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Melanoma Skin Cancer Detection using Deep Learning

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***Abstract*— Among the deadliest diseases is skin cancer, particularly melanoma. There is a lot of overlap between various skin lesions like melanoma and moles in the color skin photos. The challenge of discovery and diagnosis is made more challenging by nevus. To prevent unnecessary effort, time, and human life loss, an accurate automated method for skin lesion classification is required. This study offers a technique for categorizing skin lesions automatically. our system relies on the predictions of algorithm called CNN (Convolutional Neural Network). CNN are mainly used for finding patterns in images to identify classes, and categories and it learns from the data. The source of dataset is International Skin Imaging Collaboration (ISIC) and we chose to work with total 2836 images, from this experiment we got the accuracy of 85 to 91%.**

***Index Terms*— CNN, Deep Learning, Skin Cancer Prediction, Melanoma, Malignant, Benign.**

I. INTRODUCTION

India witnesses more than a million cases of melanoma skin cancer per year. Though it is considered as less common in skin cancer, but it can be proved fatal if diagnosed late. Thus, it is necessary to do the full-body check-up regularly. In melanoma, there are two types i.e., malignant, and benign. Benign is considered as non-cancerous and it does not spread but malignant is considered very danger because it can grow rapidly and can spread to other body parts also. Thus, it becomes very necessary to diagnose the melanoma skin cancer early in stage. Until now, no one has been able to pinpoint the exact cause of melanoma, but there are several contributing factors, including parental inheritance and ultraviolet exposure. According to research, early detection of this malignancy may assist to lower the risk of developing more serious side effects.

In previous times, there was a method used for detection called Biopsy. In Biopsy, a piece of tissue or a sample of cells is removed from the patient's body. But it was a lot of painful method. There have been and are being made several attempts to design such system which can accurately detect whether the given image is of melanoma or not. Many researchers use methods of deep learning or machine learning. Machine learning is proved to be boon for this kind of experiments. Deep learning was chosen over machine learning because with deep learning investigation of various features or dimensions of being an image or even for a textual data and from that deep learning works better when you provide more amount of data. Whereas contrary to that in machine learning, after sometimes it reaches a threshold and after that no matter how much data you provide to a machine learning model, there won't be any increase in performance or accuracy of a model but for deep learning model more the data you provide it prevents overfitting and it also acquires more dimensions thus gives us more accuracy.

Convolutional neural network (CNN) is a development of artificial neural networks which exhibit notable

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performance even for broad and challenging tasks like object detection and picture categorization. Because of their superior and efficient efficiency, CNNs are widely applied in various medical imaging procedures, including lesion classification, tumour diagnosis, breast cancer, panoptic analysis, and MR images fusion. Using CNN-inspired approaches, the images are first segmented into the several tiny pixels, and afterward operators are applied to every pixels. As a result of the research, it has been discovered that using CNN models improves the diagnostic system's effectiveness.

The phenomenon of convolution neural networks is presented. The implementation of the CNN model is done using TensorFlow and data visualization. Libraries used are as follows: OS, NumPy, Matplotlib, Pandas and TensorFlow karas. Matplotlib library has been used for visualizing the dataset for better understanding of image. TensorFlow keras are used for efficiently loading dataset and it includes data augmentation. NumPy for transforming the image into a grayscale image. All these libraries are used for image classification.

The remaining paper is organized as follows. There is a literature review in part II. Methodology is explained in part III. the results are presented in part IV. Limits and future scope are covered in sections V and VI, respectively. Section VII brings the paper to an end.

II. Literature Review

It has been noted that improved outcomes and precision can be attained by training the SVM with further images, the accuracy received is 90% [1]. Before turning the skin image into BGR-Gray and BGR-HSV, the skin images are analysed so that a computer can comprehend and interpret binary codes. The results are helpful as they allow physicians to treat ailments as soon as they appear, halting further progression [2]. Using a multi-layered CNN approach with various regularisation approaches including dropout and batch normalisation, dermoscopic pictures are identified to predict skin cancer. As a result, the system's accuracy was 93.58%.

Different methods are used for different processes like segmentation is done using thresholding, ABCD and GLCM methods are used for selecting statistical features and PCA (Principal components analysis) is used for feature selection and then SVM is applied for classification. Gained accuracy was 92.1% [4]. Using hybrid feature extraction [5], skin lesions have been categorized as benign or malignant. Machine learning techniques are used to automatically detect skin lesions by applying the HOG, ABCD rule and GLCM for extraction of features and classification. To deal with the classification, various machine learning algorithms including SVM, KNN, and Nave Bayes were suggested.

It categorizes, the displayed image into a benign or malignant melanoma. Adding GLCM, shape, and colour features [6] to the SVM classifier gives high accuracy 83%. The three separate predictions used by the proposed system are as follows: two conventional machine learning classifiers, a convolutional neural network, and a set of characteristics that describe the colour, texture, and borders of a skin lesion were used to train these models. By employing majority vote, these techniques are then integrated to enhance their performances [7]. 53 of the 906 papers that were retrieved from the three databases qualified for this review. In 14 research, AI-based techniques were employed, and in 39 studies, deep AI-based techniques. [8]. The studies evaluated the suggested models using up to 11 assessment metrics, with accuracy serving as the main criterion in 39 investigations. Studies with smaller data sets generally showed greater accuracy. ph2 dataset is used to train the model. after data augmentation and fine-tuning, the transfer learning is used to classify skin lesions in three different categories i.e., atypical nevus, common nevus, and melanoma using AlexNet by replacing last layer with SoftMax [9]. By replacing the last layer with a SoftMax to categorize three various lesions, transfer learning is used to AlexNet to be fine-tuning and data augmentation (melanoma, common nevus, and atypical nevus). [10]. The model is based on an upgraded version of XceptionNet that made use of depth wise separable convolutions and fluid activation function. [11]. In this research, we looked at melanoma detection using deep learning based on cutaneous image processing [12]. Convolutional neural network (CNN) architectures such as MobileNetV2, VGG19, Xception, VGG16, ResNet50V2, ResNet152V2, DenseNet201 and GoogleNet were investigated for this purpose, and related deep learning models were assessed on GPUs (Graphics Processing Units).

to tell difference between malignant and benign lesion criteria including symmetry, colour, size, form, etc. are used [13]. Explores the data augmentation technique and strengthen the robustness of classification of CNN model [14]. For six-class classification [15], FRCNN had an accuracy of 86.2%, compared to 79.5% ($p = 0.0081$) and 75.1% (p 0.00001) for BCDs and TRNs, respectively. Using CNN, convolution neural network may identify and categorize the type of cancer based on previous data from clinical imaging [16].

III. MOTIVATION

Deep learning algorithms have shown promising results in various medical image analysis tasks, including skin cancer detection. These algorithms can be trained on large datasets of medical images, learn to identify patterns, and features of skin lesions, and accurately classify them as malignant or benign. Thus, using deep learning algorithms for melanoma detection can provide a more objective and accurate diagnosis, and potentially reduce the workload on dermatologists.

Moreover, the availability of smartphones and digital cameras has made it easier for individuals to capture images of their skin lesions and seek medical advice. A deep learning-based melanoma detection system could be integrated into mobile health apps and allow individuals to obtain a preliminary assessment of their skin lesions without visiting a dermatologist, potentially reducing healthcare costs, and improving access to care.

IV. PROBLEM DOMAIN

The proposed work is done in biomedical domain using deep learning approach. Deep learning algorithms have shown promising results in various medical image analysis tasks, including skin cancer detection.

V. PROBLEM DEFINITION

Early detection of melanoma is critical for successful treatment and improved patient outcomes. However, visual inspection by dermatologists can be subjective, and the accuracy of diagnosis can vary among healthcare professionals. Moreover, the incidence of melanoma is increasing, and dermatologists may face an overwhelming number of cases, making it challenging to provide timely and accurate diagnosis.

VI. STATEMENT

Melanoma skin cancer detection using deep learning involves the use of advanced machine learning techniques to accurately identify and classify melanoma lesions from skin images. Deep learning algorithms are particularly well-suited for this task because they can automatically extract complex features from images, enabling them to detect patterns and subtle differences that may be difficult for humans to discern. Deep learning-based approaches have shown promising results in melanoma detection.

VII. INNOVATIVE CONTENT

Innovative content in melanoma skin cancer detection using deep learning could involve the following:

Multi-modality data fusion: Deep learning models could be trained to integrate and analyse these different types of data to provide more accurate and personalized diagnoses.

A. Explainable AI

Explainable AI techniques aim to provide insight into how deep learning models make decisions. This could be particularly important in healthcare, where doctors and patients need to understand the reasoning behind a diagnosis. Explainable AI techniques could be used to visualize the features that the model is using to make its predictions, providing transparency and accountability.

B. Real-time detection

Real-time detection of melanoma lesions could be achieved using deep learning models that are integrated into smartphone apps or other portable devices.

VIII. PROBLEM FORMULATION.

The problem formulation or representation or design of melanoma skin cancer detection using deep learning typically involves the following steps:

A. Data collection and pre-processing

The first step is to collect a large dataset of skin images with corresponding labels indicating the presence or absence of melanoma. The images are pre-processed to standardize lighting, size, and orientation, and to remove any noise or artifacts that may affect the model's performance.

B. Model selection and architecture design

The next step is to select an appropriate deep learning model and design its architecture. Popular models used for image classification include convolutional neural networks (CNNs) and their variants, such as ResNet, VGG, and Inception. The architecture is designed based on the size and complexity of the dataset, and the desired performance metrics.

C. Training and validation

The model is trained using the pre-processed data and validated using a separate dataset to ensure that it generalizes well to new data. The training process involves optimizing the model's parameters using backpropagation and gradient descent algorithms. The validation process involves evaluating the model's performance metrics, such as accuracy, sensitivity, specificity, and area under the curve (AUC).

D. Hyperparameter tuning

The hyperparameters of the model, such as learning rate, batch size, and number of epochs, are tuned to optimize its performance. This is typically done using techniques such as grid search or random search.
Testing and deployment: The final step is to test the model on a separate dataset and deploy it for real-world use. The model's performance metrics are evaluated on the testing dataset, and any necessary adjustments are made. The model is then deployed for use in clinical settings, either as a standalone tool or integrated into existing medical systems.
Overall, the design of a melanoma skin cancer detection model using deep learning involves careful selection of data, model architecture, and performance metrics, and requires expertise in machine learning, image analysis, and medical diagnosis.

IX. SOLUTION METHODOLOGIES

A. Data Collection

The image dataset was collected from the International Skin Imaging Collaboration (ISIC), which has a collection of pictures of skin cancer caused by melanoma. The ISIC melanoma project was started to improve the effectiveness of melanoma early detection and decrease the rising number of deaths associated with the disease. In this ISIC collection, there are about 23,000 photos and taken from a dermoscopy instrument. Only 2836 skin lesion photos, including benign and malignant lesions, were used in the analysis. A training set of 2529 of these images and a testing set of the remaining images will be employed.

B. Convolutional Neural Network

As shown in Fig.1, a typical neural network consists of three different kinds of layers and processes:
Input layers: This is the layer where data is feed into the model. The entire number of characteristics in the data equals to the number of neurons present in this layer.
Hidden Layers: The inputs from the input layer are subsequently passed to the hidden layers. There could be a tone of hidden levels, model dependent and size of data. Each hidden layer can have a different number of neurons, but they are generally more than number of characteristics. The network is nonlinear because the output of each and every layer is determined by multiplication of the output of the layer underneath it by its learnable weights, adding learnable biases, and then computing the activation function.
Output layer: The data from the hidden layer is used as input for a logistic function, such as sigmoid or SoftMax, to convert the output of every class into the likelihood score for every class.

C. Pooling

One of the issues with fitting neural networks has always been a high number of parameters. A summary of convolution layer performance is possible. That task has been completed using pooling. Additionally, a group of pixels has been created using the sum of their pooling values. Additionally, the pooling vert by layer has been included during convolution. Any series of 2 to 2 blocks is referred to as the pooling window size. This makes sure that pooling only uses a maximum number of pixels from input chosen for each distinct layer in output throughout a range made up of two-to-two pixels. the number of parameters has been dramatically reduced in the model by Using the pooling operation.

D. Regularization

Regularization is a tactic for controlling the classifier's complexity. Using dropout in neural networks, which makes use of the Regularizers L1 and L2, data augmentation, batch normalization, and early halting, is one of the best ways to implement this method. An important issue with deep neural networks is overfitting. When merging the output of several independent big neural networks at the time of evaluation, overfitting is tough to handle since huge networks are frequently difficult to use.

E. Dropouts

Our suggested model also includes the dropout technique. For each learning step in this technique, a subset of units in a layer have been randomly selected to be ignored. Additionally, this unit group is disregarded during both the network's forward and subsequent backward propagation states. The system has been configured with a dropout of 0.3 and then it was again used at 0.2.

F. Implementation

The entire image, measuring 224 X 224 pixels, is taken as the input for the proposed CNN model; however, before training the model pre-processing is required. Fig.2 shows the model architecture of proposed of system. There are 16 layers in the CNN model. The feature maps are down sampled using four spatial max pooling layers, followed by four convolution layers with activation function names ReLU of filter size: 3*3. Learning a feature representation of the input intensity patch is what the convolution layers are trying to do. This representation is often built using a convolution operation and an activation function, which are both linear and nonlinear operations.

More training data is the greatest way to reduce overfitting, but since there aren't enough labelled training data for medical imaging, this isn't an option. Regularization with dropout, a more contemporary regularization method, is one of the alternative alternatives. Thus, two dropout layers were added to the CNN model. After the features have been retrieved by convolution layers and downscaled by pooling layers, SoftMax function fully maps it. The likelihood that a lesion will be benign or malignant is the network's final output.

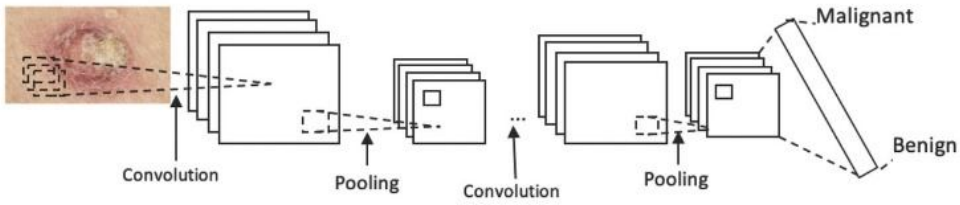

Figure 1. Flow diagram of CNN [16]

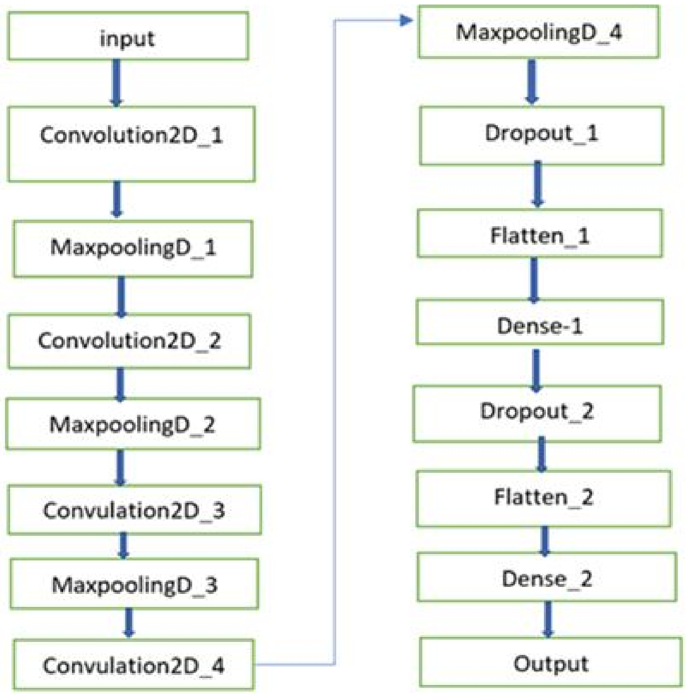

Figure 2. Proposed Model Architecture

X. RESULTS

The main objective of research is to develop multiple deep learning architectures for the categorization of melanoma skin cancer and assess how well they worked in real-world scenarios. A CNN model was customized for the binary classification of melanoma skin cancer and other deep learning architectures. The CNN was trained using 2836 224 × 224-pixel pictures. As the graph represented in Fig.3 the CNN achieved an accuracy of 85–91% and loss of around 35-10% after 15 epochs of training. Performance of different train to test ratios are stated in Table I.
Aim was to build technology tools for day-to-day use and to help dermatologists diagnose skin cancer effectively using the findings of this study. Additionally, the CNN becomes more accurate at differentiating features the more melanoma photos of various sorts it is exposed to. Research on this subject could be worthwhile in the future. Instead of relying on past research, a detailed experimental investigation using a range of deep learning architectures was conducted to compare performance behaviour and identify the best and optimized deep learning model for the melanoma skin cancer classification using dermatological images.
Fig. 4 consists of the screenshots of predictions of a given images to the system. Fig 4. (a) show that the system has predicted given image as the benign one whereas in Fig 4. (b) system predicted it as malignant one.

Figure. 3. Training and Validation Accuracy and Loss

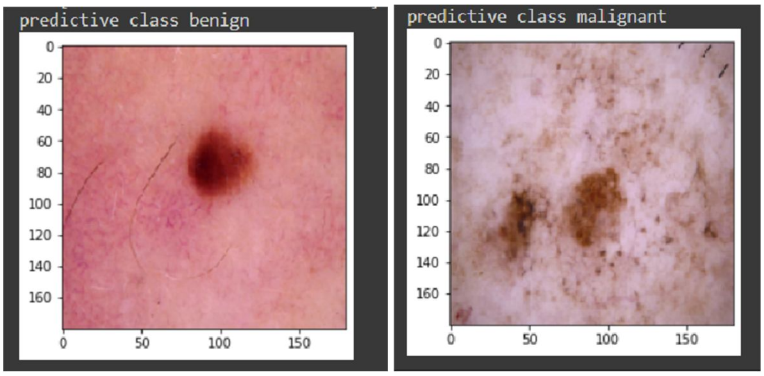

Figure 4. (a) Benign

Figure 4. (b) Malignant

Figure 4. Prediction of image

TABLE I. TEST-TRAIN RATIO AND ACCURACY

Train: Test	Accuracy
60: 40	60-75%
70: 30	77-82%
80: 20	80-87%
90: 10	85-91%

TABLE II. COMPARISON BETWEEN EXISTED PROPOSED METHOD

Existing Study	Algorithm	Accuracy
[6]	SVM	83%
[7]	KNN	57.3%
[7]	CNN	85.5%
[12]	GoogleNet	74.94 - 76.08%
[12]	DenseNet	73.96 - 74.68%
[12]	ResNet50V2	73.42 – 74.68%
	Proposed Model	85-91%

XI. COMPARISON OF RESULTS

Algorithms and accuracy of the existing studies and proposed are compared in Table II.

XII. CONCLUSION

One of the prevalent forms of skin cancer among all others is Melanoma skin cancer. This type of cancer can be completely treated if it is discovered early. However, it won't be able to treat it if it gets aggressive and spreads to other bodily parts. Therefore, early melanoma discovery can improve a person's prognosis and reduce the risk of spreading the disease to others. This study suggested a novel convolutional neural network design to deliver a reliable melanoma detection diagnosis method. The ISIC skin cancer dataset was then used to apply the suggested CNN approach. Results indicated that the suggested methodology has an accuracy range of 85-91%.

FUTURE WORK

Currently, deep learning algorithms for melanoma detection are typically used to analyze static images of skin lesions. However, there is potential to develop real-time detection systems that could be used in clinical settings to rapidly identify suspicious lesions during routine skin exams.

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