Advanced Deep Learning Technique for Skin Cancer Classification Enhanced by Grad-CAM Visualization

Ms. Devi B[1], Amalraj P R[2], Riya S[3], Geethu R Pillai[4], Sravya P[5]
[1,2,3,4,5] *Dept. of Computer Science and Engineering NSS College of Engineering Palakkad, India*

***Abstract*—Skin cancer, especially melanoma, is a major chal- lenge in medical diagnosis because of its rapid progression and the utmost necessity for early diagnosis. In this research, a new deep learning model for automatic skin cancer classification is proposed with the DenseNet121 architecture coupled with Gradient-weighted Class Activation Mapping (Grad-CAM). The model increases transparency by producing visual explanations that point out important areas in dermoscopic images that affect its predictions, thus agreeing with clinical observations and promoting trust. Employing datasets such as HAM10000 and ISIC, the model includes sophisticated preprocessing methods like artifact removal, data augmentation, and lesion segmentation to deal with class imbalance and improve training. Experimental testing proves that the suggested model is very accurate and explainable and can be used as an important diagnostic tool in dermatology. By addressing at the same time the demand for accuracy and clarity, the suggested model is an important leap toward trustworthy AI-based solutions in skin cancer diagnosis.**

***Index Terms*—Skin Cancer, Densenet, Grad-CAM, HAM10000**

I. INTRODUCTION

Skin cancer is among the most prevalent malignancies globally, with millions being diagnosed each year. Of all its forms, melanoma is the most lethal because of its aggressive nature and high metastatic potential. Early, accurate detection of melanoma will dramatically enhance survival rates because treatment is exceedingly more effective in the initial stages of the disease. Conventional methods of diagnosis, including dermoscopic evaluation, are commonly used by dermatologists to evaluate suspicious lesions. The techniques are generally subjective and dependent on the clinician's expertise, and hence there is variability in diagnostic accuracy. In addition, highly trained dermatologists the necessary healthcare infrastructure which provides helpful services is often scarce in limited resource facilities. The situation demands immediate development of automated diagnostic tools that are also re- liable. tools.Artificial intelligence (AI), especially deep the academic field of medical imaging underwent revolutionary changes because of learning. CNNs have advanced to become fundamental tools in modern computer systems. State-of- the-art performance exists because of strong image analysis tools that were developed through these methods. performance in object detection, segmentation, and classification. In skin cancer detection, CNNs have shown that they can classify dermoscopic images into benign and malignant classes with high accuracy by extracting intricate patterns from the input data. In spite of these developments, the use of CNNs in clinical practice is beset with significant challenges. Among the main concerns is the absence of interpretability of deep learning models, which tend to be viewed as" black boxes" because of their transparent decision-making processes. In the medical field, where stakes are high, clinicians need to comprehend and rely on the explanation behind AI-produced predictions. To overcome this problem, methods like Grad- CAM have has been proposed to improve the interpretability of CNNs. Grad CAMprovides visual explanations by identifying the parts of an image that most significantly contribute to the model's predictions. Clinicians can then check whether the model's attention is on clinically significant features, i.e., asymmetry, irregularities of the border, and changes of color in skin lesions. The incorporation of Grad-CAM into CNN architectures therefore has the potential to enhance both the accuracy and trustworthiness of machine learning-based diagnosis systems. In this paper, a novel skin cancer classification scheme is presented using the combination of DenseNet121 architecture and Grad-CAM visualization. DenseNet121, a computationally low-cost CNN architecture, enables dense connections to recycle features with more effectiveness to avoid overfitting and gradient flow. The model is trained on mixed dermoscopy datasets like HAM10000 and ISIC to produce robust performance over a very large range of skin lesions. Advanced preprocessing techniques like hair artifact removal, data augmentation, and lesion segmentation enhance data quality and alleviate class imbalance further. Besides high classification accuracy, this approach provides interpretable visual outputs that align with dermatologic experience, unifying AI diagnostic tools with clinical practice. Visualizations generated by Grad-CAM raise transparency, thereby the model has use in a pedagogic environment environment and instills confidence in the application of AI tools. Although accuracy and understandable visual information are joined by this approach, deeper learning application that is safer and more efficient in medical practice is attained, eventually optimizing patient outcomes as well as extensive clinical adoption.

II. LITERATURE REVIEW

The research [1] investigates the HAM10000 dataset that in- cludes 10,015 dermatoscopic images for enhancing automated skin lesion classification.It encompasses seven diagnostic cat- egories, with more than 50% of the cases validated through histopathology, expert consensus, or follow-up. Through its standardized and varied dataset between the different types of skin cancer HAM10000 serves as an assessment and training measure for deep learning models in dermatology to push forward the development of AI-based skin cancer diagnosis systems [2]. With the use of ResNeXt101 the research achieved its highest accuracy of 93.20% on the HAM10000 dataset. Transfer learning improves classification performance with- out compelling extensive preprocessing steps because of its importance in achieving better results. The multi-class skin cancer classification produced better results with ResNeXt101 because the model relied on its optimized structure combined with its high accuracy levels for analysis. A deep learning model handling skin cancer detection worked with HAM10000 dataset dermoscopic images [3]. They used a convolutional neural network that incorporated transfer learning based on AlexNet to differentiate between benign and malignant lesions. The model succeeded in reaching 84% accuracy because it eliminated manual feature extraction requirements. Another study [4] investigated deep learning approaches for classifying skin cancer images using the ISIC dataset. They trained over 24,000 high-resolution images with three different ar- chitectures—InceptionV3, ResNet, and VGG19—to identify the most effective model. InceptionV3 surpassed the other architectures, achieving an accuracy of 86.90%, precision of 87.47%. This study highlights the significance of high-quality datasets in enhancing classification performance. The paper [5] presented Grad-CAM, a technique designed to visualize and interpret deep learning models by creating class-discriminative heatmaps. This method calculates the gradients that flow into the last convolutional layer, allowing it to emphasize the crucial regions of an image that affect predictions. Ad- ditionally, the study introduced Guided Grad-CAM, which merges detailed visualizations with class-specific relevance. This technique enhances model interpretability, revealing biases,fostering trust in AI systems, thereby making deep net- works more transparent without changing their underlying structure.The authors of this research [6] utilized transfer learning to apply CNNs for skin cancer classification studies. The research team utilized ISIC dataset by implementing deep learning models including DenseNet and ResNet50 and XceptionNet and MobileNet. DenseNet201 produced the highest accuracy rate of 86% which demonstrates its excellence at ex- tracting features needed to differentiate benign from malignant lesions.The approach in [7] introduced a CNN-based method for classifying skin cancer with the goal of exceeding 80% ac- curacy while keeping false negatives under 10%. The research employed image preprocessing, data augmentation, and visual- ization techniques to enhance classification performance. The CNN model showed better accuracy than traditional methods, underscoring the promise of deep learning in automated skin cancer detection. The findings emphasized the effectiveness of AI-driven solutions in medical diagnostics.The Research work [8] utilized transfer learning with five advanced CNN architec- tures, including DenseNet201, to classify seven different types of skin lesions from the HAM10000 dataset. To tackle class imbalance, they used a hierarchical classification approach and incorporated data augmentation techniques to enhance model performance. DenseNet201 achieved the highest accuracy.The proposed strategy in [9] presents a machine learning frame- work aimed at classifying skin cancer by using explainable artificial intelligence (XAI) on features extracted from images. The research made use of the PH2 dataset and implemented traditional machine learning algorithms, such as XGBoost, decision trees, random forests, and KNN, for the classification task. By utilizing preprocessed features, the model reached an impressive accuracy of 94%. To improve interpretability, XAI techniques like SHAP and permutation importance were used, highlighting asymmetry and pigment network as crucial features for classification.Another exponential work in [10] classified brain tumors by utilizing transfer learning with VGG19 and InceptionV3 on augmented MRI datasets. They employed Grad-CAM for visualization.The findings showed impressive classification accuracy, with VGG19 reaching 98% and InceptionV3 at 96%. The research establishes deep learn- ing as a promising tool to benefit medical practice.The re- search [11] worked with the HAM10000 dataset,implementing

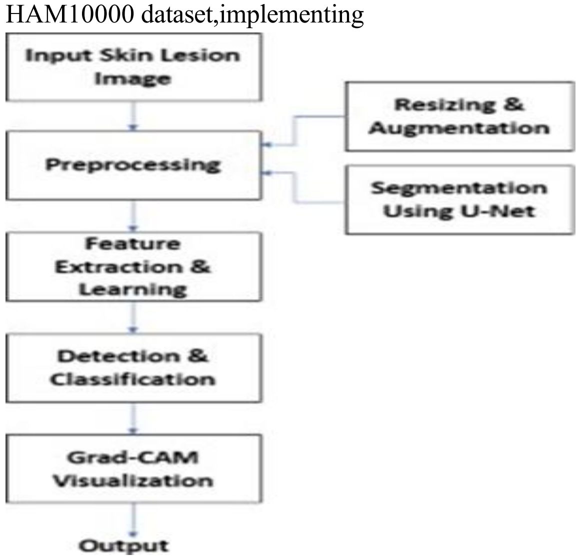


Fig. 1. Flowchart of proposed methodology.

various preprocessing methods, including sampling, dull razor techniques, and segmentation via autoencoders. They utilized transfer learning models like DenseNet169 and ResNet50, with DenseNet169 achieving an impressive accuracy of 91.2%. The study also explored both undersampling and oversampling methods, underscoring the potential of CNNs to improve diagnostic accuracy in dermatology.The model in [12] incorpo- rated transfer learning with Densenet 121 on the HAM10000 dataset. By optimizing the model with the Adam optimizer and using sparse categorical cross-entropy loss, they achieved high accuracy, showcasing the potential of AI in dermatological diagnosis.

III. METHODOLOGY

The approach centers on classifying skin cancer using DenseNet-121, complemented by Grad-CAM visualization for interpretability. Building on deep learning, the model focuses accurate classification of seven different types of skin cancer. DenseNet-121, CNN, is selected due to its high feature reuse ability and fast gradient flow. For model transparency, Grad-CAM is utilized to produce heatmaps that identify the most significant areas in the images, which can be useful for clinical evaluation and decision-making.

A. Dataset Description

The HAM10000 and ISIC are the datasets used for skin lesion segmentation and classification, which are downloaded from Kaggle. The HAM10000 dataset contains 10,015 der- matoscopic images, which cover a wide variety of skin condi- tions like melanoma, nevus, and basal cell carcinoma. Every image is supplemented with clinical metadata, histopathologi- cal results, and expert markups, lending significant context for

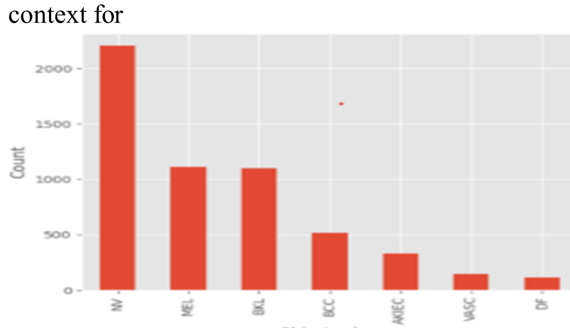


Fig. 2. Frequency distribution of classes.

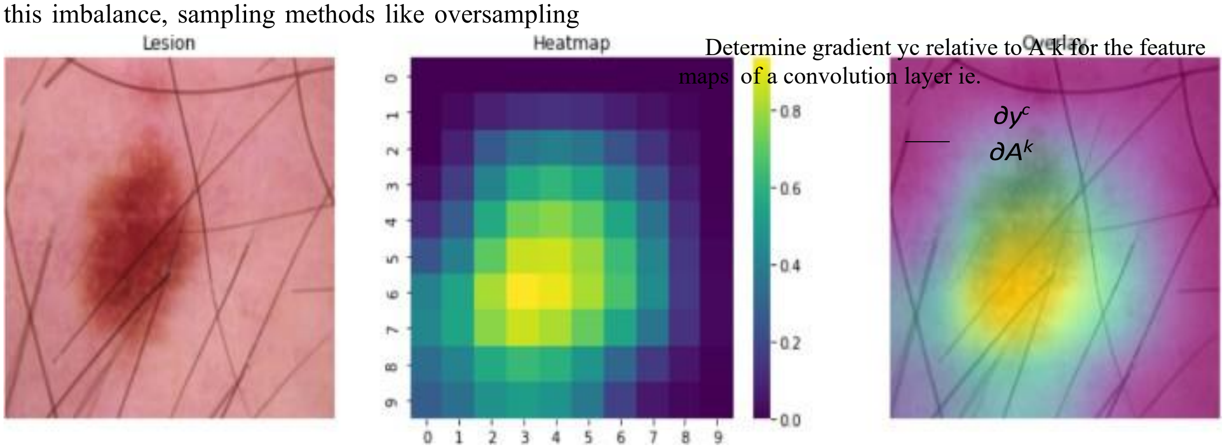
training and validation of models.ISIC dataset is supplemented by HAM10000 with the provision of an extensive library of annotated images to add to the richness and variability of training data.

B. Data Visualization

Visualization of data contributes significantly to an understanding and inspection of the dataset. It is a visual projection of information so that patterns, distributions, as well as aberrations in data can be properly understood. The graphical representation of skin lesion for different categories from the dataset can be seen through Figure 2. Preprocessing is necessary before presenting the data to any algorithm in order to transform raw data into clean and analyzable form. The dataset represented here also points out the imbalance between various classes, where some classes like NV (Nevus) are heavily predominant and others like DF (Dermatofibroma) and VASC (Vascular Lesions) have fewer samples. To resolve this imbalance, sampling methods like oversampling and undersampling are used.These techniques ensure that a standard machine learning algorithm can be employed efficiently with- out endangering its objectivity through biases towards high- voting classes. Figure 3 shows the dataset balanced through these techniques where the classes were corrected to distribute with an enhanced proportion of an equal number in both datasets.

C. Preprocessing and Data Augmentation

Preprocessing is done using UNet segmentation tech-nique.UNet segments images using encoder-decoder architecture with skip connections.Encoder extracts salient features by feeding the input image through various convolutional layers with ReLU activation, retaining significant patterns such as edges and textures. Spatial dimensions are decreased by max pooling, eliminating extraneous details but retaining important



Determine gradient yc relative to A k for the feature maps of a convolution layer ie.

$$\frac{\partial y^c}{\partial A^k}$$

Fig. 3. Grad-CAM visualization

information.The bottleneck layer,an interface between decoder and encoder tidies up these features when extracted prior to reconstruction beginning. The decoder then constructs the image through successive upsampling of feature maps back to native sizes.Skip connections shortcut high-resolution features from individual encoder layers to the decoder, maintaining spatial data as well as lesion boundaries.The outcome is a segment mask where each pixel is identified as lesion or background, and thresholding and morphological processing are employed after that as post-processing techniques for further improving the output. UNet generates accurate and consistent segmentation through the integration of feature extraction, upsampling, and skip connections, making it a crucial tool in AI-based medical diagnosis.

TensorFlow's ImageDataGenerator is used in this project to add data in order to improve model generalization and diversify training images. Rotation (up to 180°), width and height shifts (15%) and zooming (20%) to change the image's size are all part of the augmentation process. Furthermore, rescaling is utilized to normalize pixel values, and flips are applied both horizontally and vertically to provide various ori-entations.These augmentation strategies assist avoid overfitting and allow the model to diagnose skin lesions more accurately.

D. Grad-CAM in Model Explanation

Explainability is crucial for almost all machine learning tasks,particularly in image-based classifications.Explainable Artificial intelligence

(XAI) are AI systems capable of provid- ing clear and intelligent explanations for their predictions and judgements.Grad-CAM functions as an explainability tech- nique which uses gradients to determine important image regions that support predictive decisions in models. The visu- alization application generates heatmaps which identify places in the image that strongly influenced the model output.

We can implement Grad-CAM in two steps: Step 1: Compute Gradient:

These gradients flowing back are global-average-pooled over the width and height dimensions (indexed by i and j respectively) to obtain the neuron importance weights α_k^c

$$\alpha_k^c = \frac{1}{Z}\sum_i \sum_j \frac{\partial y^c}{\partial A_{ij}^k}$$

Step 2: Generate heat map the backward gradients are globally computed through an average pooling operation of both width and height dimensions (i and j) resulting in the weights α_k^c

Using the computed gradient weights α_k, Grad-CAM gen- erates the class activation map $L^c_{\text{Grad-CAM}}$:

$$L^c_{\text{Grad-CAM}} = \text{ReLU}\sum_k \alpha_k^c A^k :$$

where ReLU is applied to retain only positive values, ensuring that only features that positively influence the class score contribute to the final heatmap.

Grad cam is thereby used to get the visual explanation for the class predicted in skin cancer classification.The visualiza- tion for three classes is shown in Figure 4:

IV. SYSTEM IMPLEMENTATION

The method applies transfer learning through DenseNet121 architecture implementation. The DenseNet121 model with imagenet weights was loaded into the system but its classification layers were removed and new fully connected layers were added for customization. A new architecture built a flattening layer to transform extracted feature maps to one-dimensional form prior to dense layer processing which contained 128 ReLU activated neurons for identifying higher skin lesion patterns. The dropout layer contained a 50% probability to manage overfitting support through training-time neuron ran- dom deactivation. A softmax activation layer was added as the last element of the network since it contained seven out- put units that identified lesions within predefined categories. The modified model combines DenseNet121's general feature extraction abilities with redefined classification layers that specialize in accurate skin lesion identification. The network performs its forward computation according to the following mathematical formula:

$$Z = W_1X + b_1$$

The weighted sum of learned weights and bias combines all input features and generates the value Z. k

The ReLU activation function serves as the formula for the dense layer which appears below:

$$f(Z) = \max(0, Z)$$

The activation function along with its derivatives ensures non- linear data processing which allows the network to identify complex patterns in the input data. The last activation function for multi-class tasks uses the softmax definition:

$$P(y_i) = \frac{e^{Z_i}}{\sum_{j=1}^{C} e^{Z_j}}$$

where $P(y_i)$ The class probability function represents the probability distribution of i and the total number of classes equals c. The model design guarantees that probabilities will total one across outcomes thus enabling proper classification outcomes.

Categorical cross-entropy served as the loss function throughout compilation and training since it demonstrates effectiveness in multi-class classification problems. The math- ematical definition for categorical cross entropy loss appears as follows:

$$L = -\sum_{i=1}^{C} y_i \log(\hat{y}_i)$$

The model receives true class data through where whereas predicts a probability value for that class. The chosen Adam optimizer operated at an initial learning rate value of 0.0001 which maintained a proper trade-off between acceleration and steadiness. The model's training performance was primarily evaluated by tracking accuracy values. The training duration extended across 20 epochs where 64 batches were used to maintain enough updates while optimizing system performance. Performance enhancement along with overfitting prevention was achieved through integration of multiple call- backs. ReduceLR On Plateau utilized validation accuracy data to trigger decreases of the learning rate by 0.5 whenever vali- dation accuracy failed to improve for two consecutive epochs for better model development at advanced training stages. The training process stopped using early stopping because validation loss remained stagnant during two back-to-back epochs thus avoiding unnecessary calculations and reducing model overfitting. The implementation of Model Checkpoint saved the best-performing model based on validation accuracy so deployments could have the most efficient weights.

The trained model reached its highest training accuracy at 99.53% but maintained a validation accuracy at 84.55% which showed impressive learning capability with good generalization properties. The model reached stable convergence because the learning rate adjustments successfully prevented it from becoming trapped in local minima. During model training we continuously checked validation loss to verify the model learned all necessary patterns while remaining independent from its training data. The optimized training process enabled the model to operate effectively with various skin lesion im- ages which leads to real-world clinical application readiness.

V. RESULT AND ANALYSIS

The validated model reached 84.55% accuracy when tested on the validation dataset. The confusion matrix analysis showed that the model performed well in distinguishi

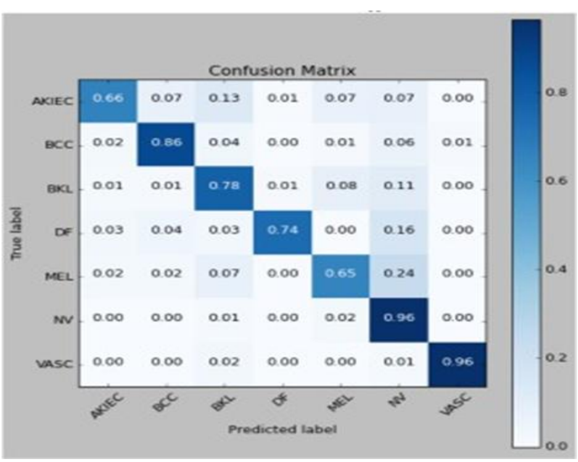


Fig. 4. Confusion matrix.

common skin cancer types, with high precision and recall for categories such as melanoma and basal cell carcinoma. There were some incorrect predictions in situations when lesions shared characteristic traits with different categories which demonstrates the requirement of increased model optimization. The model received Grad-CAM interpretation which used heatmaps to identify crucial image areas responsible for distinguishing categories during classification. The heatmaps established that the model sent its attention to inspection areas instead of background elements which proved consistent with medical diagnostic patterns. Some skin lesion images received scattered attention regions during recognition which requires further developmental work in the model's capabilities. The evaluation metrics demonstrated enhanced capabilities to re- veal the performance of different classes by using precision and recall and F1-score assessments. The classification model displayed a 85.2% precision level combined with an 83.9% recall rate which indicates effective overall model operation. The AUC value of 0.91 from ROC curves proved the strong discrimination capability of the model. Proof exists that the model succeeds well with standard situations although its classification precision might improve if researchers implement data augmentation approaches coupled with loss function optimizations. Future research directions include combining ensemble modeling and active learning schemes to enhance the Boundary classification while decreasing classification er- rors.

VI. CONCLUSION

This study presents an advanced deep learning framework for skin cancer classification, leveraging the DenseNet121 architecture enhanced with Grad-CAM visualization. By utiliz- ing diverse datasets such as HAM10000 and ISIC, along with sophisticated preprocessing techniques, the model achieves high classification accuracy while improving interpretability. The integration of Grad-CAM ensures transparency by high- lighting critical regions influencing predictions, thereby align- ing AI-based diagnostics with clinical expertise. The model demonstrated strong performance, achieving a validation ac- curacy of 84.55% with reliable classification of various skin lesion types. However, challenges such as class imbalance and overlapping features in skin lesions indicate areas for further improvement. Future enhancements may include additional data augmentation, fine-tuning with specialized loss functions, and ensemble learning techniques to further optimize classification accuracy. By combining precision with explainability, this approach contributes to the development of reliable AI-driven diagnostic tools for skin cancer detection.

REFERENCES

[1] Chaturvedi, S.S., Tembhurne, J.V. and Diwan, T. A multi-class skin Can- cer classification using deep convolutional neural networks. Multimed Tools Appl 79, 28477–28498 (2020). https://doi.org/10.1007/s11042-020-09388-2.

[2] Tschandl, Philipp and Rosendahl, Cliff and Kittler, Harald. (2018). The HAM10000 Dataset: A Large Collection of Multi-Source Dermato-scopic Images of Common Pigmented Skin Lesions. Scientific Data.5. 10.1038/sdata.2018.161.

[3] A, Ameri. "A Deep Learning Approach to Skin Cancer Detection in Dermoscopy Images." Journal of biomedical physics and engineering vol. 10,6 801-806. 1 Dec. 2020, doi:10.31661/jbpe. v0i0.2004-1107.

[4] Mijwil, M.M. Skin cancer disease images classification using deep learning solutions. Multimed Tools Appl 80, 26255–26271 (2021). https://doi.org/10.1007/s11042-021 10952-7.

[5] Agarwal, Kartikeya, and Tismeet Singh." Classification of skin can- cer images using convolutional neural networks." arXiv preprint arXiv:2202.00678 (2022).

[6] Selvaraju, Ramprasaath R., et al." Grad-CAM: visual explanations from deep networks via gradient-based localization." International journal of computer vision 128 (2020): 336-359.

[7] R. R. Subramanian, D. Achuth, P. S. Kumar, K. Naveen kumar Reddy,S. Amara and A. S. Chowdary," Skin cancer classification using Convo- lutional neural networks," 2021 11th International Conference on Cloud Computing, Data Science and Engineering (Confluence), Noida, India, 2021, pp. 13-19, doi: 10.1109/Confluence51648.2021.9377155.

[8] Thurnhofer-Hemsi, K., Dom´ınguez, E. A Convolutional Neural Network Framework for Accurate Skin Cancer Detection. Neural Process Lett 53, 30733093 (2021). https://doi.org/10.1007/s11063 020-10364-y.

[9] Khater, Tarek, et al." Skin cancer classification using explainable arti- ficial intelligence on pre extracted image features." Intelligent Systems with Applications 20 (2023): 200275.

[10] K. V. Kumar, M. Baid and K. Menon," Brain Tumor Classification using Transfer Learning on Augmented Data and Visual Explanation using GradCAM," 2023 7th International Conference on Intelligent Computing and Control Systems (ICICCS), Madurai, India, 2023, pp. 965-971, doi:10.1109/ICICCS56967.2023.10142464.

[11] H. L. Gururaj, N. Manju, A. Nagarjun, V. N. M. Aradhya and F. Flammini," DeepSkin: A Deep Learning Approach for Skin Cancer Classification," in IEEE Access, vol. 11, pp. 50205-50214, 2023, doi: 10.1109/ACCESS.2023.3274848.

[12] P. Anil, B. J. L. Narayana, G. K. T. Reddy, S. R. Choudhary and K.S. Sri," Skin Cancer Classification with DenseNet Deep Convolutional Neural Network," 2023 4th IEEE Global Conference for Advance- ment in Technology (GCAT), Bangalore, India, 2023, pp. 1-6, doi: 10.1109/GCAT59970.2023.10353529.