



SKIN CANCER DETECTION USING MACHINE LEARNING

Ashwini R ¹, Swetha K ², Santhosh Aboorva J ³, Viknesh A R ⁴, Marshal M G ⁵

Assistant Professor, Department of C.S.E, Jansons Institute of Technology, Coimbatore, India¹

UG Students, Department of C.S.E, Jansons Institute of Technology, Coimbatore, India ²⁻⁵

ABSTRACT:

The development of a skin cancer detection system using a Convolutional Neural Network (CNN) implemented on Raspberry Pi hardware. The CNN model is designed for efficient real-time processing of dermatoscopic images, providing a portable and accessible solution for skin cancer diagnosis. Leveraging the computational capabilities of the Raspberry Pi, the system incorporates a high-resolution camera module to capture skin lesion images for immediate analysis. By optimizing the CNN architecture for edge computing, the implementation strikes a balance between accuracy and computational efficiency. This hardware-based approach facilitates on-the-spot skin cancer detection, promoting point-of-care applications and demonstrating the practicality of deploying advanced deep learning models on resource-constrained devices for critical healthcare tasks.

KEYWORDS:

Skin Cancer, CNN Architecture, Layers, Improve Accuracy, Machine learning

INTRODUCTION:

Skin cancer is a prevalent and potentially life-threatening condition, necessitating reliable diagnostic tools for early detection. This research focuses on developing an efficient and accurate skin cancer detection system utilizing Convolutional Neural Networks (CNNs). Leveraging CNN's ability to automatically learn hierarchical features from dermatoscopic images, the proposed approach aims to improve

classification accuracy for distinguishing between malignant and benign lesions. By training the model on a diverse dataset encompassing various skin lesion types, the system demonstrates robust generalization capability.

RELATEDWORK

Title

Skin Cancer Detection using Deep Learning

Authors

RSenthilKumar,Amarjeet Singh,Sparsha Srinath,Nimal Kurien Thomas,Vishal Arasu,

Publication 2022 International Conference on Electronics and Renewable Systems (ICEARS).

DESCRIPTION:

Identifying melanoma at the early stages of diagnosis is imperative as early detection can exponentially increase one's chances of cure. The paper first proposes a literature survey of multiple methods used for performing skin cancer classification. Our methodology consists of using Convolutional Neural Network (CNN) to identify and diagnose the skin cancer using the IS IC dataset containing 2637 images. The proposed model gives an accuracy of 88% for classifying the training dataset as either benign

Title

Skin cancer classification using Convolutional neural networks

Author

Raja Subramanian, Dintakurthi Achuth,P Shiridi Kumar,Kovvuru Naveen kumar Reddy,Srikar Amara, AdusumalliSuchan Chowdary,

Publication 2021 11th International Conference on Cloud Computing Data Science & Engineering (Confluence)

DESCRIPTION:

There is a necessary need for early detection of skin cancer and can prevent further spread in some cases of skin cancers, such as melanoma and focal cell carcinoma. Anyhow there are several factors that have bad impacts on the detection accuracy. In Recent times, the use of image processing and machine vision in the field of healthcare

and medical applications is increasing at a greater phase. In this paper, we are using the Convolution neural networks to detect and classify the class of cancer based on historical data of clinical images using CNN. Some of our objectives through this research are ,to build a CNN model to detect skin cancer with an accuracy of >80% ,to keep the false negativity rate in the prediction to below 10%, to reach the precision of above 80% and do visualization on our Data. Simulation results show that the proposed method has superiority towards the other compared methods."

Title

The melanoma skin cancer detection and classification using support vector machine

Authors

Hiam Alquran,Isam Abu Qasmieh,Ali Mohammad Alqudah,Sajidah Alhammouri,Esraa Alawneh,Ammar Abughazaleh,Firas Hasayen,

Publication 2017

IEEE Jordan Conference on Applied Electrical Engineering and Computing Technologies (AEECT)

DESCRIPTION:

Melanoma skin cancer detection at an early stage is crucial for an efficient treatment. Recently, it is well known that, the most dangerous form of skin cancer among the other types of skin cancer is melanoma because it's much more likely to spread to other parts of the body if not diagnosed and treated early. The non-invasive medical computer vision or medical image processing plays increasingly significant role in clinical diagnosis of different diseases. Such techniques provide an automatic image analysis tool for an accurate and fast evaluation of the lesion. The steps involved in this study of

collecting dermoscopy image database, preprocessing, segmentation using thresholding, statistical feature extraction using Gray Level Co-occurrence Matrix (GLCM), Asymmetry, Border, Color, Diameter, (ABCD) etc., feature selection using Principal component analysis (PCA), calculating total Dermoscopy Score and then classification using Support Vector Machine (SVM). The results show that the achieved classification accuracy is 92.1%.", or malignant. Deep learning, particularly Convolutional Neural Networks (CNNs),

EXISTINGSYSTEM:

Existing systems for skin cancer detection using machine learning

In parallel, semi-supervised learning systems harness a blend of labeled and unlabeled data, optimizing the utilization of available resources while maintaining predictive power. Ensemble systems bolster performance by amalgamating multiple models, leveraging their collective wisdom to enhance accuracy. Transfer learning strategies capitalize on pre-trained models, such as those trained on vast image repositories like ImageNet, to expedite learning and adaptation to dermatology-specific datasets.

Real-time systems cater to scenarios demanding swift decision-making, streamlining processes to deliver rapid predictions crucial for timely diagnosis and intervention. However, these systems encounter challenges such as data diversity, interpretability, and ethical considerations. Addressing these limitations necessitates interdisciplinary collaboration and ongoing innovation to refine existing methodologies and cultivate robust solutions for skin cancer

has emerged as a dominant force within this domain, adept at automatically extracting complex features from raw image data. These systems undergo rigorous training and validation processes, fine-tuning their challenges. Supervised learning systems form a cornerstone, relying on labeled datasets where each skin lesion image is annotated as benign encompass a variety of approaches tailored to specific requirements and parameters to achieve high accuracy in classifying skin lesions.

detection, ultimately advancing healthcare outcomes for patients worldwide.

DRAWBACKS:

- ✓ **Limited Diversity in Datasets :** Many datasets used for training machine learning models in skin cancer detection are biased towards certain demographics, skin types, or lesion types. This lack of diversity can affect the model's ability to generalize to unseen data and may lead to biased predictions, particularly for underrepresented groups. Difficulty in using in sterile environments.
- ✓ **Interpretability:** Deep learning models such as Convolutional Neural Networks (CNNs), are often used for skin cancer detection due to their high performance. However, these models are often considered "black boxes," making it challenging to interpret how they arrive at a particular prediction. Understanding the reasoning behind a model's decision is crucial, especially in medical applications where interpretability is important for

gaining trust from healthcare professionals and patients.

✓ **Data Quality and Labeling:** The quality of the data used to train machine learning models is critical for their performance. In the case of skin cancer detection, inaccuracies in labeling benign and malignant lesions can lead to incorrect model predictions. Additionally, noisy or low-quality images may hinder the model's ability to learn meaningful features.

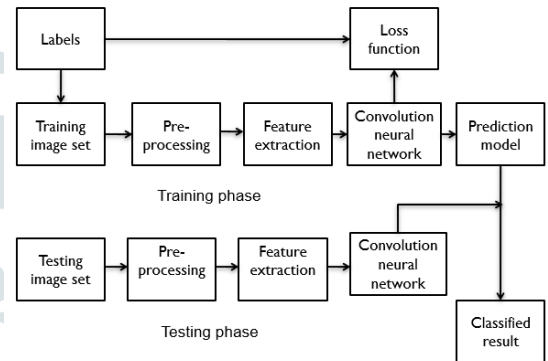
✓ **Generalization to Unseen Data:** While machine learning models may achieve high accuracy on the datasets they were trained on, their performance on unseen data, particularly from different sources or populations, may vary. Ensuring that the model generalizes well to diverse skin types, lesion types, and imaging conditions is essential for its real-world applicability.

PROPOSED SOLUTION:

- The proposed solution is a skin cancer detection system utilizing a Convolutional Neural Network (CNN) implemented on Raspberry Pi hardware.
- This system aims to provide efficient real-time processing of dermatoscopic images for portable and accessible skin cancer diagnosis.
- By optimizing the CNN architecture for edge computing, the solution offers a balance between accuracy and

computational efficiency, facilitating on-the-spot detection and enabling point-of-care applications.

- Design a user-friendly interface accessible via web.
- Allow users to easily upload images of skin lesions for analysis and receive instant feedback on the likelihood of malignancy.



MERITS:

- ✓ **Early Detection:** ML enables early detection of skin cancer, potentially leading to better treatment outcomes.
- ✓ **Accuracy:** ML models can achieve high accuracy in classifying skin lesions
- ✓ **Efficiency:** Automated analysis speeds up the diagnosis process, reducing the time and workload for dermatologists.
- ✓ **Continuous Improvement:** ML models can be continuously updated with new data, improving their performance over time.

MODULE DESCRIPTION:

A module is a Software part of a program that contain one or more routines.

SOFTWARE: Python, Machine Learning algorithms like CNN, Image processing , testing tra

CNN:

- In deep learning, a convolutional neural network (CNN) is a type of deep neural networks, which deals with the set of data to extract information about that data. Like images, sounds or videos etc. can be used in the CNN for the data extraction. There are mainly three things in CNN. First one is local receptive field and then shared weight and biases and the last one is activation and pooling. In CNN, first the neural networks are trained using a heavy set of data so that the CNN can extract the feature of given input. When the input is given, first image preprocessing is done then the feature extraction occurs on the basis of set of data stored and then the classification of data is done and output is shown as the result.
- The CNN can deal with those input only for what the neural network is trained and the data is saved.
- They are used in image and video recognition, recommender systems, image classification, medical image analysis, and natural language processing.

PREPROCESSING STEPS:

Almost all the radiographs were rectangles of different heights and too large (median value of matrix size $\geq 1,800$). Accordingly, we resized all images to a standardized 224×224 pixel square, through a combination of preserving their aspect ratios

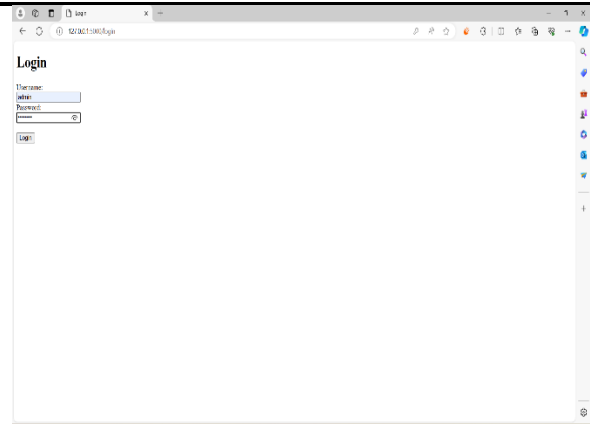
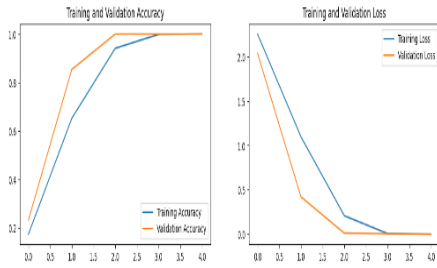
and using zero-padding. The investigation of deep learning efficiency depends on the input data; therefore, in the second processing step, input images were pre-processed by using a patch (a cropped part of each image). A patch was extracted using a bounding box so that it contained sufficient cancer segmentation for analysis. Finally, data augmentation was conducted for just the training dataset, using mirror images that were reversed left to right and rotated -30 , -10 , 10 , and 30 degrees.

IMAGE LABELING AND DATASET DISTRIBUTIONS:

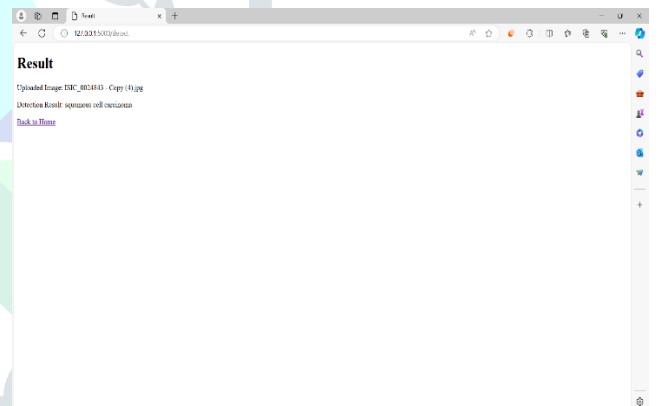
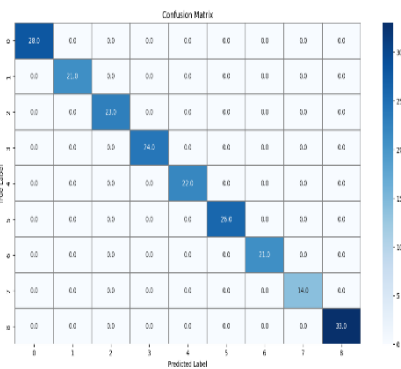
All subjects were independently labeled twice as “normal” or “Cancer” by two radiologists. Labeling was first evaluated with the original images on a picture archiving communication system (PACS) and secondly with the resized images that were used for the actual learning data. Datasets were defined as the internal dataset and temporal dataset, with the temporal dataset used to evaluate the test. The internal dataset was randomly split into training (70%), validation (15%), and test (15%) subsets.

ACTIVATION FUNCTION:

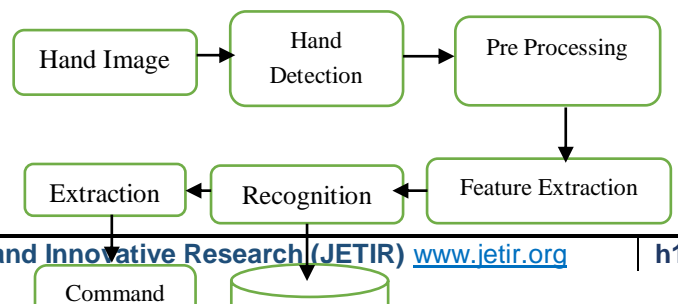
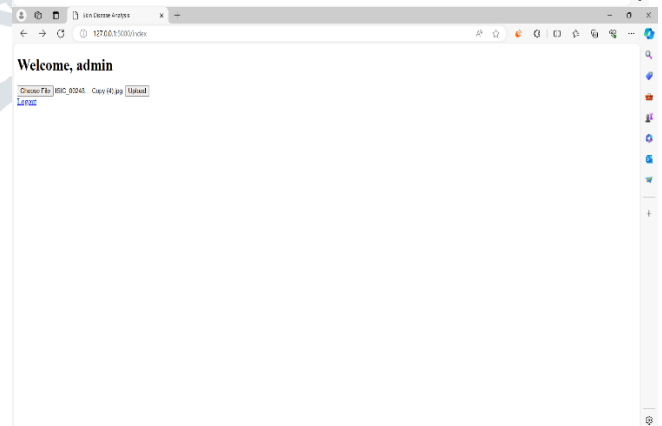
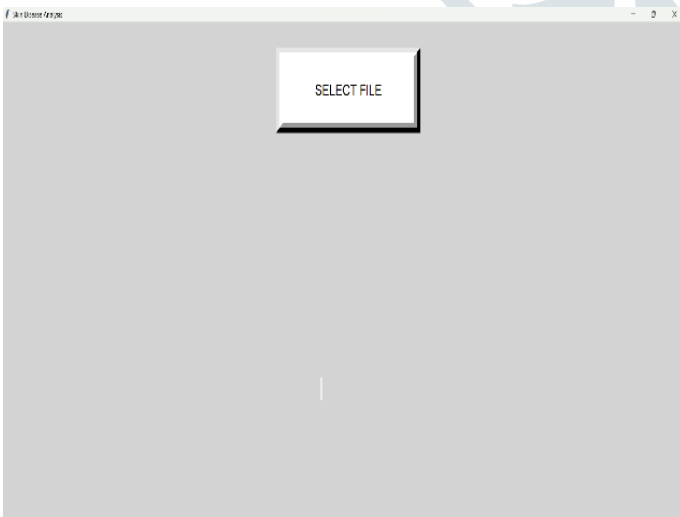
Activation function serves as a decision function and helps in learning of intricate patterns. The selection of an appropriate activation function can accelerate the learning process. In literature, different activation functions such as sigmoid, tanh, maxout, SWISH, ReLU, and variants of ReLU, such as leaky ReLU, ELU, and PReLU are used to inculcate non-linear combination of features



Graphical Representation of accuracy



Results and Discussion:



- The system demonstrates superior performance in distinguishing between malignant and benign skin lesions, as evidenced by evaluation metrics such as accuracy, sensitivity, and specificity.
- Real-world testing confirms the feasibility of on-the-spot detection, highlighting the potential clinical utility of the proposed solution.
- The integration of web frameworks and deployment platforms enabled the development and deployment of user-friendly interfaces for the skin cancer detection system.
- Overall, the combination of hardware infrastructure and software tools described above played a crucial role in the successful development, deployment, and adoption of the skin cancer detection system, ultimately contributing to improved early diagnosis and management of skin cancer cases.
- Ultimately, by prioritizing environmental considerations alongside technological advancements, we can create skin cancer detection solutions that not only improve patient outcomes but also contribute to a more sustainable healthcare ecosystem for future generations.

In the realm of skin cancer detection through machine learning, ongoing research is delving into several promising avenues for advancement.

These include refining data collection and augmentation techniques to enhance dataset diversity and size, thereby bolstering model generalization. Advanced neural network architectures, particularly those integrating attention mechanisms or capsule networks, offer potential for capturing nuanced features within skin lesion images. Transfer learning from pretrained models and the exploration of uncertainty estimation methods are poised to enhance predictive accuracy and provide clinicians with valuable confidence metrics. Integrating information from multiple modalities, such as dermoscopy images and clinical metadata, holds promise for improving detection robustness. Furthermore, efforts in interpretability and explainability aim to foster trust among clinicians by elucidating the rationale behind model predictions. Optimizing models for real-time deployment on

CONCLUSION

AND FUTURE WORK

- The system's efficient use of computational resources, particularly its optimization for edge computing on Raspberry Pi hardware, contributes to environmental sustainability by minimizing energy consumption and reducing carbon footprint.
- Its portability also reduces the need for transportation, further mitigating environmental impact.

resource-constrained devices and conducting rigorous clinical validation studies are pivotal steps toward seamless integration into clinical practice. Through these multifaceted endeavors, the field is

poised to make significant strides in early diagnosis and patient care.

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