SKIN CANCER DETECTION USING DEEP LEARNING(CNN)

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***Abstract*- One of the most prevalent types of cancer in the world is skin cancer, and improving patient outcomes and ensuring a successful course of treatment depend on early identification. Historically, skin lesion diagnosis has been carried out by dermatologists by visual examination, which is prone to subjectivity and individual differences in precision. Here, we suggested that Convolutional Neural Networks (CNNs) and the Deep Learning approach may be used to create a reliable skin cancer detection system. CNN belongs to a group of Deep Learning models that are renowned for their remarkable abilities in image identification. Our system, which eliminates the need for expert personal inspection of dermoscopy pictures by using CNN with many layers, ReLU activation function, and Adam optimizer approach, may identify skin lesions.** **Keywords— *D*eep learning, Ham10000, *S*kin lesion.**

I. INTRODUCTION

Skin cancer, especially melanoma, is a disorder that needs to be handled seriously due to its high death rate. The cancer known as melanoma begins in the melanocytes and spreads swiftly if it is not detected in time. It often arises on skin that has been exposed to the sun, including the hands and face. A good prognosis for treatment outcome is significantly enhanced by an early diagnosis. However, other than melanoma, skin tumors are typically less lethal and easier to treat. Prevention is essential, and that means using sunscreen and getting regular skin exams. Early detection of melanoma, attained by close observation of skin abnormalities, is essential for managing the disease's progression [1]. The most dangerous kind of cancer starts in melanocytes and can spread to other areas of the body if it is not discovered quickly. The prevention of skin cancer depends heavily on early identification and protection. Dermatologists face difficulties in diagnosing skin cancer since different colours might have similar appearances. Using the HAM10000 dataset, a deep learning method for multi-class skin cancer classification is proposed in this study. The presented approach improves categorization by utilizing convolutional neural networks.
improves the diagnostic results for skin lesion classification by increasing accuracy and decreasing loss. In order to solve these issues and expedite early identification, computer image analysis techniques have been the focus of extensive research. The challenges of skin cancer detection methods are examined in this study, which highlights the limitations of parametric methods in comparison to the adaptability of non-parametric ones. With 96% accuracy, dermatologists can identify skin cancer with this deep learning-based technique [3]. It tackles issues with timeliness, accuracy, and the scarcity of dermatologists in public health systems by streamlining the model. All of the current diagnostic methods are costly and only available in large cities, yet they all yield good detection findings. Therefore, it is imperative that diseases be diagnosed and treated for the benefit of people worldwide at the lowest possible cost. Deep learning algorithms are widely applied since skin cancer may be automatically detected from dermoscopic images. This makes it possible to detect and treat skin cancer early. All of the current diagnostic methods are costly and only available in large cities, yet they all yield good detection findings.
Thus, the need for a diagnosis and course of treatment is imperative of the illness to patients worldwide at the lowest possible cost. Deep learning algorithms are frequently applied as skin cancer may be automatically detected from dermoscopic images. This makes it possible to detect and treat skin cancer early[2].

II. LITERATURE REVIEW

Senthil Murugan KR[1] utilized Convolutional Neural Networks (CNNs), incorporating transfer learning and strategic dropout integration techniques, to classify skin cancer using the ISIC dataset. Their model achieved an impressive accuracy rate of 90%.

Wenting Li [2] Used ensemble deep learning models, CNN and SVM, for the early detection of skin cancer using The HAM10000 dataset. The CNN ensemble model performed better than the SVM ensemble model in terms of accuracy, specificity, sensitivity, training time, and combined file size. The CNN ensemble model showed a sensitivity of 0.712 and a specificity of 0.958, while the SVM ensemble model had a sensitivity of 0.166 and a specificity of 0.880

Nour Abuared[3] used the model VGG19, which is a deep Convolutional Neural Network (CNN) consisting of convolutional layers and max pooling layers for feature extraction. The accuracy of the skin cancer classification model based on VGG19 and Transfer Learning was measured to be 0.975, indicating a high level of accuracy in classifying skin cancer types.

KenzA.Bozed[4] Used the Models Alex Net, InceptionV3, RegNetY-320 and dataset Used is HAM10000.RegNetY-320 achieved an F1 Score of 87% and a Top-1 Accuracy of 87.91%. The study focused on skin cancer classification and achieved impressive accuracy rates with the RegNetY-320 model on the HAM10000 dataset.

Nanda Kiran [5] Velaga Used HAM10000 dataset and models used are Models Used: K-Nearest Neighbors, Decision Tree, Random Forest, Ridge Classifier, Support Vector Machine. Random Forest algorithm performed the best with the highest accuracy of 95.6% on the test set and 95.5% on the validation set.

Vineeth J [6] Used dataset International Skin Imaging Consortium (ISIC). The model achieved an accuracy of 90%Results: The study utilized a Convolutional Neural Network (CNN) for early detection of skin cancer, with the best results obtained using a combination of ReLu, Sigmoid, and SoftMax activation functions in the hidden layers.

Nanthini N[7] used Convolutional Neural Network (CNN) model. The dataset used consists of nearly 300 images of dermatoscopic images for melanoma skin cancer.The proposed model achieved an accuracy of 95.24%.The proposed model showed improved accuracy compared to existing models, with a computational speed of 15 seconds and a loss of 16.33%. The system accurately predicted whether the input image showed symptoms of skin cancer or not.

Djaroudib Khamsa [8] used a dataset from Kaggle with a total of 3297 dermatoscopic images, with 2637 images used for training and 660 images used for testing. The evaluation accuracy of the model was more than 83%. The results showed a high precision and recall for both benign and malignant skin cancer diagnosis, with an overall accuracy of 83.3%. The model successfully detected and diagnosed skin lesions, with most images classified correctly during testing.

Sweta Jain [9] used dataset ISIC2018 dataset and got Accuracy 96%. The deep learning model developed by Sweta Jain achieved an impressive accuracy of 96% in accurately identifying skin cancer from dermatoscopic images. The model showed exceptional performance in categorizing skin lesions into benign and malignant categories.

Haseeb Younis [13] used CNN & MobileNet CNN approach on HAM 1000 dataset to provide a productive method for utilizing DL to categorize skin cancer and obtain an accuracy of 97.07%.

Guergueb[14] used CNN,ResNet50, and Inception approaches on the ISIC 2017,2018,2019&2020 datasets to assess and compare several DL algorithms for a 90.33% accuracy rate in melanoma skin cancer diagnosis.

Lin Li [15] used R-CNN approach on ISIC 2018 dataset to propose an approach that utilizes transfer learning and DL techniques to train a Mask R-CNN model for lesion segmentation and lesion classification in dermoscopic images and got accuracy of 94%

Muhammad Aqib [16] used DCNN & SEG-Net approach on ISIC 2016 & 2017 datasets to propose a computerized melanoma detection framework using deep learning algorithms with an accuracy of 90%.

Nour Aburaed [17] used DCNN & MobileNet approach on ISIC2017 & HAM10000 dataset to demonstrate a skin cancer classification strategy using the HAM10000 dataset and obtain an accuracy of 94% for the DCNN.

III. PROPOSED METHOD

A. Convolution Neural Network

CNNs are exceptionally productive in picture recognizable proof since they can actually work on highlight advancing by catching spatial orders through pooling layers, boundary sharing, and neighborhood associations[1]. Its various leveled design works on translational invariance and decreases weakness to changes in object positions inside pictures by advancing dynamically confounded properties. Pre-prepared CNN models like InceptionResNetV2, InceptionV3, MobileNetV2, and EfficientNetB0 give learnt picture includes that assist the model with distinguishing designs in pictures and apply the information to new assignments[2]. By consolidating these determined qualities, powerful element extraction is guaranteed without requiring a total CNN preparing without any preparation. This is accomplished by using important various leveled highlights from ImageNet pretraining, which thus further develops learning effectiveness on more modest datasets and generally speaking model execution[3].

Since CNNs are so great at removing significant elements from pictures includes that are basic for injury grouping[4]. They are an important apparatus for applications including skin sores. Their ability to keep up with spatial connections makes it more straightforward to recognize inconspicuous examples inside sores, which is fundamental for an exact conclusion[5]. Despite changes in sore arrangements, hearty acknowledgment is made conceivable by CNNs' interpretation invariance. By using gained portrayals from huge datasets, move learning with pre-prepared models further develops execution[6]. Their capacity to precisely order pictures ensures the qualification of various sorts of injuries, which works with clinical analysis[7].

CNNs were liked over standard profound brain networks for picture recognizable proof due to their remarkable engineering for visual information. Their ability to hold spatial connections inside picture while removing complex attributes is one of their benefits[8]. CNNs are fantastic at seeing neighborhood designs in pictures and recognizing items or elements inside them. Better portrayal learning is made conceivable by their engineering, which really upgrades complex example acknowledgment[9]. The particular engineering of CNNs for picture distinguishing proof applications at last delivers them more powerful than conventional profound brain organizations.

Adjusting existing CNN structures regularly includes modifying layers, channels, or associations with work on their presentation on unambiguous errands[10]. For this situation, pre-prepared models like InceptionResNetV2, InceptionV3, MobileNetV2, and EfficientNetB0 were used without primary changes. All things considered, the attention was on include extraction, pooling, connection, and adding new layers to saddle the learned portrayals of these models for further developed characterization exactness[11]. These changes mean to use the qualities of the pre-prepared models for a consolidated methodology instead of modifying their unique designs.

B. ENSEMBLE

In profound picking up, 'ensembling' is the most common way of consolidating expectations from a few separate models, some of the time alluded to as "base models" or "powerless students." By utilizing different models to handle issues all in all, these gathering approaches look to improve generally learning results[12]. Rather than focusing just on the exhibition of individual models, the key is to involve the strength of various models for further developed speculation across a scope of conditions. Since outfits might cooperate to take care of additional troublesome issues, they are a favored technique in AI for managing different issues[13].

- Connection is utilized to incorporate four models: InceptionResNetV2, InceptionV3, MobileNetV2, and EfficientNetB0. Link Gathering: Connection is the most broadly involved strategy for consolidating different information sources. Various information sources, no matter what their aspects, are taken care of into a link group, which connects them along a foreordained pivot. Joining information next to each other may have the disservice of a blast in dimensionality. More prominent thickness dimensionalities or more organizations in the group convert into bigger link yields. This cycle might be dispersive, forestalling the last part of the organization from learning significant data or prompting overfitting.
- InceptionResNetV2: A convolutional brain organization (CNN) design called Beginning ResNet-v2 was made by Google computer-based intelligence specialists. It consolidates remaining associations with the Beginning organization engineering. Rich element portrayals can be gained from pictures utilizing the Commencement design, and lingering associations diminish the chance of the evaporating angle issue in profound organizations.
- Coming up next are a few benefits of utilizing InceptionResNetv2: This cutting-edge CNN architecture has demonstrated exceptional performance across a range of image classification tasks.
- It is reasonably effective to deploy and train.
- It can be found in many deep learning frameworks, including PyTorch and TensorFlow.

InceptionV3: Google simulated intelligence specialists made the convolutional brain network engineering known as Inceptionv3. At the point when it was first delivered in 2015, the Commencement and Inceptionv2 designs were supplanted by this one, which created cutting edge results on the ImageNet arrangement task.

With in excess of 40 layers, Inceptionv3 is an extremely complicated network. It utilizes a few unmistakable building components, like completely associated layers, pooling layers, and convolutions[14]. The use of factorized convolutions is one of Inceptionv3's significant developments. These are convolutions that have been partitioned into more modest convolutions, which might support raising the organization's proficiency.

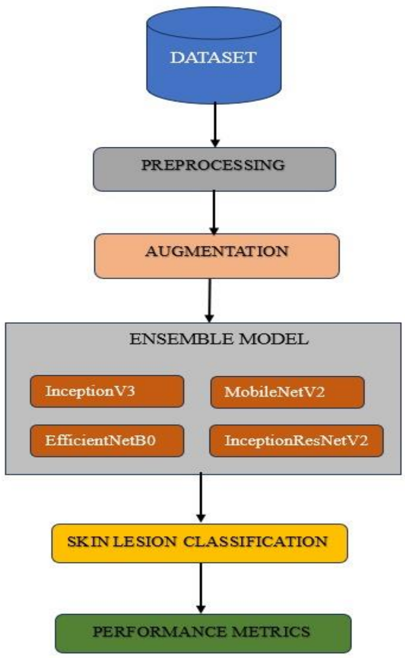
MobileNetV2: A convolutional brain network engineering called MobileNetV2 is made to be powerful and exact on cell phones. Its base is the Upset Leftover design, which utilizes lightweight profundity wise convolutions to channel highlights as a wellspring of non-linearity.

In contrast with prior MobileNet structures, MobileNetV2 is recognizably quicker and more proficient while keeping up with the exhibition of picture grouping undertakings[15]. Various cell phones, like tablets, wearables, and cell phones, have exhibited its proficiency.

There are a few purposes for MobileNetV2, for example, grouping of pictures, distinguishing objects, Division of pictures and Move learning[16].

EfficientNetB0: Google man-made intelligence scientists made the convolutional brain organization (CNN) design known as EfficientNet-B0. It has a place with the group of models called Efficient Net, which is made to be exact and productive on a scope of equipment stages, including portable ones.

EfficientNet-B0 is a 5.3 million boundary model, which makes it a moderately little model. Then again, it exhibited on a few picture characterization undertakings alongside ImageNet. A few methodologies are utilized by EfficientNet-B0 to increment the two its exactness and proficiency[17].



IV. RESULTS& DISCUSSIONS

A. Dataset

The "HAM" in HAM10000 stands for "Human Against Machine," signifying the dataset's purpose in training algorithms to distinguish and diagnose skin-lesions. The dataset typically includes images of skin lesions along with associated metadata and labels stating the type of skin condition.

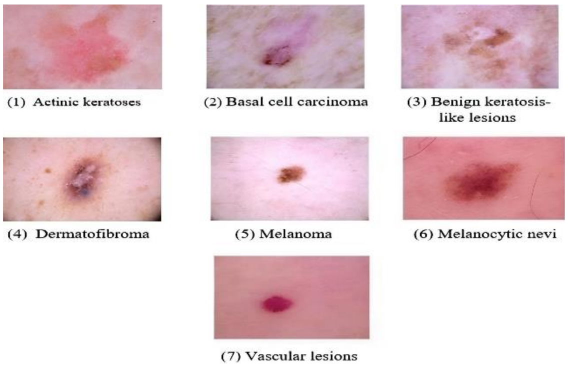


Fig 1 : Selection of sample images from the HAM 10000 Dataset.

Dataset was severely unbalanced because certain classes had a disproportionately larger no of images than other classes. Images in the dataset are listed in Table 1.

Table 1 Number of images per class

Classes	Total Images
Melanocytic Nevus (NV)	6705
Melanocytic Melanoma (MEL)	1113
Benign Keratosis (BKL)	1099
Basal Cell Carcinoma (BCC)	514
Actinic Keratosis (AKIEC)	327
Vascular Lesion (VASC)	142
Dermatofibroma (DF)	115
Combined	10015

Lopsided datasets may cause issues when a profound learning model is prepared. Forecasts made utilizing unequal datasets might be twisted and one-sided [18]. Getting exactly adjusted information for each class in a dataset in certifiable circumstances is testing [19]. Subsequently, information increase has been utilized to resolve this issue. By making new manufactured information from the ongoing information or by rolling out little improvements to the preparation information that are now accessible, expanding how much data is used. Extending the example size for unequal classes.

Fig 2. Examples of Data Augmentation techniques

B. PRE-PROCESSING

Eliminating Commotion Information: This step is utilized to eliminate clamor tests in the dataset to guarantee more exact outcomes for tracking down precision and to stay away from undesirable outcomes.

Information parting: The dataset is used to make preparing and approval sets. The preparation set was utilized to prepare the model, approval set was utilized to assess its presentation, and to change the hyperparameters.

Eliminating Hair Tests: This step was utilized to eliminate hair tests joined inside the dataset. The examples were eliminated to keep away from pointless outcomes.

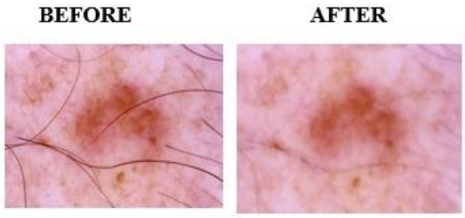


Fig 3. Example of Hair Removal

C. AUGMENTATION

Information expansion is a helpful method for expanding the quantity of preparing pictures, since it changes the first pictures without gathering more data. Accordingly, decreasing the effect of lopsided information is valuable. The boundaries for information increase comprise of picture handling methods utilized with different changes. Utilizing these qualities, the dataset was kept adjusted, and copy pictures were forestalled.

The dataset was adjusted following the Information Increase technique. The way that every one of the seven classes in the dataset had a similar size demonstrated that the dataset was adjusted. In this way, the model would work better on the off chance that tests were directed utilizing a decent dataset. Information increase can assist DL technique’s with executing better, especially when there is less train information or when the model is having overfitting.

The ideal information increase boundaries, for example, zoom range, rescale, horizontal flip, and vertical flip, were found by the utilization of Bayesian advancement.

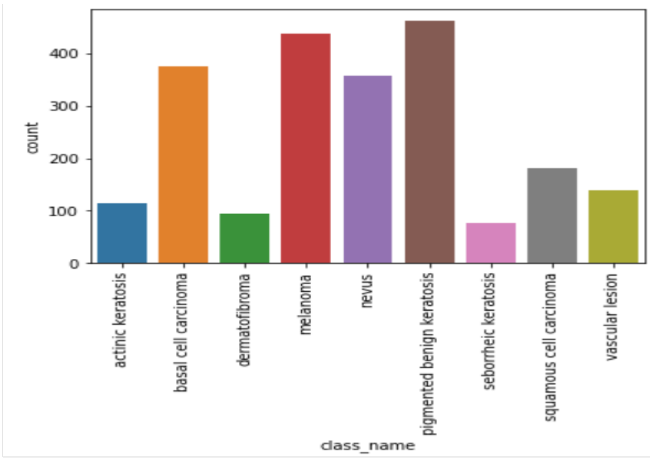


Fig 4. Distribution in classes before augmentation

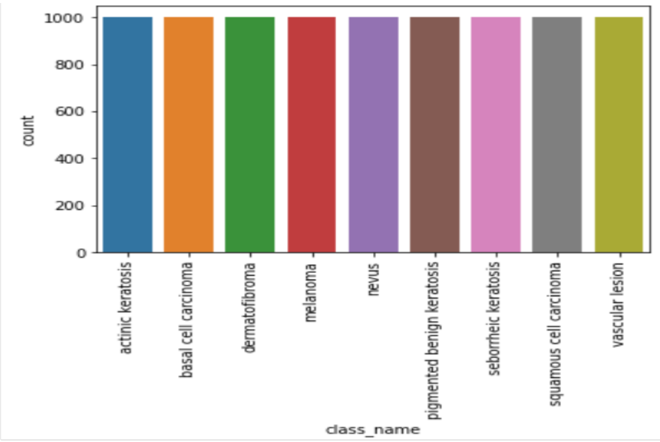


Fig 5. Distribution in classes after augmentation

By running the combined model, we got the below plots and the execution for each epoch is on average of 1214sec.

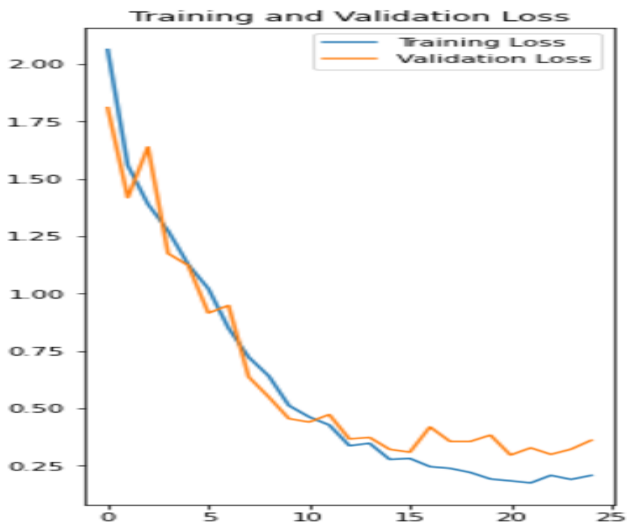


Fig-7

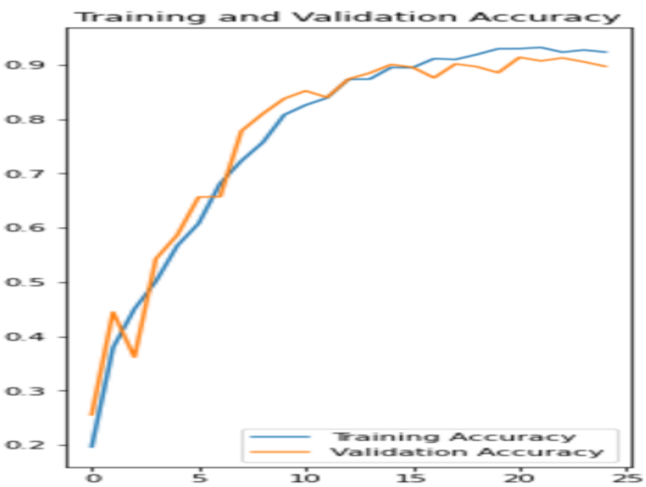


Fig 8

Fig 7 & Fig 8 display plots for Loss and Accuracy for Test and Train data of Combined Model.

Below are the metrics used for evaluation of the proposed model

a. Precision: It is the percentage of accurately anticipated positive cases among all positively predicted cases.

$$P = \frac{TP}{TP + FP}$$

b. Recall: This represents the percentage of true positive cases among all correctly predicted positive cases.

$$R = \frac{TP}{TP + FN}$$

c. Accuracy: This indicates the percentage of cases where the forecast was accurate.

$$A = \frac{TP + TN}{TP + TN + FP + FN}$$

d. F1 Score: It's calculated as the harmonic mean of precision and recall.

$$F1 = \frac{2PR}{P + R}$$

TP, TN, FP, and FN stand for True Positive, True Negative, False Positive, and False Negative, respectively. P and R stand for precision and recall.

Table 2. Comparison of Combined model with existing models

Model	Accuracy	F1_score	Precision	Recall
COMBINED MODEL	81.3%	81.31%	82.57%	80.1%
EfficientNetB0	79.58%	79.54%	78.69%	79.48%
ResNet101	79.41%	78.31%	78.39%	78.35%
ResNet50	75.21%	75.45%	74.32%	74.46%
VGG16	69.77%	68.56%	68.55%	68.31%

V. CONCLUSION

Our strategy considers the quick and precise conclusion of seven distinct types of malignant growth utilizing pictures of skin lesions. To decrease commotion in the sore picture, the proposed approach utilizes picture improving methods. InceptionV3, InceptionResNetv2, MobilenetV2, and EfficientNetB0 were completely prepared on the upper edge of the pre-handled sore pictures to forestall overfitting and improve the general exhibition of the suggested DL techniques. The HAM10000 dataset, which is a progression of injury pictures, was used to evaluate the exhibition of the proposed framework Thusly, our model accomplished a general exactness pace of 81.3 percent. It is feasible to outperform the accomplished 81% arrangement precision in resulting research by doing gray scaling and so forth, to work on the model's capacity to sum up, our endeavor is to expand the dataset by get-together more data.

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