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Skin Cancer Classification using Deep Learning

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Abstract: According to world health organization skin cancer is the one of the most common cancer types in the world. The abnormal growth of skin cells most often develops on the skin when exposed to the sun and occurs when there is a mutation in the DNA of skin cells, it begins at the top of the skin. More than five million people are affected by skin cancer each year. The proposed method aim at analyzing and detecting the significant class of skin cancer variant such as Melanoma, Basal cell Carcinoma, Nevus. Melanoma is the most dangerous form of skin cancer when compared to the other types. In this paper we have developed a webapp that could differentiate skin cancer. The data set has been taken from ISIC and the model is trained using Gcollab. The proposed work has used convolution neural network (CNN) as algorithm for deep learning as it has higher accuracy and flask is used to develop the web app and the class of cancer is classified based on historical data of dermoscopic images.

Keywords: Deep Learning, Convolutional Neural Networks (CNN), Basal Cell Carcinoma, Melanoma, Nevus, Flask.

1. Introduction

Detecting skin cancer using deep learning algorithms, specifically Convolutional Neural Networks (CNN), is a pioneering combination of medical diagnostics and cutting-edge technology. Skin cancer, one of the most common types of cancer worldwide, is extremely curable if diagnosed early. However, standard diagnostic approaches can be time-consuming and error prone. CNNs are a type of deep learning model inspired by the human brain's visual cortex that are capable of learning hierarchical image representations in dermatology , CNNs evaluate photographs of skin lesions with amazing accuracy, frequently outperforming human physicians in identifying cancers. This method is based on training the network using large datasets of tagged skin pictures, and the network learns to identify between benign and malignant lesions by extracting subtle patterns and features.

The procedure starts with preprocessing steps to improve image quality and extract key features, followed by training the CNN on a huge dataset of annotated images. During training, the network adjusts its parameters to reduce the discrepancy between its predictions and ground truth labels. Once trained, the CNN can quickly analyse new images, offering accurate diagnoses. This incorporation of deep learning into dermatological diagnostics holds the prospect of earlier diagnosis, increased accuracy, and, eventually, better results for patients with skin cancer.

1) Basal Cell Carcinoma: Basal cells are located at the bottom of the epidermis, the skin's outer layer. BCC (Figure 1) frequently arises when DNA is damaged by UV radiation from the sun. BCCs can ooze, crust, itch, or bleed. Basal cell carcinoma is highly prevalent. According to WHO, around 5.4 million people are diagnosed with BCC each year. More than one in every three new cancers is a skin cancer, with BCCs accounting for the great majority [1].

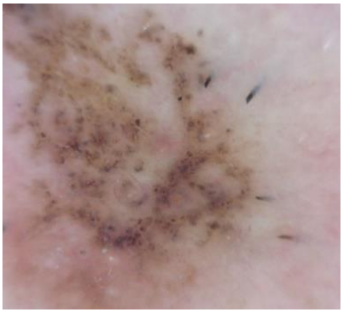

Figure 1. Basalcell Carcinoma

2) Melanoma: Melanoma (black tumour, Figure 2), the deadliest type of skin cancer, arises in the cells (melanocytes) that create melanin, the pigment that gives your skin its colour. Symptoms may include a new, unexpected growth or a change in an existing mole. Melanomas can arise anywhere on the body, and around 1.5 million people are impacted each year. Melanoma accounts for only around 1% of all skin malignancies, but it causes the vast majority of skin cancer deaths [2].

Figure 2. Melanoma

3) Nevus: A nevus is a skin mole caused by a cluster of melanocytes. Melanocytes produce melanin, which imparts colour to skin and eyes. In most circumstances, a nevus is harmless

and does not require treatment. Rarely, they progress to melanoma or other skin malignancies. A nevus, shown in Figure 3 changes shape, expands, or darkens should be considered for excision.

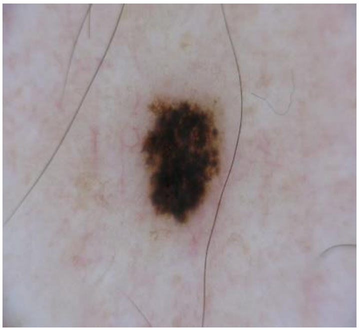

Figure 3. Nevus

1.1. Related Works

Use of machine learning (ML) and deep learning (DL) techniques such convolutional neural networks (CNNs), recurrent neural networks (RNNs), support vector machines (SVMs), and Random Forest to diagnose skin cancer [3]. The results demonstrate that convolutional neural network (CNN) has the highest accuracy, sensitivity, and specificity under the ROC curve when compared to other machine learning techniques. So, we employed a deep learning system to determine the type of skin cancer.

In another review [4], multiple neural network approaches were investigated for detecting and categorizing skin cancer. The study investigated the use of artificial neural networks (ANNs), convolutional neural networks (CNNs), and k-nearest neighbours (KNNs) to categorize lesion images. The proposed work found that the research lacks the ability to respond to a patient's inquiry concerning the presence of a certain skin cancer scar on the body while utilizing (ANN) and (KNN).So, we incorporated the CNN method to accomplish the project.

Scientists employed a CNN (convolutional neural network) technique based on RESNET-50 to detect melanoma and squamous cell skin malignancies. They applied machine learning techniques [5]. The accuracy achieved was 82.87%, and only two groups were identified. Our planned study classifies three types of skin cancer.

Basal Cell Carcinoma typically occurs on sun-damaged skin and infrequently on the mucous membranes, palms, and soles [6]. Although BCC is rarely lethal, it can be extremely damaging and disfigure local tissues if treated inadequately or late. Chronic sun exposure is one of the most significant risk factors for the development of BCC. BCC causes direct DNA damage, indirect DNA damage via reactive oxygen species, and immunological suppression. Melanin absorbs UVA, which indirectly destroys DNA via free radicals. According to the literature, the cells that give rise to BCC are immature pluripotent cells associated with the hair follicle. Notably, the PTCH1 gene is the most commonly changed in BCCs. PTCH1 gene mutations are present in 70% of patients with sporadic BCC. Therefore, the proposed method focuses on early detection of Basal Cell Carcinoma.

The most important risk factors for the development of malignant melanoma are the quantity and size of acquired melanocytic nevi (AMN) as well as the existence of dysplastic nevi. Randomly selected study participants were those who, between December 2010 and February 2011, were admitted to the dermatology outpatient clinic due to any dermatological complaints. There was documentation of sunburn, chemical exposure, nevus, malignancy, and/or melanoma in the family histories. Both globally and in Turkey, the prevalence and death rate from cutaneous melanomas are rising quickly. Consequently, MN, which are a sign of cutaneous melanomas, need to be monitored. A significant risk factor for the development of malignant melanoma in the population is the quantity of AMN and the existence of dysplastic nevi. Therefore, early Nevus detection is the main goal of the suggested approach.

2. Materials and Method

2.1 Dataset

The International Skin Imaging Collaboration (ISIC) was used to collect the dataset for this work. This dataset consists of tumor cells such as basal cell carcinoma, Melanoma, and nevus along with non tumours cells. There are a total of283, 732 images in this dataset, which includes 94,577 for each type of tumour cells and 58,732 images for non-tumor cell. Sample images of normal cell and tumour cells are demonstrated in Figure 4

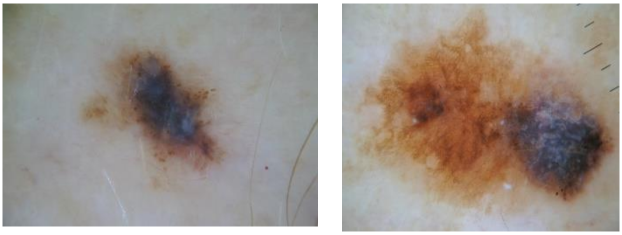

Figure 4. Normal cell and Tumour cell

3. Proposed Method

A deep learning algorithm is used to detect and classify tumor cells by using dermoscopic images of cancerous and non-cancerous cells. The flowchart in Figure 5. illustrates the proposed method.

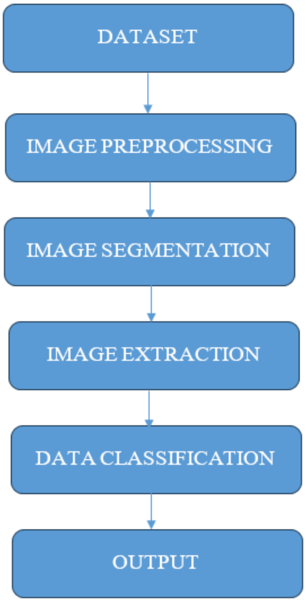

Figure 5. Methodology for classification of skin cancer

Skin cancer classification consists of numerous steps [7]. It begins with the ISIC, which contains tagged images of skin lesions for training and testing [8]. To maintain consistency and improve model resilience, image processing prepares these images by resizing, normalizing, and augmenting them. Image segmentation isolates the lesion from the backdrop [9]. The CNN then does feature extraction, in which it automatically learns and detects important elements such as edges, textures, and patterns within the lesion. The collected features are sent into the classification step, where the CNN model predicts the type of skin cancer or if the lesion is benign. Finally, the webapp displays the classification results, which include the projected lesion type and a confidence score, allowing medical professionals to formulate accurate diagnoses and treatment plans.

3.1 Image Preprocessing

The goal of pre-processing is to improve the image data by suppressing unwanted distortions or enhancing visual qualities useful for subsequent processing, though geometric manipulations of images [10]. The process of modifying an image so that the result is more suitable than the original for specific applications. The objective of enhancement techniques is to bring out elements that are concealed, or simply to highlight certain features of interest in an image.

In our preprocessing pipeline, we used numerous strategies to prepare the data for training the Convolutional Neural Network (CNN) architecture, which is a key component of deep learning for image classification tasks [11]. Initially, we used data augmentation to boost the diversity of our dataset, reducing the danger of overfitting and improving the model's generalizability. We then used standardization to normalize the pixel values, maintaining homogeneity between images and promoting faster convergence during training. Furthermore, we performed feature extraction utilizing three layers of CNN, including convolutional, pooling, and activation layers, which automatically learn noteworthy features from input photos. This hierarchical feature extraction technique allows the model to capture the complicated patterns and spatial correlations required for successful lesion classification. Finally, we fail to incorporate the preprocessing pipeline into the Flask framework, simplifying data entry and model inference for real-time classification in clinical scenarios.

3.2 Deployment Architecture

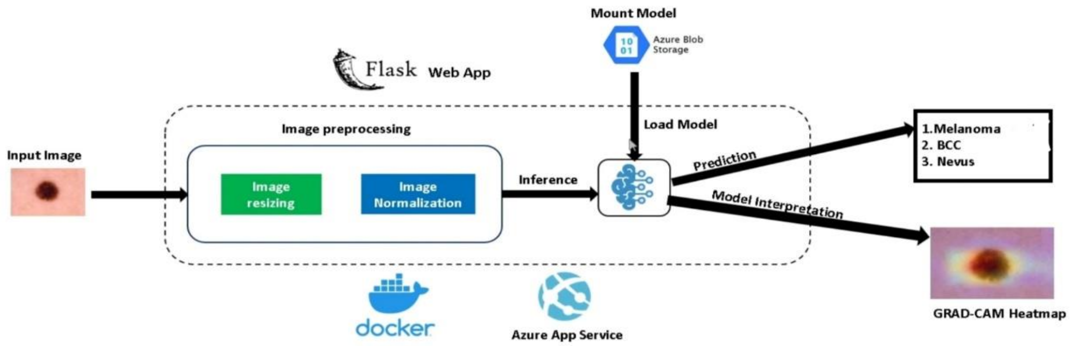

Figure 6. Deployment architecture

The deployment architecture for skin cancer categorization consists of numerous critical components and processes as shown in Figure 6. The method begins with an input image of a skin lesion, which is then pre-processed, including scaling and normalization. This is done to standardize the input to the model. The pre-processed image is then sent to a machine learning model running in a Flask web app. The model is stored in Azure Blob Storage and loaded into the application as needed. The image is entered into the model, which makes predictions about whether the lesion is melanoma, basal cell carcinoma (BCC), or a nevus. In addition, the model provides a Grad-CAM heatmap for model interpretation, which highlights the parts of the image that had the greatest influence on the prediction. The deployment is containerized with Docker, which ensures consistency across several environments. Finally, the entire application is deployed using wen app, which allows for scalability and easy management. This configuration provides efficient, reliable, and scalable skin cancer categorization via a web interface.

4. Results and Discussions

The objective of our endeavour was to categorize three forms of skin lesions: melanoma, basal cell carcinoma, and nevus, utilizing a deep learning Convolutional Neural Network (CNN) architecture connected with the Flask framework. The model attained an overall accuracy of 97% on the test dataset, demonstrating its ability to distinguish between different lesion types. While melanoma and basal cell carcinoma were correctly classified at 0.98% and 0.98%, respectively, nevus classification had an accuracy of 0.96%, indicating opportunity for improvement. The confusion matrix (Figure 7) revealed insights into misclassification trends, which guided subsequent model revisions. Integration with Flask allows for simple implementation within healthcare systems, giving dermatologists access to the categorization tool during ordinary clinical practice. Challenges include the need for larger and more diverse datasets to increase model generalization, as well as continuous research to improve interpretability and biases. Patient confidentiality, openness, and equitable access are all ethical considerations. Overall, our experiment demonstrates CNNs' promise in skin lesion categorization, providing a useful tool for early identification and treatment of skin cancer.

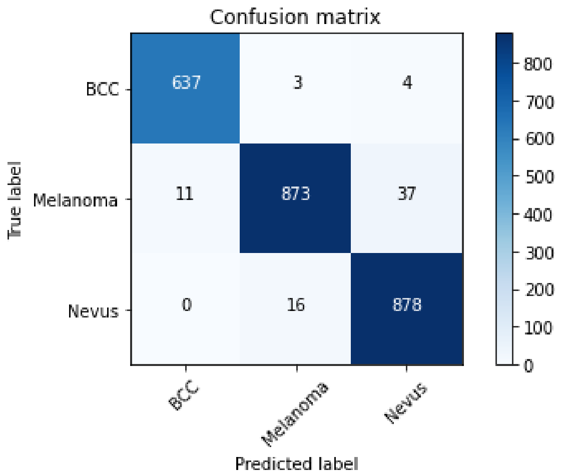

Figure 7. Confusion matrix

The confusion matrix for skin cancer categorization shows that the model is highly accurate, with correct predictions for BCC (637), melanoma (873), and nevus (878). However, there are also small misclassifications: BCC is occasionally predicted as melanoma (3) or nevus (4), melanoma as BCC (11) or nevus (37), and nevus as melanoma (16). These results demonstrate the model's high ability to distinguish between skin cancer types, albeit there is significant overlap, particularly between melanoma and nevus forecasts. The overall distribution of predictions indicates that, while the model is accurate, there is opportunity for improvement in terms of specific misclassifications.

5. Conclusion

In conclusion, our project aims at effectively illustrating the effectiveness of deep learning CNNs in reliably diagnosing melanoma, basal cell carcinoma, and nevus lesions, with the integration of the Flask framework allowing for smooth deployment within healthcare systems. While melanoma and basal cell cancer have good accuracies, nevus categorization need further improvement. By tackling problems such as dataset diversity and model interpretability while adhering to ethical norms, our study advances skin cancer detection and management, ultimately improving patient outcomes through early diagnosis and intervention.

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Conflict of interest

The Author's have no conflicts of interest to declare that they are relevant to the content of this article.

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