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Skin Cancer Diagnosis with a Customized CNN Model using Deep Learning Approaches

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Abstract:

Medical imaging has a significant challenge in accurately classifying skin lesions into benign and malignant classifications. To solve this issue, we have developed a technique that utilizes a custom convolutional neural network classifier with a support vector machine. Our customized CNN architecture is designed to address the core issue of skin cancer categorization. DenseNet121, DenseNet201, InceptionV3, InceptionResNetV2, MobileNet, ResNet50V2, ResNet101, VGG16, VGG19, and Xception are among the most prominent pre-trained models evaluated in our study. The customized CNN exceeds existing models on an average basis, displaying greater accuracy, recall, precision, and F1-Score for both benign and malignant cases. This technique has significant prospects for enhancing early skin cancer diagnosis, perhaps leading to better patient results and more efficient medical treatments.

Keywords: Artificial intelligence, Skin cancer detection, Deep learning, Pretrained Models, CNN.

1. Introduction

Skin cancer detection is a critical aspect of healthcare due to its increasing prevalence worldwide. The conventional methods of visual examination used by dermatologists for detecting skin cancer are subjective. The use of DL techniques has gained significant attention for improving the accuracy and efficiency of skin cancer detection. To offer an extensive analysis of Deep learning approaches in the identification of skin cancer through integrating various datasets and reviewing relevant literature [1]. By examining existing study, the objective is to identify the latest methodologies, address challenges, and propose potential solutions to increase the accuracy and generalizability of skin cancer models for detection. To accomplish this goal, Skin lesion datasets containing dermoscopy images, clinical photographs, and histopathological slides will be collected and curated. These datasets will be utilized in DL technique training and evaluation across different imaging techniques and patient demographics. The inclusion of a wide range of data sources will enhance the reliability and applicability of the developed models [2]. Moreover, an extensive literature review will be conducted to identify the advancements and limitations of existing Deep learning approaches in skin cancer detection. The analysis will focus on the methodologies employed, such as feature extraction techniques, classification algorithms, and model evaluation metrics. By understanding the advantages and disadvantages of certain strategies, opportunities for improvement and innovation can be identified [3].

1.1 Review of Deep Learning classifier for Skin Cancer Detection

Deep learning has emerged as a revolutionary force within the DL sector, particularly within the last few decades. It is recognized as a sophisticated subfield that focuses on ANN methods, drawing inspiration from the structure and functionality within the human mind. DL techniques have been successfully applied in various domains, including speech recognition, pattern recognition, and bioinformatics, producing impressive results when compared to traditional DL approaches [4].

In recent years, DL approaches have gained significant traction in computer-based skin cancer detection. This research goal is to provide a thorough and structured survey of the literature on DL techniques employed in skin cancer detection. The focus is on classical DL approaches such as CNN. To ensure a valuable systematic review of neural network-based classification techniques for identifying skin cancer, a rigorous strategy was devised.

1.2 Analyzing Deep Learning Methods for the Identification of Skin Cancer

DL techniques for skin cancer detection were explored. Skin cancer datasets were integrated, and a comprehensive literature review on DL methods was conducted [5]. Various DL models were applied, and their performances were compared. The potential of DL for enhancing skin cancer detection mechanisms was demonstrated. Accurate detection of skin cancer was achieved using these techniques. The significance of early detection in improving patient outcomes was emphasised. Key factors influencing accurate detection were identified and analysed. The role of DL in aiding medical professionals in making timely diagnoses and treatment decisions was highlighted [6].

2. Literature review

Skin cancer stands as a prevalent form of cancer on a global scale, posing a substantial concern for people annually. Early detection and accurate diagnosis play pivotal roles in improving patient outcomes and reducing the mortality and morbidity associated with this disease. Over the years, study and healthcare professionals have explored various innovative approaches to enhance skin cancer detection and treatment.

In their study, Shi Wang et al. [7] suggested an innovative method for skin cancer detection, combining the Extreme Learning Machine (ELM) with an enhanced version of Thermal Exchange Optimization (TEO). By leveraging ELM and TEO, they achieved improved accuracy, sensitivity, and specificity in identifying malignant skin lesions, leading to reliable and timely diagnoses. The ELM-TEO system has shown great potential for lowering mortality and morbidity associated with skin cancer, proving its usefulness within the healthcare industry. In addressing the problem of cervical cancer detection, Umesh Kumar Lilhore et al. [8] developed a Model that integrated Causal Analysis and Deep Learning techniques. This novel approach allowed the identification of potential risk factors and their relationships through causal analysis, which, in turn, contributed to building a predictive model using Deep Learning algorithms. The developed Model showcased substantial improvements in accuracy and sensitivity for cervical cancer detection, providing valuable insights for better healthcare management and improved patient outcomes.

However, not all innovations in skin cancer detection have been successful. Ahmad M. Khasawneh et al. [9] investigated the problem of immediate identification by DL-based medical picture evaluation. Unfortunately, the study faced challenges with data quality, algorithmic limitations, and potential biases, leading to the retraction of the reported results. This highlights the importance of addressing such issues and ensuring the reliability and validity of study outcomes in the domain of medical diagnostics. On a different note, M. Shobana et al. [10] successfully addressed the challenge of mesothelioma cancer classification and detection using a Feature Selection-Enabled Deep Learning technique. By identifying the most informative and discriminative features from the dataset, their method achieved high-performance classification and early-stage detection of this aggressive form of cancer. This development showed greater sensitivity and accuracy in detecting mesothelioma malignancy, with positive implications for better patient treatment and healthier outcomes.

CNN has displayed known potential in various fields, including skin cancer detection. Mohammed Rakeibul Hasan et al. [11] performed a comparative analysis using CNNs to separate equally benign and malignant skin cancer cases. Their approach demonstrated significantly improved accuracy, sensitivity, and specificity compared to conventional methods, proving the efficacy of CNN-based techniques in analyzing complex image patterns and identifying cancerous conditions. Beyond diagnosis, researchers have explored the impact of diet on skin cancer risk. Sreevidya R. C. et al. [12] suggested an innovative approach to identify potential correlations between antioxidant-rich diets and their impact on skin cancer risk. By utilizing AI and Deep Learning algorithms to analyze vast datasets of dietary information and skin cancer cases, this method revealed valuable insights into the potential preventive properties of antioxidants against skin cancer. Such AI-driven approaches hold promise in supporting healthcare professionals and individuals in making informed dietary choices to mitigate skin cancer risks and enhance overall health outcomes. Hamza Abu Owida et al. [13] focused on skin cancer therapy and detection using Biomimetic Nanoscale Materials. These nanomaterials were designed to mimic biological processes, effectively targeting and treating skin cancer cells. Additionally, they were utilized in the initial identification of skin cancer by selectively binding to cancer-specific biomarkers or signaling molecules. The data proven important advancements in the area of skin cancer diagnosis and treatment, showing the potential of biomimetic nanoscale materials as a viable and novel strategy to improve therapeutic results and boost skin cancer early detection rates.

Taher M. Ghazal et al. [14] employed Transfer Learning to address the challenge of detecting benign and malignant tumors in the skin. Their approach involved fine-tuning pre-trained deep learning models on large datasets from unrelated tasks, leading to significant improvements in accuracy and efficiency for skin tumor classification. The use of Transfer Learning empowered the method with valuable insights from unrelated datasets, offering a valuable tool for healthcare professionals in early diagnosis and effective treatment planning for patients with skin cancer. Machine Vision with Texture Features was employed by Syeda Shamaila Zareen et al. [15] to address skin cancer classification. The extraction and combination of various texture features from dermatoscopic images of skin lesions significantly enhanced the accuracy of skin cancer classification. This Machine Vision-based method demonstrated notable improvements in differentiating benign and malignant skin tumors, indicating its potential in assisting healthcare professionals in making more informed and timely decisions for skin cancer diagnosis and treatment, ultimately leading to improved patient outcomes. Muhammad Arif et al. [16] will propose another notable advancement in skin cancer evaluation. They developed an automated system using DCNN to detect nonmelanoma skin cancer. A convolutional neural network has learned from an extensive dataset of dermatoscopic pictures, enabling the automated identification and differentiation of nonmelanoma skin cancer cases based on benign lesions. Substantial advancements in enhancing the precision and reliability of nonmelanoma skin cancer detection were demonstrated, showcasing the effectiveness of Deep CNN in analyzing complex image patterns and identifying cancerous conditions. Automated detection systems can assist healthcare professionals in the initial stages of detection and timely intervention, thus contributing to improved patient care and better outcomes for individuals with nonmelanoma skin cancer.

3. Methodology

Using deep learning technology, our study improves skin cancer diagnosis by combining pre-trained CNN models, data augmentation, and image normalization. Relevant characteristics are extracted using CNN models such as DenseNet121, DenseNet201, InceptionV3, InceptionResNetV2, MobileNet, ResNet50V2, ResNet101, VGG16, VGG19, Xception, and bespoke CNNs. These attributes are then used to classify skin cancers as benign or malignant using deep learning techniques such as SVMs or random forests. This complete method creates an effective and accurate structure for detecting skin cancer.

3.1 Summary of dataset

Table 1 presents a summary of the image distribution within a medical imaging dataset. This dataset is divided into two main folders: 'benign' and 'malignant,' and further categorized into three subfolders: 'training,' 'validation,' and 'testing.' The 'training' subfolder is dedicated to images used for classifying them as benign or malignant. Model efficiency is analyzed within the "validation" subfolder during the training process, and the model's effectiveness is assessed using previously unseen data in the 'testing' subfolder. The dataset comprises a total of 2360 images, with 1180 classified as benign and 1200 as malignant. This medical imaging data set is organized according to several subfolders: 'training,' 'validation,' and 'testing,' with each subfolder containing 300 images.

Table 1. Medical Imaging Dataset

Label	Benign	Malignant	Total Images
Training Folder	1180	1180	2360
Validation Folder	1180	1180	2360
Test Folder	300	300	600

3.2 Balanced Skin Lesion Dataset for Binary Classification

The data appears to be organized into three main categories: Training, Validation, and Test sets, as seen in Figure 1. Each folder contains images of skin lesions, which have been classified into two categories: Benign and Malignant. In each of the Training and Validation folders, there are 1,180 pictures depicting benign cancers and 1,180 pictures depicting malignant cancer. This balanced distribution is important for training and evaluating deep learning models, as it helps prevent bias. In the Test folder, 300 pictures of benign lesions and 300 pictures of malignant cancers are maintained in a balanced distribution. The maximum total of pictures in the Training and Validation folders is

2,360 each, and there are 600 images in the Test folder. This dataset is going to be used for Skin Cancer Binary Classification.

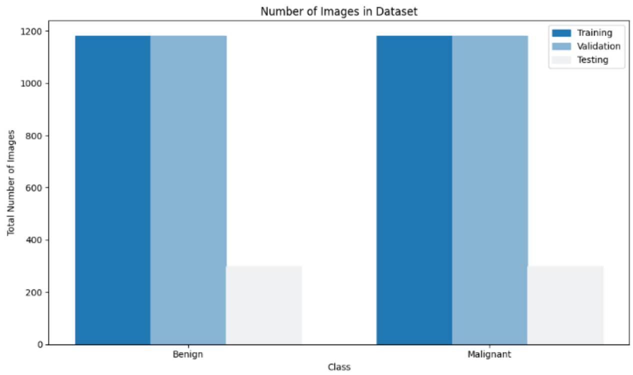

Figure 1. Skin Cancer Data Distribution

3.3 Comparative Analysis of Pre-trained Deep Learning Models by Model Complexity and Parameters

Table 2 provides a comprehensive analysis of various pre-trained deep learning models, highlighting their model complexity in terms of modifiable and fixed parameters. Trainable parameters represent those components that are fine-tuned during training, while non-trainable parameters are fixed weights that are usually pre-trained on large datasets. The overall parameter count in a model equals the sum of these two components. DenseNet121 and DenseNet201 demonstrate relatively compact architectures with lower trainable and non-trainable parameters. DenseNet121 features 32,770 trainable parameters, making it computationally efficient. InceptionV3 is characterized by a moderate number of trainable parameters (16,386) and a substantial number of non-trainable parameters (21,802,784). InceptionResNetV2 features a comparatively low number of trainable parameters (12,290) but possesses a significant number of non-trainable parameters (54,336,736). This points to its complex architecture. MobileNet is notable for having no trainable parameters, offering efficient inference with a smaller parameter footprint. ResNet50V2 and ResNet101 are more parameter-heavy models, boasting 65,538 trainable parameters each, combined with a substantial number of non-trainable parameters. VGG16 and VGG19 exhibit balance with moderate trainable and non-trainable parameters, offering a good trade-off between model complexity and computational requirements. Xception is characterized by a considerable number of trainable parameters (65,538) and non-trainable parameters (20,861,480), reflecting its complex architecture.

Table 2. Comparison of Pre-Trained Deep Learning Models Based on Model Complexity

Pre-Trained Deep Learning Models	Trainable Parameters	Non-Trainable Parameters	Total Parameters
DenseNet121	32,770	7,037,504	7,070,274
DenseNet201	61,442	18,321,984	18,383,426
InceptionV3	16,386	21,802,784	21,819,170
InceptionResNetV2	12,290	54,336,736	54,349,026
MobileNet	0	3,228,864	3,228,864
ResNet50V2	65,538	23,564,800	23,630,338
ResNet101	65,538	42,658,176	42,723,714
VGG16	16,386	14,714,688	14,731,074
VGG19	16,386	20,024,384	20,040,770
Xception	65,538	20,861,480	20,927,018

Deep Learning Approach for Skin Cancer Detection

Technology employs DL to detect skin cancer using an advanced approach. It leverages pre-trained weights from a CNN model recently adapted for image categorization tasks. Methods for enhancing data, including techniques like resizing and orientation adjustment, are used to augment the training dataset with skin lesion images. All images are standardized to a uniform size of 224x224x4 pixels. Image normalization is used to ensure consistent pixel values. Various convolutional neural network frameworks, including DenseNet121, DenseNet201, InceptionV3, InceptionResNetV2, MobileNet, ResNet50V2, ResNet101, VGG16, VGG19, Xception, and custom CNN models, are employed to extract features relevant to skin cancer identification. These features undergo a decision-making process, typically implemented using deep learning techniques like SVMs or random forests, to determine the category of skin lesions as benign or malignant. The use of pre-trained weights accelerates the process, data augmentation mitigates overfitting, image normalization ensures consistency, and a robust framework for accurate skin cancer detection is established through feature extraction and decision-making, as illustrated in the figure 2.

3.4 Convolutional Neural Network Based Skin Cancer Detection

CNNs are a vital type of deep neural network that finds effective applications in visual recognition. It is employed for image categorization, creating a compilation of the supplied images, and performing picture identification. A convolutional neural network is an excellent method of collecting and processing local and global data because it combines basic features such as curves and edges to build more intricate elements such as shapes and edges. Convolutional Neural Network intermediate layers are made up of convolutional, fully connected, and nonlinear pooling layers. CNN may contain several convolutional layers, preceded by several fully linked layers. The three primary types of layers utilized in CNN are convolution, pooling, and full-connected layers. Fig 3 presents CNN's fundamental architecture [19].

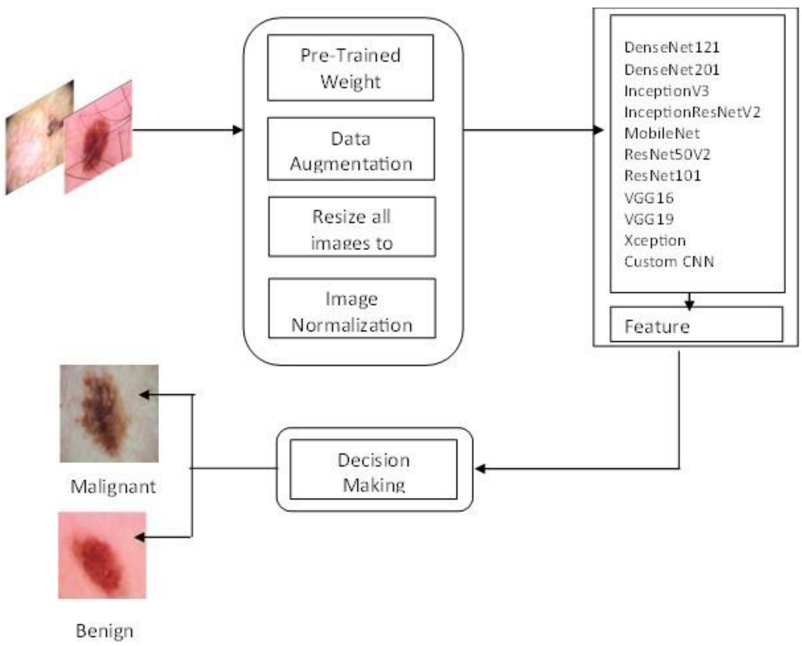

Figure 2. Deep Learning-based Skin Cancer Detection Pipeline

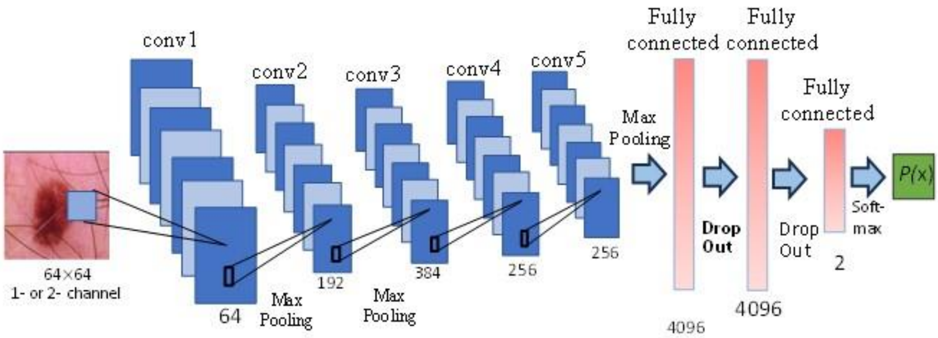

Figure 3. Skin Cancer Detection CNN Architecture

4. Experimental Results and Data Analysis

4.1 Model Performance in Skin Cancer Classification

The utilization of pre-trained deep learning models has become a prominent approach in various domains, particularly in the field of computer-aided diagnosis for skin cancer. This study offers a comprehensive performance evaluation of several pre-trained models when employed in skin cancer classification. The focus lies on five different deep learning classifiers: SVM, KNN, Decision Tree, Gradient Boosting, and Random Forest. Analyzing the models mentioned as follows: DenseNet121, DenseNet201, VGG16, VGG19, Xception, MobileNet, ResNet50V2, InceptionV3, and InceptionResNetV2. Table 3 further shows that pre-trained DL algorithms demonstrate quite distinct when applied to the categorization of skin cancer. The presented table illustrates the classification performance of each model using the five deep learning classifiers, evaluated in terms of accuracy. DenseNet121 exhibits relatively low performance across all classifiers. It struggles to achieve high accuracy in most cases. DenseNet201 demonstrates improved performance compared to DenseNet121, especially with the KNN and Decision Tree classifiers. InceptionV3 achieves consistent performance across all classifiers, indicating its robustness and suitability for various tasks. InceptionResNetV2 performs well with SVM and Decision Tree, showcasing its versatility. MobileNet achieves modest accuracy and shows potential for lightweight applications due to its efficient architecture. ResNet50V2 and ResNet101 deliver strong performance, especially with the Gradient Boosting classifier. Xception exhibits a moderate level of performance, with availability for higher-level challenges. VGG19 and VGG16 show relatively high accuracy with most classifiers, particularly with Gradient Boosting. This study highlights the impact of model complexity on classification accuracy, illustrating the drawbacks between model efficiency and performance in the context of skin cancer diagnosis.

Table 3. Performance Evaluation of Pre-Trained Deep Learning Models with DL Classifiers in Skin Cancer Classification

Pre-Trained Model \ Names of Classifiers	SVM	KNN	Decision Tree	Gradient Boosting	Random Forest
DenseNet121	0.0144	0.4766	0.40084	0.3203	0.4245
DenseNet201	0.0427	0.5152	0.6644	0.6072	0.6453
InceptionV3	0.4949	0.5084	0.4911	0.5127	0.4911
InceptionResNetV2	0.5419	0.4991	0.4949	0.4974	0.4949
MobileNet	0.0347	0.4355	0.2457	0.2042	0.2487
ResNet50V2	0.5322	0.4889	0.4936	0.5173	0.4944
ResNet101	0.7402	0.4699	0.4966	0.5245	0.4966

VGG19	0.1038	0.4762	0.4838	0.4101	0.4838
VGG16	0.0919	0.4635	0.4877	0.3292	0.4868
Xception	0.0347	0.4648	0.2313	0.2233	0.2368

4.2 Evaluation of Binary Skin Cancer Classification Models

The custom CNN algorithm outperformed the trained methods in measures of accuracy, recall, precision, and F1-score for both benign and malignant classes. Among the pre-trained models, DenseNet121, DenseNet201, MobileNet, and ResNet50V2 showed relatively good performance. In terms of Accuracy, the Custom CNN, DenseNet121, VGG16, and VGG19 models performed the best. Regarding Recall, the MobileNet model performed exceptionally well for malignant cases, but DenseNet121, VGG19, and the Custom CNN also had high Recall values. In terms of Precision, the MobileNet model showed high precision for benign cases, while DenseNet121, VGG19, and the Custom CNN had good precision values for malignant cases. The F1-Score, which balances precision and recall, demonstrated that the Custom CNN and DenseNet121 performed well for both benign and malignant cases.

Table 4. Testing for Evaluation Metric based on Deep Learning Models in Skin Cancer Binary Classification

Sr. No	Model Name	Metric	Class Benign	Class Malignant
1	Densenet121	Accuracy	0.8400	0.8400
		Recall	0.8033	0.8767
		Precision	0.8669	0.8168
		F1-Score	0.8339	0.8457
2	DenseNet201	Accuracy	0.8217	0.8217
		Recall	0.9167	0.7267
		Precision	0.7703	0.8971
		F1-Score	0.8371	0.8029
3	InceptionResNetV2	Accuracy	0.7783	0.7783
		Recall	0.7033	0.8533
		Precision	0.8275	0.7420
		F1-Score	0.7604	0.7938
4	InceptionV3	Accuracy	0.7933	0.7933
		Recall	0.7867	0.8000
		Precision	0.7973	0.7895
		F1-Score	0.7919	0.7947
5	MobileNet	Accuracy	0.8217	0.8217
		Recall	0.6667	0.9767
		Precision	0.9662	0.7455
		F1-Score	0.7890	0.8456
6	ResNet50V2	Accuracy	0.8217	0.8217
		Recall	0.8733	0.7700
		Precision	0.7915	0.8587
		F1-Score	0.8304	0.8120
7	ResNet101	Accuracy	0.7450	0.7450
		Recall	0.8300	0.6600
		Precision	0.7094	0.7952
		F1-Score	0.7650	0.7213
8	VGG16	Accuracy	0.8250	0.8250

		Recall	0.8867	0.7633
		Precision	0.7893	0.8707
		F1-Score	0.8352	0.8135
9	VGG19	Accuracy	0.8367	0.8367
		Recall	0.7467	0.9267
		Precision	0.9106	0.7853
		F1-Score	0.8205	0.8502
10	Xception	Accuracy	0.7833	0.7833
		Recall	0.8233	0.7433
		Precision	0.7623	0.8080
		F1-Score	0.7917	0.7743
11	Custom CNN	Accuracy	0.8617	0.8617
		Recall	0.8533	0.8700
		Precision	0.8678	0.8557
		F1-Score	0.8605	0.8628

4.3 Comparative analysis

The confusion matrices for several DL algorithms with the task of categorizing skin lesions as benign or malignant give fascinating perspective into their performance.

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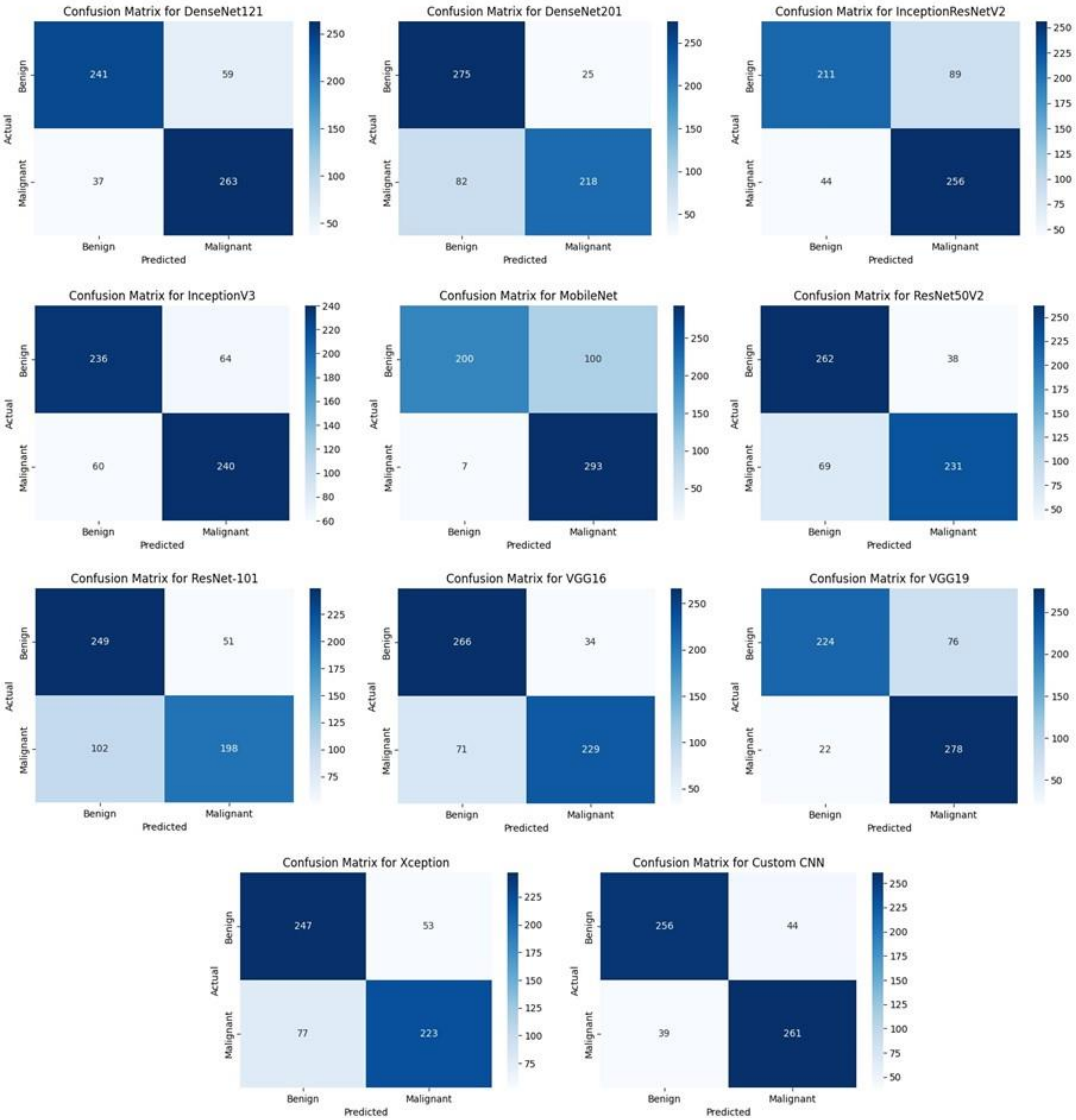

Figure 4. Performance Comparison of Deep Learning Models for Skin Cancer Categorization

Xception produced a moderately satisfactory categorization, properly detecting 225 benign and 223 malignant lesions, with a few misclassifications in each group. DenseNet201, exhibited a greater percentage of misclassification, notably for benign lesions, where 200 were correctly recognized. The frequency of misclassifications was much greater for VGG19 and VGG16, suggesting a less accurate performance in discriminating between benign and malignant cases. DenseNet121 and MobileNet produced a significantly improved misclassifications, particularly DenseNet121, which showed a high accuracy in properly diagnosing benign lesions. InceptionV3 and InceptionResNetV2 performed well, with a very even distribution of properly and wrongly categorized lesions in both categories. ResNet-101 had more difficulty with benign lesions, misclassifying a significant percentage of them as malignant. ResNet50V2 also had difficulty identifying benign instances. Finally, the Custom CNN model produced mixed results, with a large number of misclassifications, particularly in the case of malignant lesions. These findings imply that the deep learning algorithm used has a considerable impact on the precision of skin cancer lesion classification, with certain models outperforming others in this task.

5. Conclusion

This research findings present a unique and accurate mechanism for accurately classifying skin cancer lesions into benign and malignant categories. Our technique consistently outperforms renowned pre-trained models by merging a custom CNN with a SVM model. For both benign and malignant instances, the custom CNN outperforms in terms of accuracy, recall, precision, and F1-Score. Models such as DenseNet121, DenseNet201, MobileNet, and ResNet50V2 also performed well, with the custom CNN, DenseNet121, VGG16, and VGG19 dominating in accuracy. For malignant cases, the MobileNet model offers the best recall, but DenseNet121, VGG19, and the custom CNN also offer excellent recall scores. In terms of accuracy, MobileNet performs in benign situations, whereas DenseNet121, VGG19, and the custom CNN excel in malignant ones. The custom CNN's and DenseNet121's outstanding F1-Score performance demonstrates the dependability of our technique. This novel technology has the potential to enhance patient outcomes and medical treatment efficiency, consequently contributing to the evolution of healthcare imagery and improving skin cancer detection and treatment quality.

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