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MELANOMA DETECTION USING MACHINE LEARNING

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Abstract--- **Melanoma and other skin malignancies are among the most serious medical problems of the twenty-first century due to their difficult and subjective human interpretation and extremely expensive and complex diagnosis. When it comes to lethal illnesses like melanoma, early detection is crucial for assessing the likelihood of recovery. We think the use of automated approaches will aid in early diagnosis, particularly when a batch of photos has a variety of diagnoses. Therefore, in contrast to traditional medical personnel-based detection, we describe in this report a fully automated approach for identifying dermatological diseases using images of lesions. Our model is developed in three stages, which include data gathering and augmentation, model construction, and prediction. Convolutional Neural Networks and Support Vector Machine are two AI algorithms that we combined with image processing technologies to create a better structure and achieve an accuracy of 90%.**

Index Terms **– Melanoma, Malignant, Convolutional Neural Network (CNN), Support Vector Machine (SVM).**

I. INTRODUCTION

Millions of individuals worldwide are affected by the deadly skin cancer illness melanoma, which has a high fatality rate. Dermatologists manually examine pigmented skin lesions and visually analyze them to identify melanoma at an early stage. However, due to varying accuracy and a dearth of dermatologists, manual examination for melanoma identification is constrained. Therefore, the creation of automated melanoma detection techniques that can precisely identify and categorize skin lesions is urgently required. The most dangerous kind of skin cancer, termed melanoma, arises in melanocytes, which are skin cells.

According to research, alone in the US, around 10,000 people every year pass away from melanoma skin cancer. The aberrant synthesis of skin particles, which later create body cells, is what gives rise to the melanoma skin lesion. These skin moles come in a variety of textures and hues, including brown, pink, red, and black, depending on the melanoma's risk factors. A thorough examination by a dermatologist is required if moles are larger than 6 mm and have an atypical color to determine whether melanoma may be contained. The two categories of melanoma lesions are benign and malignant. Due to the low contrast information between moles and skin, the massive color similarity between infected and uninfected skin portions, the presence of noise, hairs, and tiny blood vessels, variations in color, texture, illumination, contrast, blurring, and melanoma size, accurate localization, and classification of melanoma lesions can be difficult. We provide a powerful and practical melanoma detection technique to overcome the difficulties.

Speed is still a crucial component in the identification of skin cancer. It becomes worse with time, much like any other medical problem. In this study, a machine learning model for detecting malignant melanoma skin cancer was constructed utilizing integrated convolutional neural networks and support vector machines. 3300 photos of both malignant and benign skin cancer were obtained as part of an open-source dataset from the Kaggle website. A total of 80% of the dataset was utilized to train the models, while the remaining 20% was used to test the models. The models were run at Google Colab using TensorFlow, NumPy, and Keras.

Handcrafted characteristics and deep learning (DL) based methodologies can be used to classify existing automated melanoma detection methods. The handmade features employ the essential elements of extraction-based techniques for identifying skin moles. However, because of variations in the size, texture, and color of skin moles, these approaches are unable to detect skin lesions with any degree of accuracy. Following the professional dermatologist’s segmentation of the melanoma region from the healthy skin, classification is carried out to improve the accuracy of melanoma detection systems.

II. FLOW CHART OF PROPOSED SYSTEM

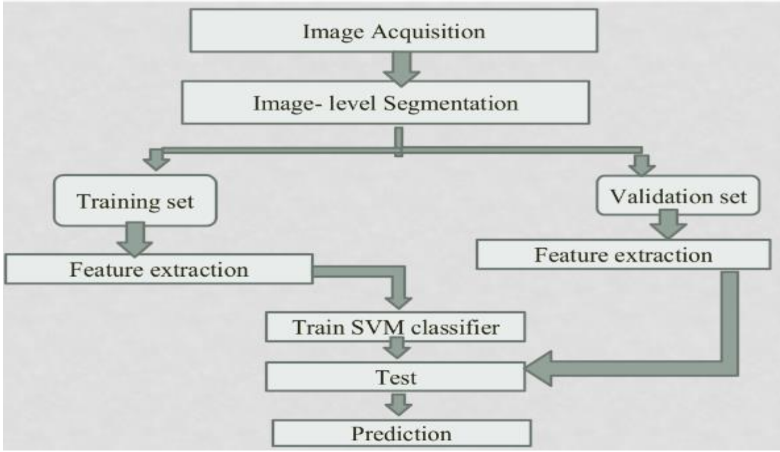

Fig. 2.1. Flowchart of Proposed System

The above flowchart fig. 2.1 describes the flow of steps that take place in detection of Melanoma. Initially, Images are acquised from any of the websites or sources of the datasets. Then, Image level segmentation is done i.e., image is segmented into different levels. From that dataset is then disturbed as 80% to Training set and 20% to Validation set. Features like dimensions, color, texture, illumination, contrast, blurring, and melanoma size, accurate localization are extracted from both sets. Features extracted from training set are sent to train SVM classifier. Now both are tested, and prediction is made.

DATASET:

The pictures are offered in the widely used medical imaging data format DICOM. Images are also available in TFRecord and JPEG formats (TFRecord has been resized to a consistent 1024x1024). The following Fig.2.2 shows the sample dataset of Benign and Malignant Melanoma.

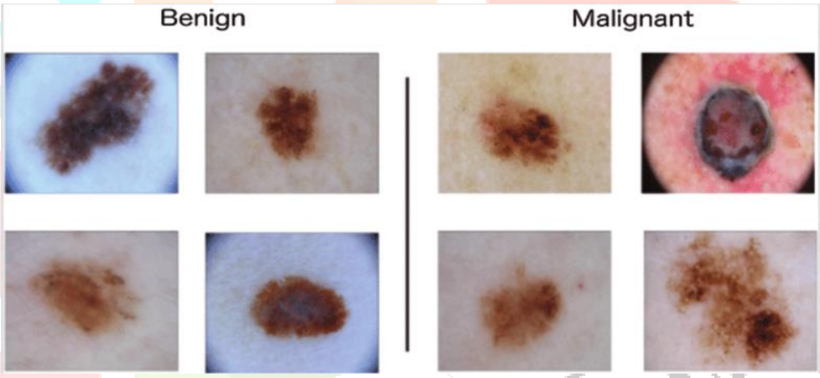

Fig. 2.2 Dataset

CONVOLUTIONAL NEURAL NETWORK:

Convolutional Neural Network is a Deep Learning approach that can take image as input, allocate various objects and elements quantity (learnable weights and biases), and also be able to distinguish among them. Relatively speaking, pre-processing time for a Convolution is significantly lower than other methodologies. With enough training, CNN can learn these qualities, but in more classical approaches, filters are created manually. Due to its connection to image processing, CNN is another well-liked classifier for spotting skin cancer. Research has consistently shown that CNN, an unsupervised classifier, is effective in detecting skin cancer. TensorFlow and the Keras libraries are utilized for CNN. CNN can analyze both stationary and moving objects. CNN has layers for input, convolve, pooling, normalizing, completely connected, and output. By removing features from an item, CNN operates.

SUPPORT VECTOR MACHINE:

Skin cancer may be found using the well-liked classifier SVM. The accuracy, high dimensionality, and datasets capabilities of the SVM, a supervised learning classifier, have been demonstrated in these studies to be useful. Additionally, they have shown that SVM may identify illnesses in their early stages. Even with non-linear data, SVM translates data to a feature so that points may be distinguished. SVM may be used for regression in addition to classification. Although it has been noted, SVM has trouble with extremely large amounts of data.

INTEGRATED CNN AND SVM:

CNNs are effective in learning the aspects of the images that are constant, however they may not always produce the best classification outcomes. Contrarily, SVMs produce effective decision interfaces by employing soft-margin techniques to maximize margins instead of learning complex invariances through their fixed activation functions. The suggested technique is aimed to study a hybrid framework in this situation where only CNN is capable of learning subjective qualities and is mostly insensitive to minor input alterations. In this situation, a non-linear kernel SVM can simply offer the best class label solution in the learnt feature space. The SVM exchanges the CNN's output layer, so the CNN's fully linked layer acts as the SVM's input. The following figure 2.3 shows the way of integration of CNN and SVM algorithms.

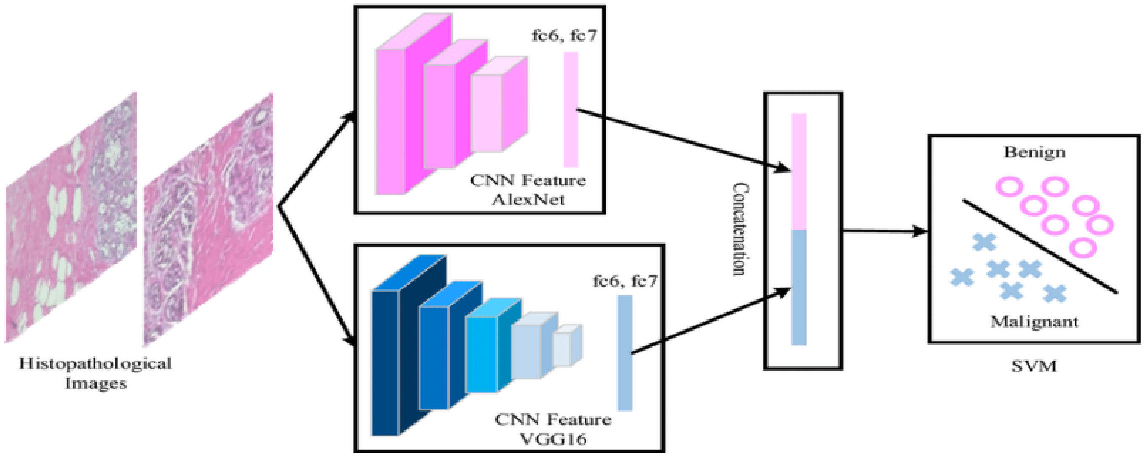

Fig. 2.3 Integration of CNN and SVM

TENSORFLOW:

Google created the open-source library TensorFlow specifically for deep learning applications. Traditional machine learning is also supported. TensorFlow was first created without having deep learning in mind in order to handle huge numerical computations. However, it turned out to be quite helpful for the development of deep learning as well, so Google made it open source. Tensors, which are multi-dimensional arrays with more dimensions, are the only type of data that TensorFlow takes. When processing a lot of data, multi-dimensional arrays come in quite helpful. Data flow graphs with nodes and edges serve as the foundation for TensorFlow's operation. It is considerably simpler to spread the execution of TensorFlow code using GPUs across a cluster of computers since the execution mechanism takes the form of graphs.

KERAS:

Google's Keras is a high-level deep learning API for creating neural networks. It is built in Python and is used to make neural network construction simple. It also allows for the calculation of various backend neural networks. Keras has been chosen as TensorFlow's official high-level API. Keras is integrated into TensorFlow and can be used to execute deep learning quickly since it has modules for all neural network calculations. Simultaneously, computations involving tensors, computation graphs, sessions, and so on may be customized using the TensorFlow Core API, giving you complete freedom and control over your application and allowing you to execute your ideas in a very short period.

III. RESULTS AND DISCUSSION

The selected image is:

Fig.3.1 Sample Dataset
The image is classified as BENIGN Melanoma.

The selected image is:

Fig. 3.2 Sample Dataset
The image is classified as MALIGNANT Melanoma.

Accuracy Comparison of CNN model:

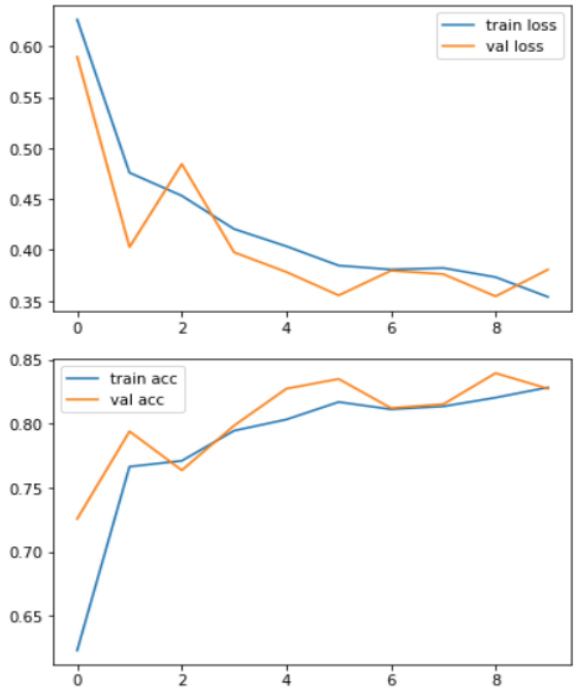

Fig. 3.3 Accuracy and loss comparison of CNN model.

By using only CNN model ,we got an accuracy 82%, and training and value accuracy is less as compared to fusion model of CNN and SVM. Comparison of the accuracy and loss is graphically represented in the fig. 3.3.

Accuracy comparison of Integrated CNN and SVM:

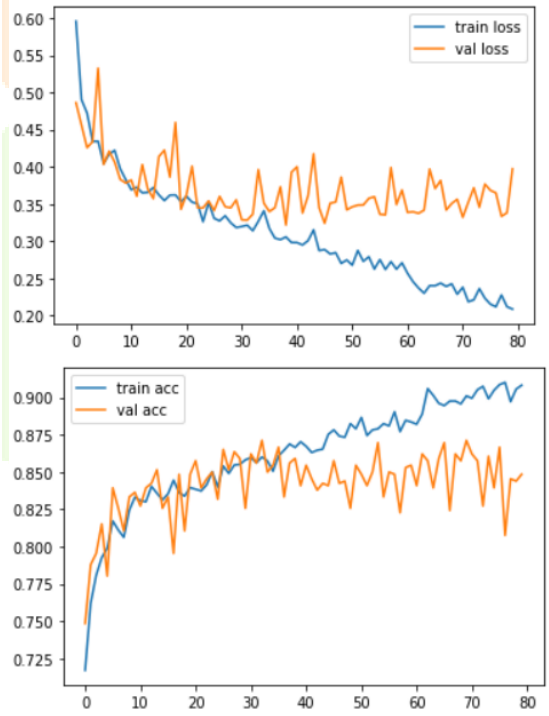

Fig. 3.4 Accuracy and loss comparison of integrated CNN and SVM model.

By using combined model of CNN and SVM we got an accuracy of 90%, as compared to CNN Model we got 10% more accuracy, and training and value accuracy are less as compared to CNN Model. The above figure 3.4 represents the accuracy and loss comparison of integrated CNN and SVM model.

IV. CONCLUSION

Remote sensing image analysis, measurement, and computing frequently demand an improved computation model that combines classifiers to approach a desirable result. By considering all of the benefits of the feature on different classifiers, it would be possible to combine them if multiple classifiers could be merged to get a superior result. As a result, we created a comprehensive picture categorization technique to find melanoma. The idea was to develop binary classification using a support vector machine and convolutional neural network and the two-stage classification method.

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