

Epidermal Neoplasm Detection Using Convolutional Neural Networks

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Abstract— Skin cancer is the dangerous medical condition which is observed by the abnormal growth of skin cells. It is majorly caused due to ultraviolet radiations. Detecting it in the early stage may reduce its severity. This research delves into a comprehensive analysis of skin cancer prediction, employing three distinct deep learning models: ResNet50, Inceptionv3 and VGG16. Utilizing a diverse dataset comprising dermoscopic images, the study rigorously evaluates and compares the performance of these models across various metrics such as accuracy, sensitivity, and specificity. Also we have created an user interface to test the skin cancer images. After a great deal of testing, ResNet50 is the best option for detecting skin-cancer since it can identify a wide range of skin tumors with greater accuracy. The research incorporates advanced data augmentation techniques to bolster model resilience and generalization, ensuring robust performance in real-world scenarios. This highlights its potential significance in clinical applications, highlighting how deep machine learning is essential to improving medicinal image processing and improving the results for patients.

Keywords— *ResNet50, Inceptionv3, VGG16, Dermoscopic Images, Comparative Analysis.*

I. INTRODUCTION

The surging global incidence of skin cancer, a pervasive and potentially fatal affliction, has intensified the demand for innovative diagnostic strategies. Groundbreaking initiatives have prepared the way for the identification of skin cancer that is melanoma, leveraging a synthesis of image processing and machine learning methodologies [1]. The study of lesions of the skin categorization using ensembles of deep convolutional neural networks opened up fresh possibilities for progress and marked a significant turning point in the field of artificial intelligence [2].

An important next step in the identification of skin tumors is to compare algorithms based on deep-learning and machine-learning [3]. An innovative approach integrating individual advantage and group decision ensembles to amplify classification accuracy marked a significant stride towards preventive diagnostic measures [4]. The significance of feature variety in automated skin tumor diagnosis was highlighted by research conducted on skin cancer identification using integrated decision making driven by

deeper drivers [7]. Integration of convolutional neural networks with texture features highlighted the importance of feature diversity in automating skin cancer detection [8].

A revisit to ensemble learning underscored its persistent efficacy in skin lesion classification, contributing to the discourse on ensemble learning in dermatological diagnostics [13]. An important turning point in the merging of dermatologists and technology was the investigation of applications for computers in the detection and prediction of cancer of the skin [16]. Many researches have been made in this skin cancer detection. Mostly they have predicted melanoma since it is very common type of skin cancer. They have used many machine learning and deep learning models like SVM, Mobilenet, inception, sequential models, vgg19, Resnet and so on. Other types of skin cancers were also predicted such as benign, melanoma, basal cell carcinoma etc.

In our research we have taken three models such as ResNet50, Inceptionv3 and VGG16. These 3 models are compared to know which model is giving the best accuracy for skin cancer detection. We trained these models on HAM10000 dataset which contains 10015 dermoscopic images. The dataset is preprocessed in a wide range before giving it to the model. Each model is trained with the dataset one by one and we have taken the observations from the accuracy and loss given by the models. From the observations drawn we have concluded that Resnet50 gives the highest accuracy compared to other 2. We have created a user interface which takes skin image as input and predicts the class.

In this research first section consists of brief description on skin cancer and the models we used. Later it is followed by the significance of skin cancer detection and the introduction of CNN importance in this research with a small note of previous works done by the dermatologists and researchers on this research. Next section consists of the related work done on this research. Next followed by methodology and continues with the experimental setup. In the last section we have given the results with the comparison between 3 models followed by future scope and conclusion.

II. LITERATURE SURVEY

Skin tumors, especially a form of is a major worldwide medical problem that requires sophisticated detection techniques. Significant progress in the identification of skin tumors has been sparked by current developments in computational biology and artificial intelligence. The groundwork for further research was laid by Vijayalakshmi [1], who led investigations into identifying melanoma using computational imaging and artificial intelligence. Dermal lesion categorization underwent an evolution with the introduction of deep learning, namely convolutional artificial neural networks (CNNs).

Harangi [2] introduced ensemble methods with deep CNNs for skin lesion classification, enhancing diagnostic accuracy. Gong et al. [4] explored the classification of dermoscopy images using CNNs, emphasizing the effectiveness of ensemble strategies.

Efficient Nets gained prominence in multiclass skin cancer classification, as demonstrated by Ali et al. [5]. Pacheco and Krohling [6] proposed, combined for improved classification. Imran et al. [7] highlighted the significance of combined decision-making by deep learners in skin cancer detection.

Alizadeh and Mahloojifar [8] integrated CNNs with texture features for automatic skin cancer detection, showcasing the synergy of different methodologies. Han et al. [9] focused on keratinocytic skin cancer detection, leveraging region-based CNNs for enhanced accuracy. Tschandler et al. [10] achieved expert-level diagnosis using combined CNNs, underscoring the potential for leveraging deep learning in clinical settings.

A systematic review by Haggemüller et al. [11] emphasized the growing body of literature on skin cancer classification via CNNs. Albahar [12] introduced a novel regularizer in CNNs for improved skin lesion classification.

In addition to algorithmic advancements, several studies explored the integration of clinical knowledge into the diagnostic process. The ABCDE rule, proposed by Nachbar et al. [15], provided a valuable framework for dermoscopic analysis. Faziloglu et al. [14] contributed to melanoma discrimination using color histogram analysis, showcasing the interdisciplinary nature of skin cancer research.

The latest findings, as revealed by the studies by Esteva et al. [17], showed that deep brain networks could classify skin cancer at the physician level, underscoring the transformative potential of artificial intelligence in clinical practice. Shanthi et al. [18] furthered this progress by proposing an automatic diagnosis system based on AI.

In summary, the integration of deep neural networks, artificial intelligence, and computer vision has ushered in an entirely novel phase in skin tumor diagnosis. The cited works collectively contribute to a robust foundation for future research, emphasizing the interdisciplinary collaboration between medical professionals and technologists.

III. METHODOLOGY

A. Components

The initiative to classify skin tumors uses a structure known as a neural network based on convolution (The CNN network), specifically utilizing ResNet50 as the backbone for

feature extraction. The architecture can be summarized as follows:

Initially dataset is imbalanced and contains noise, hence data preprocessing is done before giving it to the model. First we have 10015 images after oversampling we got 46935 images, this will help in increasing the accuracy. Then we have replaced null values with standard deviation and removed the noise in the data.

After data is splitted into training (80%) and testing (20%). Next we have reshaped the image to 128 x 128 pixels. The input layer processes dermoscopic images resized to 128x128 pixels. These images serve as the raw input for the subsequent layers.

The ResNet50 architecture is utilized for its ability to capture complex hierarchical features. It is composed of many remaining blocks with disconnects, rectified linear unit (ReLU) activations, batch normalization, and layers of convolution in every.

Global Average Pooling(GAP) Layer a World means pooling level is implemented after the layers of convolution to offer an efficient representation of learned information and to minimize physical dimensions. whatever the dimensions of the input data, Gaps calculates the mean of every feature map to produce a fixed-size vector.

In Fully Connected layer the result of the Gaps level is linked to the final forecasting level by the use of an entirely linked layer. Understanding intricate correlations between the collected characteristics is made easier by this component.

Softmax Activation is a function where the result of the completely linked layer is subjected to a soft max activated function, producing a probability distribution across the predefined skin cancer classes. This enables the model to assign probabilities to each class and make a final prediction.

The following training strategies are used in which the model is trained using the Adam optimizer, incorporating both momentum and adaptive learning rate techniques. The measure of loss is category cross-entropy, which quantifies the difference in actual and anticipated class densities.

To enhance model generalization, data augmentation techniques are applied during training. These include random rotations, shifts, and zooms, ensuring the model is exposed to diverse variations of skin lesion images.

The effectiveness of the framework is assessed on distinct test and verification datasets. Accuracy, along with a confusion matrix, is used to assess classification performance across multiple skin cancer categories.

Transfer learning is leveraged by initializing the ResNet50 backbone with pre-trained weights on a large dataset. By modification, a model may be made to fit the unique features of the skin cancer dataset that was employed for the present study.

Once trained, the model can be deployed to predict skin cancer types in new dermoscopic images. The research provides a comprehensive approach to automated skin lesion classification, aiding in early detection and diagnosis.

TABLE I. GENERALISED PARAMETER DESCRIPTION

Parameter	Description
Input Size	Standardized size, e.g., 128x128 pixels
Convolution Layers	Extract features through convolution operations
Pooling Layers	Down sample feature maps for spatial hierarchies
Dense Layers	Fully connected layers for classification

Activation Functions	ReLU (Rectified Linear Unit) for non-linearity
Dropout	Regularization technique to prevent overfitting

B. block diagram

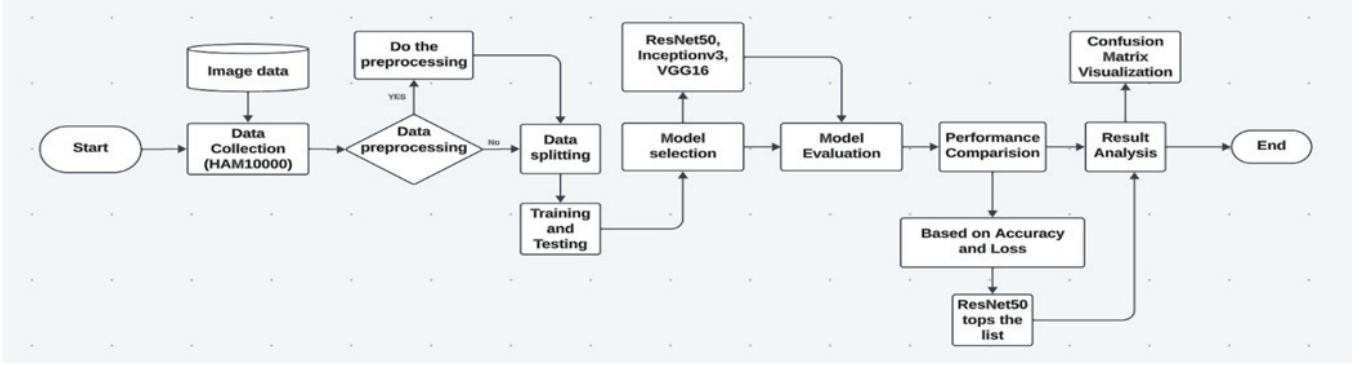


Fig. 1. Overall Architecture

CNN Parameters:

TABLE II. CNN PARAMETERS

Layer	Parameter	Description	Mathematical Equation
Conv2D_1	Filters(Convolution)	Learnable filters applied to input data for feature extraction	$W_{out} = S(W_{in} - F + 2P) / S + 1$
	Filter Size	Size of the convolutional filter	$H_{out} = (H_{in} - F + 2P) / S + 1$
MaxPooling_1	Pool Size	Factor by which to downscale	$W_{out} = (W_{in} - F) / S + 1$
Flatten	-	Flatten layer output for dense layers	None
Dense_1	Neurons	Number of neurons in a dense layer	$Output = Activation(Input \times Weights + Biases)$
	Activation Function	Activation function applied to layer output	$P(y_i) = (e^{x_i}) / (\sum_j e^{x_j})$

where,

The input tensor's width and height are represented by W_{in} and H_{in} .

Filter size is denoted by F , padding by P , and stride by S .

The values in the table are specific to each layer and are calculated based on the layer's parameters.

C. models description

ResNet50: ResNet50 is based on residual learning, introducing skip connections to address vanishing gradient issues. Its depth allows it to capture intricate features and learn complex representations. ResNet's skip connections aid in

smoother gradient flow during training, making it relatively easier to train deep networks. This can result in faster convergence and reduced susceptibility to overfitting. ResNet's depth and skip connections contribute to superior performance in capturing intricate features. Because of its capacity to learn hierarchy visualizations, it frequently proves useful for healthcare visualization applications. ResNet models, including ResNet50, are commonly used for transfer learning due to their pre-trained weights on large datasets. This can be advantageous when working with limited medical imaging datasets.

Inceptionv3: Inceptionv3, based on the Inception architecture, employs parallel filter operations of varying sizes within each module. This facilitates multi-scale feature extraction and can capture diverse patterns. Inception modules allow for efficient use of parameters, potentially reducing the risk of overfitting. However, training may require careful optimization due to the parallel structure. Inception's multi-scale feature extraction can be beneficial for skin lesion classification, capturing both fine and coarse details. However, fine-tuning may be necessary for optimal performance. Inception models may also benefit from transfer learning, but careful consideration is needed to open the past-trained segments to the particular characteristics of dermoscopic images.

VGG16: VGG16, following the VGGNet, opens of a series of small convolutional filters in a consistent receptive field. It emphasizes the importance of depth in neural network architectures. VGG's straightforward architecture can make training relatively simple, but the model may require more data and computational resources to generalize well. VGG's simplicity may limit its ability to capture intricate features compared to more complex architectures. However, its straightforward design can yield competitive results, especially with sufficient data. VGG's transfer learning potential is notable, but its larger parameter count may require more data to avoid overfitting during fine-tuning.

D. algorithm

Input:

X: Input image data

W: Convolution filter/kernel

b: Bias

s: Pooling stride

wi: Weights for the dense layer

bi: Bias for the dense layer

Step1: Convolutional Operation $Y[i,j] = \sum m$

$$\sum_n (X[I+m, j+n]) \times (W[m, n]) + b$$

Perform convolution operation on the input image X using the kernel W and bias b to obtain the feature maps Y.

Step 2: Activation ReLU: $f(x) = \max(0, x)$

Apply the ReLU activation function element-wise to the feature maps Y to introduce non-linearity.

Step 3: Pooling Operation (Max Pooling): $[i,j] = \max_{m,n} X[i \times s + m, j \times s + n]$

Perform max pooling on the feature maps Y with a pooling window size of (m, n) and a stride of s to obtain the pooled feature maps.

Step 4: Flatten the pooled feature maps to prepare for input into the dense layer.

Step 5: Dense Layer Output: $Y = f(\sum i w_i \times x_i + b)$

Compute the output of the dense layer by taking the dot product of the flattened feature maps with the weights wi, adding the bias bi, and applying the ReLU activation function.

Step 6: The output of the dense layer represents the probability of skin cancer presence.

IV. EXPERIMENTAL SETUP

A. dataset description

The HAM10000 dataset, a poignant acronym for "Human Against Machine with 10000 training images," emerges as an inspired initiative to invigorate the intersection of biology, medicine, and machine learning.

Where traditional datasets falter in size and diversity, HAM10000 rises to the occasion. Curated with meticulous attention, 10,015 dermoscopic pictures from different demographics and collection techniques are stored in it. This deliberate diversity enhances its utility as a robust training set, encompassing a spectrum of challenges encountered in real-world clinical scenarios.

The collection of data includes vascular tumors, dermatofibroma, melanoma, carcinoma of basal cells, benign keratosis-like tumors, and melanoma. mirrors the complexity inherent in dermatology diagnostics.

Beyond the image pixels, each entry in the dataset is a repository of rich contextual information, gender, age, diagnostic (dx), diagnostic type (dx_type), lesion_id, image_id, and localization contribute to a multifaceted understanding of each case, elevating the dataset's potential for academic machine learning pursuits.

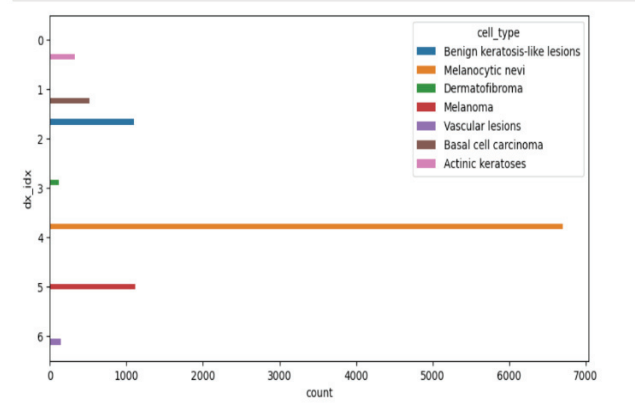


Fig. 2. Dataset Description

Setting a benchmark for rigor, HAM10000 surpasses the 50% mark in histopathological confirmation (histo) as the ground truth.

In essence, the HAM10000 dataset etches its uniqueness through a confluence of diversity, meticulous context, and pioneering features. Beyond a mere repository of images, it stands as a catalyst for innovation and exploration in the realm of skin cancer diagnosis through machine learning.

V. RESULT AND ANALYSIS

The ResNet50, Inceptionv3 and the VGG16 model models are compared. Among these three models ResNet50 got highest accuracy of 99.05% hence we have predicted the seven classes of diseases using ResNet50 model. The predictions are as below:

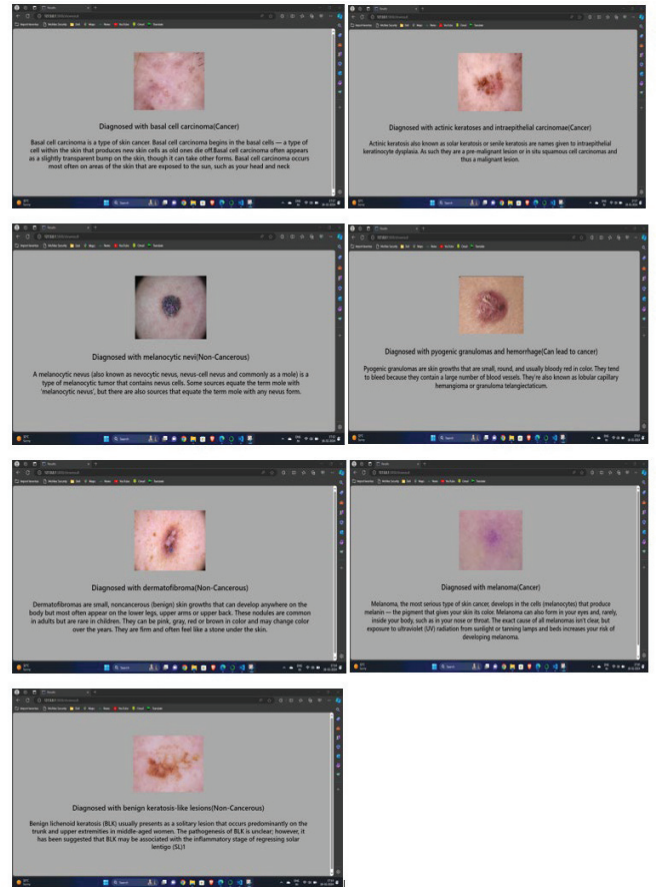


Fig. 3. 7 classes prediction

A. Results Comparison of ResNet50, Inceptionv3, and VGG16 Models:

TABLE III. COMPARISON METRICS

Model	Accuracy	Loss	Precision	Recall
ResNet50	98.9	0.02	99.16	99.15
Inceptionv3	94.8	0.15	97.27	97.25
VGG16	93.2	0.22	95.3	95.29

B. Formulae for Comparison:

Accuracy: $(TP + TN) / (FP + FN + TP + TN)$.

Precision: $(TP) / (FP + TP)$

Recall (Sensitivity) = $(TP) / (FN + TP)$

The proposed method's success in achieving high accuracy and balanced precision and recall values demonstrates its potential for real-world applications.

ResNet50:

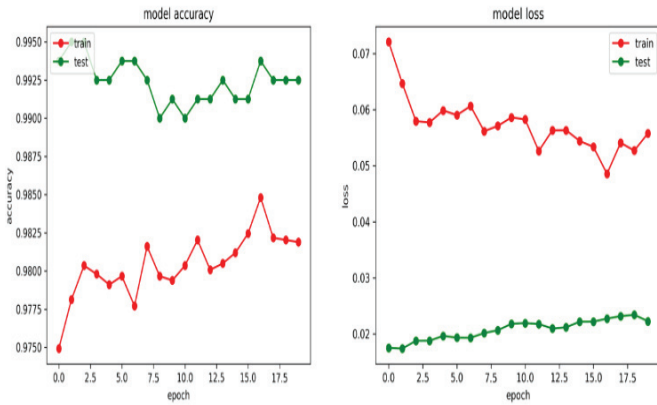


Fig. 4. ResNet50 Accuracy and loss plots

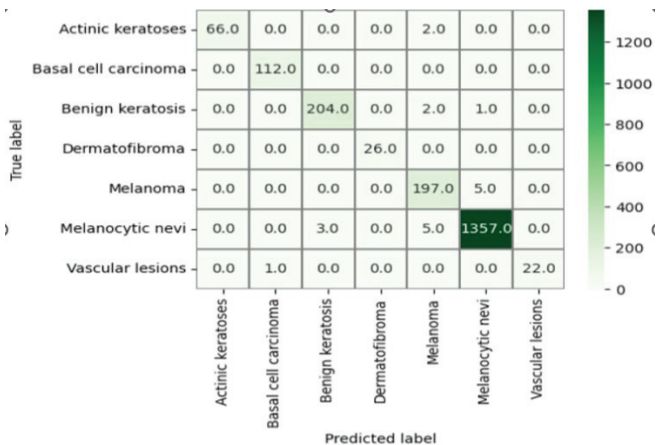


Fig. 5. ResNet50 Confusion matrix

Inceptionv3:

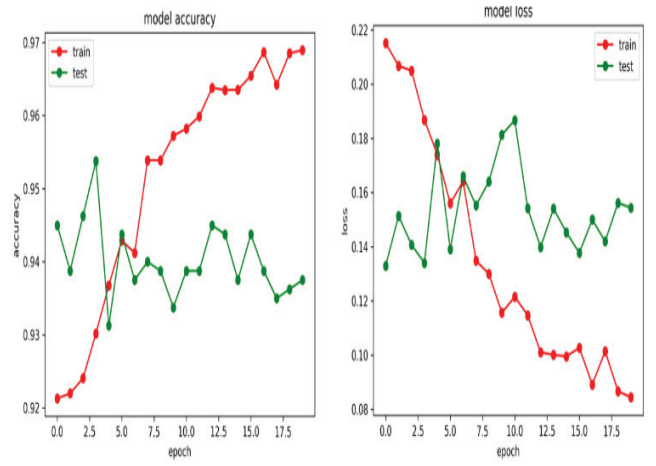


Fig. 6. Inceptionv3 Accuracy and loss plots

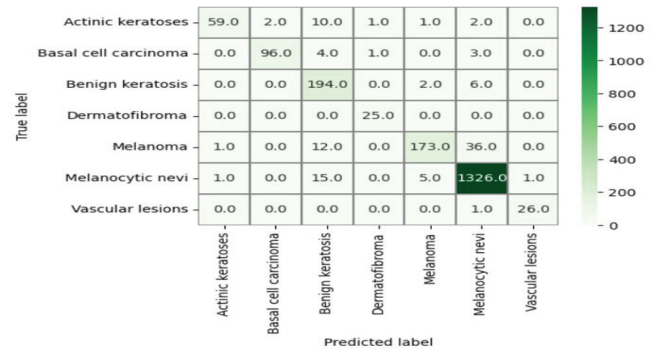


Fig. 7. Inceptionv3 Confusion matrix

VGG16:

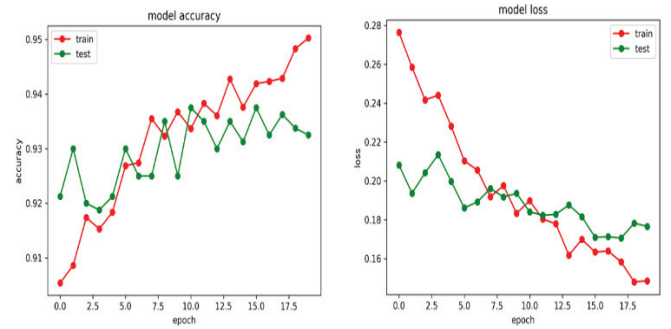


Fig. 8. VGG16 Accuracy plot

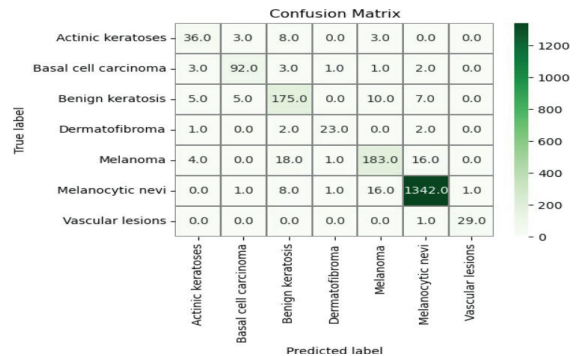


Fig. 9. VGG16 Confusion matrix

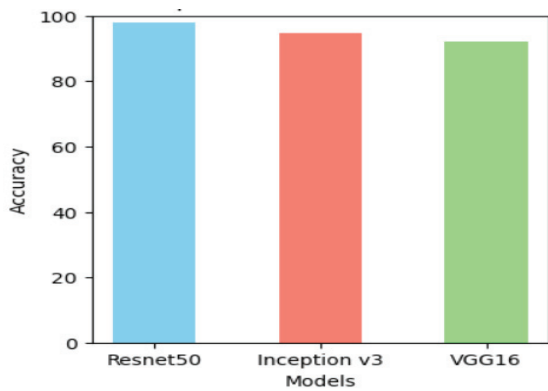


Fig. 10. Comparison of 3 models accuracies

C. Observations

ResNet50 demonstrates superior predictive performance, achieving the highest success rates and lowest loss values.

Inceptionv3 performs reasonably well, with accuracy and loss values indicating effective skin cancer classification.

VGG16, while providing acceptable results, lags behind ResNet50 and Inceptionv3 in terms of accuracy.

We compare the performance of the suggested technique with current algorithms in the literature to assess its efficacy. Resnet50 model introduced residual connections that enable training of much deeper networks. These architectural differences affected the model's ability to capture and represent complex patterns in the data. Resnet50 is known for its parameter efficiency due to the use of residual connections. This means it can achieve good performance with fewer parameters compared to models like VGG16, which can be advantageous especially in scenarios with limited computational resources or data availability. Resnet50 is deeper compared to InceptionV3 and VGG16. Deeper models can potentially learn more intricate features and representations, which might be beneficial for complex tasks like skin cancer detection.

VI. FUTURE SCOPE

Looking ahead, there are promising avenues to explore for refining existing models. Investigating ensemble methods that combine ResNet50, Inceptionv3, and VGG16 could yield a hybrid model harnessing the strengths of each architecture. Enhancing datasets with more diversity and volume holds the potential for improving generalization. Exploring transfer learning and adapting models to evolving datasets can contribute to increased accuracy. Collaborative efforts with healthcare professionals and integration into clinical workflows may facilitate practical applications, advancing the role of automated dermatological diagnosis in health care.

VII. CONCLUSION

In closing, the study successfully illustrates the possibility of models based on deep learning for the categorization of skin tumors, with ResNet50 exhibiting superior performance in accuracy and minimal loss. While ResNet50 emerges as a robust choice, acknowledging the distinct strengths of Inceptionv3 and VGG16 emphasizes the importance of a tailored model selection based on specific needs. The results underline the nuanced nature of model comparisons and the

significance of understanding individual architectural characteristics.

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