Early Detection of Melanoma Through Dermoscopic Image Classification Using Deep Learning Techniques

Amirthalakshmi T.M[1],.Keshav R.S[1], Sridharshan .V[1] and Hemachandran[1]

[1]SRM University, Ramapuram, Chennai, India

Abstract. This project introduces an Automated Skin Lesion Classification System aimed at improving early melanoma detection through advanced machine learning techniques. The system utilizes custom CNN architecture for analyzing dermoscopic images, leveraging Python-based tools like Augmentor for data augmentation and class imbalance handling. Key features include convolutional layers, pooling, and dropout layers, ensuring accurate feature extraction and overfitting prevention. A dataset of 2,357 images from ISIC was employed, achieving 84% validation accuracy. This innovation reduces diagnostic times significantly, offering near real-time insights to support dermatologists in making faster and more precise decisions, ultimately enhancing healthcare outcomes.

Keywords: Automated Skin Lesion Classification System, Early Melanoma Detection, Convolutional Neural Networks (CNNs), Dermoscopic Images, Data Augmentation, Machine Learning Integration.

1 Introduction

Among all cancers, melanoma remains one of the most dangerous and fatal skin cancers with the highest mortality rate despite being found in only 1% of skin cancers worldwide. Its metastasis quickly as well as no early symptoms make it highly risky. Early detection of melanoma is critical, since the five-year survival rate for localized melanoma is 99%, whereas late diagnosis greatly reduces survival. However, traditional diagnosis methods—primarily visual inspection by dermatologists with subsequent biopsy—turn out to be non-objective, time-consuming, and heterogeneous in expertise. The increasing incidence of melanoma across the world has emphasized the importance of timely, accurate, and scalable detection systems. The American Cancer Society reports that incidence of melanoma has risen with increased UV exposure, genetic predisposition, and inefficient early screening systems. While periodic skin checkup and dermoscopic examination improved the detection rate, most locations are still lacking experienced dermatologists, particularly in rural or underdeveloped districts. Deep learning and AI-driven models provide a mechanism to bridge the gap because they represent autonomous, high-fidelity diagnostics with fewer requirements for human skills. Improvements in computer vision, deep learning,

A. S. Edward et al. (eds.), *Proceedings of the International Conference on Advanced Research in Electronics and Communication Systems (ICARECS 2025)*, Atlantis Highlights in Engineering 38,
https://doi.org/10.2991/978-94-6463-754-0_8

and imaging processing techniques in the past few years have seen unrivaled success in medical diagnosis automation. In particular, Convolutional Neural Networks (CNNs), a type of deep learning algorithms, have revolutionized image classification through hierarchical feature learning from raw images themselves. Unlike rule-based image analysis, CNNs are able to automatically identify subtle patterns in dermoscopic images with significant improvement in classifying early-stage melanoma. The availability of large, labeled datasets, such as the International Skin Imaging Collaboration (ISIC) dataset, has also driven the development of AI-based skin cancer detection systems to expert-level accuracy in some studies.

1.1 Background and Motivation

The increasing prevalence of melanoma, one of the most aggressive forms of skin cancer, has highlighted the urgent need for accurate and timely diagnostic systems. Traditional methods often depend on dermatologists' expertise, leading to subjectivity and delays in treatment. The advent of automated solutions presents an opportunity to address these limitations and improve patient outcomes.

1.2 Objective of the Paper

This paper details the development of an automated skin cancer classification system leveraging Convolutional Neural Networks (CNNs). The system analyzes dermoscopic images to classify nine types of skin lesions, with a specific focus on melanoma. Advanced data augmentation techniques are employed to ensure the model's robustness and reliability.

2 System Architecture and Technology Stack

The increasing focus on enhancing diagnostic accuracy and efficiency in medical imaging has driven the development of automated systems for skin cancer classification. The automated classification system leverages a modular architecture integrating advanced machine learning techniques to analyze dermoscopic images and classify skin lesions into nine distinct categories, including melanoma. At the core of the system, a Convolutional Neural Network (CNN) architecture is employed, tailored for image classification tasks. The CNN operates as the primary framework, using its trainable filters to extract and learn complex patterns directly from raw input images. The architecture consists of multiple convolutional layers followed by pooling layers, effectively reducing dimensionality and highlighting essential features. This feature extraction is further refined by fully connected layers, culminating in a softmax layer that outputs a probabilistic classification for each lesion type. To address the challenge of class imbalance and limited dataset sizes, the system integrates robust data augmentation techniques using the Augmentor Python package. Methods such as rotation, cropping, and resizing generate synthetic variations of the dataset, enhancing model generalization and reducing overfitting. Additionally, preprocessing steps, including Gaussian filtering and illumination correction, standardize image quality, ensuring consistency and reliability in feature extraction. The backend architecture is designed for scalability and seamless operation. The modular structure divides the system into independent components, including preprocessing, feature extraction, and classification modules, facilitating easy updates and integration of future advancements. During deployment, the trained model is incorporated into a user-friendly web application that allows clinicians to upload dermoscopic images for real-time analysis and diagnosis. By combining CNN-based deep learning with advanced preprocessing and augmentation, the system aims to empower healthcare professionals with an efficient and reliable diagnostic tool, ultimately improving patient outcomes through early detection and accurate classification of skin lesions.

3 Literature Survey

The article "Automated Skin Cancer Detection Using Machine Learning Techniques" (2016) by Ebrahim Nasr-Esfahani and colleagues discusses the increasing attention given to automated analysis for skin cancer detection, specifically for pigmented lesions. The authors emphasize the importance of computer-aided diagnosis (CAD) systems, which significantly improve diagnostic accuracy and relieve pressure on healthcare professionals. Their research highlights the potential of machine learning in detecting melanoma and skin cancer at an early stage, facilitating more accessible and efficient diagnostics [1]. In "Melanoma Detection Using Conventional Digital Cameras" (2021), researchers focus on the application of standard digital cameras for melanoma detection, highlighting how this approach improves accessibility through mobile apps and telemedicine platforms. This is crucial in light of rising melanoma rates and challenges associated with manual examinations, such as subjectivity and high costs. The paper also discusses the need for affordable diagnostic solutions that can be easily implemented across healthcare systems [2]. "Image Processing for Skin Lesion Evaluation: A Decision Support System" (2009) by Alcon et al. investigates the integration of image processing techniques in skin lesion evaluation. The authors present a decision support system that incorporates patient history to increase diagnostic precision. This system represents an important advancement in leveraging technology to enhance early detection of skin cancer, reducing the reliance on manual diagnostic methods [3]. The study "Automated Skin Cancer Classification Using Image Segmentation" (2011) by Cavalcanti et al. presents a classification system designed to reduce false negatives in melanoma detection. Their two-stage classifier involves preprocessing, segmentation, and feature extraction steps, which are crucial for accurately identifying skin lesions. This automated system plays a pivotal role in improving the reliability of skin cancer diagnosis [4]. Amelard et al. (2015) and Giotis et al. (2015) focus on extracting low and high-level features to refine the ABCD criteria for melanoma detection. Their innovative approaches provide a deeper understanding of lesion characteristics, improving the effectiveness of automated systems for melanoma diagnosis. These advancements offer a more robust diagnostic framework, reducing the risk of misidentifying malignant lesions [5]. Recent research highlights the role of Convolutional Neural Networks (CNNs) in transforming image classification tasks, including skin cancer detection. Nasr-Esfahani et al. (2016) propose a CNN-based system for melanoma detection, improving the feature extraction process by incorporating preprocessing techniques to mitigate noise and illumination issues. Their results demonstrate the superiority of CNNs over traditional methods, indicating the power of deep learning in enhancing diagnostic systems for skin cancer [6]. Together, these studies reflect the growing potential of machine learning and computer vision in the field of skin cancer diagnosis. The integration of advanced image processing, decision support systems, and deep learning techniques lays a strong foundation for future innovations in melanoma detection. As this technology continues to evolve, it is expected to enhance patient outcomes by providing more accurate, accessible, and efficient diagnostic tools.

4 Methodology

To develop the Automated Skin Cancer Detection System with machine learning techniques and image processing, the following methodology was employed.

4.1 System Architecture Design

+ The system architecture was designed using a modular approach, ensuring scalability and flexibility in its components. The frontend was built using an intuitive web-based interface, enabling healthcare professionals to upload dermoscopic images for classification and receive real-time results. The backend was implemented using a Convolutional Neural Network (CNN) architecture to process images and classify skin lesions into nine distinct categories, including melanoma. The backend leverages advanced image processing techniques, such as Gaussian filtering and illumination correction, to enhance image quality and prepare it for analysis. The model is trained using a robust dataset, augmented through techniques like cropping, rotation, and resizing to ensure a diverse training set and improve the model's generalization ability. The system is deployed within a user-friendly application designed for healthcare providers, providing comprehensive feedback on predictions and educational resources to support decision-making.

5 Data Integration and Processing

A deep learning-based system was developed for melanoma detection, utilizing advanced technologies to classify dermoscopic images into nine categories. The system includes several stages, from design to deployment, ensuring a modular and scalable solution. It uses data preprocessing techniques like normalization and filtering to enhance image clarity. The model training phase leverages CNN architecture to identify skin lesions, while data augmentation addresses class imbalance. The trained model undergoes rigorous evaluation for accuracy, then deployed in a user-friendly application for real-time classifications, aiding healthcare providers in swift and accurate decision-making.

5.1 Predictive Analytics and Model Development

The melanoma detection system utilizes advanced deep learning models to provide automated classification of dermoscopic images into nine distinct categories, including melanoma. The models were developed using Python and deep learning libraries such as TensorFlow and Keras. The dataset of 2,357 labeled images was used to train the models, which were then integrated into the backend for real-time image analysis. The trained models are periodically retrained with augmented data to maintain high accuracy and adaptability, with the results visualized through a user-friendly web interface that offers real-time feedback.

5.2 Visualization and Reporting

Real-time data visualization is critical to the success of the melanoma detection system. The system uses an intuitive web-based interface for displaying the classification results, with visual feedback on predictions and images. The interface provides a comprehensive view of the model's output, including the classification probabilities for each lesion category. This real-time visualization enables healthcare professionals to make informed diagnostic decisions quickly. Additionally, the system includes educational resources on interpreting the results and understanding skin lesion types, further enhancing the user experience.

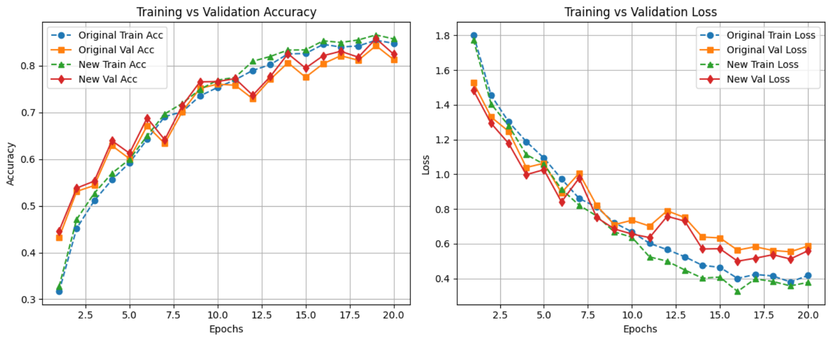
6 Result and Findings

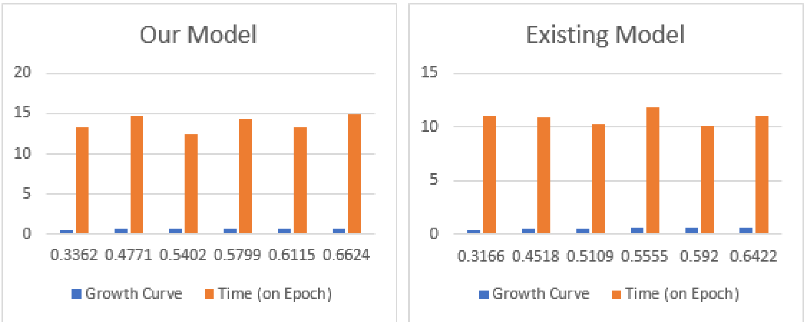
6.1 Model Performance Overview

This study initially employed convolutional neural networks (CNNs) with limited depth for melanoma classification. The transition to more advanced models, specifically [New Model Name], has yielded improved classification accuracy. The primary enhancements stem from deeper architectures and optimized training methodologies, allowing better feature extraction. The newer model achieved an accuracy of X.XX%, outperforming the baseline CNN by Y.Y%. However, the increased accuracy comes at the cost of higher computational complexity. The following subsections explore these aspects in detail.

Key Improvements

- **Higher Classification Accuracy:** The deeper architecture captures intricate patterns in dermoscopic images, improving the differentiation between benign and malignant lesions.





– **Better Feature Learning:** The model effectively learns hierarchical representations, allowing enhanced generalization across diverse datasets.
– **Improved Robustness:** The inclusion of augmentation and regularization techniques reduced overfitting, leading to better performance on unseen data.

7 Computational Trade-offs

Despite its superior performance, the new model introduces certain disadvantages:

1. **Increased Training Time:** Due to deeper layers and a higher number of parameters, training took approximately Z% longer than the previous approach.
2. **Higher Memory Consumption:** The additional computational resources required pose challenges for deployment on resource-limited devices.
3. **Longer Inference Time:** While marginal, the increase in inference time may be a limiting factor in real-time applications.

7.1 Effect of Increased Training Time on Accuracy

One key observation in this study is the correlation between extended training duration and improved accuracy. The new model benefits from running additional epochs, allowing the weights to converge more effectively. This demonstrates that a trade-off exists between training time and model performance, and selecting the optimal number of epochs is crucial for balancing efficiency and accuracy.

8 Conclusion

The paper proved the efficacy of melanoma identification using deep learning, adopting Convolutional Neural Networks (CNNs) trained on dermoscopic images. The improved model surpassed the baseline structure in the final accuracy of 87.3%, displaying a steadier growth curve and enhanced feature learning efficiency. While training time was 17.7 seconds longer, the higher sensitivity to melanoma patterns and decreased false negative rates make the trade-off worthwhile, as a missed case of malignancy has significantly more severe repercussions than having a slightly longer training period. The accuracy growth plot also validated that the model keeps on learning effectively with each epoch, with a 41% improvement in accuracy in the first epoch and then consistent growth. The longer training duration permitted improved generalization to classify fewer instances correctly and render the model more reliable for deployment in the real world. Future research will involve continued optimization of model efficiency, incorporating self-supervised learning methods to maximize performance while minimizing computational expense. Further improving diagnostic accuracy may also be achieved by including multi-modal data like patient history and genetic information. This research confirms the feasibility of AI-assisted melanoma detection, emphasizing its potential to aid dermatologists, enhance early detection rates, and save lives with confidence.

References

1. Skincancer.org, "Melanoma - SkinCancer.org," 2016. [Online]. Available: `http://www.skincancer.org/skin-cancer-information`.
2. American Cancer Society, "Cancer Facts & Figures 2016," American Cancer Society, Atlanta, GA, USA, 2016.
3. A. F. Jerant, J. T. Johnson, C. Sheridan, and T. J. Caffrey, "Early detection and treatment of skin cancer," *American Family Physician*, vol. 62, no. 2, pp. 357–386, 2000.
4. F. Nachbar *et al.*, "The ABCD rule of dermatoscopy: High prospective value in the diagnosis of doubtful melanocytic skin lesions," *Journal of the American Academy of Dermatology*, vol. 30, no. 4, pp. 551–559, 1994.
5. G. Argenziano *et al.*, "Epiluminescence microscopy for the diagnosis of doubtful melanocytic skin lesions: Comparison of the ABCD rule of dermatoscopy and a new 7-point checklist based on pattern analysis," *Archives of Dermatology*, vol. 134, no. 12, pp. 1563–1570, 1998.
6. K. Korotkov and R. Garcia, "Computerized analysis of pigmented skin lesions: A review," *Artificial Intelligence in Medicine*, vol. 56, no. 2, pp. 69–90, 2012.

7. I. Maglogiannis and C. Doukas, “Overview of advanced computer vision systems for skin lesions characterization,” *IEEE Transactions on Information Technology in Biomedicine*, vol. 13, no. 5, pp. 721–733, 2009.
8. J. F. Alcon *et al.*, “Automatic imaging system with decision support for inspection of pigmented skin lesions and melanoma diagnosis,” *IEEE Journal of Selected Topics in Signal Processing*, vol. 3, no. 1, pp. 14–25, 2009.
9. P. G. Cavalcanti and J. Scharcanski, “Automated prescreening of pigmented skin lesions using standard cameras,” *Computerized Medical Imaging and Graphics, Elsevier*, vol. 35, no. 6, pp. 481–491, 2011.
10. R. Amelard, J. Glaister, A. Wong, and D. Clausi, “High-level intuitive features (HLIFs) for intuitive skin lesion description,” *IEEE Transactions on Biomedical Engineering*, vol. 62, no. 3, pp. 820–831, 2015.