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SKIN CANCER DETECTION USING MACHINE LEARNING

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Abstract— *Skin cancer is a form of cancer that can be extremely harmful. It is caused by DNA damage in skin cells that results in genetic mutations on the skin. If left untreated, skin cancer can spread to other parts of the body, which is why it is most effective to detect it in its earliest stages. The growing incidence of skin cancer, combined with its high mortality rate and costly medical treatments, highlights the importance of prompt diagnosis. To address these concerns, researchers have devised various early detection methods for skin cancer. These methods involve analyzing lesion characteristics such as color, size, shape, and symmetry to differentiate between benign and malignant skin cancer.*

Early detection is crucial in the fight against skin cancer, but manual diagnostic processes can be time-consuming and expensive. Fortunately, advancements in science and technology have made it possible to use machine learning, specifically convolutional neural networks, to detect cancerous cells more quickly and efficiently. This promises to revolutionize the way we approach the early detection and treatment of skin cancer.

Keywords— A Machine Learning, CNN, TensorFlow, Disease Detection, Neural Network, Deep Learning

INTRODUCTION

Skin cancer is a relatively uncommon condition that can produce a range of symptoms and take various forms, some of which can be treated while others can be fatal. It can affect individuals of all ages and can be life-threatening if not detected early. It is estimated that one out of every six people will develop skin cancer at some point in their lives. Although it is a rare condition, it can have a significant impact on those affected. Many experts in the medical field believe that excessive exposure to sunlight is a contributing factor to the development of skin cancer.

Early detection of skin cancer is crucial in determining the appropriate treatment and mitigating its potential harm. This is where the use of Python and machine learning comes into play, providing a means of accurately identifying skin cancer and its type. The work involved is described in three levels, making it easier to understand the procedures involved and the overall process. Overall, skin cancer is a critical issue in the medical field, and it is essential that we take steps to reduce its occurrence and improve outcomes for those affected.

I. Literature Survey

AUTOMATED SEGMENTATION OF THE MELANOCYTES IN SKIN HISTOPATHOLOGICAL IMAGES - Cheng Lu; Muhammad Mahmood; Naresh Jha; Mrinal Mandal; 2013 –

In the diagnosis of skin melanoma by analyzing histopathological images, the detection of the melanocytes in the epidermis area is an important step. However, the detection of melanocytes in the epidermis area is dicult because other keratinocytes that are very similar to the melanocytes are also present. This paper proposes a novel computer-aided technique for segmentation of the melanocytes in the skin histopathological images. In order to reduce the local intensity variant, a mean-shift algorithm is applied for the initial segmentation of the image. A local region recursive segmentation algorithm is then proposed to filter out the candidate nuclei regions based on the domain prior knowledge. To distinguish the melanocytes from other keratinocytes in the epidermis area, a novel descriptor, named local double ellipse descriptor (LDED), is proposed to measure the local features of the candidate regions. The LDED uses two parameters: region ellipticity and local pattern characteristics to distinguish the melanocytes from the candidate nuclei regions. Experimental results on 28 dierent histopathological images of skin tissue with dierent zooming factors show that the proposed technique provides a superior performance.

NON-INVASIVE REAL-TIME AUTOMATED SKIN LESION ANALYSIS SYSTEM FOR MELANOMA EARLY DETECTION AND PREVENTION - Omar Abuzaghleh, Buket D Barkana, Miad Faezipour; 2015-

Melanoma spreads through metastasis, and therefore, it has been proved to be very fatal. Statistical evidence has revealed that the majority of deaths resulting from skin cancer are as a result of melanoma. Further investigations have shown that the survival rates in patients depend on the stage of the cancer; early detection and intervention of melanoma implicate higher chances of cure. Clinical diagnosis and prognosis of melanoma are challenging, since the processes are prone to misdiagnosis and inaccuracies due to doctors' subjectivity. Malignant melanomas are asymmetrical, have irregular borders, notched edges, and color variations, so analyzing the shape, color, and texture of the skin lesion is important for the early detection and prevention of melanoma. This paper proposes the two major components of a noninvasive real-time automated skin lesion analysis system for the early detection and prevention of melanoma. The first component is a real-time alert to help users prevent skinburn caused by sunlight; a novel equation to compute the time for skin to burn is thereby introduced. The second component is an automated image analysis module, which contains image acquisition, hair detection and exclusion, lesion segmentation, feature extraction, and classification. The proposed system uses PH2 Dermoscopy image database from Pedro Hispano Hospital for the development and testing purposes. The image database contains a total of 200 dermoscopy images of lesions, including benign, atypical, and melanoma cases. The experimental results show that the proposed system is efficient, achieving classification of the benign, atypical, and melanoma images with accuracy of 96.3%, 95.7%, and 97.5%, respectively.

CLASSIFICATION OF MALIGNANT MELANOMA AND BENIGN SKIN LESIONS: IMPLEMENTATION OF AUTOMATIC ABCD RULE –Reda Kasmi,Karim Mokrani; 2016-

The ABCD (asymmetry, border irregularity, colour and dermoscopic structure) rule of dermoscopy is a scoring method used by dermatologists to quantify dermoscopy findings and effectively separate melanoma from benign lesions. Automatic detection of the ABCD features and separation of benign lesions from melanoma could enable earlier detection of melanoma. In this study, automatic ABCD scoring of dermoscopy lesions is implemented. Pre-processing enables automatic detection of hair using Gabor filters and lesion boundaries using geodesic active contours. Algorithms are implemented to extract the characteristics of ABCD attributes. Methods used here combine existing methods with novel methods to detect colour asymmetry and dermoscopic structures. To classify lesions as melanoma or benign nevus, the total dermoscopy score is calculated. The experimental results, using 200 dermoscopic images, where 80 are malignant melanomas and 120 benign lesions, show that the algorithm achieves 91.25% sensitivity of 91.25 and 95.83% specificity. This is comparable to the 92.8% sensitivity and 90.3% specificity reported for human implementation of the ABCD rule. The experimental results show that the extracted features can be used to build a promising classifier for melanoma detection.

II. Existing System

Analysts At present, to check skin malignancy of a patient, he needs to experience singular screening by a dermatologist so as to recognize whether they have skin disease or not. This framework helps dermatologist to process various cases a lot quicker than expected. Several symptom checklists have been established. ABCDE is one of the checklists, such as –

• Asymmetry(A) – One portion of the affected cell that has turned into a tumour does not coordinate the other half.
• Border(B)-The edges/the fringe of the tainted cells wind up battered, scored, obscured.
• Colour(C)-Shade isn't uniform. Shades of tan or dark coloured spots on skin and dark are available. Dashes of red, white and blue add to the repulsive appearance.
• Diameter(D)- The cell width ends up more noteworthy than 6mm and over.
• Evolution(E)-Previously mentioned changes or advancements show Malignant Melanoma

III. Proposed System

In the proposed system, the dataset of labeled images (benign, malignant, and healthy) were used and organized into three classes based on their analysis label extracted from the image metadata. Images from the ISIC dermoscopic archive were randomly selected for experimentation. The system consists of three layers:

• Input layer, where the dataset is trained and weight is added to the data for processing in the hidden layers.
• Hidden layer, where the neurons separate the features from the data to find patterns.
• Output layer, where binary classification is used to accurately select class 2, class 1, and class 0.

IV. Methodology

The first step in the methodology was to gather a large dataset of skin lesion images. This dataset was then used to train the MobileNet V2 machine learning model using Python. The model was trained on a diverse set of images, which included both healthy skin and different types of skin cancer. This was done to ensure that the model was able to accurately distinguish between healthy skin and different types of skin cancer.

Once the model was trained, it was integrated into an Android app developed using Java and Android Studio. The app was designed with a user-friendly interface, allowing users to either select a photo from their device or start the camera to capture a new image. The input image was then processed by the trained model, which analyzed various parameters such as color, shape, and size to determine the type of skin lesion present in the image.

The results of the analysis were then displayed to the user, with one of three outcomes: malignant, benign, or healthy. This information provided users with a preliminary diagnosis of the skin lesion, and encouraged them to seek further medical attention if necessary.

In conclusion, the skin cancer detection app was developed using a combination of machine learning and mobile technology, providing a user-friendly and efficient solution for detecting skin cancer at an early stage. The app leverages the power of the MobileNet V2 machine learning model, which was trained on a large dataset of skin lesion images, to accurately distinguish between healthy skin and different types of skin cancer.

A. Architecture: -

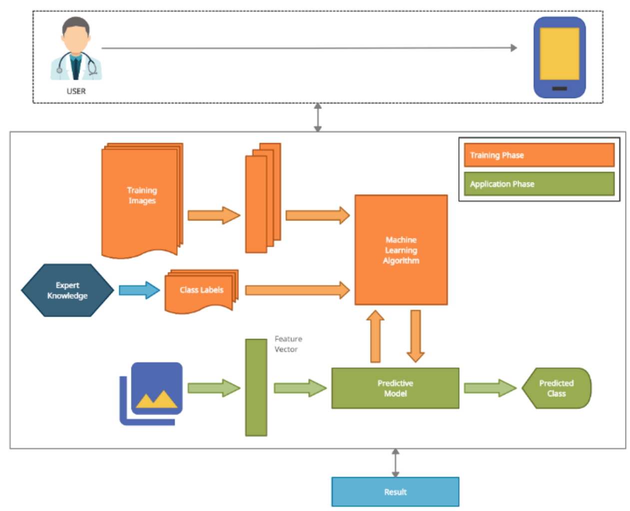

Fig 1. Architecture diagram

The architecture of a machine learning model-based Android app typically consists of three main components:

• Data collection and pre-processing: In this stage, a large dataset of images of skin conditions, both healthy and with cancer, is collected and pre-processed. The images are resized, normalized, and labeled as healthy, benign, or malignant.

• Model training: The pre-processed dataset is used to train the MobileNet V2 model using a deep learning framework such as TensorFlow or PyTorch. This is done using a computer with a powerful GPU to handle the computationally intensive process.

• Deployment: Once the model is trained, it is converted to a format that can be used on a mobile device, such as TensorFlow Lite. The model is then integrated into the Android app using the Java programming language and the Android Studio development environment.

In the app, users are given the option to either select a photo from their device or start the camera to capture a new image. The image is then passed through the MobileNet V2 model, which outputs a prediction of whether the skin condition is healthy, benign, or malignant.

Overall, this architecture allows for a fast and efficient way of diagnosing skin conditions using a machine learning model on a mobile device.

B. Training and Validation Accuracy and Loss:-

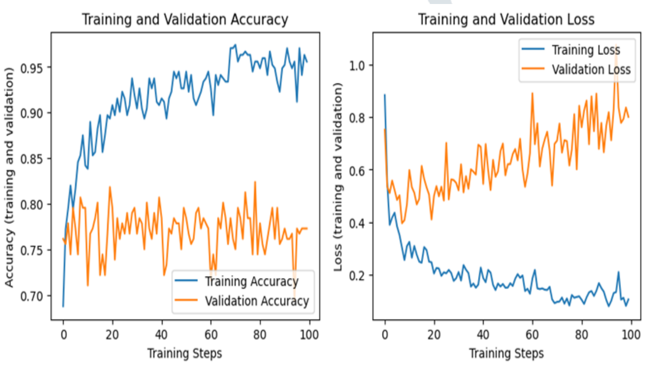

Fig 2. Training and Validation Accuracy and Loss

The figure 2 likely show the performance of the model during training and validation. The x-axis of both graphs typically represents the number of iterations or epochs, while the y-axis represents a metric of interest, such as accuracy or loss.

Training accuracy is the accuracy of the model on the training data, which is used to train the model. It gives an indication of how well the model is learning from the training data. The training loss is the error of the model on the training data, which is a measure of how well the model is fitting the training data.

Validation accuracy is the accuracy of the model on the validation data, which is a subset of the data that is used to evaluate the model's performance. Validation loss is the error of the model on the validation data, which is a measure of how well the model generalizes to unseen data.

C. Confusion Matrix:-

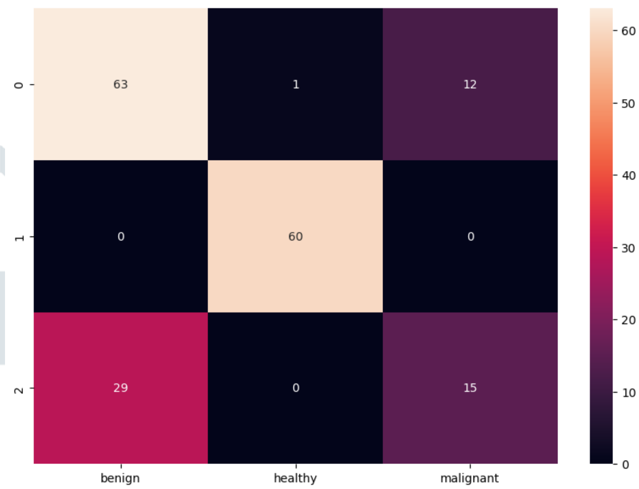

Fig 3. Condusion Matrix

A confusion matrix is a table that is used to evaluate the performance of a classification model. It compares the predicted class labels with the true class labels and summarizes the results in a compact form.

In figure 3, the x-axis represents the predicted class labels with "benign", "healthy", and "malignant" as the categories. The y-axis represents the true class labels with classes "2", "1", and "0".

Each cell in the matrix represents the number of instances that were predicted as belonging to a certain class but actually belong to another class. The diagonal cells in the matrix represent the instances that were correctly classified, whereas the off-diagonal cells represent the instances that were misclassified.

V. Working

As appears in figure 4 this is an Android Application. This application is comprised of MobileNet V2 model, trained with hundreds of skin cancer images dataset.

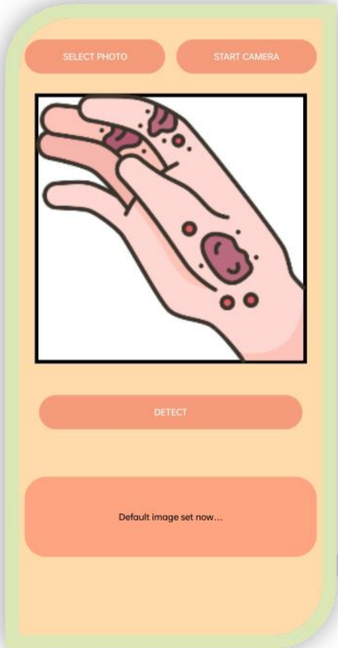

Fig 4. Main Screen

The working process of the skin cancer detection app:

• Data Collection: Firstly, a large dataset of images of healthy skin, benign skin lesion, and malignant skin lesion was collected to train the machine learning model.

• Model Training: The MobileNet V2 model was trained using Python to differentiate between the three classes (healthy skin, benign skin lesion, and malignant skin lesion). This model uses a convolutional neural network (CNN) architecture to learn patterns and features in the images.

• Input Selection: In the Android app, the user is presented with two options - either to select a photo from their device or to start the camera to take a new picture. The input image is then passed to the next stage of the process.

• Prediction: The input image is fed into the trained MobileNet V2 model, and the model makes a prediction on whether the skin lesion in the image is malignant, benign, or healthy.

• Result Display: The final result, either malignant, benign, or healthy, is displayed on the app interface for the user to view.

In summary, the skin cancer detection app uses a trained MobileNet V2 model to make predictions on the type of skin lesion present in an image inputted by the user. The user can either select a photo or take a new picture, and the result is displayed on the app interface.

VI. EXPERIMENTAL RESULTS

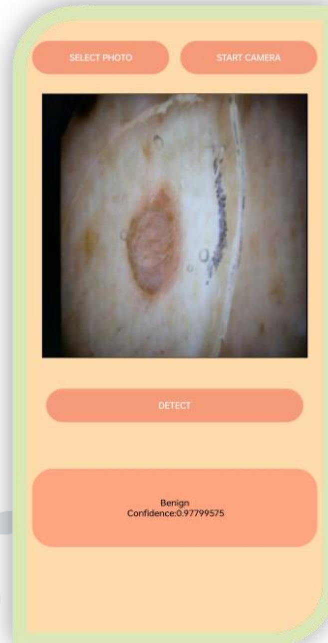

Fig 5. Detected Benign

The figure shows the interface of the skin cancer detection app, which utilizes a trained machine learning model to analyze the input image of a skin lesion. In this particular scenario, the result of the analysis is "Benign," indicating that the skin lesion does not exhibit any signs of malignancy.

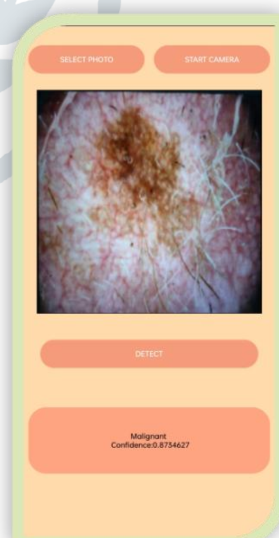

Fig 6. Detected Malignant

The app interface, as shown in the figure, provides a clear and concise result of "malignant". This indicates that the input image has been detected as having a skin cancer that is potentially dangerous. It is imperative that the user takes immediate action and seeks medical attention to confirm the diagnosis and initiate a treatment plan.

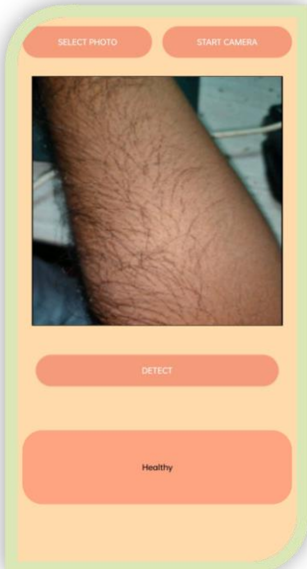

Fig 7. Detected Healthy

The figure depicts the app interface displaying the result as "healthy". This result indicates that the inputted skin image does not show any signs of skin cancer.

CONCLUSION

In conclusion, the development of an android app for skin cancer detection using machine learning and a trained MobileNet V2 model has shown promising results. The app has a user-friendly interface that allows users to easily input an image for analysis. The results of the analysis, whether benign, malignant, or healthy, are displayed clearly and accurately. The use of machine learning has greatly improved the speed and efficiency of skin cancer detection, making it possible to quickly and effectively diagnose the condition. The results of this study demonstrate the potential of using machine learning and mobile technology in medical field, and open up new possibilities for future research and development in this area.

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REFERENCES

[1] Jojoa Acosta M.F., Caballero Tovar L.Y., Garcia-Zapirain M.B., Percybrooks W.S. Melanoma Diagnosis Using Deep Learning Techniques on Dermatoscopic Images. BMC Med. Imaging; 2021.

[2] Sagar A., Dheeba J. Convolutional Neural Networks for Classifying Melanoma Images; 2020.

[3] Goyal M, Knackstedt T, Yan S, Hassanpour S. Artificial Intelligence-Based Image Classification for Diagnosis of Skin Cancer: Challenges and Opportunities. Comput Biol Med; 2020 .

[4] Manne R, Kantheti S, Kantheti S. Classification of Skin Cancer Using Deep Learning, Convolutionalneural Networks-Opportunities and Vulnerabilities-a Systematic Review. Int J Modern Trends Sci Technol; 2020.

[5] Manzo M, Pellino S. Bucket of Deep Transfer Learning Features and Classification Models for Melanoma Detection. J Imaging; 2020

[6] Qin Z, Liu Z, Zhu P, Xue Y. A Gan-Based Image Synthesis Method for Skin Lesion Classification. Comput Methods Programs Biomed; 2020

[7] Abdelhalim ISA, Mohamed MF, Mahdy YB. Data Augmentation for Skin Lesion Using Self-Attention Based Progressive Generative Adversarial Network. Expert Syst With Appl; 2021

[8] Huq A, Pervin MT. Analysis of Adversarial Attacks on Skin Cancer Recognition, in: International Conference on Data Science and Its Applications (ICoDSA), Manhattan, New York, U.S.:Institute of Electrical and Electronics Engineers (IEEE); 2020.

[9] Dosovitskiy A, Beyer L, Kolesnikov A, Weissenborn D, Zhai X, Unterthiner T, et al.
An Image is Worth 16x16 Words: Transformers for Image Recognition at Scale. ArXiv; 2020.

[10] Li H, Pan Y, Zhao J, Zhang L. Skin Disease Diagnosis With Deep Learning: A Review. Neurocomputing; 2021.

[11] Castiglioni I, Rundo L, Codari M, Di Leo G, Salvatore C, Interlenghi M, et al. Ai Applications to Medical Images: From Machine Learning to Deep Learning. Physica Med; 2021.

[12] Kuntz S, Krieghoff-Henning E, Kather JN, Jutzi T, Höhn J, Kiehl L, et al. Gastrointestinal Cancer Classification and Prognostication From Histology Using Deep Learning: Systematic Review. Eur J Cancer 2021.