

DEEP LEARNING- BASED SEGMENTATION AND CLASSIFICATION OF SKIN LESIONS

Anila Abraham¹, Neema George²

^{1,2}Mangalam College of Engineering, Kottayam, India.

DOI: <https://www.doi.org/10.58257/IJPREMS35121>

ABSTRACT

Skin cancers such as melanoma are difficult to detect in their early stages because they often resemble harmless moles. It is important to detect melanoma early, treat it effectively and prevent its spread. While using a computer to diagnose melanoma is a good idea, current methods can be inaccurate and time-consuming. DermoScan is a cancer screening site using the Efficient Net B3 standard. It analyses skin photos uploaded by users to determine whether they look normal or show signs of melanoma. Users can also choose from a list of symptoms they are experiencing. The system will tell them when to consult a doctor based on their preferences. Additionally, a list of top dentists and Oncologists is also provided for further assistance. It can learn quickly and accurately after training on many images. Our method is powered by a large database of 8000 high-resolution images representing different skin types, including melanoma, benign lesions, and healthy skin. Instead of a binary classification, our model divides the disease into seven different categories to give an idea of the severity of the disease. You can use the training you have previously received on the EfficientNet B3 model by requesting a training transfer. This leads to faster learning and less labor, ultimately helping to better detect melanoma. After the initial training, the model should be properly tuned by making small adjustments to its location. This improvement is very important because it improves the model's ability to detect small differences between different types of skin diseases, which is especially important for diagnosis in melanoma. This planning process is an important step in the diagnosis and treatment of melanoma. It works well by combining advanced technology, medical knowledge and understanding of what causes skin cancer.

Key words: Skin Lesion, Image Augmentation, Deep Learning, Normalization, F1-Score

1. INTRODUCTION

Skin cancer is a global health problem with an increasing incidence, putting pressure on early diagnosis and treatment. Despite advances in medical technology, accurate diagnosis of skin diseases remains difficult and often depends on the evaluation of dermatologists. Differentiating between benign and malignant tumors like melanoma, basal cell carcinoma, and squamous cell carcinoma can be especially challenging. Early diagnosis is important for rapid treatment, but inaccurate feedback can lead to missed diagnoses or unnecessary biopsies. Artificial intelligence (AI) and computer vision promise to increase detection accuracy and efficiency. Artificial intelligence technology can identify the characteristics of malignant tumors by analyzing dermoscopic images. However, challenges remain, including data size, scope and regulatory considerations. Save lives, lower healthcare costs, and improve patient

Outcomes by increasing early diagnosis and detection. Big and diverse data should be prioritized in the development of AI supported diagnostic tools, consistency of algorithms in patient and measurement models should be ensured, and information should be provided on governance and ethics in the use of medical drugs. Collaboration between clinicians, experts, and regulators is critical to advance AI-based cancer diagnosis and improve health outcomes worldwide. Skin cancer detection tools and methods contribute to reducing healthcare costs by enabling efficient resource allocation and management. With the advent of advanced technologies like artificial intelligence and image analysis, there is a unique opportunity to enhance the accuracy and efficiency of skin cancer diagnosis. Leveraging these tools can empower healthcare professionals to make informed decisions and provide personalized care to patients. By addressing the challenges associated with skin cancer detection, such as inaccuracies and delays in diagnosis, we can ultimately save lives, improve patient quality of life, and alleviate the burden on healthcare systems. Thus, investing in research and innovation in skin cancer detection is crucial for advancing healthcare and public health initiatives.

2. LITERATURE SURVEY

Multiclass skin cancer classification using Efficient Nets—a first step towards preventing skin cancer (Ali, K., Shaikh, Z. A., Khan, A. A., & Laghari, A. A. 2022,[1]) Skin cancer poses a significant challenge in dermatology, demanding precise and timely diagnosis for effective treatment and patient outcomes. Traditionally, this diagnosis heavily relies on visual inspection by dermatologists, which, while effective, can be time-consuming and subject to human error. However, recent advancements in artificial intelligence, particularly in the realm of convolutional neural networks (CNNs), have sparked new possibilities for improving skin cancer classification. In this study, we delve into the

optimization of CNNs, focusing specifically on the highly efficient EfficientNet models, renowned for their superior performance in image classification tasks. To enhance the efficacy of these models, we implement a comprehensive pre-processing pipeline, which includes techniques such as hair removal, dataset augmentation, and image resizing. Leveraging transfer learning, we fine-tune the EfficientNet models using the HAM10000 dataset, capitalizing on pre-trained weights from the ImageNet dataset to expedite training and improve generalization. Through rigorous evaluation using metrics such as Precision, Recall, Accuracy, F1 Score, and Confusion Matrices, we meticulously assess the performance of each EfficientNet variant, from B0 to B7. Our findings underscore the exceptional capabilities of these models, with the EfficientNet B4 variant particularly standing out for its remarkable performance. Interestingly, our analysis reveals intriguing insights into the relationship between model complexity and classification accuracy, indicating that intermediate complexity models, such as EfficientNet B4, often yield the most optimal results. Furthermore, our exploration of Confusion Matrices sheds light on the models' generalization across various skin cancer classes, offering valuable insights for further refinement and optimization. Ultimately, this research represents a significant step forward in the quest to harness artificial intelligence for skin cancer diagnosis, with the potential to revolutionize dermatology practice and improve patient care outcomes.

A deep neural network using modified EfficientNet for skin cancer detection in dermoscopic images (Venugopal, V., Raj, N. I., Nath, M. K., & Stephen, N. 2023,[2]) This study introduces a deep neural network (DNN) model to accurately detect skin cancer from dermoscopic images. The model uses the power of artificial intelligence (AI) in analyzing medical images to provide valuable tools for early disease detection while reducing the risks associated with human error. The new DNN architecture was optimized using the finely tuned EfficientNetV2-M framework and trained on acknowledge base integrating different dermoscopic datasets. Using the transfer learning strategy and data augmentation techniques, the model was successfully trained on data of 58,032 images despite its size. More importantly, the hierarchical architecture can realize binary classification of skin cancer cells and perform better compared to existing deep learning models. Rigorous analysis proves the effectiveness of the design, especially in the context of multi-class and binary classification. Additionally, this paper presents a DNN model based on the improved EfficientNet B4 and EfficientNetV2-M architectures, learned from a knowledge base of 58,032 dermoscopic images selected from various datasets. A comparison with state-of-the-art deep learning models shows the superiority of the EfficientNetV2-M model; this is indicated by its peak accuracy and area under the curve score (AUC). Looking ahead, future research projects include the use of artificial neural networks (GANs) to generate images, the integration of learning and tracking model systems, and associative tissue-level information to improve diagnostic capabilities of associated diseases. The plan, which has the potential for computer-aided diagnosis for dermatologists, is expected to provide significant advances in the detection and diagnosis of skin cancer.

Lung-EffNet: Lung cancer classification using Efficient Net from CT-scan images (Raza, R., Zulfiqar, F., Khan, M. O., Arif, M., Alvi, A., Iftikhar, M. A., & Alam, T. 2023,[3]) The threat of lung cancer (LC) has a major impact on the global health landscape, and early detection methods are urgently needed to control the progression of this massive damage. Although computed tomography (CT) scans have become an important tool in the fight against LC, manual analysis remains laborious and error-prone, underscoring the need for computational interventions. In this context, machine learning and deep learning algorithms provide an effective way to accelerate and improve CT scan analysis, paving the way for more efficient and customized treatments. Our research shows that by leveraging the power of adaptive learning, Lung-EffNet, a decision maker using the Efficient Net architecture, transforms LC classification. Through rigorous evaluation of the "IQ-OTH/NCCD" dataset, Lung-EffNet demonstrates the ability to accurately classify lung cancer patients as benign, malignant, or into one group. To strengthen the model against the challenges of different classes, we use a complex data augmentation process to ensure the performance of different patients. More importantly, Lung-EffNet achieved accuracy and ROC scores, outperforming existing pre-trained CNN architectures and verifying that it is capable and effective for automatic LC testing. Looking to the future, our research trajectory is marked by progress and development. Future efforts will include investigating other deep learning methods as well as effectively using larger datasets to improve model detail and site performance. In addition, we advocate in-depth exploration of translation technology and integration of multiple data sources and look forward to the future of LC testing that will enable doctors to inform doctors knowledgeably and effectively that pain is not only accurate but also positive. decisions. their patients.

Automation of brain tumor identification using efficient net on magnetic resonance images (Tripathy, Sushreeta, Rishabh Singh, and Mousim Ray, 2023,[4]) The distribution of brain tumors is an important part of diagnosis and is key to early detection and effective treatment strategies. Traditionally, these procedures have relied on invasive biopsy procedures that are risky and can cause long-term pain. But as artificial intelligence and machine learning technologies

develop, there's hope that non-invasive techniques—like magnetic resonance imaging (MRI) scans—will become more common. In this context, research becomes a beacon of innovation by proposing a new technology that leverages the power of the EfficientNet model, a suite of advanced pre-learning deep learning models for transition to education. Leveraging the power of Efficient Net variants such as B2, B3, and B4, our framework surpasses traditional convolutional neural network (CNN) architectures and exceeds the performance benchmarks set by established models such as Resnet. The mixing coefficient method is included in the Efficient Net model. This specification requires simultaneous measurement of all dimensions of the input image, making the capture process and detailed information important for accurate tumor classification. Therefore, our frameworks not only accurate but also computationally efficient; is important for real-world applications, especially in areas with limited resources. Many promising avenues for research and development have been identified. First, by delving deeper into the potential of EfficientNet variants such as B7, we intend to unlock greater efficiency in these cases and increase the effectiveness of the framework. We also aim to expand our classification to include nuances of the nervous system and facilitate treatment planning. By interpreting the process and effectiveness of the EfficientNet- based research model through the combination of technology and clinical experience, we propose to update the challenging landscape of neuro-oncology and bring new hope and optimism to patients and doctors.

Utilizing Efficient Net for sheep breed identification in low-resolution images (Himel, Galib Muhammad Shahriar, Md Masudul Islam, and Mijanur Rahaman.2024,[5]) - For commercial sheep farming, automatic sheep identification is highly helpful in helping

producers satisfy market demands. But it might be challenging to distinguish the real differences between sheep, particularly for inexperienced farmers. While biometric-based identification is a solution, its effectiveness decreases if large numbers of sheep are handled quickly. It will therefore be important to use sheep classification methods that can replicate the expert's statistical knowledge. This model is especially useful for new farmers who can use hand tools for a variety of distributions. To meet this need I present a convolutional neural network (CNN) model that recognizes sheep in photos with poor resolution. We use a database of 1680 face photos from four distinct sheep breeds for our experiment. I tested a number of different EfficientNet models and discovered that EfficientNetB5 performed the best, with 97.62% accuracy at 10% classification. Farmers can evaluate more and divide different business operations more specialized by using the distribution model to help them discriminate between different species. Our study demonstrates the effectiveness and efficiency of using the EfficientNet model in sheep identification and classification in the context of smart agriculture. The model provides farmers with useful information that will enable them to make informed decisions. Continued progress in this field has the potential to change the way sheep farming is done, making the business more profitable and profitable. Even new farmers can benefit from our model, and our potential customers can seamlessly identify sheep using their mobile devices. While previous studies investigated sheep breeding patterns, our model passed with a classification accuracy of 97.62%. Future improvements will include incorporating new data into the training process to improve the model's performance.

3. PROPOSED SYSTEM

By providing an online platform that enables users to quickly and easily examine their skin issues, the proposed system aims to transform skin health assessment and consultation. Our system uses cutting-edge technology to give users initial assessments and assistance in response to the rising incidence of skin illnesses and the difficulties in obtaining dermatological expertise, especially in disadvantaged areas. DemoScan system is built to accomplish a number of important goals. First and foremost, our goal is to create an intuitive website that makes it simple for users to post pictures of skin lesions or other trouble spots. Second, using the submitted photographs as a basis, we apply an advanced image analysis algorithm that can identify possible skin diseases. Thirdly, deliver users outcomes that are both instructive and practical, such as advice on when to seek medical assistance. In conclusion, we provide a thorough network of dermatologists and medical professionals who specialize in skin issues for additional guidance and care. A variety of features are included in our system to improve user experience and enable efficient skin health assessment. It has simple image uploading capabilities that are supported by a strong prediction system that evaluates submitted photos to produce precise evaluations. Users are supplied with pertinent information regarding the ailment, common symptoms, and suggested actions in addition to their results. Furthermore, depending on the severity of symptoms or suspected illnesses, our system provides advice on when to seek medical assistance. Users can also identify skilled dermatologists and doctors via a directory, which helps them locate appropriate medical specialists for additional consultation and treatment. Users can take use of many advantages provided by the system, such as early detection, accessibility, ease, and expert referral. Through the provision of easily accessible healthcare information and guidance, our system guarantees that users can quickly assess their skin health and receive timely intervention when necessary, regardless of

their geographic location. While the ease of online evaluation saves users time and effort, the system's early identification helps to enhance health outcomes. Furthermore, the method guarantees thorough treatment and professional consultation by matching consumers with licensed dermatologists and physicians.

3.1 SYSTEM DESIGN

In this figure 3.1 shows the level 0 DFD depicts an image processing system's basic data flow. DFD shows how a user interacts with the by input the image and receiving corresponding results.



Fig 3.1: Data Flow Diagram Level 0 for a skin cancer detection system

3.2 DFD LEVEL 1

In the figure 3.2 show the diagram represents a level 1 DFD of a skin cancer detection system. It depicts how users (including admins) interact with the system.

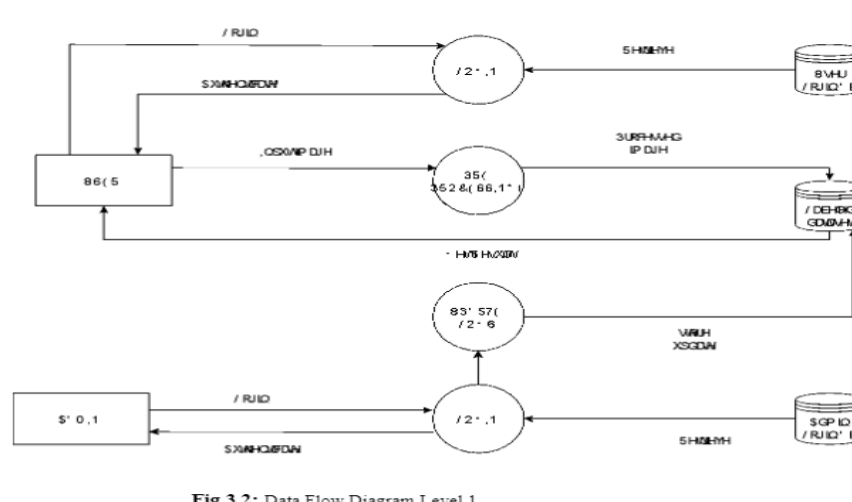
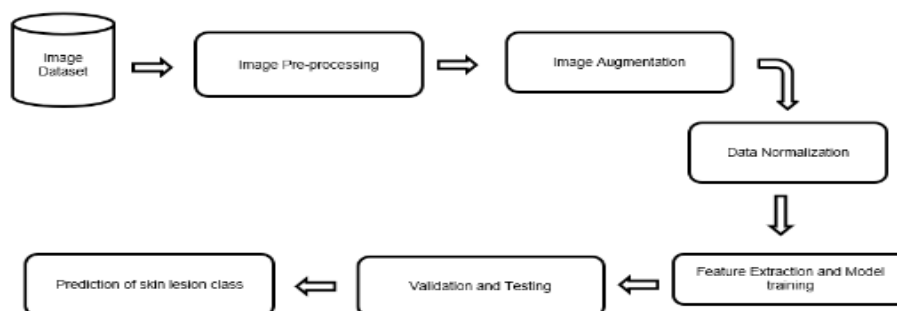


Fig 3.2: Data Flow Diagram Level 1

In the figure 3.3 The block diagram illustrates a system depicting the various steps associated with image classification, from image pre-processing to the prediction of the corresponding class.



1. Dataset Acquisition: This module involves obtaining a diverse and well-labelled dataset containing skin lesion images along with corresponding labels indicating the type of lesion present. The dataset is carefully curated to ensure it encompasses various lesion types, variations, and severity levels, essential for training a robust model.

2. Pre-processing: In this module, the acquired images undergo several transformations to prepare them for input into the classification model. This includes resizing the images to a standardized dimension, typically 224x224 pixels, normalization of pixel values to a common scale (e.g., [0, 1]), and applying data augmentation techniques such as rotation, flipping, and scaling to increase dataset variability.

3. Feature Extraction: The core of the system lies in this module, where a pre-trained convolutional neural network (CNN) architecture, such as EfficientNet B3, is utilized for feature extraction. The pre-trained model is loaded, and its convolutional layers are typically frozen to preserve learned hierarchical features. Additional layers may be added on top to adapt the model to the specific task of skin lesion classification.

4. **Model Training:** Once the model architecture is defined, it is compiled with appropriate loss functions, optimizers, and evaluation metrics tailored to the classification task. Common choices include categorical cross-entropy loss, Adamax optimizer, and accuracy metric. The model is then trained on the training dataset using techniques such as mini-batch stochastic gradient descent (SGD) or adaptive learning rate methods.

5. **Validation and Testing:** After training, the performance of the trained model is evaluated using a separate testing dataset. Various evaluation metrics such as accuracy, sensitivity, specificity, and F1-score are computed to assess the model's effectiveness in classifying skin lesions. Confusion matrices and ROC curves may also be analysed to gain insights into the model's performance across different lesion types and severity levels.

4. EXPERIMENT AND RESULT

Confusion matrix: It is a table that describes the performance of a classification model by comparing the actual labels with the predicted labels.

True Positive (TP): The number of samples that were correctly classified as positive.

True Negative (TN): The number of samples that were correctly classified as negative.

False Positive (FP): The number of samples that were incorrectly classified as positive.

False Negative (FN): The number of samples that were incorrectly classified as negative.

Accuracy: The proportion of correctly classified samples out of the total samples.

$$\text{Accuracy} = (TP + TN) / (TP + TN + FP + FN)$$

Precision: The proportion of true positive classifications out of all positive classifications made by the model.

$$\text{Precision} = TP / (TP + FP)$$

Recall (Sensitivity or True Positive Rate): The proportion of true positive classifications out of all actual positive samples.

$$\text{Recall} = TP / (TP + FN)$$

F1 Score: The harmonic mean of precision and recall. It provides a balance between precision and recall.

$$\text{F1 Score} = 2 \times ((\text{Precision} \times \text{Recall}) / (\text{Precision} + \text{Recall}))$$

Specificity (True Negative Rate): The proportion of true negative classifications out of all actual negative samples.

$$\text{Specificity} = TN / (TN + FP)$$

Confusion matrix: It is a table that describes the performance of a classification model by comparing the actual labels with the predicted labels.

$$\text{Accuracy} = (TP + TN) / (TP + TN + FP + FN)$$

$$\text{F1 Score} = 2 \times ((\text{Precision} \times \text{Recall}) / (\text{Precision} + \text{Recall}))$$

Specificity (True Negative Rate): The proportion of true negative classifications out of all actual negative samples.

$$\text{Specificity} = TN / (TN + FP)$$

detection research and fostering innovation in medical imaging and diagnostic technologies. The figure 4.1 shows the confusion matrix which helps to visualize the performance of the classifier by showing which classes are being classified correctly and which are being misclassified.

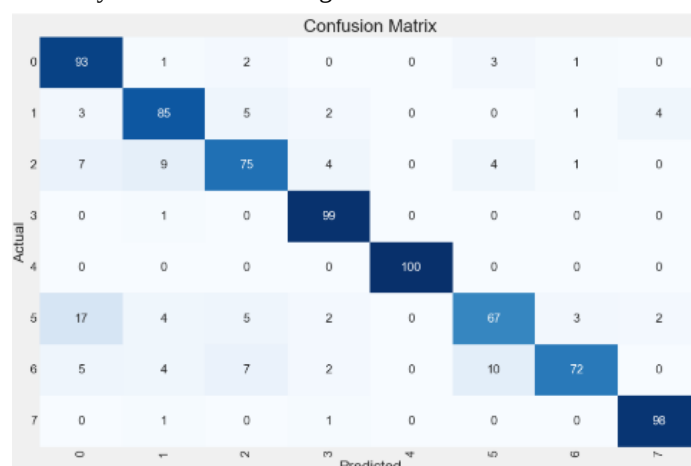
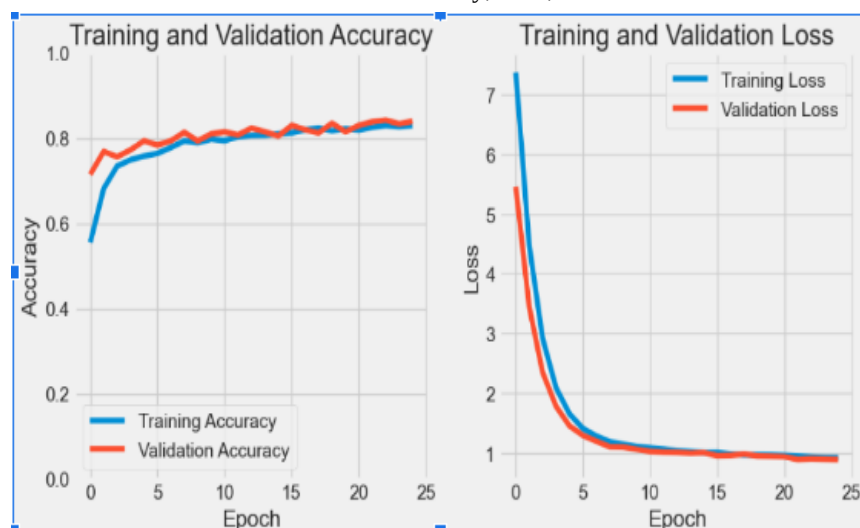


Figure 4.2 displays the classification report, which used various metrics such as precision, recall, F1-score, and support

Classification Report:				
	precision	recall	f1-score	support
0	0.7440	0.9300	0.8267	100
1	0.8095	0.8500	0.8293	100
2	0.7979	0.7500	0.7732	100
3	0.9000	0.9900	0.9429	100
4	1.0000	1.0000	1.0000	100
5	0.7976	0.6700	0.7283	100
6	0.9231	0.7200	0.8090	100
7	0.9423	0.9800	0.9608	100
accuracy			0.8612	800
macro avg	0.8643	0.8613	0.8588	800
weighted avg	0.8643	0.8612	0.8588	800

figure 4.3 an analysis is carried out with regard to a collection of training data, in order to evaluate the effectiveness of EfficientNetB3 based on accuracy, TPR, and FPR measures.



The Dermoscan system demonstrates 87% accuracy in classifying skin lesions, showcasing its potential as an effective tool for early skin cancer detection.. Machine Learning Model Performance:evaluated the performance of different machine learning models, such as CNNs and transfer learning models, in classifying skin lesions based on dermoscopic images. In our evaluation of machine learning models, we found that EfficientNetB3 emerged as the top performer in terms of accuracy and overall performance. Impact of Data Quality: The quality and diversity of the dataset used for training and testing significantly influence the performance of our Dermoscan system. Ensuring a well-curated and representative dataset is crucial for achieving reliable classification results. User Experience: We considered the user experience aspect of Dermoscan, emphasizing the importance of user feedback and interface design in enhancing the usability and acceptance of the system by dermatologists and patients alike.

Discussion:

Balancing Sensitivity and Specificity: Dermoscan system aims to strike the right balance between sensitivity (accurate detection of malignant lesions) and specificity (minimization of false positives). Depending on the clinical context, prioritizing one metric over the other may be necessary. **Continuous Improvement:** We recognize the importance of ongoing optimization and refinement of the Dermoscan system. This includes fine-tuning machine learning models, incorporating new data sources, and updating classification algorithms to adapt to evolving dermatological knowledge and diagnostic criteria. **Ethical Considerations:** As with any medical technology, ethical considerations surrounding patient privacy, informed consent, and equitable access to healthcare must be addressed. We discussed the ethical implications of using Dermoscan and the importance of ensuring its responsible and ethical deployment in clinical settings. Through comprehensive evaluation of Dermoscan's performance and its implications for skin cancer detection and diagnosis, we aim to contribute to the advancement of dermatological care and improve patient outcomes.

5. CONCLUSION

In conclusion, DermoScan epitomizes the potential of interdisciplinary collaboration and technological innovation within healthcare. By bridging medical expertise with technological advancements, DermoScan heralds a shift towards more personalized and efficient healthcare delivery. Its creation signifies a pivotal moment where the convergence of medical and technological fields propels us towards unprecedented levels of healthcare excellence. Moreover, DermoScan's intuitive interface and seamless integration into existing healthcare workflows ensure accessibility and usability for healthcare professionals across diverse settings. This user-centric approach not only enhances adoption rates but also facilitates widespread utilization in various healthcare environments. Furthermore, the scalability of DermoScan offers promise for global adoption, empowering healthcare systems worldwide to tackle the escalating burden of skin cancer with heightened efficacy and efficiency. As DermoScan continues to evolve through ongoing refinements and advancements, it holds the potential to redefine standards of care in dermatology. Beyond its immediate impact, DermoScan is positioned to inspire future innovations in medical imaging and diagnostics. Its success story serves as a testament to the tireless pursuit of excellence in leveraging technology to safeguard human health and well-being. By pushing the boundaries of what is possible in healthcare, DermoScan lays the groundwork for a brighter and healthier future for generations to come. DermoScan embodies the spirit of innovation and collaboration, driving transformative change in healthcare delivery models. As we journey towards a future where precision medicine becomes the norm, DermoScan stands as a beacon of hope, guiding us towards a world where healthcare is not just reactive but proactive, personalized, and profoundly impactful.

6. REFERENCES

- [1] Ali, Karar, Zaffar Ahmed Shaikh, Abdullah Ayub Khan, and Asif Ali Laghari. "Multiclass skin cancer classification using EfficientNets—a first step towards preventing skin cancer." *Neuroscience Informatics* 2, no. 4 (2022): 100034
- [2] Venugopal, Vipin, Navin Infant Raj, Malaya Kumar Nath, and Norton Stephen. "A deep neural network using modified EfficientNet for skin cancer detection in dermoscopic images." *Decision Analytics Journal* 8 (2023): 100278
- [3] Raza, Rehan, Fatima Zulfiqar, Muhammad Owais Khan, Muhammad Arif, Atif Alvi, Muhammad Aksam Iftikhar, and Tanvir Alam. "Lung-EffNet: Lung cancer classification using EfficientNet from CT-scan images." *Engineering Applications of Artificial Intelligence* 126 (2023): 106902
- [4] Tripathy, Sushreeta, Rishabh Singh, and Mousim Ray. "Automation of brain tumor identification using efficientnet on magnetic resonance images." *Procedia Computer Science* 218 (2023): 1551-1560
- [5] Himel, Galib Muhammad Shahriar, Md Masudul Islam, and Mijanur Rahaman. "Utilizing EfficientNet for sheep breed identification in low-resolution images." *Systems and Soft Computing* 6 (2024): 200093