Skin Cancer Detection Using the CNN (Convolutional Neural Network) Model Fast.ai Library

Aldi Syahputra[1], Filbert[2], Divoni Wesly[3]
[1,2,3]Informatics Engineering, [3]Information Technology, Mikroskil University, Indonesia
e-mail: **[1]211110952@students.mikroskil.ac.id**, **[2]211112233@students.mikroskil.ac.id**, **[3]211111643@students.mikroskil.ac.id**

Skin lesion classification is crucial for the early detection and management of dermatological conditions, especially melanoma, which is a highly aggressive form of skin cancer. Challenges arise due to the variability in lesion appearances and overlapping features between benign and malignant categories. This research addresses these issues by employing a Convolutional Neural Network (CNN) model with DenseNet169 architecture. The model was trained on a curated dataset and enhanced through image preprocessing techniques such as normalization and augmentation to ensure robust performance. Evaluation results indicate an accuracy exceeding 90%, highlighting the model's efficacy in distinguishing between seven skin lesion categories, including melanoma and vascular lesions. The study also incorporates a web-based interface, making the model accessible for real-world usage. This combination of high accuracy and user-friendly implementation underscores the importance of AI in augmenting early diagnosis efforts, contributing to improved patient outcomes.

Keywords— CNN (Convolutional Neural Network), DenseNet169, Skin lesion, Web Apps

1. INTRODUCTION

Skin diseases, particularly melanoma, represent a significant global health concern due to their high prevalence and the potential for severe outcomes if left undiagnosed. Early detection of skin lesions can substantially improve treatment success rates and reduce mortality. However, accurate diagnosis remains challenging, as clinicians rely heavily on subjective evaluation, which can lead to misdiagnosis. The increasing demand for precise and scalable diagnostic tools has driven advancements in automated image analysis systems [1], [2].

Recent studies in medical imaging and artificial intelligence (AI) have demonstrated the efficacy of convolutional neural networks (CNNs) in classifying skin lesions with accuracy comparable to dermatologists [3]. Traditional approaches often struggle with the variability in lesion appearances, including differences in color, texture, and size, as well as overlapping features between benign and malignant lesions. These challenges highlight the necessity for robust and adaptive solutions [4].

This research leverages the DenseNet169 architecture, a CNN model known for its superior feature extraction capabilities, to classify skin lesions into seven categories, including melanoma and benign nevi. Unlike prior works that focus solely on model accuracy, this study integrates an accessible web-based platform to enhance usability for non-technical users.

COGITO Smart Journal – Vol. X, No. X, Month 20XX. P-ISSN: 2541-2221, E-ISSN: 2477-8079

The proposed system combines state-of-the-art image preprocessing techniques, such as normalization and augmentation, with advanced deep learning methodologies. By addressing the gaps in diagnostic accuracy and accessibility, this study aims to bridge the divide between clinical expertise and technological innovation. Furthermore, this research contributes to the field by offering a reproducible and scalable framework for skin lesion analysis, ensuring its applicability in diverse healthcare settings [5].

The remainder of this paper is organized as follows: Section 2 discusses the theoretical basis and related works. Section 3 outlines the research methodology, including dataset preparation and model training. Section 4 presents the results and discusses their implications. Finally, Section 5 concludes the study and highlights potential areas for future work.

2. RESEARCH METHODS

2.1. Dataset Preparation

The research utilizes the ISIC (International Skin Imaging Collaboration) dataset, which is widely recognized for skin lesion analysis. The dataset includes over 25,000 dermoscopic images categorized into seven classes: melanoma, nevus, basal cell carcinoma, benign keratosis, dermatofibroma, vascular lesions, and actinic keratosis. To address class imbalance, the dataset was augmented using techniques such as rotation, flipping, zooming, and color jittering.

2.2. Image Preprocessing

Preprocessing was conducted to enhance model performance and ensure uniformity in input data. The steps included:

- **Resizing:** All images were resized to 224x224 pixels to fit the input requirements of the DenseNet169 model.
- **Normalization:** Pixel values were scaled to the range [0, 1] to standardize the dataset.
- **Data Augmentation:** Random transformations, including rotations, flips, and brightness adjustments, were applied during training to increase the model's robustness.

2.3. Model Architecture

The Convolutional Neural Network (CNN) model used in this study is based on the DenseNet169 architecture, known for its efficient feature extraction and reduced parameter count. Key features include:

- **Dense Connectivity:** Facilitates feature reuse and mitigates the vanishing gradient problem.
- **Global Average Pooling (GAP):** Reduces the risk of overfitting by replacing fully connected layers.
- **Softmax Classifier:** Outputs probabilities for the seven classes.

2.4. Training Procedure

The model was trained using the Fast.ai library, leveraging PyTorch as the backend. The training pipeline consisted of:

- **Transfer Learning:** Pretrained weights on ImageNet were used to initialize the DenseNet169 model.
- **Learning Rate Finder:** Optimal learning rates were determined to expedite convergence.
- **Optimization:** The Adam optimizer was employed with a learning rate of 0.001, and categorical cross-entropy was used as the loss function.
- **Batch Size:** A batch size of 32 was chosen based on hardware limitations and model performance.
- **Early Stopping:** Training was halted when validation loss plateaued to prevent overfitting.

2.5. *Evaluation Metrics*

Model performance was evaluated using the following metrics:

- **Accuracy:** The proportion of correctly classified images.
- **Precision, Recall, and F1-Score:** Used to assess the performance for each class, particularly for the minority categories.
- **Confusion Matrix:** Provided insights into misclassification patterns.
- **ROC-AUC Curve:** Assessed the model's discriminative ability across all classes.

2.6. *Web-Based Application Development*

A web-based interface was developed to integrate the trained model for practical use. The application allows users to upload dermoscopic images and receive real-time predictions. The front end was built using HTML and JavaScript, while the back end utilizes Flask to handle model inference.

By combining a robust CNN model with an accessible user interface, this research bridges the gap between complex AI methodologies and practical clinical applications, facilitating early detection and diagnosis of skin lesions.

3. RESULT AND DISCUSSION

3.1. *Performance Metrics*

- **Accuracy**: The model achieved a test accuracy of 92.3%, indicating its high reliability in classifying skin lesions.
- **Precision and Recall**: Scores across the seven categories averaged 91% and 93%, respectively, demonstrating balanced performance.
- **F1-Score**: The overall F1-score was 92%, validating the robustness of predictions across classes.

3.2. *Comparative Analysis*

- The proposed DenseNet169-based model outperformed other architectures like ResNet50 and VGG16, which achieved accuracies of 88.5% and 86.7%, respectively, on the same dataset.
- The use of data augmentation and transfer learning contributed significantly to the improved performance.

3.3. *Challenges and Limitations*

- **Dataset Imbalance**: The ISIC dataset has a lower representation of certain lesion types, affecting recall for those categories.
- **Computational Resources**: Training the model required high-performance GPUs, limiting accessibility for researchers with limited resources.

3.4. *Practical Implications*

- **Web-Based Application**: A user-friendly interface was developed, enabling clinicians to upload dermoscopic images for real-time predictions.
- **Clinical Relevance**: The model's high accuracy and explainability can assist dermatologists in making informed decisions.

3.5. *Future Directions*

- Expanding the dataset to include more diverse samples could further enhance model generalization.
- Integrating explainability techniques such as Grad-CAM to visualize the decision-making process of the model.

4. CONCLUSION

This research demonstrates that CNNs, coupled with the Fast.ai library, provide an effective solution for skin cancer detection. The methodology can be adapted for other medical imaging tasks, contributing to the broader field of AI in healthcare.

5. ACKNOWLEDGMENTS

The authors extend their heartfelt gratitude to the International Skin Imaging Collaboration (ISIC) for providing the dataset used in this study. We are also deeply grateful to the Fast.ai community and Jeremy Howard for their invaluable resources and guidance. Special thanks go to the Informatics Engineering Department at Mikroskil University for their technical support and encouragement throughout this research. Lastly, we thank our families and colleagues for their unwavering support and motivation.

REFERENCES

1. Howard, J., & Gugger, S. (2020). *Deep Learning for Coders with fastai and PyTorch*. O'Reilly Media.
2. ISIC Archive. (n.d.). *International Skin Imaging Collaboration Dataset*. Retrieved from ISIC.
3. He, K., Zhang, X., Ren, S., & Sun, J. (2016). *Deep Residual Learning for Image Recognition*. Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition (CVPR).
4. Deng, J., Dong, W., Socher, R., Li, L., Li, K., & Fei-Fei, L. (2009). *ImageNet: A Large-Scale Hierarchical Image Database*. Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition (CVPR).