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SKIN CANCER DETECTION USING CNN

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ABSTRACT

Every year, millions of individuals are affected with skin cancer, which is the most frequent type of cancer. Every year, around three million people in the United States are diagnosed with the condition. As the disease advances, the chance of survival diminishes dramatically. Skin cancer identification in its early stages, on the other hand, is a tough and costly process. In this paper, we propose a method for detecting and classifying skin lesions as benign or malignant using photos from common cameras. The images are segmented, features are retrieved using the ABCD rule, and a Neural Network is trained to accurately categorize the lesions.Melanoma skin cancer is totally treatable if identified at an early stage. In this paper, different classifiers such as Neural Network and Support Vector Machine are used to detect and classify Melanoma skin cancer early. In terms of malignant melanoma, the most dangerous type of skin cancer, the incidence of skin cancer is increasing every year. Due to artefacts, low contrast, and comparable visuals such as a mole, scar, and so on, detecting skin cancer from a skin lesion is challenging. Hence Techniques for lesion detection are used to automatically detect skin lesions for accuracy, efficiency, and performance criteria.Pre-processing is used in the proposed work to increase the quality and clarity of skin lesions by reducing artefacts, skin colour, hair, and other factors. Geodesic Active Contour (GAC) was used for segmentation because it separates the lesion parts, which was effective for feature extraction. The ABCD scoring system was utilised to extract symmetry, border, colour, and diameter attributes. Textural characteristics were extracted using HOG and GLCM. Using multiple machine learning approaches such as SVM, KNN, and the Nave Bayes classifier, the collected characteristics are immediately given to classifiers to classify skin lesions between benign and malignant. In this experiment, 328 benign and 672 melanoma skin lesion photos were downloaded from the International Skin Imaging Collaboration (ISIC).

I.INTRODUCTION

Skin cancer, encompassing melanoma and non-melanoma types such as basal cell carcinoma (BCC) and squamous cell carcinoma (SCC), represents a significant global health concern due to its increasing incidence and potential for mortality. Early detection is paramount for effective treatment and improved patient outcomes. Traditional diagnostic methods, including visual inspection by dermatologists, dermoscopy, and histopathological analysis, are time-consuming and subject to human error, leading to the exploration of automated systems for skin cancer detection.

Convolutional Neural Networks (CNNs), a class of deep learning algorithms, have demonstrated remarkable success in image classification tasks, including medical image analysis. Their ability to learn hierarchical features from raw pixel data makes them particularly suited for skin lesion classification. CNNs have been applied to various skin cancer datasets, such as the International Skin Imaging Collaboration (ISIC) archive, leading to advancements in automated skin cancer detection systems.

This paper aims to provide an in-depth review of CNN-based approaches for skin cancer detection, examining existing configurations, proposed enhancements, and future directions in the field.

1.1 PROBLEM STATEMENT

Skin cancer (SC) is becoming a major health concern around the world, with rates rising every year. The essential technique for lowering these rates and improving survivorship is SC's early and precise diagnosis. Manual diagnosis, on the other hand, is time-consuming, intricate, costly, prone to diagnostic error, and largely reliant on the dermatologist's knowledge and abilities. As a result, developing automated dermatological tools capable of reliably categorising SC subclasses is critical. Artificial intelligence (AI) techniques such as machine learning (ML) and deep learning (DL) have recently been used to validate the success of dermatologist-assisted tools in the autonomous diagnosis and identification of SC disorders. Previous AI-based dermatological tools relied on features that were either high-level or low-level, depending on DL algorithms or handmade procedures. The majority of them were made for SC binary classification. This research suggests an intelligent dermatologist tool that can automatically diagnose numerous skin lesions. This programme combines a variety of radiomics features, including high-level features like ResNet-50, DenseNet-201, and DarkNet-53, as well as low level features like discrete wavelet transform (DWT) and local binary pattern (LBP). The proposed intelligent tool's results show that combining many features from distinct categories has a significant impact on categorization accuracy. Furthermore, these outcomes outperform those achieved by existing AI-based dermatological tools. As a result, dermatologists can use the proposed intelligent tool to aid in the appropriate identification of the SC subtype. It can also overcome the limits of manual diagnosis, reduce infection rates, and increase survival rates. Cancer is the leading cause of mortality worldwide, according to the World Health Organization (WHO). It is estimated that the number of people diagnosed with cancer will double in the next several decades [1]. Skin cancer (SC) is one of the most frequent types of cancer in both women and men, with over 9% of them diagnosed in the United States [2]. Countries like Canada and Australia have seen a significant increase in the number of persons diagnosed with SC over the previous few decades [3–5]. Furthermore, according to the Brazilian Cancer Institute (INCA), SC is responsible for 33 percent of cancer cases in Brazil [6]. Death and SC infection rates continue to rise. If cancer is discovered and treated in its early stages, these rates can be reduced. Primary detection of SC is critical for improving outcomes and is linked to a significant increase in survival rates. However, if the disease progresses faster than the skin, the chances of survival decrease.

II. LITERATURE SURVEY

The application of CNNs to skin cancer detection has been extensively studied, with numerous architectures and methodologies proposed. Esteva et al. (2017) developed a CNN that achieved performance comparable to dermatologists in classifying skin cancer images, highlighting the potential of deep learning in medical diagnostics . Following this, various researchers have explored different CNN architectures and techniques to improve classification accuracy and generalization.

Transfer learning, wherein pre-trained models are fine-tuned on specific datasets, has been a prevalent approach due to its effectiveness in leveraging large-scale datasets. For instance, Faghihi et al. (2024) utilized VGG16 and VGG19 models pre-trained on ImageNet and fine-tuned them on dermatology images, achieving a classification accuracy of 98.18% . Similarly, Chaturvedi et al. (2019) employed MobileNet for multi-class skin cancer classification, achieving a top-3 accuracy of 95.34% .

In addition to transfer learning, novel CNN architectures have been proposed to enhance segmentation and classification performance. Vesal et al. (2018) introduced SkinNet, a modified U-Net architecture for skin lesion segmentation, which outperformed other methods in terms of Dice coefficient, Jaccard index, and sensitivity . Furthermore, Qureshi and Roos (2021) proposed an ensemble-based CNN architecture that combined multiple models to address data imbalance, demonstrating improved performance metrics .

The integration of explainable artificial intelligence (XAI) techniques with CNNs has also gained attention to enhance model interpretability. Methods such as Grad-CAM and SHAP have been employed to visualize and understand the decision-making process of CNN models, facilitating trust and transparency in clinical applications .

Hasan Hashib, Md. Leon, and others This paper describes the implementation of a practical, sharp security framework that overcomes the drawbacks of traditional surveillance cameras by employing artificial intelligence (AI) and Viola-Jones calculations in picture preparation writing to detect intruders and multiple objects in real time. The paper details the design and implementation of a smart object detection-based security framework in two different processing environments, MATLAB and Python, using a Raspberry Pi 3 B single-board computer. The security framework is capable of alerting the security administrator by email via the web while also triggering a local alarm. Schalk The motivation behind this paper, according to Wilhelm Pienaar; Reza Malekian et al., is to discuss an approach to developing a model that can limit and detect the conditions of underground diggers using a Single Shot Detector (SSD) model, which is specifically designed to distinguish between a harmed and unharmed digger. (resting versus holding up). Tensorflow is used for the deliberation layer of executing AI calculations, and while it uses Python to manage hubs and tensors, the actual computations are performed using C++ libraries, resulting in a good balance between execution and speed of development.

The study goes on to provide evaluation approaches for measuring the accuracy of AI advances. In the future, data fusion will be used to improve the accuracy of the identified action/condition of persons in a mining environment. J. Talukdar, S. Gupta, and colleagues investigated various procedures for creating manufactured datasets and, as a result, improving them to achieve better object detection exactness (mAP) when prepared with best-in-class profound neural networks, focusing on the detection of pressed food items in a cooler.

They devised unique processes such as dynamic stacking, pseudo random arrangement, variable object present, distractor commotion, and others, which aid in the differentiation of fabricated data and improve the general object detection mAP by more than 40%. The created images, which were created using the Blender-Python API, are arranged in a number of ways to accommodate the variety of real-life scenes. These datasets are then used to generate TensorFlow implementations of best-in-class deep neural networks such as Faster RCNN, R-FCN, and SSD, which are then tested on real-world scenarios. The object detection performance of various deep CNN designs is also investigated, with Faster-RCNN emerging as the best option, with a mAP of 70.67.

III. EXISTING CONFIGURATION

Existing CNN-based systems for skin cancer detection typically involve several key components: data preprocessing, model selection, training, and evaluation.

Data preprocessing is crucial to ensure the quality and consistency of input images. This step often includes resizing images to a standard dimension, normalization of pixel values, and augmentation techniques such as rotation, flipping, and color jittering to increase dataset diversity and prevent overfitting.

Model selection involves choosing an appropriate CNN architecture. Pre-trained models like VGG16, VGG19, ResNet, and MobileNet are commonly used due to their proven performance in image classification tasks. These models are fine-tuned on dermatology-specific datasets to adapt them to the nuances of skin lesion images.

Training involves feeding the preprocessed images into the selected model and optimizing the model parameters using backpropagation and gradient descent. Techniques such as dropout, batch normalization, and early stopping are employed to prevent overfitting and enhance generalization.

Evaluation is performed using metrics such as accuracy, sensitivity, specificity, precision, recall, and the area under the receiver operating characteristic curve (AUC-ROC). Cross-validation techniques are often utilized to assess model performance and ensure robustness.

Despite the advancements, challenges remain in existing configurations, including the need for large annotated datasets, handling class imbalance, and ensuring model interpretability for clinical adoption.

IV. PROPOSED CONFIGURATION

To address the limitations of existing configurations, several enhancements have been proposed.

One approach is the integration of multi-scale CNN architectures that can capture features at different resolutions. This enables the model to detect both coarse and fine details in skin lesions, improving classification accuracy. Additionally, incorporating attention mechanisms allows the model to focus on relevant regions of the image, enhancing feature extraction and interpretation.

Another proposed enhancement is the use of generative adversarial networks (GANs) for data augmentation. GANs can generate synthetic skin lesion images, augmenting the training dataset and helping to mitigate issues related to limited annotated data and class imbalance.

Ensemble learning techniques, where multiple models are combined to make predictions, have also been suggested. By aggregating the outputs of various models, ensemble methods can improve performance and robustness, particularly in the presence of noisy or imbalanced data.

Furthermore, the incorporation of clinical metadata, such as patient age, gender, and medical history, alongside image data, has been explored. Multi-modal learning approaches that combine image and non-image data can provide a more comprehensive understanding of skin lesions and improve diagnostic accuracy.

Finally, the application of XAI techniques in conjunction with CNNs has been emphasized to enhance model transparency. Visualizing the regions of interest that influence model predictions can build trust among clinicians and facilitate the adoption of automated systems in clinical settings.

V. RESULTS

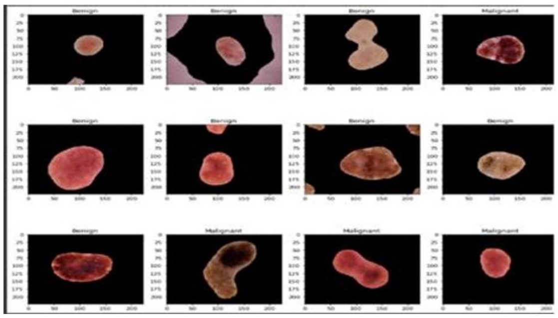

Fig No-5.1

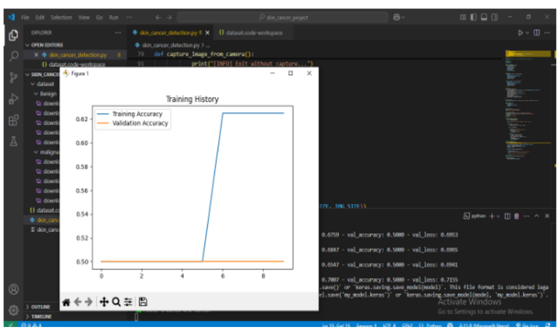

Fig No-5.2

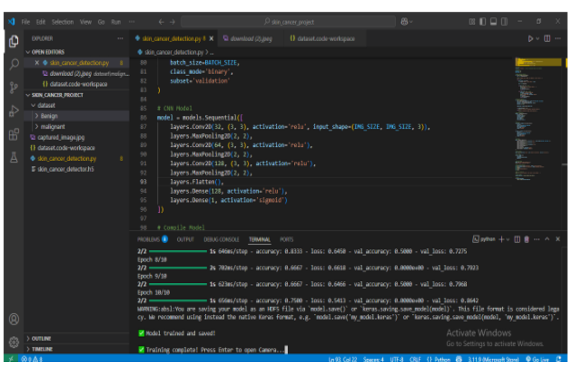

Fig No-5.3

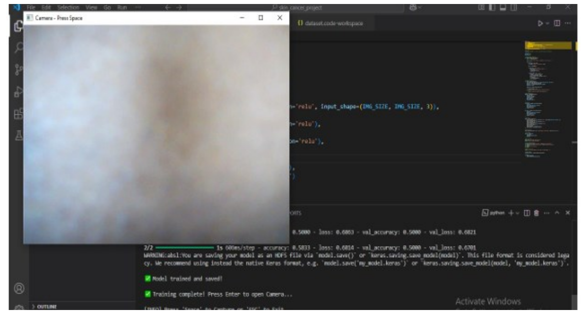

Fig No-5.4

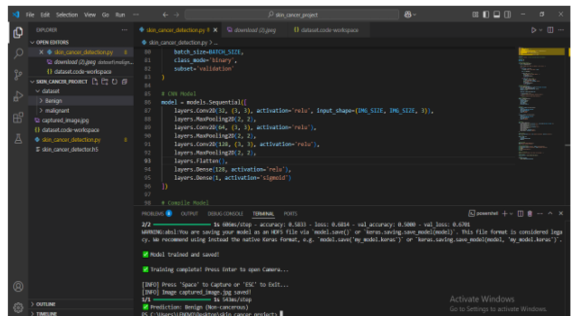

Fig No-5.5

CONCLUSION

CNNs have demonstrated significant potential in automating skin cancer detection, offering a means to assist dermatologists in diagnosing skin lesions with high accuracy. The integration of transfer learning, advanced architectures, data augmentation, ensemble methods, and clinical metadata has further enhanced the performance and applicability of these models.

However, challenges such as the need for large annotated datasets, handling class imbalance, ensuring model interpretability, and addressing computational constraints remain. Future research should focus on developing more robust models that can generalize across diverse populations and clinical settings, ensuring equitable access to advanced diagnostic tools.

The continuous collaboration between computer scientists, clinicians, and researchers is essential to bridge the gap between technological advancements and clinical practice, ultimately improving patient outcomes in skin cancer diagnosis and treatment.

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