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A robust CNN Deep Learning and InceptionV3 model Techniques for Enhanced Skin Cancer Detection

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ABSTRACT

Skin cancer, a dangerous form of cancer, originates from DNA damage that causes unchecked cell growth, resulting in a rapid rise in its occurrence. Earlier research has explored the application of computerised analysis for detecting malignancy in images of skin lesions. Nonetheless, challenges remain, including complications with light reflections, variations in colour, and the diverse shapes and sizes of lesions. This research explores how deep learning techniques can improve the detection of skin cancer. We developed and meticulously evaluated two models: a custom-built Convolutional Neural Network (CNN) and a tailored InceptionV3 model that was pre-trained and adapted for our needs. Our primary goal with the HAM10000 dataset was to execute binary classification, distinguishing between malignant melanoma and benign nevus. The custom Convolutional Neural Network (CNN), noted for its efficient design, achieved a precision rate of 91.80%, while the more complex adapted InceptionV3 model secured an impressive accuracy of 95.72%. The findings showcased here demonstrate the effectiveness of both tailored and pre-trained deep learning models in identifying skin cancer. This showcases their capability to enhance diagnostic accuracy and efficiency, even when encountering various resource and computing constraints. This study highlights how deep learning can significantly improve the accuracy of skin cancer diagnoses, ultimately leading to better outcomes for patients.

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1. Introduction

Skin cancer remains one of the most pervasive and life-threatening malignancies worldwide, arising primarily from DNA damage that triggers uncontrolled cellular proliferation, often induced by prolonged exposure to ultraviolet (UV) radiation [1]. Despite notable advancements in medical imaging and diagnostic technologies, the accurate and early detection of skin cancer remains a formidable challenge due to the inherent variability in lesion morphology, pigmentation, and texture, as well as inconsistencies in imaging conditions [2]. Conventional diagnostic methods, including biopsies and visual examinations conducted by dermatologists, are often invasive, time-consuming, and prone to subjective interpretation [3]. In recent years, the integration of artificial intelligence (AI) and deep learning methodologies has emerged as a transformative approach in medical image analysis, offering non-invasive, highly efficient, and scalable solutions for diagnostic tasks [4]. Among these methodologies, Convolutional Neural Networks (CNNs) and pre-trained architectures such as InceptionV3 have demonstrated exceptional proficiency in image classification tasks, particularly in the domain of skin lesion analysis [5]. However, significant challenges persist, including the intricate nature of skin lesion features, pronounced class imbalances within medical imaging datasets, and the substantial computational resources required for model deployment in clinical environments [6][7][8].

To address these challenges, this study proposes the development and evaluation of two computational models tailored for skin cancer detection. The first model is a Custom Convolutional Neural Network (CNN) meticulously designed to capture intricate dermatoscopic features with computational efficiency. The second model leverages a Modified InceptionV3 Architecture, pre-trained on the ImageNet dataset and fine-tuned to accommodate the specific characteristics of the HAM10000 dataset, a widely acknowledged benchmark dataset for skin lesion classification [9]. The primary objective of this investigation is to perform binary classification, differentiating between malignant melanoma and benign nevus lesions, while rigorously optimizing key performance metrics, including accuracy, precision, recall, and F1 score.

This research contributes to the existing body of knowledge by developing a bespoke CNN architecture tailored for dermatoscopic image analysis, fine-tuning the InceptionV3 model for enhanced classification accuracy, and providing a comparative analysis to highlight the strengths and practical applicability of both models [10][11][12]. The empirical findings reveal that the Custom CNN achieved an accuracy of 91.80%, while the Modified InceptionV3 model attained an impressive accuracy of 95.72%. These results underscore the potential of deep learning models to revolutionize dermatological diagnostics by enhancing diagnostic precision, reducing diagnostic delays, and ultimately improving patient outcomes in clinical practice.

2. Literature Review

Skin cancer is a major concern for public health and is known as one of the most dangerous types of cancer because it can lead to some serious consequences and high death rates. The main of this condition is all about that DNA getting wrecked by UV rays, leading to some wild, unregulated cell growth. The rise in skin cancer cases shows we seriously need to step up our game with quick and accurate detection methods to boost patient and survival chances.

Xie et al. [10] introduced a skin lesion categorization method that divided lesions into two categories: benign and malignant. The system worked in three steps: first, it pulled out the original lesion with a self-generating neural network; then, it grabbed features like tumour edges, texture, and colour vibes; and lastly, it sorted the lesion using a model that mixes a bunch of neural networks. The model totally crushed it with an accuracy of 91.11%, outshining other classifiers like SVM, KNN, random forest, and Adaboost by at least 7.5% in sensitivity.

Masood et al. [11] created a computerized system for diagnosing skin cancer using artificial neural networks (ANNs). They compared three different learning algorithms: Levenberg–Marquardt (LM), robust backpropagation (RP), and scaled conjugate gradient (SCG). The LM algorithm demonstrated the best specificity score (95.1%) in diagnosing benign lesions, but the SCG algorithm exhibited improved performance with an increased number of epochs, achieving a sensitivity of 92.6%.

Machine learning methods have demonstrated excellent efficiency in analyzing images for skin cancer diagnosis [15]. However, the accuracy of these systems may be enhanced by extracting additional characteristics. Hoshyar et al. [16] suggested a series of image processing processes to improve the accuracy of detection, but they did not provide a specific model for efficient detection. A different research proposed a model based on deep learning algorithms, which efficiently predicted outcomes but necessitated immediate integration with medical pictures for improved implementation [17].

A skin cancer diagnostic method based on Convolutional Neural Networks (CNN) was developed by Hasan et al. [18] and tested with an accuracy of 89.5%. But for real, the overfitting vibes between training and testing were a major red flag, showing we gotta level up. In order to identify and categorise skin cancer, Li et al. [19] created a lesion indexing network (LIN) that makes use of deep learning (DL). Their study yielded impressive outcomes, however, they emphasized the necessity for improved segmentation performance.

A Convolutional Neural Network (CNN) was used by Tschandl et al. [20] to detect skin cancer in pigmented melanocytic lesions. But they hit some bumps when trying to spot non-melanocytic and non-pigmented cancers, which totally made their accuracy drop. A multi-step Deep Convolutional Neural Network (DCNN) model was presented by Saba et al. [21]. It includes colour transformation, Convolutional Neural Network (CNN)-based lesion boundary extraction, and transfer learning-based deep feature extraction. So, like, the method totally worked for some datasets, but it was kind of hit or miss with others.

To detect melanoma, Jafari et al. [22] developed a convolutional neural network (CNN) model. They used some dope preprocessing tricks to level up the picture quality before segmentation and then hit it with post-processing to make the images pop after segmentation. The model totally nailed the predictions and sorted the lesions like a pro, but it didn't spill the tea on how long it took to get it done. ResNet50, a transfer learning model presented by Le et al. [23], demonstrated greater accuracy without requiring feature handcrafting or preprocessing. But for real, you can totally boost those precision, recall, and F1 scores by adding some preprocessing steps.Tables.

3. Methodology

The goal of this project is to develop trustworthy computer models for skin cancer detection and diagnosis. To tackle the challenges posed by the large number of skin photographs in real-world circumstances, our models prioritise efficiency while maintaining accuracy. We take a close look at two computational models: one that has been tweaked from InceptionV3 and the other that is a Custom Convolutional Neural Network (CNN). To further increase accuracy, the upgraded InceptionV3 model has additional layers above the ultimate output layer. Data complexity and speed are both improved by using dense layers. Classification accuracy is much enhanced by the last layer, which uses softmax activation to forecast image classes. The best results are achieved by combining the InceptionV3 architecture with the SGDM optimiser and making small adjustments to it. Data prep, architectural design, training methods, and evaluation standards are all part of our scientific process. The procedure begins with collecting dermatoscopic images and ends with evaluating the produced models. Our strategy makes use of state-of-the-art innovations and best practices in deep learning as well as medical image analysis. Figure 1 shows the general procedure that the proposed models follow.

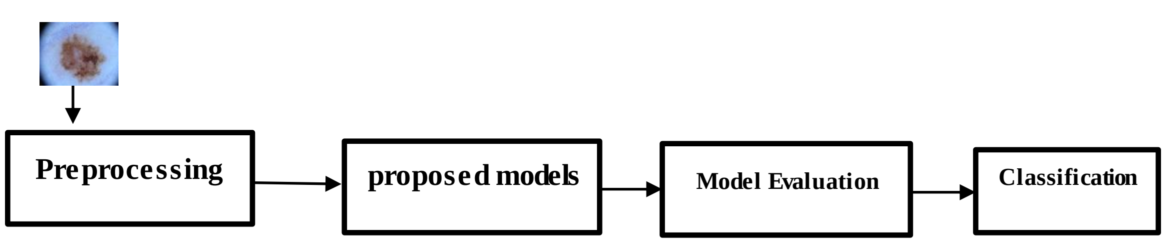


Fig. 1 - The overall flow chart of the proposed models.

3.1. Dataset

Our technique has been evaluated using the standard HAM10000 dataset. HAM10000 is an acronym that represents the Human Against Machine using a dataset of 10,000 training photos. The ultimate dataset comprises 10,015 dermatoscopic pictures sourced from the ISIC repository, which were employed as a training set by ISIC [24]. The HAM10000 dataset consists of pigmented skin lesion classifications, namely akiec, bcc, bkl, df, mel, nv, and vasc. Table 1 displays the quantities and proportions of photos in each category. The dataset clearly exhibits a substantial class imbalance, as almost two-thirds of the photos are categorized under the nv class. Figure 2 exhibits a collection of skin cancer images extracted from the dataset.

(a) (b)

Fig. 2 - Example skin cancer(a) Melanoma; (b) Nevi.

3.2. *Preprocessing Techniques*

The HAM10000 dataset comprises dermatoscopic pictures of pigmented skin lesions belonging to several classes, including akiec, bcc, bkl, df, mel, nv, and vasc. An image preprocessing pipeline consisting of many stages was developed to improve the visibility of important features and minimize noise. The pipeline includes the following steps: contrast enhancement, noise reduction, and edge sharpening. Figure 3 illustrates the flowchart of the Preprocessing Stage.

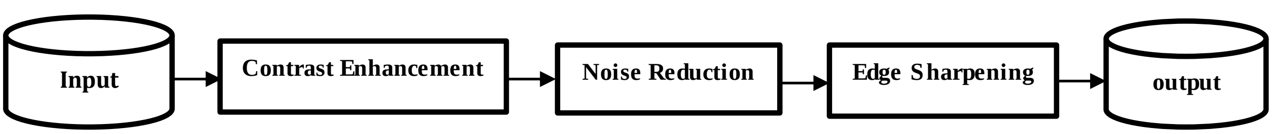


Fig. 3 - Flowchart illustrating the Preprocessing Stage.

CLAHE, or Contrast Limited Adaptive Histogram Equalization, was used to enhance dermatoscopic pictures of pigmented skin lesions with different lighting and texture due to its ability to retain edge detail well. The image clarity was enhanced by eliminating random noise using a Gaussian Blur filter with a 5x5 pixel kernel. A 3x3 kernel-sharpening filter was employed to enhance the high-frequency edge elements, hence enhancing the apparent sharpness of the edges. The calibrated preprocessing methods significantly improved the clarity of features and reduced noise, enabling machine learning algorithms to detect lesions with more accuracy.

3.3. Data Augmentation

When training a network, data augmentation technology may be used to increase the dataset size by gathering additional hidden data and changing the original data's structure. To do this, we use a generator to progressively enlarge each image before sending it across the network. There are a lot of techniques used in the approach, but scaling, rotating, flipping, zooming, and adding Gaussian noise are the most common ones [25]. To improve the performance of the resulting model and reduce the likelihood of overfitting, this method is used when training data is scarce, especially in crucial real-world contexts like medical datasets. When comparing various machine learning algorithms, this is the main difference.

3.4. Custom CNN Model architecture

The work primarily focuses on using a specialized Custom CNN Model architecture to capture detailed images of pigmented skin lesions. The model begins with an Image Input Layer that is set up to handle pictures with dimensions of 299x299x3. The network utilizes convolutional layers with 3x3 filters with sizes of 32, 64, 128, and 'same' padding to maintain the spatial dimensions. Batch normalization and ReLU activation functions are employed to improve feature extraction and introduce non-linearity. Max pooling layers are utilized with a pool size of 2x2 and a stride of 2 to minimize storage space and computational demands. The model wraps up with a fully connected layer for multi-class, a softmax layer to figure out those class probabilities, and a classification layer to make the final calls. This design totally nails the balance between being super detailed and effective, making it perfect for spotting skin lesions.

Optimising parameters such as the learning rate, number of epochs, and batch size during the training and compilation of the CNN improves its performance. The whole vibe of feature extraction totally depends on the layers and filters in the setup. Activation functions like ReLU, sigmoid, or tanh are totally for adding non-linearity to the model, helping it vibe with those complex patterns. Choosing an optimiser, like Adam or SGDM, totally vibes with how we minimise the loss function. These tweaks are super important for making sure the model is reliable, while also keeping it efficient and on point with predictions. Table 1 contains information on various arrangements.

Table 1 - Displays the settings used for training and compilation.

Parameter	Value
Optimizer	SGDM
Loss Function	Categorical Cross-Entropy
Performance Metric	Accuracy
Batch Size	32
Number of Epochs	50
Validation Split	Typically 0.2 (20% for validation)

3.5. The modified InceptionV3 model architecture

With the use of the ImageNet dataset, the InceptionV3 model comes with pre-trained weights. To match the exact count of categories in the dataset for eye diseases, the highest level of categorisation is removed. To match the input image's dimensions, which are (299, 299, 3), the input dimensions are set accordingly. A Global Average Pooling 2D layer is applied to the output of the InceptionV3 base model in order to decrease the spatial dimensions. To enhance the creation of more abstract features, a Dense layer with 1024 units and ReLU activation is utilised. To make multi-class classification possible, the model is enhanced by a final dense layer that uses units and softmax activation. Along with the newly added classification layers, the model is built using the modified InceptionV3 base model. To keep the information from the initial training session intact, the InceptionV3 base model's layers are configured as non-trainable. This approach is frequently used with models that have already been trained. Table 2 displays the InceptionV3 model's comprehensive training and compilation parameters. When it comes to sophisticated machine learning applications that demand extensive image processing, this architecture truly shines.

Table 2 - Displays the parameters used for training and compilation.

Parameter	**Typical Value/Setting**
Batch Size	32
Optimizer	SGDM
Learning Rate	0.001
Loss Function	Cross-entropy
Epochs	50
Metric(s) for Evaluation	Accuracy, Precision, Recall, F1 Score.
Validation Split	Typically 0.2 (20% for validation)

4. Results and Discussion

The proposed models are executed on the training subset of the HAM10000 dataset and later assessed on the testing subset. The test set comprises a diverse collection of dermatoscopic images illustrating various forms of skin lesions. Evaluation measures like as the Area Under the Curve (AUC) and the F1 score, obtained from the confusion matrix, are utilized to assess the concordance between predicted labels and actual labels. The AUC signifies a balance between the sensitivity and specificity of a diagnostic test. The receiver operating characteristic (ROC) curve illustrates sensitivity and specificity across various threshold levels for classification. The metrics of accuracy (1), precision (2), and recall (3) are calculated with true positive (TP), false negative (FN), false positive (FP), and true negative (TN) values. The F1 Score is determined as the harmonic mean of the accuracy and recall metrics.

$$Acc. = \frac{correct\ predictions\ result\ in\ the}{whole\ number\ of\ results} * 100\% \quad (1)$$

$$\text{Precision} = \frac{TP}{FP+TP} \quad (2)$$

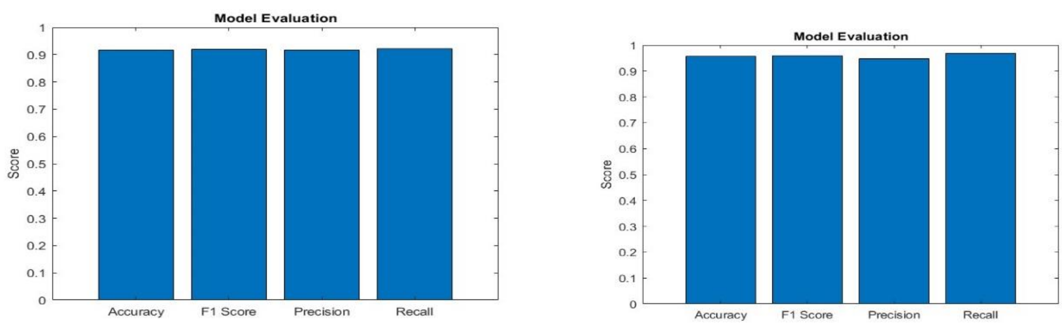
$$\text{recall} = \frac{TP}{TP+FN} \quad (3)$$

$$\text{F1} = \frac{2(\text{Precision} * \text{recall})}{\text{Precision} + recall} \quad (4)$$

The Custom CNN and modified InceptionV3 models are evaluated using the HAM10000 dataset, which consists of dermatoscopic pictures. Upon conducting a thorough comparison of the findings, it has been shown that the most optimal model may be enhanced by incorporating additional layers positioned above the output layer. Dense layers are employed to decrease the dimensions of data and enhance performance. The last layer is utilized to forecast picture categories by softmax activation. The skin lesion dataset was subjected to two rounds of testing, where the two suggested models and the modified model were evaluated. The data shown in Table 3 and Figure 3 offer a thorough assessment of the model's performance.

Table 3 - Performance Metrics

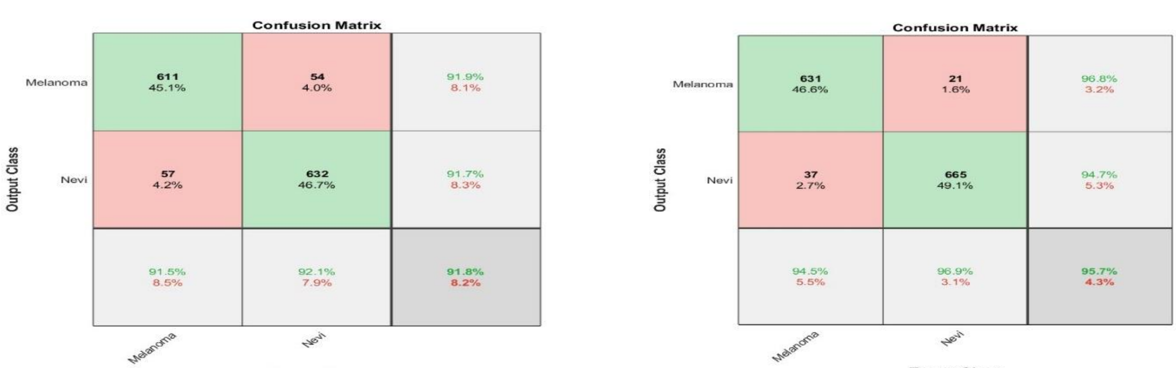
Model	Accuracy	Precision	Recall	F1-Score	AUC
Custom CNN	91.80%	91.73%	92.13%	91.93%	97.64%
Modified InceptionV3	95.72%	94.73%	96.94%	95.82%	99.12%



(a) **(b)**

Fig. 3 - Custom CNN and modified InceptionV3 Performance (a) Custom CNN Performance; (b) InceptionV3 Performance.

The confusion matrix is a useful tool for evaluating the performance of classification models, especially pre-trained models. It provides a comprehensive elucidation of the model's forecasts for several categories. Figure 4 compares the confusion matrices of the proposed models, Custom CNN and modified InceptionV3.



(a) **(b)**

Fig. 4 - Confusion matrix (a) Custom CNN; (b) modified InceptionV3.

4.1. Comparison with Previous Works

Utilizing the identical dataset employed in our work, we performed a meticulous comparison examination of our findings in relation to the outcomes of recently formulated methodologies in the domain of skin lesion categorization. The results, as shown in Table 4, demonstrate that our suggested models attained an accuracy of 91.80% for the Custom CNN and 95.72% for the modified InceptionV3 model. This comparison with previous studies emphasizes the progress and efficacy of our models:

Table 4 - Comparison with Previous Works

References	Method	Dataset	ACC
[26]	SVM	Dermques	76.1%
[27]	SVM	ISBI 2012	89.8%
[28]	HSV	HAM10000	74.75%
[29]	CNN	HAM10000	81.59%
[29]	Fusion method	HAM10000	82.95%
This study	Custom CNN model	same as used	91.80
This study	Modified InceptionV3 model	same as used	95.72

5. Conclusions

Skin cancer, a highly perilous type of cancer, is caused by DNA damage that results in uncontrolled cellular proliferation, and its occurrence is fast escalating. Although there have been improvements in the use of computerized analysis to detect malignancy in skin lesion photos, there are still difficulties to overcome, including issues with light reflections, changes in color, and the presence of various lesion forms and sizes. This study investigated the utilization of deep learning techniques to improve the identification of skin cancer. We created and thoroughly assessed two models: a specifically built Convolutional Neural Network (CNN) and a modified InceptionV3 model that was pre-trained and adjusted. Using the HAM10000 dataset, which is all about telling apart malignant melanoma and benign nevus, our models have totally some serious potential.

The CNN that was built totally slayed with an accuracy rate of 91.80%, showing it performs like a champ even though it's not super complicated. The upgraded InceptionV3 model, with its dope design, hit a sick accuracy of 95.72%. The results show that both custom and pre-trained deep learning models are totally lit at spotting skin cancer.

The findings from our research show that these models can seriously boost the accuracy and efficiency of diagnoses. The customized CNN is a total solution, giving you a solid solution while keeping the computing needs.

The upgraded InceptionV3 model is totally boosting accuracy and making it perfect for those heavy-duty applications. This work shows how deep learning can totally level up skin cancer diagnosis and boost patient outcomes, opening the door for way more accurate and effective detection methods in clinical settings.

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