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ENHANCE SKIN CANCER DEEP LEARNING-BASED CATEGORIZATION: A THOROUGH EXAMINATION AND COMPARATIVE STUDY

[1]Ragini Dhanjode, Prof. Prerna Dangra,Prof.Anupam Chaube
[1]P G Scholar, [2]Assistant Professor,[3]Dean
Master of Computer Application
G. H. Raisoni University, Amravati

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Abstract: One of the most prevalent types of cancer in the world is skin cancer, which includes melanoma, squamous cell carcinoma, and basal cell carcinoma. While increasing survival rates requires early discovery and treatment, conventional diagnostic techniques frequently have subjectivity and inconsistent results. The purpose of this study is to better understand how deep learning techniques, namely convolutional neural networks (CNNs), might improve the detection of skin cancer. Using the ISIC dataset, eight advanced models—DenseNet121, InceptionV3, ResNet50V2, VGG16, VGG19, InceptionResNetV2, Xception, and CNN—were trained and verified to categorize different types of skin lesions. The outcomes highlight the superior accuracy that models like as Xception and InceptionV3 can accomplish, highlighting their potential for accurate and timely detection. This investigation assesses how well different deep learning models diagnose different skin diseases. Models like Densenet121, InceptionV3, and VGG16 are compared based on metrics like accuracy, recall, precision, and F1-score. When it comes to multi-classification, InceptionResNetV2 and VGG16 stand out as the best performers with 0.9547 accuracy, while Custom CNN performs the worst with 0.8040. A thorough comparison of the accuracy, precision, recall, and F1-score performance indicators identifies the unique advantages and disadvantages of each model. This study demonstrates how artificial intelligence (AI) is revolutionizing medical imaging by offering a reliable, unbiased, and highly accurate method for detecting skin cancer. The integration of deep learning models into clinical practice is made possible by these discoveries, which might enhance patient outcomes and diagnostic accuracy in dermatology.

IndexTerms – Python, Machine Learning, Deep Learning, Skin Cancer, Deep Learning Algorithms, Medical Imaging, Neural Network Models.

I. INTRODUCTION

Millions of new instances of skin cancer are reported each year, making it one of the most prevalent malignancies globally. Types including squamous cell carcinoma, basal cell carcinoma, and extremely malignant melanoma are among them. Skin cancer is a common disease, however survival chances can be greatly increased with early identification and treatment. The knowledge of dermatologists is frequently dependent on traditional diagnostic techniques, which might be arbitrary and unreliable. Deep learning algorithms have emerged as a potentially effective remedy, and this has sparked the creation of more dependable diagnostic tools. Neural network models that mirror the structure of the brain are used in deep learning, a type of artificial intelligence (AI), to handle massive quantities of data. In particular, convolutional neural networks (CNNs) are excellent at image identification tasks, which makes them perfect for medical imaging applications like the diagnosis of skin cancer. Deep learning's application in this industry has attracted a lot of attention lately. Identification of worrisome lesions is made possible by medical imaging techniques like dermoscopy, which produce finely detailed pictures of the skin's surface. Historically, interpreting these pictures has required a high level of skill, and even dermatologists with years of training occasionally overlook early warning indicators of skin cancer or misidentify benign tumors. Deep learning algorithms provide a more reliable and accurate way to analyze these photos since they can identify complex patterns and learn from big datasets.

Once pre-processed, the images are input into the neural network model. Models like DenseNet121, InceptionV3, ResNet50V2, VGG16, VGG19, InceptionResNetV2, Xception and Customized Convolutional neural Network are commonly used. These models,

pre-trained on large datasets like ImageNet, can be fine-tuned for skin cancer detection. Transfer learning, which adapts a pre-trained model to a new task, is particularly useful as it mitigates the need for large, labeled medical datasets, which are often hard to obtain. A significant advantage of deep learning in skin cancer detection is the potential for early and accurate diagnosis, crucial for effective treatment. These models can be deployed in various healthcare settings, including remote and underserved areas, providing access to high-quality diagnostic tools. AI technologies, especially deep learning, are transforming skin cancer diagnosis by offering a consistent, objective, and highly accurate tool for early detection. Ongoing research continues to enhance neural network models, improving patient outcomes and advancing skin cancer care. As these technologies evolve, they promise to become indispensable assets in combating skin cancer, ultimately saving lives through earlier and more reliable detection.

II. LITERATURE REVIEW

The accuracy of traditional computer-aided diagnosis tools for skin cancer is impacted by their inability to accurately process complex visual aspects of lesions. suggested KNN using Grey Wolf Optimizer-optimized AlexNet and pretrained DNN feature extractors. On the ISIC dataset A, almost 99% accuracy was attained by Magdy et al. [1]. Terahertz metamaterials (MTMs) were the topic of previous research that investigated high-sensitivity biosensors for non-melanoma skin cancer diagnosis in order to improve accuracy. Many studies were conducted on the design and optimization of triple-band combinations for high-resolution detection and perfect absorption. Improvements in manufacturing methods led to better biosensor performance, which provided the basis for the current investigation by M. N. Hamza et al. [2]. A thorough joint learning system for the diagnosis of skin cancer was created in the study by Riaz et al.; their results were published in IEEE Access in 2023 [3]. The goal of the study was to increase the precision and dependability of skin cancer diagnosis by utilizing cutting-edge machine learning techniques. Methods to improve skin cancer diagnosis by integrating RNA-Seq and microarray datasets were investigated in different research by Galvez et al. [4]. The findings were published in the IEEE Journal of Biomedical and Health Informatics in 2020. The study demonstrated how integrating several genetic data sources might enhance diagnosis accuracy. Both investigations improved the methods for diagnosing and detecting skin cancer, which made a substantial contribution to the field of biomedical informatics.

The possibility of generative AI to improve skin cancer categorization has been investigated in recent publications. Deep learning techniques may greatly enhance skin cancer categorization, utilizing the potential of generative AI to increase diagnostic precision, as Saeed et al. [5] showed. Simultaneously, Di et al. [6] presented ECRNet, a hybrid network tailored for the identification of skin cancer that has demonstrated the ability to successfully combine many computational methodologies in order to get good classification performance. The progress in AI-driven approaches for medical image processing was highlighted by these works jointly, emphasizing how effective they are at increasing the precision and dependability of skin cancer detection. Recent studies have shown that great progress has been made in the field of skin cancer diagnosis. They M. N. Hamza et al. [7] created a very small dual-band biosensor in the terahertz range that uses metamaterials (MTMs) as the ideal absorber for diagnosing skin cancer that is not melanoma. This invention is a promising tool for early detection because of its remarkable terahertz spectrum sensitivity and specificity. To improve skin cancer detection, they performed a multimodal analysis using imbalanced dermatological data. The work utilized sophisticated computational methods to enhance the precision of diagnostic models, tackling the difficulties caused by imbalanced data in datasets related to dermatology. By offering fresh perspectives and improving the accuracy of early detection techniques, both research have added to the changing field of skin cancer diagnosis P. A. Lyakhov et al. [8]. New computational methods have been used in recent research to improve the detection and segmentation of skin cancer images. X. Qian et al. [9] introduced a multi-scale identification network called SPCB-Net that improved the recognition accuracy of skin cancer pictures by using cross-layer bilinear- trilinear pooling in conjunction with a self-interactive attention pyramid. To improve the segmentation of skin cancer photos, they proposed an enhanced version of the Particle Swarm Optimization (PSO) technique that included a visit table and various direction search algorithms. Through creative algorithmic techniques, both systems demonstrated notable advancements in the processing and interpretation of skin cancer photos when they were published in IEEE Access in 2024 Y. Olmez et al. [10].

III. METHODOLOGY

Xception and CNN, DenseNet121, InceptionResNetV2, Inception_V3, ResNet50V2, VGG16, VGG19, and Inception are some of the eight deep learning models that are used in the detection of skin cancer. The first step involves gathering and pre-processing a heterogeneous collection of skin lesion photographs, including both benign and malignant instances. To improve the generalization capacity of the model, augmentation, normalization, and resizing are part of this preprocessing step. Once the selected architecture is initialized with pre-trained weights from ImageNet, transfer learning is applied. It then learns particular traits indicative of malignancy by fine-tuning on the skin cancer dataset. The model's performance measures, such as accuracy, precision, recall, and F1-score, are evaluated during the validation and assessment phases. To ensure robustness, techniques like cross-validation are frequently used. To maximize performance, hyperparameter tweaking further fine-tunes the model's parameters. Ultimately, the trained model is used to real-world skin cancer detection applications, guaranteeing scalability and effectiveness. Using the deep learning powers of the previously stated architectures, this technology can detect skin cancer in photos with high accuracy.

- **ISIC Dataset**

The distribution of pictures for a skin cancer detection model across training, validation, and testing datasets is shown in the table. Actinic Keratosis, Basal Cell Carcinoma, Dermatofibroma, Melanoma, and Pigmented Benign Keratosis are among its six classifications. For a total of 2000 photographs each category, 400 images are present in the training and validation files. There are three hundred photographs in the testing folder, sixty in each category. In order to construct an effective skin cancer detection model, it is necessary to guarantee that each class is evenly represented through a balanced distribution. This promotes robust model training, impartial validation, and accurate performance evaluation on unseen data.

Table 1: ISIC Dataset

Label	**Actinic Keratosis**	**Basal Cell Carcinoma**	**Dermatofibroma**	**Melanoma**	**Pigmented Benign Keratosis**	**Total Images**
Training Folder	400	400	400	400	400	2000
Validation Folder	400	400	400	400	400	2000
Testing Folder	60	60	60	60	60	300

- **Categorizing Skin Cancer Using Deep Learning Pre-Trained Models**

In Figure 1, The deep learning model-based skin cancer detection system's process is shown in full in the diagram. In the preprocessing stage, skin lesion photos are divided into training, validation, and testing datasets, cropped and shrunk to a standard input size, and enhanced to improve the variety and resilience of

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the data. The models' ability to generalize is enhanced by this preprocessing, which makes sure they are exposed to a broad range of skin lesion appearances. Next, a number of pre-trained models are used for feature extraction, including Xception, DenseNet121, InceptionV3, ResNetV2, VGG16, VGG19, InceptionResNetV2, and a bespoke CNN. Pre-trained weights from the ImageNet dataset are used to start these models, giving them a strong base of learnt features. In certain instances, rotation augmentation is done to further improve model resilience and no pre-trained weights are required. Subsequent levels of processing are applied to the retrieved features, beginning with global average pooling to incorporate spatial information and minimize the size of the feature map. Dense layers with batch normalization and ReLU activation functions come next, which aid in stabilizing and accelerating the training process. By randomly removing a portion of the units during training, dropout is employed for regularization to avoid overfitting. The last layer generates the probability distribution across the various skin cancer classifications. It is a dense layer with softmax activation.

The ISIC dataset, which covers conditions such as Actinic Keratosis, Basal Cell Carcinoma, Dermatofibroma, Melanoma, and Pigmented Benign Keratosis, is used to train and verify the models. The objective of this evaluation process is to determine which convolutional neural network (CNN) performs the best for the detection of skin cancer by analyzing the models' accuracy, precision, recall, and F1-score. By employing cutting-edge deep learning algorithms, this methodology guarantees a comprehensive and methodical approach to creating an efficient and trustworthy skin cancer detection system.

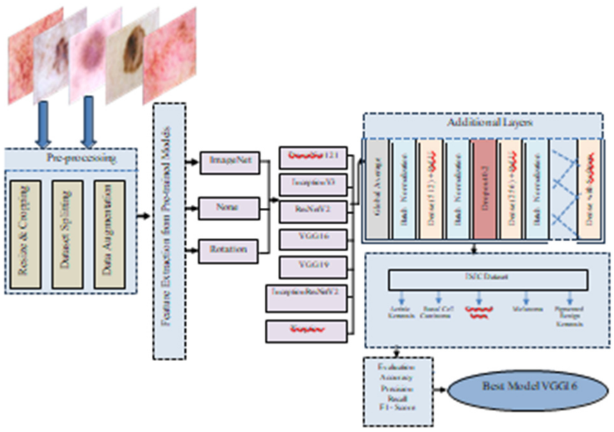
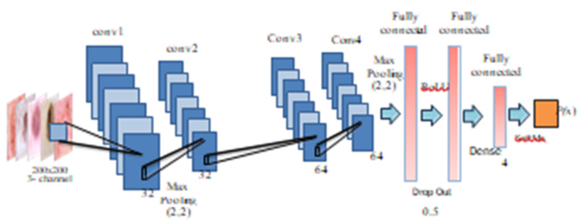


Figure 1: Deep Learning-Based Method for Classifying Skin Cancer



- **Particular CNN Structure**

In Figure 2, Edges and forms are among the characteristics that are extracted from the image using the first layer group's convolution process, known as "conv1,". The ability to recognize patterns in the image requires certain qualities. Pooling is the next layer group, called "pool2," and it is the process of reducing the dimensionality of the data by grouping the information into distinct regions of the image. The network's enhanced resistance to little alterations in the image is facilitated by this decline. As the network grows, more convolutional and pooling layers are added in order to extract ever more complex properties from the image. The fully connected layers at the end of the network identify the image by using the convolutional layers' data. The last layer uses a softmax method to generate the odds that the image will fit into different categories.

These many layers are essentially used by convolutional neural networks, which can perform tasks like image recognition and classification, to learn complex patterns in pictures.

- **Performance assessment**

As mentioned in Equations (1) to (4), we use many basic metrics to evaluate the effectiveness of our skin cancer classification technique. These criteria consist of precision, recall, F1 score, and accuracy.

Table 2: Metrics for evaluating effectiveness

Metric	Equation
Accuracy	$Acc = \frac{Tp+TN}{TP+TN+FP+FN}$ (1)
F1 score	$F_1 = \frac{2TP}{2TP+FP+FN}$ (2)
Sensitivity or Recall	$SE = \frac{TP}{TP+FN}$ (3)
Precision	$Pr = \frac{TP}{TP+FP}$ (4)

IV. FINDINGS AND DISCUSSION

- **Improved Skin Cancer Categorization Using a Larger Dataset: Including Conditions Other Than Cancer**

Actinic Keratosis, Basal Cell Carcinoma, Dermatofibroma, Melanoma, and Pigmented Benign Keratosis are the six categories that make up the ISIC dataset for a skin cancer detection program. For a total of 2000 photographs each category, 400 images are present in the training and validation files. There are 60 photos in each category in the testing folder, for a total of 300 photographs. In order to construct an efficient skin cancer detection model, it is essential to guarantee that each class is equally represented across the training, validation, and testing sets. This balanced distribution promotes robust model training, objective validation, and accurate performance assessment on unseen data.

- **Comparing Deep Learning Models for the Identification of Skin Cancer Using Skin Cancer Dataset**

A comparison of several image classification models, such as Custom CNN, Xception, VGG19, VGG16, ResNet50V2, Inception ResNetV2, InceptionV3, and DenseNet121, is shown in the bar chart. The models are shown on the x-axis, while accuracy is shown on the y-axis, which runs from 0.4 to 0.9. With Xception reaching near to 0.9 accuracy, a larger bar denotes more accuracy. On the other hand, DenseNet121 has a lesser accuracy of 0.4 to 0.5. It's critical to understand that the best model selection is dependent on certain facts and goals. While some models do exceptionally well across the board, others could focus on certain picture types or categorization tasks. As such, taking into account the dataset and the intended categorization results is imperative when choosing the best model.

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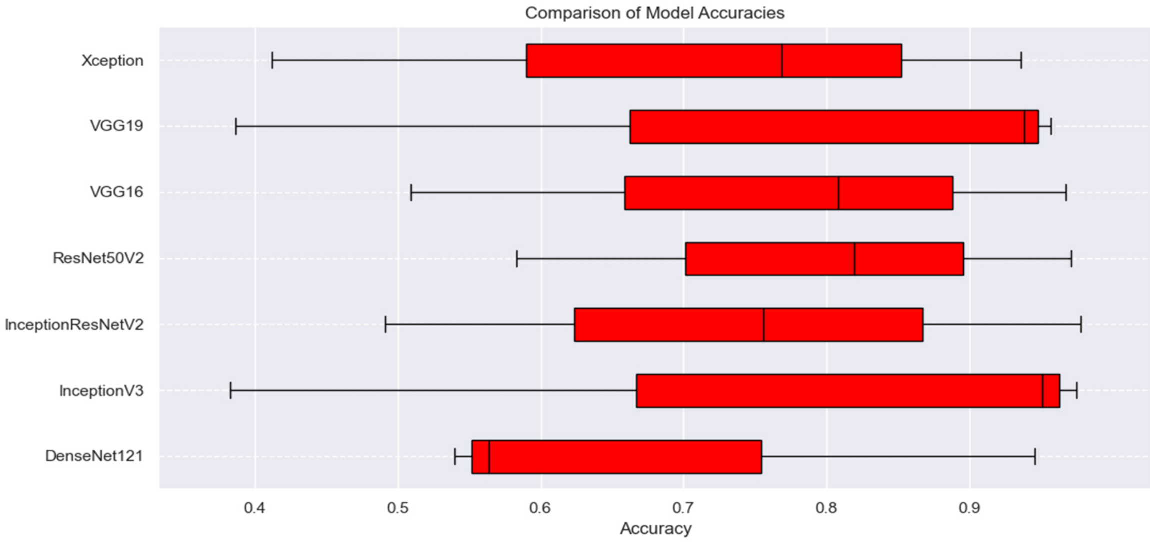

Figure 3: Model Accuracy Using a Skin Lesion Dataset

- **Evaluating Deep Learning Methods' Efficacy in Skin Cancer Classification**

The performance of several image classification models under two different training conditions—ImageNet and None with Rotation—is shown in figure 4. DenseNet121, InceptionV3, Inception ResNetV2, ResNet50V2, VGG16, VGG19, Xception, and CNN are the eight models listed on the x-axis. The accuracy is represented by the y-axis, which runs from 0.0 to 1.0. Greater bars signify superior picture classification results. While None with Rotation entails training the model without any data and then adding a rotation transformation to the pictures, ImageNet training entails using a sizable dataset of tagged images. When trained using ImageNet, models perform better on average. As an example, Xception attains almost perfect accuracy when trained on ImageNet, which is significantly different from its significantly reduced accuracy when no training data is provided. This emphasizes how important it is for models to train on a sizable dataset of labeled photos in order to achieve high accuracy levels. However, it is essential to recognize that the best model selection depends on particular data and intended results. While some models may perform better overall, others may perform better on certain picture types or classification tasks; hence, it is important to carefully weigh these considerations when choosing the best model.

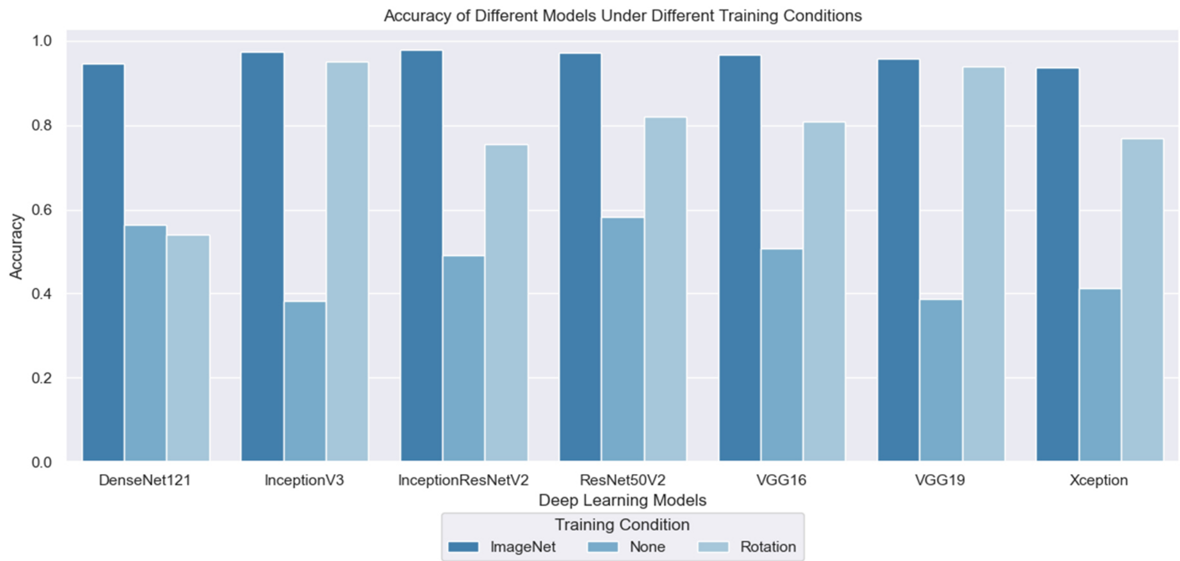

Figure 4: Model Performance in Skin Cancer Classification

V. EVALUATION VIA COMPARISON

- **Comparative Evaluation of Skin Lesion Dataset Skin Cancer Classification Models**

Actinic Keratosis, Basal Cell Carcinoma, Dermatofibroma, Melanoma, and Pigmented Benign Keratosis are the five kinds of skin lesion that are represented by the performance measures shown in table 3. For each category, the accuracy, recall, precision, and F1-score of each model are shown in detail. Important insights may be gleaned from the performance metrics of several models used to diagnose skin disorders such Actinic Keratosis, Basal Cell Carcinoma, Dermatofibroma, Melanoma, and Pigmented Benign Keratosis. The two models that do the best overall in properly identifying the circumstances are InceptionResNetV2 and VGG16, with respective accuracy of 0.9440 and 0.9547. Despite having a little lower accuracy, Densenet121 has an impressive recall of
1.000 for Basal Cell Carcinoma and Actinic Keratosis, indicating its dependability in identifying these disorders without overlooking any real positives. The trade-off between sensitivity and specificity is shown by the poor accuracy of 0.4167 for Pigmented Benign Keratosis.
Despite having a lower overall accuracy of 0.8960, InceptionV3 does well in terms of precision and F1-score under many scenarios, particularly when it comes to Dermatofibroma, where it has an F1-score of 0.8468. With accuracies of 0.9320 and 0.9120, respectively, Xception and VGG19 show good recall values but inconsistent precision, which has an impact on their F1-scores. Despite having the lowest accuracy (0.8040), the Custom CNN offers useful information about possible areas where recall and precision might be improved for greater overall performance. This thorough comparison highlights the many advantages and disadvantages of each model, assisting in decision-making for particular clinical application requirements. Together, these metrics provide information about the models' overall effectiveness and adaptability for different skin lesion categorization tasks, which is helpful in determining which model is best depending on priorities and intended results.

Table 3: Models for classifying skin cancer according to their respective performances

Model Name	Performance Metrics	Actinic_Ke ratosis	Basal_Cell_ Ca rcinoma	Dermatofibroma	Melanoma	Pigmented _ Benign_Ke r atosis

Densenet 1 21	Accuracy	0.9373	0.9373	0.9373	0.9373	0.9373
	Recall	1.000	1.000	0.8667	0.9333	0.4167
	Precision	0.8955	0.7229	1.000	0.7778	0.9615
	F1-Score	0.9449	0.8392	0.9286	0.8485	0.5814
InceptionV 3	Accuracy	0.8960	0.8960	0.8960	0.8960	0.8960
	Recall	1.000	0.5167	0.7833	0.7500	0.6500
	Precision	0.9091	0.7750	0.9216	0.6716	0.5132
	F1-Score	0.9524	0.6200	0.8468	0.7087	0.5735
InceptionR esNetV2	Accuracy	0.9440	0.9440	0.9440	0.9440	0.9440
	Recall	1.000	0.9667	0.9667	0.7667	0.6000
	Precision	0.9524	0.7436	0.9831	0.8519	0.7826
	F1-Score	0.9756	0.8406	0.9748	0.8070	0.6792
ResNet50 V2	Accuracy	0.9160	0.9160	0.9160	0.9160	0.9160
	Recall	1.000	0.9833	0.8333	0.8667	0.2667
	Precision	0.8696	0.7108	1.000	0.6582	0.8421
	F1-Score	0.9302	0.8252	0.9091	0.7482	0.4051
VGG16	Accuracy	0.9547	0.9547	0.9547	0.9547	0.9547
	Recall	1.000	1.000	0.9833	0.9000	0.5500
	Precision	0.9091	0.7500	0.9833	0.8852	1.000
	F1-Score	0.9524	0.8571	0.9833	0.8926	0.7097
VGG19	Accuracy	0.9120	0.9120	0.9120	0.9120	0.9120
	Recall	1.000	0.9333	0.8667	0.9500	0.1500
	Precision	0.8000	0.6829	0.9811	0.7125	0.9000
	F1-Score	0.8889	0.7887	0.9204	0.8143	0.2571
Xceptio n	Accuracy	0.9320	0.9320	0.9320	0.9320	0.9320
	Recall	1.000	0.9667	0.8833	0.7667	0.5333
	Precision	0.8824	0.7250	0.9464	0.7931	0.8421
	F1-Score	0.9375	0.8286	0.9138	0.7797	0.6531
Custom CNN	Accuracy	0.8040	0.8040	0.8040	0.8040	0.8040
	Recall	0.2833	0.4500	0.5167	0.9667	0.3333
	Precision	0.8947	0.9000	0.9118	0.3037	0.7692
	F1-Score	0.4304	0.6000	0.6596	0.4622	0.4651

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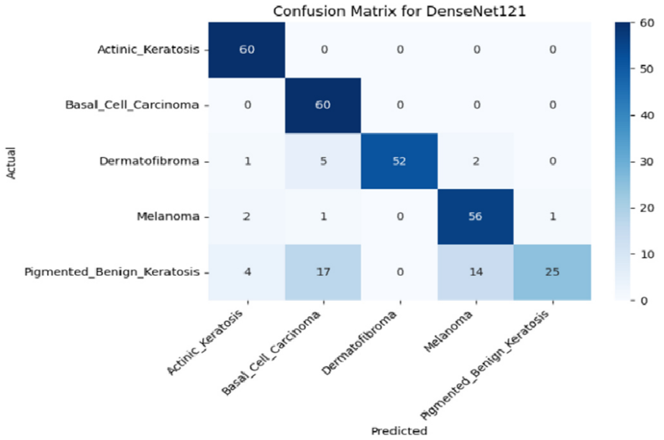

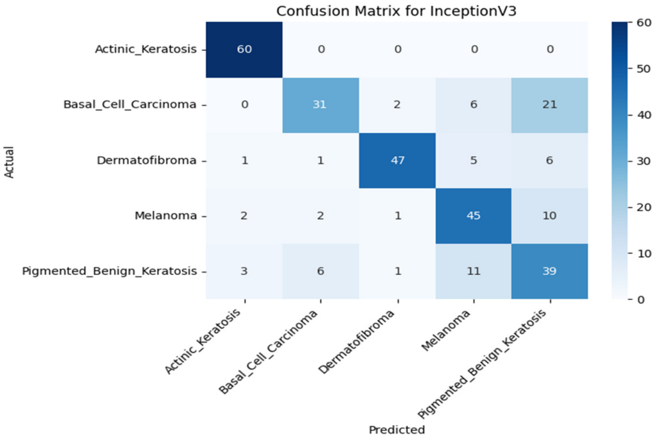

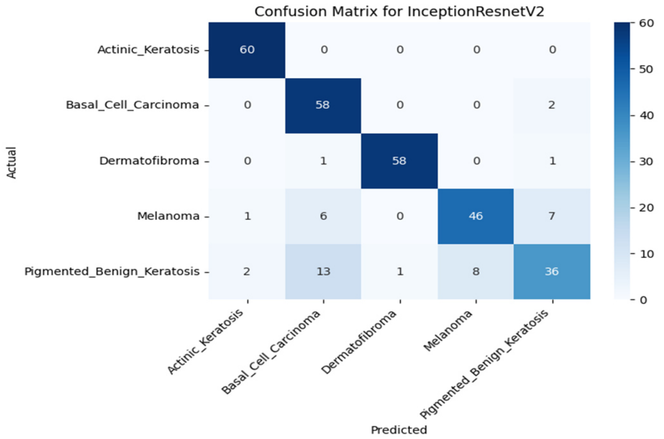

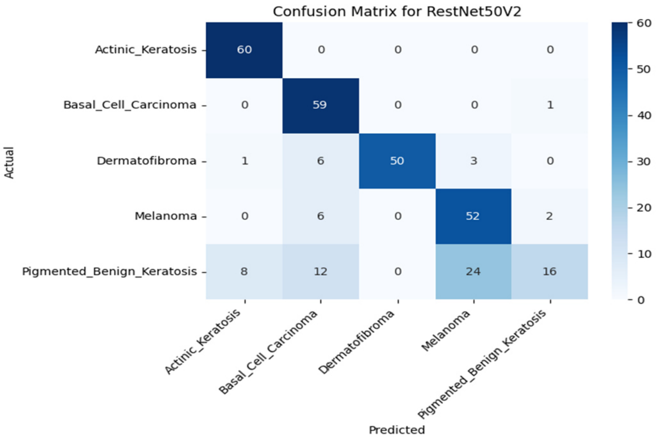

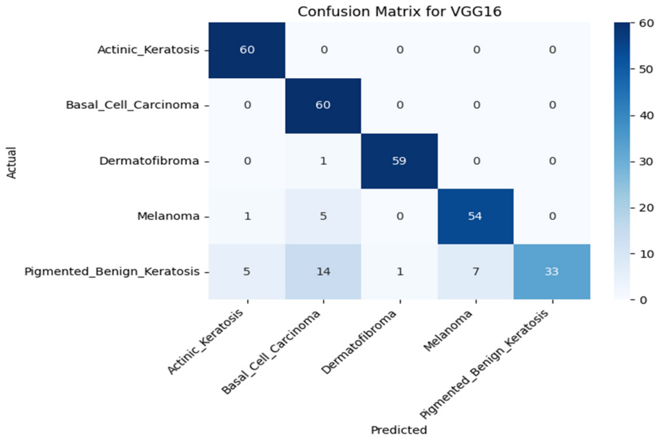

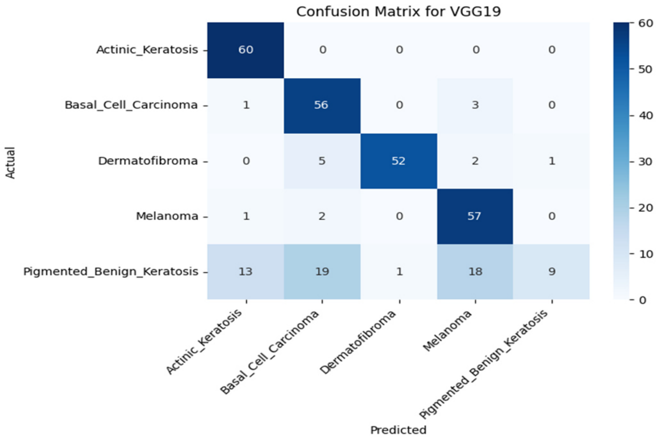

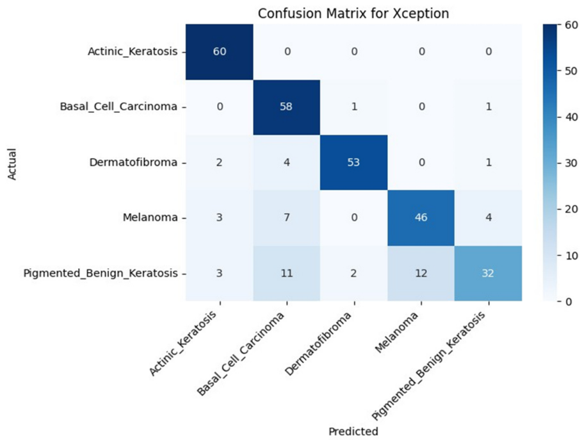

Figure 5: Comparison of Skin Cancer Classification Models

VI. Conclusion

The potential for improving skin cancer diagnosis with sophisticated deep learning models is highlighted by this work. With the use of CNN architectures trained and validated on the ISIC dataset, such as DenseNet121, InceptionV3, ResNet50V2, VGG16, VGG19, InceptionResNetV2, Xception, and Custom CNN, we were able to identify between different skin lesions with good accuracy. Higher performing models, such as InceptionV3 and Xception, showed that they were appropriate for accurate and timely skin cancer diagnosis. Selecting the best model for clinical application was made easier by the thorough examination of performance measures, which included accuracy, precision, recall, and F1-score. These metrics highlighted the unique advantages and disadvantages of each model. The optimal model, VGG16, is dependable for clinical application as it attains the maximum accuracy and balanced metrics. The Custom CNN requires a lot of work because it has the lowest accuracy and erratic recall and precision. These results highlight how AI is revolutionizing dermatology by providing reliable, impartial, and extremely accurate diagnostic instruments.

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