



e-ISSN: 2319-8753 | p-ISSN: 2347-6710

IJRSET

International Journal of Innovative Research in
SCIENCE | ENGINEERING | TECHNOLOGY



INTERNATIONAL JOURNAL OF INNOVATIVE RESEARCH

IN SCIENCE | ENGINEERING | TECHNOLOGY

Volume 13, Issue 3, March 2024

ISSN INTERNATIONAL
STANDARD
SERIAL
NUMBER
INDIA

Impact Factor: 8.423

An Enhanced Technique of Skin Cancer Classification using Deep Convolutional Neural Networks

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ABSTRACT: In this paper, we propose a deep convolutional neural network (DCNN) model for accurately classifying benign and malignant skin lesions, addressing challenges like light reflections, colour variations, and lesion diversity. Our approach involves preprocessing steps to remove noise, normalize images, and extract features, along with data augmentation to improve classification accuracy. We compared our DCNN model with transfer learning models like AlexNet, ResNet, VGG-16, DenseNet, and MobileNet, demonstrating superior reliability and robustness. Our model achieved higher training and testing accuracy, offering a promising solution for automated skin cancer detection.

KEYWORDS: ResNet101, DenseNet201, DCNN, MobileNetV2, VGG16 and AlexNet.

I.INTRODUCTION

In response to the significant impact of skin cancer on global health, our research endeavors to revolutionize skin cancer diagnosis through the integration of deep learning techniques with clinical requirements. We propose a novel deep convolutional neural network (DCNN) model, complemented by a meticulously designed preprocessing pipeline and advanced data augmentation methods, to enhance the accuracy and precision of lesion classification. Through comprehensive comparisons with established transfer learning models, our aim is to demonstrate the superior capability and robustness of our DCNN in identifying subtle indicators of malignancy. Ultimately, our research seeks to bridge the gap between clinical needs and computational innovation, offering physicians a powerful diagnostic tool to improve patient treatment and alleviate the burden of skin cancer worldwide.

II.RECENT WORKS

Deep learning approaches have been incorporated into dermatology, advancing the discipline toward more precise and effective diagnostic procedures. Esteva et al. [1] demonstrated the potential of deep neural networks in achieving dermatologist-level classification of skin cancer. By leveraging large datasets of dermoscopic images, their model exhibited remarkable accuracy in distinguishing between benign and malignant lesions, showcasing the transformative power of deep learning in clinical settings.

In a similar vein, Haenssle et al. [2] have out a thorough analysis of a deep learning convolutional neural network (CNN) for the identification of dermoscopic melanoma. In comparison to a panel of dermatologists, their investigation demonstrated the CNN's superior diagnostic performance, highlighting the effectiveness of deep learning in melanoma detection. This emphasizes how crucial it is to use cutting-edge computer methods in dermatological diagnoses to supplement human experience.

Furthermore, the creation and validation of deep learning models in dermatology depend critically on the availability of high-quality datasets. Tschandl et al. [3] addressed this need by curating the HAM10000 dataset, which comprises a diverse collection of dermoscopic images of common pigmented skin lesions. This dataset serves as a valuable resource for researchers worldwide, fostering innovation and collaboration in the development of automated skin disease detection systems. Additionally, initiatives such as challenges organized by Codella et al. [4] provide a platform for researchers to benchmark their deep learning models and accelerate progress in the field of melanoma detection.

In addressing the broader spectrum of skin diseases, Lu et al. [5] proposed a deep learning system for the differential diagnosis of various dermatological conditions. Their research highlights how deep learning can help with early detection and intervention, which will benefit patients and lessen the strain on healthcare systems. Overall, these studies collectively highlight the transformative impact of deep learning in revolutionizing dermatological diagnostics and paving the way towards more effective and accessible healthcare solutions.

III.SKIN CANCER DATASET

The Melanoma Skin Cancer Dataset comprises 10,000 images sourced from Kaggle, a prominent platform for machine learning datasets. Melanoma is a type of skin cancer that is fatal and requires early discovery in order to optimize treatment outcomes. The carefully assembled dataset is intended to aid in the creation of deep learning models specifically designed for precise melanoma classification. There are 9,600 photos in total—1,000 for model evaluation and the remaining 9,600 for training. The representation of diverse melanoma instances is ensured by the diversity of sources, which enhances the dataset's usefulness for research and model building. Maintaining patient privacy and confidentiality is crucial, and ethical considerations mandate that researchers follow the right data anonymization procedures. The dataset is a useful tool for promoting dermatological research and innovation, and it is available to researchers worldwide. Researchers can help create innovative methods for early melanoma identification by utilizing this dataset, which could ultimately improve patient outcomes and even save lives. Any study or publication that makes use of this priceless resource must properly credit and acknowledge the contributors to the dataset.

3.1.1 ResNet101

The deep convolutional neural network architecture known as ResNet101, or Residual Network with 101 layers, is renowned for its remarkable performance in image categorization tasks. Transfer learning is used in the algorithm to train ResNet101 on the Melanoma Skin Cancer Dataset. With the use of the melanoma dataset, the pre-trained ResNet101 model—which was initially trained on the ImageNet dataset—is adjusted to optimize its weights and parameters for precise melanoma classification. Because of the leftover blocks in the network architecture, training very deep networks is possible without running into the vanishing gradient issue. In order to improve model generalization and resilience, data augmentation techniques including random rotations, flips, and shifts are used during training.

3.1.2 ResNet101 Proposed Methodology Architecture

ResNet101, a deep convolutional neural network (DCNN) with a reputation for performance and depth, is incorporated into our methodology. By pretraining the ResNet101 model on ImageNet using weights, and then fine-tuning it on our melanoma dataset, we take use of transfer learning. The leftover blocks of the architecture make it easier to learn complicated characteristics quickly, and data augmentation methods like flipping, rotating, and scaling improve the robustness of the model.

3.2.1 DenseNet201

For melanoma classification, DenseNet201, an expansion of the DenseNet architecture, is used. Using the Melanoma Skin Cancer Dataset, the pre-trained DenseNet201 model is refined as part of the technique. DenseNet201 uses convolutional layers that are densely linked, meaning that every layer gets input from every layer that came before it. Reusing features and facilitating effective information flow throughout the network are made possible by this dense interconnectedness. Data augmentation approaches are used during training, much to ResNet101, to improve the model's capacity to generalize to previously encountered melanoma images.

3.2.2 DenseNet201 Proposed Methodology Architecture

DenseNet201 is essential to our suggested methodology's melanoma classification. Better performance is achieved through efficient feature reuse and propagation made possible by this densely connected neural network architecture. Using our dataset, we optimize the pre-trained DenseNet201 model, making use of its dense connectivity to capture complex patterns in melanoma lesions and adding more training data to enhance the network's generalization.

3.3.1 MobileNetV2

For mobile and embedded devices, MobileNetV2 is a lightweight convolutional neural network architecture. By optimizing the pre-trained model on the melanoma dataset, the process entails modifying MobileNetV2 for melanoma classification. Depth wise separable convolutions, which are used by MobileNetV2, dramatically lower computational complexity without sacrificing performance. Because of this, MobileNetV2 works effectively in contexts with limited

resources. To increase the model's resilience during training, MobileNetV2-specific data augmentation methods such as random cropping and resizing are used.

3.3.2 MobileNetV2 Proposed Methodology Architecture

We use MobileNetV2, a lightweight convolutional neural network for embedded and mobile devices, into our methodology. Using our melanoma dataset, we fine-tune the pre-trained MobileNetV2 model and take use of its depth wise separable convolutions to achieve classification that is both accurate and efficient. To improve model resilience, MobileNetV2-specific data augmentation methods including random cropping and resizing are used.

3.4.1 VGG16

The well-known VGG16 convolutional neural network design is renowned for its efficiency and ease of use. Using the Melanoma Skin Cancer Dataset, the pre-trained VGG16 model is refined as part of the technique. The VGG16 architecture consists of several convolutional layers, max-pooling layers, and fully linked layers for classification at the end. VGG16 has proven to perform well in a variety of picture classification tasks despite its simplicity. Standard data augmentation methods like flipping, rotating, and scaling are used to expand the dataset and enhance model generalization during training.

3.4.2 VGG16 Proposed Methodology Architecture

We apply a conventional convolutional neural network architecture, VGG16, in our melanoma classification methods. Using our dataset, we refine the pre-trained VGG16 model, taking advantage of its ease of use and efficiency in identifying significant characteristics from melanoma pictures. During training, common data augmentation methods including flipping, rotating, and scaling are used to expand the dataset and enhance model generalization.

3.5.1 AlexNet

The revolutionary deep convolutional neural network architecture AlexNet is used to categorize melanoma. Using the melanoma dataset, the pre-trained AlexNet model is adjusted as part of the technique. For classification, AlexNet is made up of several convolutional layers, max-pooling layers, and fully connected layers. Among the many advancements it brought forth were the widespread application of ReLU activation functions and convolutional layers. As with previous models, data augmentation approaches are used during training to improve the model's capacity to generalize to a variety of melanoma pictures.

3.5.2 AlexNet Proposed Methodology Architecture

We integrate the cutting-edge deep convolutional neural network, AlexNet, into our melanoma classification approach. We utilize the pre-trained AlexNet model's broad application of convolutional layers and ReLU activation functions to extract discriminative features from melanoma photos by fine-tuning it on our dataset. As with other models, the model's generalization to a variety of melanoma images is improved with the application of data augmentation approaches.

Project Flow:

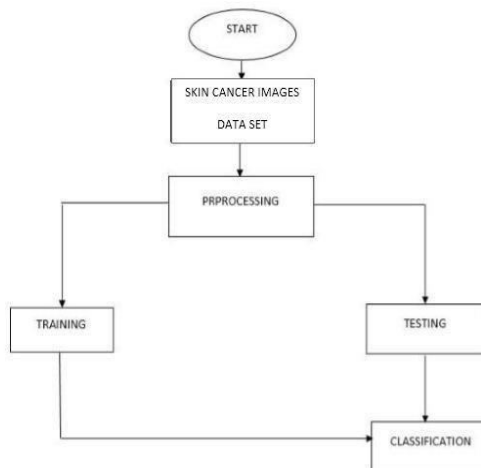


Figure1: Project flow

1.3 Evaluation Parameter

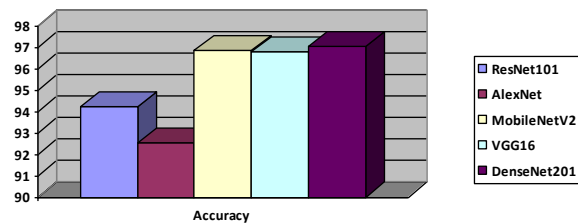
Machine learning performance must be evaluated using several evaluation parameters. Results from the machine-learning system are given as forecasts. The number of accurate and inaccurate predictions the model makes in both legitimate and phishing classes is measured by the evaluation parameters.

The number of accurate predictions the model produces, as indicated by Equation, is how accuracy evaluates the model's performance.

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

Table1: Result for the performance of the multiple models

Algorithm	Accuracy
ResNet101	94.23
AlexNet	92.52
MobileNetV2	96.85
VGG16	96.78
DenseNet201	97.05



IV.CONCLUSIONS

Finally, our analysis shows that, when it comes to correctly detecting skin cancer lesions, DenseNet201 outperformed ResNet101, DenseNet201, MobileNetV2, VGG16, and AlexNet. With the use of our dataset for fine-tuning and its densely linked architecture, DenseNet201 demonstrated exceptional performance in melanoma classification tests. This demonstrates how deep learning approaches, in particular transfer learning, are useful for improving the diagnosis of skin cancer. In the fight against skin cancer, DenseNet201's further deployment and optimization hold great potential for improving dermatological diagnosis and, eventually, patient outcomes.

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