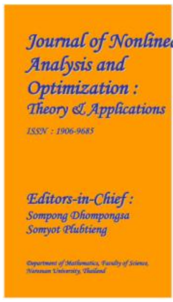
Journal of **N**onlinear **A**nalysis and **O**ptimization
Vol. 15, Issue. 1 : 2024
ISSN : **1906-9685**



SKIN CANCER DETECTION USING DEEP LEARNING

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ABSTRACT: A common and potentially fatal disease, skin cancer affects the outer layers of the skin. Increasing knowledge about the disease, its risk factors, and the value of early detection is essential to fighting skin cancer and reducing its impact on people and communities around the world. In this work, we present a novel use of deep learning methods for dermatoscopic image-based early detection of skin cancer. Actinic keratoses and intraepithelial carcinoma, basal cell carcinoma, benign keratosis-like lesions, dermatofibroma. melanoma, melanocytic nevi, pyogenic granulomas, and hemorrhage are the main types of skin cancer that the goal of this study is to predict accurately and reliably. A convolutional neural network (CNN) architecture is the main algorithm/model used in this project. Because CNNs can automatically extract important features from the input, they are particularly well suited for image classification applications. The dataset HAM10000 ("Human vs. Machine with 10000 training images") is used to train our model, which contains 10,015 high-resolution dermatoscopic images obtained from different populations using different methods.
Keywords: Skin Cancer, Skin diseases, Convolutional Neural Networks, Dermatoscopic images.

1. INTRODUCTION

One of the most common forms of cancer is skin cancer, which begins when skin cells multiply out of control. UV radiation from sunlamps and tanning beds can trigger it, leading to the proliferation of skin cells and the development of malignant tumors.

One of the leading causes of death on Earth is skin cancer. Statistics released by the publisher show that in 2023, 97,160 Americans were diagnosed with skin cancer, accounting for 5.0 percent of all cancer cases in the country, and 7,990 Americans lost their lives to skin cancer, accounting for 1.3 percent of all skin cancer cases. - related deaths. on the ground

One of the most common and dangerous forms of skin cancer, which can quickly spread to other areas of the body, is melanoma. From 2016 to 2020, 21 cases of melanoma were diagnosed in the United States per 100,000 cases. The death rate for melanoma was 2.1 per 100,000 diagnosed cases; by 2020, the disease affected 1,413,976 people. The five-year survival rate for cutaneous melanoma is 93.5%, which is relatively high.

If skin melanoma is diagnosed early, the five-year survival rate is 99.6%. Although only 77.6% of skin melanomas are found in the localized stage, the chances of survival are higher if the skin melanoma is contained, meaning that it has not spread to other areas of the body. Early detection of melanoma of the skin can reduce the number of deaths caused by the disease.

2. REVIEW OF LITERATURE

In the field of skin cancer detection, there has been extensive research on the application of deep learning techniques. This literature review summarizes some of the key findings and contributions in this area.Over time, there has been a significant advancement in the research on image analysis-based skin cancer detection. Numerous methods have been attempted. By holding a challenge

competition, the 2018 International Skin Imaging Collaboration (ISIC) event has established itself as the de facto standard for skin cancer detection.
Additionally, it has been reported that skin cancer can be identified using a mobile app. Through the use of various classification algorithms and techniques, researchers have attempted to increase the accuracy of diagnosis in all of these efforts.
With the introduction of the convolutional neural network (CNN) structure by Fukushima (1988) and Le-Cunn (1990), image classification reached new heights. CNNs were used to classify the images. CNNs are probably the best state-of-the-art for image classification because they essentially mimic the human visual thinking system. We will limit our literature review to deep learning techniques for skin cancer images, although there is a large literature on image classification.
The first success in skin cancer classification with the pre-trained GoogLeNet Inception V3 CNN model came from Esteva et al. In 2016, Yu et al. developed a CNN with more than 50 layers to classify malignant melanoma cancer on the ISBI 2016 challenge dataset.
In 2018, Haenssle et al. used a deep convolutional neural network to classify the binary diagnostic class of dermatoscopic melanocyte images. Dorj et al. developed a multi-class classification using ECOC SVM and deep learning CNN. The approach was to use the ECOCSVM with a pre-trained Alex Net Deep Learning CNN and classify multi-class data.

3. METHODOLOGY

Data collection: Collect a large dataset of skin images marked as skin cancer or not. Make sure cancer ages, skin types, and shapes are varied.
Pre-processing: Resize, normalize, and enhance the data to prepare the photos . . . Use methods such as cropping, rotation, and rotation to make the dataset more diverse.
Model selection: Convolutional neural networks are a popular deep learning model that can be used for image classification. Discover models that have shown potential performance in similar tasks, such as VGG16, ResNet, or Inception.
Training: Split the dataset into a model training and validation set. Use methods such as fine-tuning or transfer learning to train the selected model on the training set.
Evaluation: Use a different test set to measure the performance of the trained model. Calculate metrics such as F1 score, recall, accuracy, and precision. Compare results with current benchmarks or state-of-the-art models.
Usage: Use the trained model as a web or mobile application for real-time skin cancer detection. Make sure the app is easy to use and provides accurate predictions. Update and improve the model frequently based on user input and new information.

MODELS AND ALGORITHMS USED:

One deep learning neural network design commonly used in computer vision is a convolutional neural network (CNN). A branch of artificial intelligence known as "computer vision" allows computers to understand and analyze images and other visual input. Artificial neural networks perform incredibly well in machine learning. Many types of data, including text, audio and image data, use neural networks. Different neural networks are used for different tasks. For example, recurrent neural networks – specifically, LSTMs – are used to predict sequences of words, while convolutional neural networks are used to classify images.

CNN ARCHITECTURE

There are various layers in a convolutional neural network, including an input layer, a convolutional layer, a join layer, and a fully connected layer.
A convolutional neural network usually has several layers, each serving a general-purpose architecture. Here is an overview of CNN's general levels:
1. Input layer: Strings of text or images are taken as raw input data to this layer.
2. Convolution layer: -Convolution layers use filters, sometimes called kernels, to extract features from input data by applying a convolution function to the input. Some characteristics are identified during the training.
3. Activation layer: - An activation function such as ReLU (Rectified Linear Unit) is applied element-by-element after the convolution operation to ensure model nonlinearity and learn complex patterns.

4. Aggregation Layer: -Aggregation layers reduce the spatial dimension of data while preserving important features by reducing the feature maps created by convolutional layers. Maximum sharing and average sharing are two common redundancy methods

5. Fully Connected Layer: layers form the connections between each neuron in one layer and each neuron in another layer. These layers, usually near the end of the CNN architecture, are responsible for predicting things using features extracted from previous layers.

6. Output layer: - The last layer of the network that generates the output predictions. Depending on the type of work performed, this layer uses a different activation function.

4. CONCLUSION

In conclusion, the proposed framework leverages the control of convolutional neural systems and consolidates different improvements to move forward precision, effectiveness, and generalization capabilities. Our proposed framework accomplished preparing exactness of 96.00% and approval exactness of 97.00%. Through thorough information preprocessing and dataset organization, the venture viably handles dermatoscopic pictures from different populaces and different skin cancer sorts. The usage of exchange learning and information expansion procedures contributes to the system's capacity to handle varieties in picture quality and lighting conditions, improving its vigor and decreasing overfitting concerns. The secluded plan of the extend guarantees a organized and organized approach, making it less demanding to create and keep up the framework.

Each module plays a vital part in information taking care of, demonstrate development, preparing, assessment, and result investigation, encouraging consistent integration and reusability of the framework. The assessment of the demonstrate on a partitioned test set uncovers its tall precision in recognizing between distinctive skin cancer sorts. The interpretability strategies consolidated within the framework offer straightforwardness and bits of knowledge into the model's decision-making prepare, cultivating believe and understanding from healthcare experts. The proposed system's real-time deduction capability makes it down to earth for sending in clinical settings, possibly helping healthcare experts in incite & exact skin cancer analyze.

Overall, the project is a significant step forward in the application of deep learning to skin cancer prediction. Combining cutting-edge technology and industry-specific expertise, the system provides an effective and reliable tool for early detection and classification of skin cancer types that can help improve patient outcomes and reduce the global burden of skin cancer. Although the proposed system shows promising results, further validation and comparison with larger and more diverse datasets are needed to confirm its applicability and robustness. Continued research and development in medical image analysis and deep learning will undoubtedly lead to more advanced and accurate predictive models in the future. However, this project lays a strong foundation for further development of skin cancer prognosis, which will benefit both medical professionals and patients in the fight against this common and potentially life-threatening disease.

5. FUTURE ENHANCEMENT

Although the current skin cancer prediction project using deep learning techniques has made significant progress in terms of accuracy and efficiency, there are several opportunities for future work and improvement

Larger and more diverse datasets: Expanding the dataset to include more dermatoscopic images. studies of different populations and skin types can improve the ability of the model to generalize to different patient populations. Access to larger data sets would provide a better representation of rare skin cancer types and help create a more robust and reliable prognostic system.

Model hyperparameter tuning: Explore hyperparameter tuning techniques such as automatic hyperparameter optimization algorithms (eg Bayesian). optimization or genetic algorithms can help find the best settings for a deep learning model. This can lead to even better performance and convergence, optimizing model accuracy and training efficiency.

Ensemble methods: Exploring the integration of ensemble learning methods, such as model averaging or stacking, can potentially improve forecast performance. Combining predictions from several different models can reduce variance and improve overall accuracy.

Multi-task learning: Multi-task learning, where a model learns to classify multiple types of skin cancer simultaneously, can lead to better performance and better performance. across all classes.

Explanatory AI techniques: Integrating advanced model interpretation techniques can provide clearer insights into model characteristics that influence decisions. Explanatory AI methods such as SHAP (SHapley Additive Explanations) or LRP (Layer-wise Relevance Propagation) can provide deeper insights into the decision-making process of the model.

Cross-domain transfer learning: exploring the application of transfer learning to medical images.analytical tasks can facilitate data transfer and improve the generalizability of the model to other skin diseases or even different diseases.

Clinical Validation: Conducting rigorous clinical validation studies based on real patient data in collaboration with medical professionals is critical to evaluating system performance. in clinical settings. This can help identify potential challenges and ensure system reliability and safety in practical healthcare applications.

Implementation in telemedicine and mobile applications: adapting the system to telemedicine platforms or mobile applications can facilitate remote screening and early detection of skin cancer. underserved populations and enabling timely intervention.

Treatment of rare cases: A special focus on treatment and improving the prognosis of rare types of skin cancer can be beneficial, as early diagnosis of these cases is particularly important for positive patient outcomes.

By research. these areas, in future work, the Skin Cancer Prediction Project can continue to develop, providing an increasingly accurate, reliable and effective tool for the early detection and classification of skin cancer, ultimately improving patient care and outcomes in dermatology.

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