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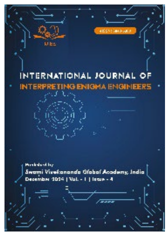
MACHINE LEARNING IN MELANOMA DETECTION ANALYZING THE ROLE OF FEATURE ENGINEERING IN SKIN LESION CLASSIFICATION



Bandari Manisha, Dr. GVS Raju

Original Article

Professor Department of Computer Science Engineering [1,2].
Stanley College of Engineering & Technology For Women, India.

*Corresponding Author's Email: bandarimanisha40@gmail.com

Abstract

Skin cancer is one of the most common types of cancer in people. Doctors usually find it through visual inspections, starting with a clinical screening, then followed by a biopsy and lab tests. We can improve the prediction of skin cancer and determine if it is melanoma or benign by using automated systems that categorize images of skin lesions. This is made possible by machine learning and artificial intelligence (AI).) approaches. This chapter describes Spotting skin cancer early can make a big difference in treatment and recovery! using Spark and a deep neural network. To find the best algorithm for skin cancer prediction, a comparison study of the several algorithms currently in use has also been conducted. Based on findings gathered from several iterations, skin lesion photographs might be categorized using a CNN approach. Then, many transfer learning models were employed for fine-tuning, This study focuses on several advanced image recognition models, specifically Resnet50, InceptionV3, and Inception Resnet, to improve how we analyze skin lesions. One of the key contributions of this research is the use of a technique called ESRGAN to enhance images before they are processed by these models. By applying this preprocessing step, we aimed to boost the accuracy of the results.We tested multiple models, including our customized model and a standard CNN, to see how well they performed. Interestingly, both the standard pre-trained model and our own produced similar results, indicating that our approach is effective. The effectiveness of our method was shown through simulations using the ISIC 2020 skin lesion dataset, a well-known collection of images used for this kind of research. We found that our CNN model achieved an impressive accuracy of 89.2%, showcasing the potential of our approach in helping to improve skin lesion analysis.

Keywords: Machine Learning, skin lesions, computer vision, decision trees, K-Nearest Neighbors (KNN), image segmentation.

Salient points: sonidegib is an effective inhibitor for basal cell carcinoma linked to Sonic Hedgehog pathway dysregulation.

In cutaneous squamous cell carcinoma, we observe that the epidermal growth factor receptor pathway is often overexpressed. This is particularly significant when considering the mutational profile of mucosal head and neck squamous cell carcinoma.

Recent advancements have established new adjuvant standards in melanoma treatment through 1. checkpoint blockade inhibitors and focused therapies for Exploring the dynamic duo of BRAF and MEK! These two play a crucial role in cellular signaling pathways. Sonidegib and vismodegib are effective inhibitors for basal cell carcinoma linked to Sonic Hedgehog pathway dysregulation.

Introduction

Carcinoma is defined as uncontrolled increase of tissues in a specific human body part. Carcinoma is one fastest-spreading Afflictions in the world. This condition occurs when abnormal skin cells grow uncontrollably. Accurate diagnosis and early detection are essential for identifying potential cancer treatments. In developed countries, the majority of malignancy. -related deaths are caused by melanoma, the most deadly form of the disease[1]Basal cell carcinoma Explore the intriguing world of skin conditions, from the aggressive nature of squamous cell carcinoma and the rare yet formidable Merkel cell cancer to the benign dermatofibroma and the intriguing complexities of vascular anomalies. Each of these conditions tells a unique story about our skin's health and resilience. lesions, and keratotic lesion are the main forms of skin cancer. Diagnostic imaging assessment is essential for diagnosing abnormalities in several parts of the body, including Brain tumors, stomach cancer, lung cancer, breast cancer, and skin cancer are critical health issues that demand our urgent attention[2]In 2020, we are facing a staggering 9.9 million cancer-related deaths and a shocking 19.2 million new cancer diagnoses, as reported by the GLOBOCAN survey. This alarming data highlights the urgent need for increased awareness, funding, and research to combat this critical health crisis.[3]This crisis demands immediate action through increased awareness, funding, and research. While solid tumor detection often hinges on screening mammography, which is notoriously low in sensitivity, early identification of skin cancer is crucial for improving survival rates and outcomes. We must prioritize these efforts to combat this pressing health challenge. now utilizing enhance the speed up the Resolution process related to diagnoses. However, despite some evidence showing improvements in area, precise assessment the proper describe potential deficiency in these AI systems have often been overlooked or inadequately addressed in the current research on AI for clinical diagnosis. [4] Computer vision technologies have advanced significantly as a result of the exponential expansion in processing power, especially in the creation of deep learning models like CNN. It is now necessary to diagnose skin cancer as early as feasible. The most prevalent cancer in women aged 25 to 29 is skin cancer, which also the most familiar disease in women aged 30 to 35 (after breast cancer).[5]Dr. Lee is dedicated to treating pediatric diagnosed with skin carcinoma. Recent advancements in technology have shown that deep learning algorithms excel in the skin cancer screening, outperforming human experts in various computer vision tasks. This innovative approach has significantly contributed to reducing mortality rates among affected individuals, offering hope and improved outcomes for these young patients.[6]Poole S. et al. Indicators of internal cancer in the skin: II. Environmental carcinogens and paraneoplastic dermatoses. Dermatology Journal American Academy.

Literature Review

In her 2020 research, M. Krishna Monika examines several key factors that contribute to the troubling rise in skin cancer cases. This increase underscores the essential of early diagnosis and pinpointing, which is vital accurate diagnosis and medical care. By identifying skin cancer in its early stages, we can improve outcomes and increase the chances of successful interventions for those affected. In 2019, Vijayaalaxmi M. M. proposed an innovative project focused on enhancing the accuracy of skin cancer predictions while also distinguishing between malignant and nonmalignant melanoma. To accomplish this goal, a series of comprehensive pre-processing techniques were utilized. These techniques included hair removal to eliminate distractions in the images, shadow reduction to improve clarity, glare removal to enhance visibility, and segmentation to isolate the regions of interest within the skin samples. Together, these methods aimed to refine the analysis and improve the overall precision of skin cancer detection. Alaa Haddad and Shihab A. Hameed have developed an effective low-cost method for detecting skin diseases, specifically designed to minimize noise and eliminate unwanted objects. This innovative approach provides valuable analysis results that empower doctors to make accurate initial diagnoses and confidently identify the type of disease. Mirbeket, Amir, and others studied the dielectric characteristics of both healthy and cancerous skin tissues, which are accurately represented by three semi-solid phantoms. Malignant skin diseases are estimated to have a penetration depth of millimeter waves that reaches sufficient depths in human skin tissue to affect most of the skin's structures. They proposed centralized algorithms for data processing and analysis, ensuring that the data is accessible and coordinating all other system nodes within a specific range. They recommended segmentation methods for identifying specific skin conditions using the Python programming language. The adaptable methods for detecting skin diseases utilize morphology-based image segmentation, kmeans clustering, and thresholding, The study proposed multiple types of skin cancer and introduced a deep learning-based skin classification system. This system utilizes a pre-trained MobileNet convolutional neural network, which can classify skin photos in just two to three seconds. The approach demonstrates high accuracy rates of 0.90 and 0.91, making it lightweight, fast, and reliable.

Proposed System

Article Represents a basal cell carcinoma classifier that uses the examination of skin surface microscopy and combines the Ant Colony Optimization (ACO) algorithm with a pre-trained Convolutional Neural Network (CNN) called EfficientNetB0. The model employs preprocessing techniques to enhance image quality and utilizes a custom dataset developed from the ISIC dataset. After extracting features from both the original and modified datasets, the model employs various Support Vector Machine (SVM) kernels to classify the optimized features. Additionally, it utilizes Ant Colony Optimization (ACO) to minimize dimensional complexity. To validate the effectiveness of the model, four tests were conducted, each based on a different dataset and a distinct combination of methodologies. All the trials were execute in labR2023a.

Trial 1

In the first trial, we divided an initial dataset of 20,000 photos into two equal classes: malignant and benign, reflecting the severity of skin cancer. To analyze these images, we employed the pretrained EfficientNetB0 model. This model, like other convolutional neural networks (CNNs), effectively utilizes in deep layers to get significant characteristics from the input photos, enabling us to enhance the accuracy of our analysis.

The Refinement of SVM Classifier Results:

Upscale	Accuracy%	Exactitude%	Recall	F1 Score	Acuity	Selectivity	MCC
L-SVM	87.2	98.3	78.7	82.5	75.3	84.2	68.4
Q-SVM	85.3	81.4	71.4	95.4	74.1	81.6	85.5
CB-SVM	90.4	84.45	87.45	94.27	81.83	87.71	94.23
MG-SVM	82.36	74.23	79.63	98.36	84.25	75.8	88.25
CG-SVM	75.89	98.43	78.56	99.48	85.36	45.25	90.47

The results indicate that CB-SVM significantly outperforms the other classifiers, achieving an impressive accuracy of 97.40%. This highlights its effectiveness and potential for further applications.

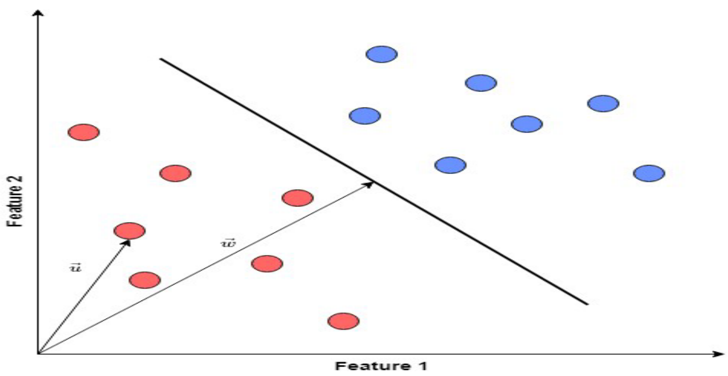


Fig1 Positive and negative cases in Trial 1.

Trial-2

Trial 2 clarifies that the model cannot attain accuracy levels over 95.486% performance doesn't increase after preprocessing, instead it slightly declines. As a result, the other trial uses the feature fusion approach, which allows the suggested model to consider a wider variety of visual features and acquire complementary information. integrating numerous features improves generalization and discrimination, boosting the model's robustness and usefulness in detecting and categorizing carcinoma of the skin.

Upscale	Accuracy %	Exactitude%	Recall	F1Score	Sensitivity	Specificity	MCC
L-SVM	87.23	93.45	85.36	74.45	75.41	98.78	75.73
Q-SVM	73.49	87.49	73.85	99.23	88.45	78.15	55.69
CB-SVM	78.63	74.58	49.36	78.89	99.77	68.97	96.87
MG-SVM	85.66	75.69	84.33	89.47	58.74	95.26	74.58
CG-SVM	77.51	25.69	85.69	95.51	90.48	85.06	88.12

This shows that combining feature fusion with preprocessing methods and CNN Results improved performance for classifying skin cancer.

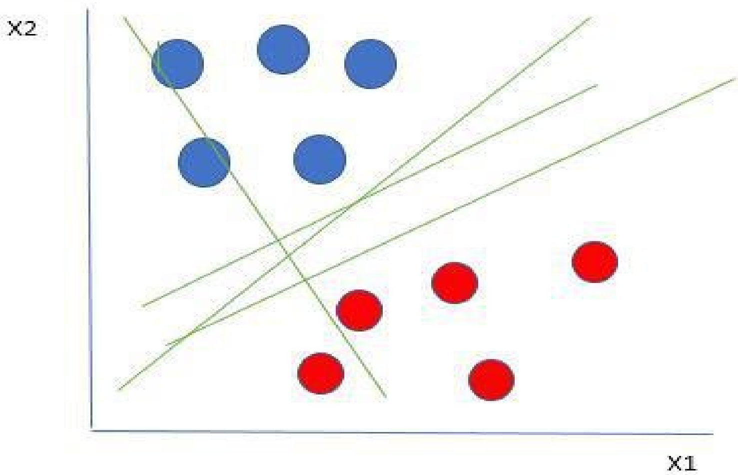


Figure 1Fig 2 Positive and negative cases in trial-2.

Results and Discussion

Trials on the ISIC2021 information set were used for experiments to demonstrate the efficacy of the proposed contrast result utilizing modern technology.

The way proposed was demonstrated by using the ISIC2018 dataset for simulations, and their outcomes were compared to the state-of-the-art. TensorFlow Kera's was tested on a Windows desktop with a GPU RTX3060 for the current scheme. IC2018 dataset was used for experiments to demonstrate the efficacy of the proposed and to contrast the result.

The recommended training set consisted of a 70% array of diagnosis images, which is used for all testing. During the learning phase, 10% of the data was utilized for verification.

The recommended training set consisted of a randomized array of lesion images, in which 80% of the data was used for testing. During the learning stage, we utilized 10% of the data for verification.

We retained the weight combinations that produced the highest accuracy ratings. In our results, no other method achieved the same level of accuracy. This can be attributed to three main resolution improvements provided by ESRGAN, our fine-tuning process that allowed us to learn specific characteristics of the dataset, of multiple flows, each with a varying requirement to generalize and adapt to diverse information.

Fig 3 Beginning Stage of Skin Cancer Table

Fig 4 Different Types Of Skin Cancer

<u>Accuracy Comparison:</u>

Studied	Year	Accuracy(%)
[23]	2022	98.63
[24]	2021	78.36
[28]	2020	88.67
[29]	2023	94.48
[30]	2021	71.96
[31]	2023	99.72
Present	2023	86.24

Conclusion

In conclusion, we have shown melanoma skin carcinoma By developing a distinctive dataset and employing meticulous preprocessing techniques, the model is capable of effectively identifying and extracting important features from microscopic depicts of skin cancer and benign skin cancer. This comprehensive approach enhances the subtle differences in the cellular structures, contributing to more diagnosing and a deeper understanding of skin cancer characteristics. We have developed a method for rapidly and accurately diagnosing both benign and malignant types of cancer by analyzing photographs of skin lesions. Our proposed system employs image enhancement techniques to reduce noise and improve the brightness of the lesion images. To prevent overfitting and enhance the general capabilities of the proposed deep learning techniques, we trained ResNet50, InceptionV3, and ResNet Inception models on the preprocessed medical images of lesions. The Inception model achieved a total accuracy rate of 85.7% using the proposed method, which is comparable to the performance of experienced dermatologists. This analysis is noteworthy for testing with many models, including planned CNN, ResNet50, InceptionV3, and Inception ResNet, as well as for its creative use of ESRGAN as a preliminary stage. The customized models produced effects that were comparable to those of the pre-trained models.

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