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Comparative Analysis of Machine Learning Models for Skin Cancer Detection

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Abstract: *Detecting and classifying skin lesions in an early manner is crucial for the prevention of skin cancer, which is still a major global health concern. To classify skin lesions into seven categories—melanocytic nevi, melanoma, basal cell carcinoma, actinic keratoses, vascular lesions, and dermatofibroma—we compare machine learning and deep learning methods in this paper. To improve model generalization, we preprocess the data using resizing and augmentation techniques by utilizing the HAM10000 dataset, which provides a variety of samples of skin lesions. We use multiple models in our analysis: a Decision Tree classifier, Linear Regression, K-Nearest Neighbors (KNN), Random Forest, and a Convolutional Neural Network (CNN) specifically constructed for skin lesion classification. We use appropriate optimization approaches to train each model, and we assess each model's performance using measures like accuracy, precision, recall, and F1-score on a held-out test dataset. We also examine class distributions and confusion matrices to obtain a further understanding of the advantages and disadvantages of the approach. The outcomes of the experiment show that deep learning techniques, in particular the CNN model, are successful in correctly diagnosing skin lesions with an accuracy of 82%. Still, conventional machine learning algorithms like Random Forest (33%) and KNN (55%) demonstrate competitive performance as well, highlighting their importance in the detection of dermatological conditions. While Decision Tree produced an accuracy of 47%, Linear Regression produced a mean squared error of 0.169. All things considered, our comparative analysis offers insightful guidance to academics and doctors regarding the best methods for automated skin lesion classification.*

Keywords: *Skin cancer, skin lesion classification, deep learning, machine learning, Convolutional Neural Network (CNN), Random Forest, K-Nearest Neighbors (KNN), Linear Regression, Decision Tree, HAM10000 dataset.*

1. INTRODUCTION:

Skin cancer constitutes a substantial global public health concern, representing a considerable proportion of cancer diagnoses. To effectively treat and manage the condition, skin lesions must be accurately classified and detected as soon as possible. Dermatologists reliably diagnose and categorize skin lesions using a variety of diagnostic procedures, such as dermoscopy and ocular inspection. These techniques, however, are sensitive to subjectivity and inter-observer variability. Consequently, there is a growing interest in creating automated systems to help physicians classify skin lesions that are based on machine learning and deep learning algorithms.

In this study, we use deep learning and machine learning methods to conduct a thorough investigation into the classification of skin lesions. We use the HAM10000 dataset, a sizable compilation of magnificent images corresponding to seven different diagnostic classifications of skin lesions. Melanocytic nevi, melanoma, lesions resembling benign keratosis, basal cell carcinoma, actinic keratoses, vascular lesions, and dermatofibroma are among these groups. Every image in the dataset has a unique diagnostic label attached to it, which offers useful ground truth data for training and assessing models.

Skin cancer classification involves categorizing skin lesions into distinct diagnostic classes based on their visual appearance and characteristics. Dermatologists typically classify skin lesions into several categories, including[9]:

- Melanocytic Nevi: Common moles, typically benign and characterized by a uniform color and round or oval shape.

- Melanoma: The most severe type of skin cancer, arising from melanocytes. Melanomas often exhibit irregular borders, asymmetry, and variations in color and diameter.

Fig. 1. Classification of Skin cancer in the dataset

- Benign Keratosis-Like Lesions: Non-cancerous growths on the skin, such as seborrheic keratosis, characterized by thick, wart-like patches.

- Basal Cell Carcinoma: The predominant form of skin cancer, developing in the basal cells located in the skin. Basal cell carcinomas often appear as pearly or waxy bumps with visible blood vessels.

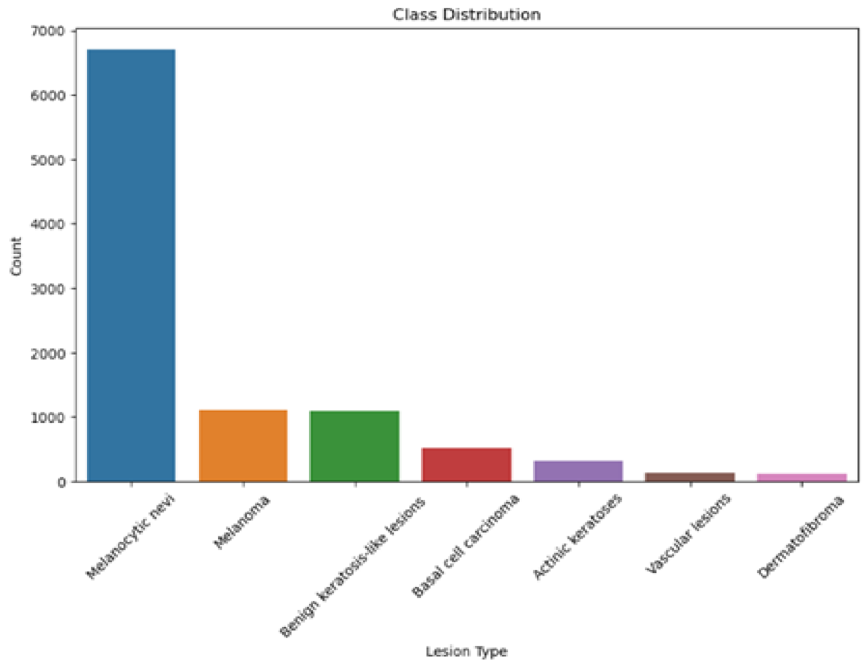
- Actinic Keratoses: Precancerous growths caused by sun damage, typically appearing as rough, scaly patches on sun-exposed areas of the skin.

- Vascular Lesions: Skin abnormalities involving blood vessels, such as hemangiomas and port wine stains, which may appear as red or purple discolorations on the skin.

- Dermatofibroma: Benign skin lesions that often arise from minor trauma, presenting as firm, raised nodules on the skin.

Precise categorization of skin lesions is essential for choosing suitable therapeutic strategies and forecasting patient results. Dermatologists evaluate skin lesions and make well-informed clinical judgments by using a variety of diagnostic procedures, like visual inspection, dermoscopy, and histopathology. These techniques, however, are sensitive to subjectivity and inter-observer variability. Dermatologists may benefit from automated classification systems that use machine learning and deep learning algorithms to provide objective, reliable, and effective lesion classification.

2. LITERATURE REVIEW:



This research compares various algorithms for detecting skin cancer, such as Support Vector

Machines, VGG16, VGG19, Inception, Xception and Convolutional Neural Networks (CNN). The study assesses algorithm performance using a dataset of 30,000 skin pictures divided into training (21,000) and testing (9,000) sets. Analysis of skin lesions is made easier by machine learning, which helps in early cancer identification and prompt treatment. The results demonstrate CNN's superiority, with a 74% accuracy rate, underscoring its potential to enhance intervention and diagnosis precision. The results highlight the need for continued research to increase AI integration in clinical practices, incorporate large datasets, and improve algorithmic performance for better cancer diagnosis.[1]

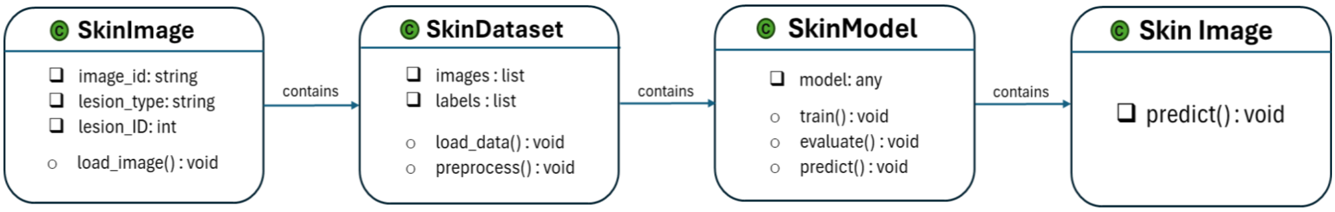
Using image processing techniques, we developed a convolutional neural network (CNN) model in our research to accurately detect skin cancer. We performed a comparison analysis using seven alternative CNN architectures, namely ResNet50, VGG16, InceptionV3, VGG19, Xception, MobileNetV2, and MobileNet, using a dataset of approximately 3000 images classified into benign and malignant groups. With an accuracy of roughly 85.303%, Xception was found to be the most appropriate model despite differences in architecture. While tweaking parameters like epochs, batch size, and dropout may improve model performance, accuracy may be limited by factors like processing power and image quality. Notably, with an accuracy of 54.545%, MobilenetV2 showed the lowest accuracy.[2]

This study emphasizes the significance of a precise diagnosis while examining the application of deep learning (DL) and machine learning (ML) approaches for early skin cancer prediction. A dataset that is accessible to the public is used to analyze different algorithms, such as CNNs and RF. With accuracy rates of 58.57% and 87.32%, respectively, without and with augmentation, RF performs better. Promising outcomes are also shown by MobileNetv2, an ensemble of DenseNet and Inceptionv3, which achieves accuracies of 88.81% and 88.80% without augmentation and 97.58% and 97.50% with augmentation. On both raw data and augmented datasets, customized CNN models with 5 and 3 layers achieve an accuracy of 97.72% and 98.02%, respectively, indicating their potential for clinical integration. The effectiveness of transfer learning models is found to support their potential use in clinical practice, subject to additional validation and investigation.[3]

This study stresses the significance of an accurate diagnosis while examining the application of deep learning (DL) and machine learning (ML) approaches for early skin cancer prediction. In the study they used the HAM10000 dataset to analyze different algorithms, such as CNNs and RNN. With accuracy rates of 72% and 69%, respectively, without augmentation, CNN performs better. Promising outcomes are also shown by Xception and ResNet50, which achieve accuracies of 93% and 79% without augmentation and 90.58% and 73% with augmentation. These results indicate their potential for clinical integration. The effectiveness of transfer learning models is found to support their potential use in clinical practice, subject to additional validation and investigation.[4]

In this paper, we conducted a comparative analysis of diagnostic methods and recent advancements in detecting various types of cancer using traditional machine learning (ML) and deep learning (DL) models. They have focused on four types of cancers—brain, lung, skin, and breast—and their detection using ML and DL techniques. Traditional machine learning (ML) techniques yielded an accuracy of 99.89%; deep learning (DL) techniques achieved a maximum accuracy of 100%. When using DL and ML approaches, the lowest accuracy values were 70% and 75.48%, respectively. Notably, there was a notable 28.8% accuracy difference in skin cancer detection between the models with the best and lowest performance. This study also highlights important discoveries and difficulties related to the use of ML and DL techniques for the detection of each type of cancer.[5]

This study clarifies lung cancer prediction in the given context of the COVID-19 pandemic, a topic that has received less attention recently. Based on a synthesis of secondary metrics,



tertiary indicators, and ROC curves, the research determines that random forest ensemble learning is the most effective method for lung cancer prediction through a thorough comparison of machine learning models. This emphasizes how important it is to use cutting-edge algorithms to improve lung cancer preventive tactics.[6]

To lower death rates from skin cancer, this study investigates how well convolutional neural network (CNN) models perform in early skin cancer diagnosis. A dataset of pictures of benign and malignant skin cancer is used to assess different CNN architectures, such as VGG16, SVM, and ResNet50. The best accuracy of 93.18% was achieved by VGG16 in the results, demonstrating its efficacy in the classification of skin cancer.[7]

Another recent investigation delves into the role of deep learning algorithms in improving the detection of rare and aggressive forms of skin cancer, such as Merkel cell carcinoma (MCC). Leveraging a diverse dataset comprising MCC images, the study employs state-of-the-art CNN architectures, including DenseNet and InceptionResNetV2, to discern malignant lesions from benign ones. Remarkably, DenseNet achieves an accuracy of 97.86%, outperforming other models, thereby underscoring the potential of deep learning in facilitating early detection and intervention for challenging dermatological conditions. This underscores the significance of ongoing research efforts aimed at harnessing AI for enhancing diagnostic capabilities and ultimately saving lives threatened by rare skin cancers.[8]

3. METHODOLOGY AND ARCHITECTURE

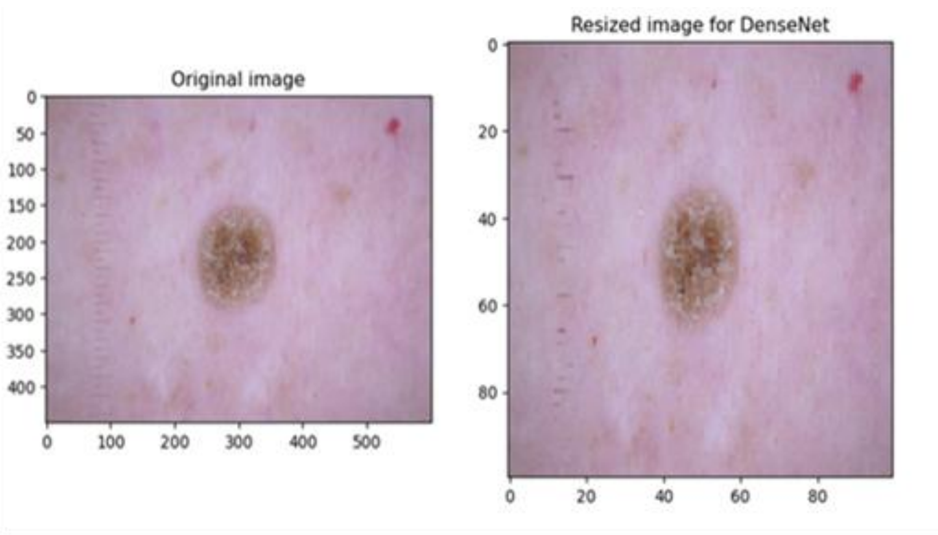
Fig. 2. Architecture

Fig.2 depicts the architecture of the skin cancer classification project intended to classify photographs of skin lesions into different subtypes of skin cancer. First, a wide range of skin image datasets are gathered, including different kinds of lesions such as benign keratosis-like lesions, melanoma, and melanocytic nevi. Preprocessing is applied to these photos to improve model performance and guarantee consistency. Resizing as depicted in Fig.3, normalization, and augmentation techniques are used in preprocessing to improve dataset diversity and standardize the format of the photos.

Fig.3 Preprocessed image for training

The preprocessed photos are then sent into a Convolutional Neural Network (CNN), a powerful deep learning architecture well known for its effectiveness in image categorization applications. CNN is composed of multiple layers, including convolutional layers for feature extraction, pooling layers for dimensionality reduction, and fully connected layers for classification. By modifying its internal parameters in response to the labeled data it receives, the CNN gains the ability to recognize patterns and features that correspond to various types of skin lesions during the training phase. The trained CNN model can be put to practical use in automated skin cancer diagnosis systems after satisfactory evaluation findings are obtained. To implement the model, it must be integrated into platforms or software applications that allow it to recognize input photos, classify them, and deliver end users or healthcare professionals diagnostic results. All things considered, the project's architecture makes it easier to accurately classify the many forms of skin cancer, which helps with early detection and efficient treatment plans.

A Convolutional Neural Network (CNN), a potent deep learning architecture renowned for its effectiveness in image classification tasks, is then fed the preprocessed images. A Convolutional Neural Network (CNN) consists of several layers including convolutional layers for feature extraction, pooling layers for dimensionality reduction, and fully connected layers for



classification. In the training phase, the CNN learns to recognize patterns and features associated with various types of skin lesions by adjusting its internal parameters based on the labeled data it receives.

The trained CNN model can be put to practical use in automated skin cancer diagnosis systems after satisfactory evaluation findings are obtained. In order to implement the model, it must be integrated into platforms or software applications that allow it to recognize input photos, classify them, and deliver end users or healthcare professionals diagnostic results. All things considered, the project's architecture makes it easier to accurately classify the many forms of skin cancer, which helps with early detection and efficient treatment plans.

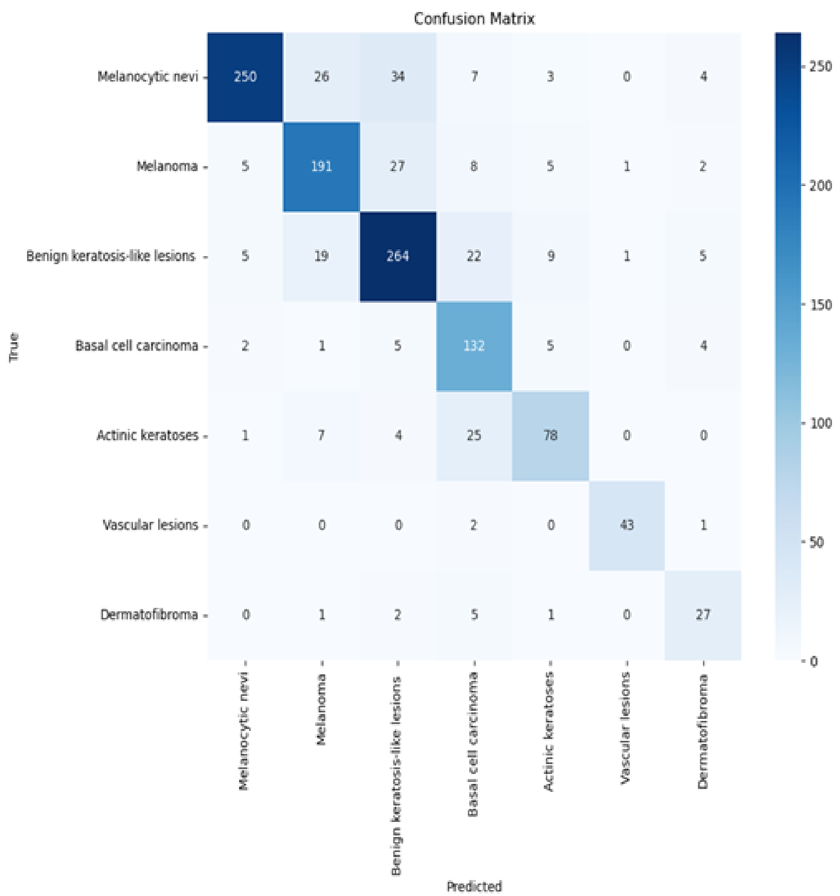


Fig.4 Confusion Matrix with the output from proposed methodology

4. MODELS USED

4.1 Convolutional Neural Network

Deep learning models called CNNs are created especially for image categorization applications. They consist of several layers, such as pooling layers for dimensionality reduction and convolutional layers for feature extraction. Convolutional filters are used by CNNs to help them recognize patterns and features in images. They have demonstrated outstanding performance in the classification of skin cancer and are very useful for problems involving huge image datasets.

4.2. Random Forests

During training, several decision trees are built using the Random Forest ensemble learning technique. To arrive at a final forecast, it combines the predictions from each separate decision tree. Because of its versatility, Random Forest can be used for both regression and classification applications. It works well on high-dimensional data and is resistant to overfitting, which makes it appropriate for image classification applications like detection of skin cancer.

4.3. K-Nearest Neighbours (KNN)

It is a simple and intuitive classification algorithm for instance-based learning. It classifies new data points by assigning them the majority class label among their k nearest neighbors in the training dataset. KNN is non-parametric and requires no training phase, making it computationally efficient for small to medium-sized datasets. It is dependent on the value of k and the selected distance metric. Thus, while KNN serves as a valuable baseline algorithm, its efficacy can be further enhanced by considering the specific characteristics of the data and employing techniques such as feature scaling and dimensionality reduction to mitigate its limitations and improve classification accuracy.

4.4. Linear Regression

A fundamental regression technique for forecasting continuous numerical values is called Linear Regression. In the context of classification, it can be applied as a baseline model by converting the problem into a multi-class classification task. By using Linear Regression, one can determine a linear relationship between the target variable and the input features. Although it is interpretable and computationally effective, complicated relationships in the data may not be captured by it. Consequently, while it provides a solid starting point, more sophisticated models may be required to fully grasp the nuances of the data and achieve higher predictive accuracy.

4.5. Decision Tree

Decision trees are structures resembling hierarchical trees that are employed in problems related to regression and classification. They divide the feature space into regions, giving each region a numerical value or class designation. Decision trees are helpful for determining the value of features since they are simple to understand and display. However, they are prone to overfitting, especially when dealing with high-dimensional data or complex relationships.

5. CONCLUSION

Various machine learning techniques were utilized in this skin cancer categorization study to identify distinct kinds of skin lesions. With an astounding accuracy of 86.6%, the Convolutional Neural Network (CNN) was the best performance among these classifiers. CNNs are especially well-suited for image classification tasks like classifying different types of skin cancer because of their reputation for being adept at automatically extracting complex information from images. On the other hand, with only 33% accuracy, the Random Forest classifier performed worse than the others. Despite their robustness and versatility, Random Forests might have trouble capturing the subtle patterns found in photos of skin lesions. With an accuracy of 55%, K-Nearest Neighbors (KNN) performed mediocrely, demonstrating both its ease of use and sensitivity to hyperparameters. As a baseline model in this case, Linear Regression produced a Mean Squared Error (MSE) of 0.169, which is a decent but less reliable method. Compared to CNNs, Decision Trees offered a classification that was easier to understand but less accurate, with an accuracy rate of 47%. In the end, a variety of factors such as the dataset's complexity, interpretability, processing capacity, and accuracy needs will determine which classifier is best.

Fig.5 Training Loss VS Validation Loss

Fig.6 Training Accuracy VS Validation Accuracy

	Training Loss	Validation Loss
Min	0.227832004	0.413494051
Max	1.65495491	1.45166409
Average	0.714712924	0.799667404

Table.1 Training Loss VS Validation Loss

	Training Accuracy	Validation Accuracy

Min	0.400000006	0.448136151
Max	0.914690971	0.868719637
Average	0.724498483	0.698525121

Table.2 Training Accuracy VS Validation Accuracy

The varying performance of the machine learning models indicate the difficulties that come with classifying images of skin cancer. Although CNNs are effective at capturing complex visual patterns, they tend to have problems when compared to some other models. Random Forest - known for its versatility in handling assorted types of data - may not be appropriate for skin lesions' complexities. On the other hand, KNN becomes ineffective where distances become complicated like that in image data because it is proximity-based. Linear Regression, designed primarily for continuous values functions inaccurately due to its application on this classification issue while Decision Trees do not really have enough depth required to make sound judgments based on a picture alone. Therefore, these results assert reasons why model selection should always be possible according to project details including nature of the dataset and expected outcomes taking into consideration all factors influencing them.

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