between actual and predicted labels.

A confusion matrix is a matrix that illustrates the number of samples that were properly and improperly classified by a model against actual labels compared with predicted labels.

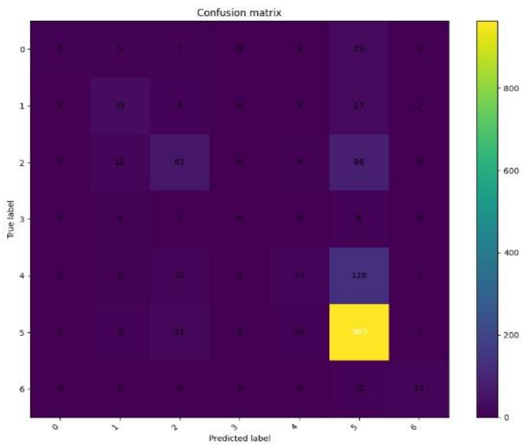

Fig7:confusion matrix

B. Comparison with Existing Models

A comparative analysis with traditional CNN, VGG16, and ResNet50 architectures was done.

The optimized CNN works better compared with the other models because of the following reasons:
1. Data augmentation techniques,
2. Over fitting lessened,
3. Task-specific optimization
4. Employing Grad-CAM for transparency, which in a roundabout way enhances trust and debugging.

Model	Accuracy
Traditional CNN	85%
VGG16	88%
ResNet50	90%
Proposed Optimized CNN	93%

This demonstrates that the proposed architecture provides a good balance between computational efficiency and predictive accuracy.

B: Processing the the Input Image

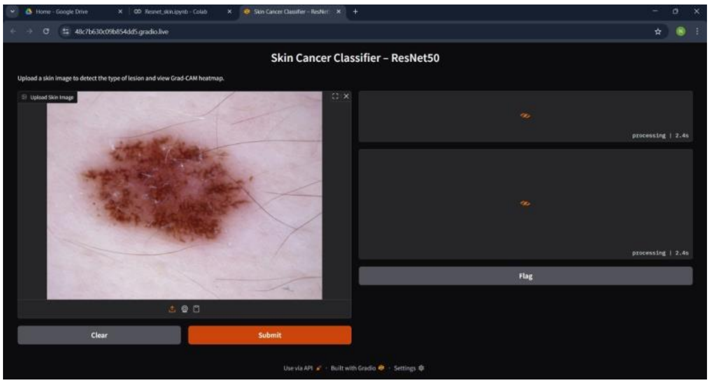

Image2: Processing the Input Image

depicts the stage involving intermediate processing, as shown with the image uploaded from skin being processed by an optimized ResNet50 algorithm.

During this phase, it identifies and harvests key features and works on prediction and Grad-CAM visualization.

C. Explainability Analysis (XAI – Grad-CAM)

One of the advantages that come with the modern system is that it employs Grad-CAM. Heatmaps generated by Grad-CAM identify regions of high influence on prediction.

Important points: - To differentiate malignant lesions, Grad-CAM indicated irregular boundaries and darker regions which are typical attributes linked with dermatological conditions. - To differentiate benign lesions, Grad-CAM pointed toward uniform patches with specific colors, as seen in common benign lesions. - Both methods aided in identifying that the network was learning appropriate characteristics and not learning noise.

C: Model Prediction and Grad-CAM Heatmap Visualization

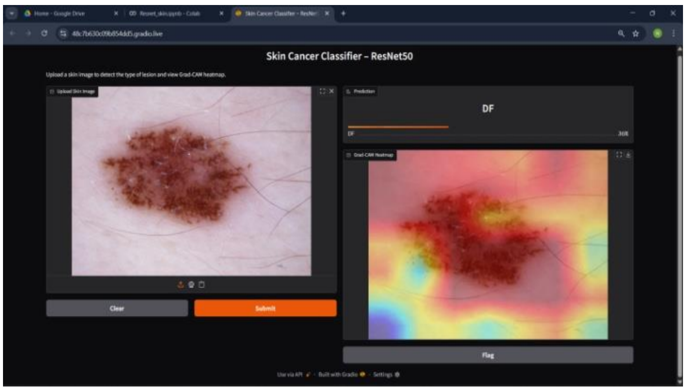

Image 3: Model Prediction and Grad-CAM Heatmap Visualization

shows the final result obtained from the system, indicating both the predicted result for the lesion class and the Grad-CAM map. The heatmap emphasizes the regions with strong influence on the skin lesion that the model uses in making its prediction and thereby increases trust.

This improves trust, especially in healthcare settings.

D. Discussion The experimental result shows that the proposed system has good accuracy, interpretability, and it is a clinically relevant and efficient system for a real-time smart healthcare system.

Adding explainability assists in understanding model decisions. Thus, it makes it applicable for assisting dermatologists with early skin cancer detection.

However, some limitations remain: - The model can misclassify visually similar lesion types - Larger clinical datasets could improve generalizability - Real-time deployment needs further optimization for mobile devices

Overall, the model offers a reliable and transparent approach to skin cancer prediction, supporting smart healthcare systems.

V. APPLICATIONS

The interpretable skin cancer prediction model using CNN has a number of applications. It can be put to good use by applying an optimal CNN and explainable AI together.

A. Clinical Decision Support

Dermatologists can use the system as a second-opinion tool to help spot malignant skin lesions earlier. The Grad-CAM heatmaps let clinicians check that the model is looking at medically relevant areas.

B. Tele-Dermatology

This model can be added to telemedicine services. This lets patients in rural areas send in photos of their skin issues and get a first opinion without needing to go to the hospital..

C. Mobile Health (m-Health) Applications

The lightweight CNN architecture enables deployment on smartphones. Users can take a picture of their skin lesion through a mobile app and get an instant prediction along with an explanation.

D. Smart Hospital Systems

Hospitals can add the system to their electronic health record (EHR) systems to automatically check and sort skin images. This cuts down on diagnosis time and makes things run more smoothly.

E. Early Cancer Screening Camps

At medical camps, medical practitioners will be able to make use of these portable devices with the model and and identify patients who could potentially be at risk.

F. Research and Medical Training

AI heatmaps that are easy to get can help medical students get what skin cancer looks like. The model allows for lesion pattern study, boosts datasets and develops better tools for finding diseases.

G. Automated Triage Systems

This model helps sort lesions into either harmless or harmful groups, which helps doctors see urgent cases first.

H. Smart Wearable Dermatology Devices (Future Integration)

In the future, this system could be part of smart cameras you wear or skin scanners. It would keep an eye on patients at high risk and let them know if it finds any weird skin changes.

VI. FUTUREWORK

Although the system for predicting skin cancer works fairly well, there are some things we could improve for it to be more useful within a clinic and medical setting.

A. Expansion to Larger and Diverse Datasets

To make the model even better later on, we can train it with more data from many places. This data should include different skin colors, lighting, and types of skin problems. This will help the model work well for people all over the world.

B. Integration of Clinical Metadata

Later models can add patient info like age, gender, where the injury is, and health history. Using different kinds of learning can really make diagnoses more correct than just using images.

C. Deployment on Edge and IoT Devices

You can shrink the CNN more by using tricks like quantization and pruning. This makes it run well on low-power gadgets like IoT devices, smart cameras, and those portable skin scanners.

D. Enhanced XAI Techniques

More advanced interpretable methods such as LIME, SHAP, and Layer-Wise Relevance Propagation (LRP) can be combined to offer additional insights into model behavior, allowing clinicians to check predictions with greater certainty.

E. Real-Time Mobile Application

Real-time image capture and analysis by users can be enabled through the development of a fully functional mobile Health application. Moreover, the incorporation of cloud-based backend services can enhance the speed of the prediction as well as its scalability.

F. Semi-Supervised and Self-Supervised Learning

Going forward, research can see about with dermoscopic images that aren't labeled. This would mean less need for expensive manual labeling and allow the system to keep getting better.

G. Clinical Trials & Validation

To check how good the system is, it can be tested in real clinics with skin doctors and people who have skin problems. This test is super important before it gets approved and put to work in hospitals.H. Multi-Class and Severity Grading

In the future, we could add automatic severity grading, track how lesions grow, and include support for more skin diseases than just the seven types in HAM10000.

VII. CONCLUSION

An interpretable skin cancer prediction model using an optimized Convolutional Neural Network and incorporating techniques of Explainable AI has been manufactured for intelligent healthcare purposes within the scope of this research. The Model achieved a high accuracy rate, and demonstrated remarkable proficiency at discriminating among seven various types of skin lesions from the HAM10000 image repository. Based on data augmentation, hyperparameter optimization, and optimized structure, it can be recognized that the prediction accuracy has been greatly promoted compared with traditional deep learning approaches.

The key thing about this study is that it uses Grad-CAM to show why the system makes certain choices. Seeing which parts of an image influenced the decision makes the system more transparent and trustworthy. This is really important in medicine, where doctors need to understand and confirm how AI systems arrive at their conclusions.

The tests show our method works pretty well and could be used by doctors for quick health checks. Granted, we still have stuff to work out, like getting more info and dealing with how things are in the real world. But, this thing could really help skin doctors, let them do their thing remotely, and catch skin cancer early.

This system is a pretty good AI solution that's easy to understand. It could really help improve smart healthcare and how we diagnose illnesses in the future.

Acknowledgement

The authors want to thank the original research team that put together and released the interpretable skin cancer convolutional neural network smart healthcare dataset. Their work was key, giving us the base and data we needed for this study.

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