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Enhanced skin cancer classification via Xception model

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ABSTRACT

Skin cancer is a prevalent and deadly cancer, and early detection is crucial for improving treatment success. Intelligent technologies are currently being used to classify skin lesions. The fundamental goal of this experimental research is to investigate biomedical skin cancer datasets to develop an effective approach for determining whether a cancer is malignant or benign. Well-known deep learning classification models (convolutional neural network (CNN) (sequential), ResNet50, InceptionV3, and Xception) are employed to train and categorize the dataset images. Two large and balanced datasets are collected and employed in this research. One is used to compare the performance of the employed model algorithms. Next, the selected model(s) are again trained on the second dataset for validation and generalization purposes. It turns out that the performance of the Xception model is superior and can be generalized. The performance results obtained from various simulations are tabulated and graphed. Comparative results are also presented.

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1. INTRODUCTION

Skin cancer is the formation of abnormal cells in the tissues of the skin. New skin cells grow to replace the aging and dying ones. When this process malfunctions, as it does after being exposed to the sun's ultraviolet (UV) radiation, cells proliferate more quickly. Symptoms include new bumps or spots on the skin, as well as alterations in the size, form, or color of skin growths. These cells might not spread or cause harm to the body if they are not malignant. They could also be malignant. The UV radiation from tanning beds and sunlamps can also raise the risk of skin cancer.

There are three classifications for skin cancer. Squamous cell carcinoma grows in squamous cells in the skin's outer layer; basal cell carcinoma originates in basal cells in the lower epidermis (the skin's outer layer); and melanoma originates from melanocyte cells, which produce melanin. Melanin is a brown pigment that gives color to the skin and protects it from some of the sun's harmful UV rays. This is the worst form of skin cancer, and it is the main cause of skin cancer mortality because it can easily spread to other body parts.

Despite the introduction of multiple campaigns and initiatives aimed at prevention, the mortality rate due to skin cancer is rising. The key preventive strategies that received the greatest media attention included education campaigns, risk modeling to identify people who are more likely to get melanoma, and encouraging the use of sunscreen. The secondary preventive strategies that were most frequently noted included visual diagnosis in population-based screening, smartphones, new technology, and imaging devices

for early skin cancer detection. Primary prevention education initiatives aimed at improving sun protection habits are shown to be the most effective measures.

Early detection of most skin cancers leads to effective treatment. However, diagnosis and treatment pose significant health risks, affecting patient outcomes and healthcare costs. Suspicious lesions found during physical exams typically require a skin biopsy. If the pathologist confirms cutaneous cancer through tissue examination, further action is usually necessary. The dermatologist then identifies the type of skin lesion, assesses if it indicates skin cancer, and explores possible treatment options.

Scientific and technological developments are changing how medical professionals perceive, identify, and manage skin malignancies. Emerging technologies, from whole-body scanning to genomic testing, are assisting dermatologists in making better judgments to enhance patient outcomes and health outcomes. At the center of everything is data. Physicians are getting more access to big data, which is accurate and can be used to improve patient management and skin cancer diagnosis. The ultimate goal is to assist patients in leading longer and healthier lives.

Diagnosing skin cancer is challenging for dermatologists because it requires invasive procedures like biopsies and histological analysis, which are time-consuming, stressful, and can cause mental health issues. Current methods for predicting recovery combine population-based data with clinical and test results but remain invasive. Treating melanoma is particularly difficult due to the aggressiveness and recurrence of cancer cells, as well as the toxicity and side effects of repeated conventional treatments. While less invasive options like topical chemotherapies exist, their use has been limited by issues with microneedle size and rapid polymer dissolution. A wearable patch [1] offers a potential new approach to treatment.

For the best results, prompt identification and classification are necessary. Enhancing or supplementing image recognition with artificial intelligence seems to be a workable way to early detection of various cancer types [2], [3]. Machine learning (ML) and hybrid techniques may also be utilized for identification and classification, even though deep learning (DL) algorithms are frequently used [4]. These methods have demonstrated remarkable classifier performance, with encouraging early detection results. This research explores the application of well-established DL algorithms for early classification of skin cancer cells and evaluates the generalization performance of the most effective algorithm over multiple datasets. Searching for "skin cancer detection" on Google yielded 129,000,000 studies, including publications, resources, support centers, and foundations. This demonstrates the wealth of general information on research publications, grants, institutes, and support services related to preventive measures, among other things. A selection of well-known research publications is shown as follows.

In the literature review from 2017 to 2021, Haggenmüller *et al*. [5] analyzed 19 studies on artificial intelligence (AI)-based skin cancer classification. Of these, 11 used convolutional neural network (CNN)-based methods for dermoscopic images, six focused on clinical images, and two employed digitalized histopathological images. CNN-based classifiers generally outperformed or matched clinicians but were tested in simulated environments with limited image diversity. Additionally, the test sets lacked a full representation of patient demographics and melanoma subtypes. CNN models were found to have superior accuracy compared to other ML algorithms, achieving over 90% accuracy in some cases [6]. Medical professionals could use these models to aid in early skin disease detection. A survey [7] provided an overview of DL models and datasets for skin cancer classification, while a similar study [8] compared the efficiency of various supervised learning methods such as linear regression, random forests, and support vector machines.

Mokoatle *et al*. [9] use raw deoxyribonucleic acid (DNA) sequences from matched tumor/normal pairs as input to the technique, which is subsequently processed by sentence transformers to provide DNA representations. Such representations are classified through a series of machine-learning methods to improve cancer detection. Another study by Koh *et al.* [10] addresses the challenges and potential of AI and ML in cancer imaging, including the use of freely available resources for algorithm development to improve collaboration and openness across centers, as well as the formation of the ecosystem required to encourage artificial intelligence and ML adoption in the field of cancer imaging. Magdy *et al*. [11] suggested two approaches for detecting and classifying benign and malignant cancers in dermoscopic imagery. The first method employs a k-nearest neighbor, which utilizes pre-trained deep networks as feature extractors. AlexNet with Grey Wolf optimizer is the second. In categorizing skin cancer images, the results are compared to ML and DL techniques. From the International Skin Imaging Collaboration (ISIC) archive dataset with four thousand images, the experiments are trained and tested. The results demonstrated that the proposed methods exceeded the other examined techniques.

Riaz *et al*. [12] propose a collaborative learning system based on CNN and local binary patterns (LBP), followed by the conjunction of all retrieved features using CNN and LBP architecture. To handle multiclass skin-related challenges, the suggested system is trained and tested using a commonly utilized accessible public dataset for skin cancer diagnosis. The architectures and their fusion are compared in terms of results, which demonstrate the fusion architecture's robustness, with 98.6% accuracy and 97.32% validation

accuracy. Kadampur and Riyaee [13] discuss how a model-based architecture in the cloud employing learning algorithms is utilized to build models that help detect skin cancer. The learning models created are assessed on common datasets, and the area under the curve is measured at 99.77%.

Moataz *et al*. [14] enhance the Xception model for skin lesion classification by adding layers after the basic ones and re-tuning it using the human against the machine with 10000 training images (HAM10000) dataset. The modified model shows improved dependability and efficiency compared to earlier models. Ma *et al*. [15] in their research, a skin cancer classification model is developed using feature fusion and random forests. It pre-trains the EfficientNetV2 model and fine-tunes it on the HAM10000 dataset. Enhanced bilinear pooling is introduced to capture feature interactions across layers, leading to high performance with an accuracy of 94.96%, precision of 93.16%, recall of 93.70%, and an F1-score of 93.24%. The study of Mridha *et al*. [16] focuses on building trustworthy models for skin cancer classification, with an emphasis on model interpretability and a comprehensive smart healthcare system. The model, evaluated using six classifiers, achieved a classification accuracy of 82% through optimization and activation functions.

In the research of Huang *et al*. [17], the performance of two models, a hyperspectral narrowband image (HSI) model, and a red, green, blue (RGB) classification model, was evaluated using a confusion matrix and metrics such as recall, precision, accuracy, specificity, and F1-score. The HSI model outperformed the RGB model by learning features better, resulting in a 7.5% improvement in recall rates (HSI: 0.792, RGB: 0.722). And Tajerian, *et al*. [18], pre-processing techniques like resizing, data augmentation, and labeling were applied to enhance the dataset. Transfer learning was then used to create a model with EfficientNet-B1, a global pooling layer, and a softmax layer with 7 nodes. This approach showed promise for diagnosing skin lesions, achieving an F1 score of 0.93 on melanocytic nevi lesions.

Based on the literature review, it is found that most of the approaches are tested on a single limited dataset, thus the results may not be generalized. This research study aims to propose a DL-based skin cancer detection approach that is applied to two publicly found datasets with images of skin cancer lesions to improve the confidence of the physician/dermatologist in detecting cancer in the early stage. The paper is structured as follows. In the next section, the proposed approach is represented, where details of the architecture and methodology are discussed. This section also presents models under investigation, datasets, and evaluation metrics. Section 3 presents experimental results and comparisons done with works found in the literature. In section 4, conclusions are discussed.

2. PROPOSED METHODOLOGY

The training process of deep networks to recognize patterns in data and make decisions or predictions based on detected patterns is central to ML. The DL models are statistical and allow investigators to evaluate the performance of the model after learning from available data. As labeled datasets are now easily accessible in the public domain, several learning models have been published in the literature with claimed accuracy related to skin cancer detection reaching 90% on selected datasets. With the availability of high-power computational machines, it seems easy to validate the claimed accuracy on a given dataset. But the issues faced are many. The foremost is the training of complex models on large datasets. This takes a lot of time, as most of the time the resources are shared amongst users. Next, sometimes it is not possible to find models that are tested on more than one dataset.

In this research, the methodology is to investigate a set of learning models (like CNN sequential, InceptionV3, ResNet50, and Xception), which are selected based on their performance on skin cancer detection. To save training time, their performance is calculated based on phases to optimize the computational cost versus selected models. In the first phase, a balanced dataset (dataset 1) is employed to train learning models for performance. Next, the trained models are cross-validated and tested based on performance metrics. Some of the learning models in this phase are dropped due to poor performance, and the rest move on to the next phase. In the second phase, a subset of a large dataset (dataset 2) is used to assess the generalized performance of the selected models. The better-performing models in this phase enter the last stage, where their generalized performance is investigated on the full dataset (dataset 2). The methodology is depicted in Figure 1.

The loaded dataset 1 needs to be preprocessed and labeled before being supplied to algorithms for model building. It was made sure that the dataset chosen for the model was balanced for accurate prediction. In the first phase, four algorithms frequently reported in the literature for skin cancer classification are to be trained, cross-validated, and tested before being declared suitable for further investigation on generalization. The criterion chosen for the performance measure was classification accuracy. In the next phase, the chosen model(s) are selected for generalization, i.e., they are trained on a balanced subset of a larger dataset (dataset 2). The performance measures include computing the confusion matrix for validating accuracy measured in phase 1. The selected model(s) in this phase are trained and tested on full dataset 2 and compared with approaches found in the literature. In the following, the selected models and datasets are discussed briefly.

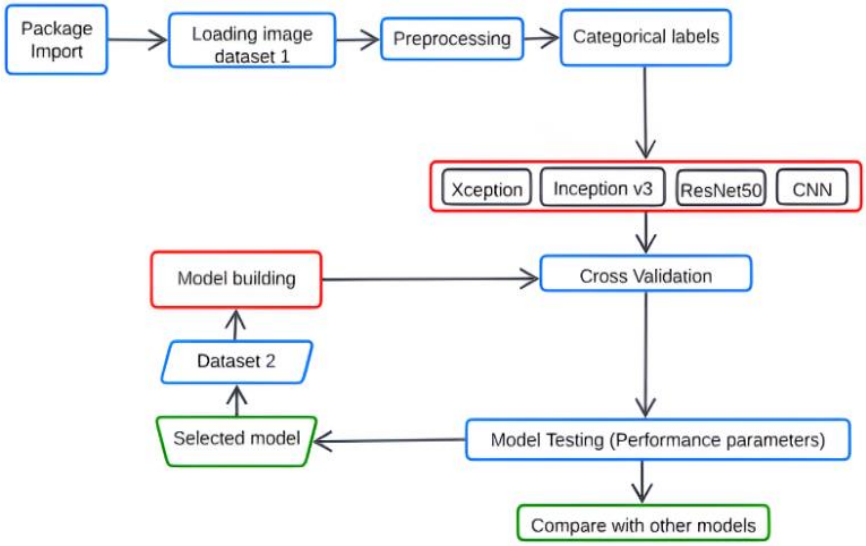

Figure 1. Proposed methodology

2.1. Deep neural network models

CNN, a form of deep neural network, uses a grid-like architecture to process data and analyze it for early detection of disease for patient care, and community services. With the growth in medical data, collecting medical records is increasingly convenient and useful. However, the accuracy of prediction depends upon the quality of the medical data. Simple patterns (lines and curves) are detected initially by assigning priorities to various object features, followed by more intricate feature patterns. CNN is intended to learn the feature hierarchies via a learning algorithm by utilizing several convolution and pooling layers, which are followed by a fully connected layer [19]. The simple form of CNN is known as traditional or sequential CNN.

The study of Szegedy *et al.* [20] discusses enhancements to deep convolutional networks through the inception architecture, specifically InceptionV2, and V3, which improve accuracy and reduce computational complexity without compromising generalization. These upgrades make the networks both deeper and wider by stacking multiple inception layers. The key innovation in inception models is the inception block, which concatenates the outputs of various filters applied to the same input tensor. InceptionV3 also incorporates 1×1 convolutions to divide the input into multiple 3D spaces before applying standard convolutions. InceptionV3 includes all improvements from V2, along with the root mean squared propagation (RMSProp) optimizer and techniques like factorized 7×7 convolutions, batch normalization (BatchNorm), and label smoothing.

ResNet50 is a deep CNN architecture with up to 152 layers, utilizing heavy BatchNorm to improve weight values. The term "Residual" refers to the use of residual blocks in the network, which include skip connections, allowing the network to learn residual functions. These connections enable not only the linking of consecutive layers but also the bypassing of certain layers, helping to address the vanishing gradient problem by directly conveying information from earlier layers to later ones. Trained on image datasets like ImageNet, ResNet50 has strong feature extraction capabilities and can be fine-tuned for specific visual identification tasks [21].

Xception is a deep neural network pre-trained on over a million images from the ImageNet repository [22]. It builds upon the principles of inception, using depth-wise separable convolutions to improve efficiency. Xception extends the InceptionV3 architecture by replacing the spatial dimensions of convolutional filters (1×1, 3×3, 5×5) with a single 3×3 dimension, followed by a 1×1 convolution to control computational cost and improve learning efficiency. This design results in better performance than InceptionV3 with the same number of parameters. Xception outperforms InceptionV3 not only on the ImageNet dataset but also on larger datasets containing 350 million images and 17,000 classes [22].

2.2. Datasets and evaluation metrics

DL architectures require powerful machines and large datasets to perform effectively, but the smaller size and limited diversity of dermatoscopic images can hinder their performance in diagnosing pigmented skin lesions. To address these challenges, a two-phase approach was adopted for comparing DL architectures on a personal computer. In the first phase, a smaller dataset is used to train and test various DL architectures, shortlisting the best-performing ones for the next phase. This dataset consists of 2,637 images (1,440 benign and

1,197 malignant) with a testing set of 660 balanced images (360 benign and 300 malignant). The second phase [23] involves evaluating the selected models on a larger dataset to assess their generalized performance.

The HAM10000 dataset is a collection of 10015 dermatoscopic images from different populations stored by different modalities and collected over 20 years. This imagery [24], freely available for building and validating DL algorithms for categorizing skin lesions, represents all important diagnostic categories of pigmented lesions. In this dataset, the use of histopathology confirmed the presence of more than 50% of lesions; in the remaining cases, follow-up investigation, expert consensus, or in-vivo confocal microscopy confirmed the lesion. To calculate performance parameters, several values need to be measured, which are calculated from the confusion matrix. The confusion matrix includes true positive (TP), true negative (TN), false positive (FP), and false negative (FN) measurements. These measurements determine precision, recall, accuracy, and F1-score [4]. In the next section, the results are shown based on the training and testing of these models on two datasets. Preliminary testing results of this work are reported in [25].

3. EXPERIMENTAL RESULTS

Preprocessing clinical images is a crucial stage in ML applications in healthcare for many reasons. The primary goals of picture preprocessing are to improve image quality, and clarity, and remove unwanted effects or background noise. Preprocessing in the context of skin cancer classification essentially consists of multiple procedures aimed at preparing and improving the quality of medical images and associated data for subsequent analysis and diagnosis. After loading images from dataset 1, two steps were performed: i) standard scaler processing removed the mean and scaled each feature or variable to unit variance and ii) each image was normalized from 0 to 1. After preprocessing, the resulting images were labeled.

3.1. Simulation 1

Four models, i.e., sequential CNN, ResNet50, InceptionV3, and Xception, were employed on the first public dataset that contained 3297 skin cancer images. These images were divided into two sets: training and testing, with a ratio of approximately 80:20. The CNN model was trained for fifty epochs with a learning rate of 0.00001. The training and validation were performed threefold, and the model performance turned out to be moderate with an average accuracy of 74.63%. The ResNet50 model was also trained for fifty epochs with a learning rate of 0.00001. The training and validation accuracy improved compared to CNN and were recorded at 96.92 and 80.5%, respectively. The InceptionV3 and Xception models were applied as well to the same dataset for ten epochs, and the resulting training accuracy was scored at 93.45 and 97.84%, respectively, and the testing accuracy was at 86.7 and 86.9%. For comparison purposes, the results are displayed in Table 1. For visual inspection, Figure 2 shows the training and validation accuracies of each of the three models i.e. CNN (Figure 1(a)), ResNet50 (Figure 1(b)), and Xception (Figure 1(c)), and illustrates how the final accuracy value is achieved. It is clear from this simulation that the performance of the InceptionV3 and Xception models is superior to those of the CNN and ResNet50 models.

3.2. Simulation 2

To generalize the performance of InceptionV3 and Xception models, dataset 2 (HAM10000) was employed. To avoid CPU crashes due to heavy computations on both the InceptionV3 and Xception models, a balanced subset (3250 images) of the HAM1000 dataset was chosen to train the InceptionV3 and Xception models, and a balanced set of 1000 images was employed for testing both models. The models carried the same parameters, and the resulting training accuracy turned out to be 94.51 and 97.85% for the InceptionV3 and Xception models, respectively, and testing accuracy of 86.9 and 89.4% for the InceptionV3 and Xception models. The results are shown in Table 2. The results suggest that the Xception model's performance is superior to the InceptionV3 model for skin cancer classification. The resulting confusion matrix shows values of 89.4, 97.1, 81.2, and 88.4% for accuracy, precision, recall, and F1-score, respectively.

3.3. Simulation 3

To investigate further, the whole HAM10000 dataset was employed to assess the generalized accuracy performance of the Xception 3 model with the same parameters. The resulting accuracy of the Xception model for skin cancer classification turned out to be 98 and 92.3% for training and testing, respectively. The resulting accuracy graph is shown in Figure 3; Figure 3(a) shows accuracy on the HAM10000 subset and Figure 3(b) shows accuracy on the full dataset. For comparison purposes, the accuracy based on testing 1000 images (from simulation 2) was also computed and is also plotted in Figure 3. Both graphs suggest that increasing the dataset improved model accuracy, and reaffirmed the superior generalized performance of the Xception model. Further, the results of this research were compared with recent literature on skin cancer classification employing different datasets, and are displayed in Table 3. The comparative results show the better performance of the Xception model over multiple datasets.

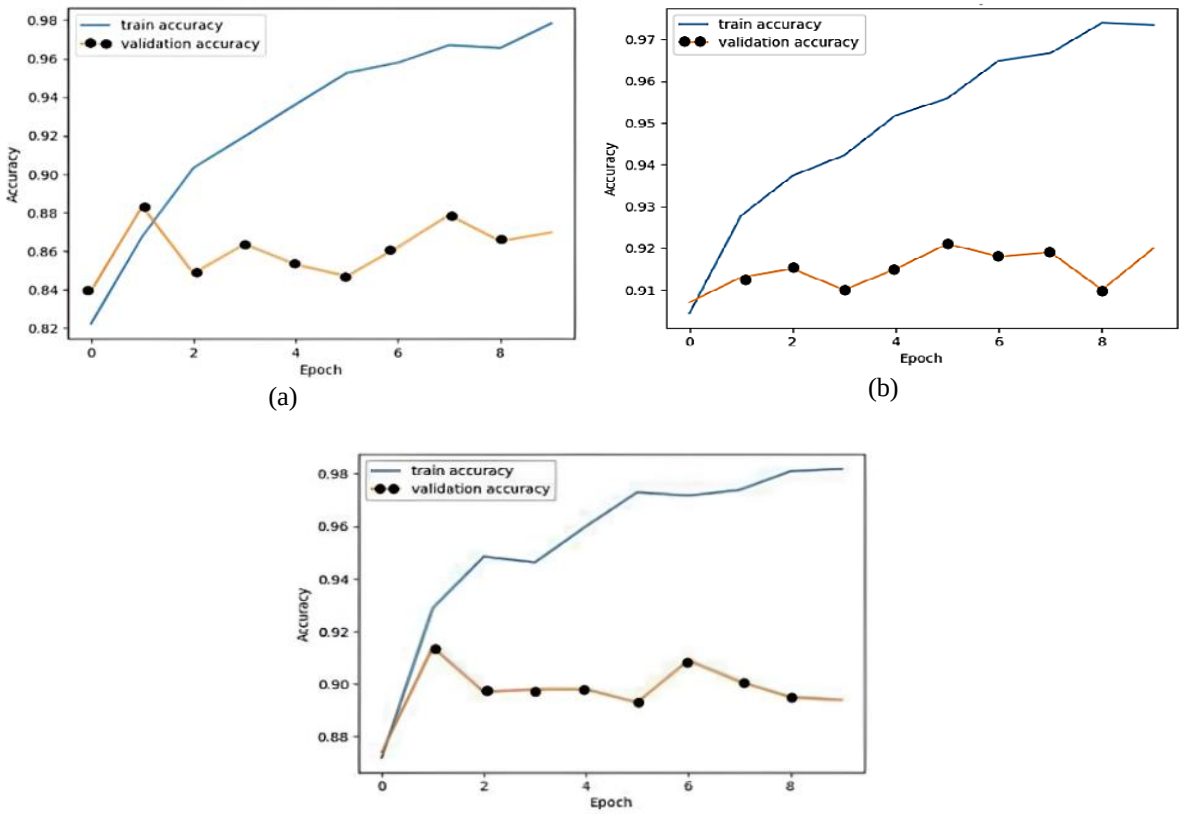

Figure 2. Training accuracy of (a) CNN sequential, (b) ResNet50, and (c) Xception

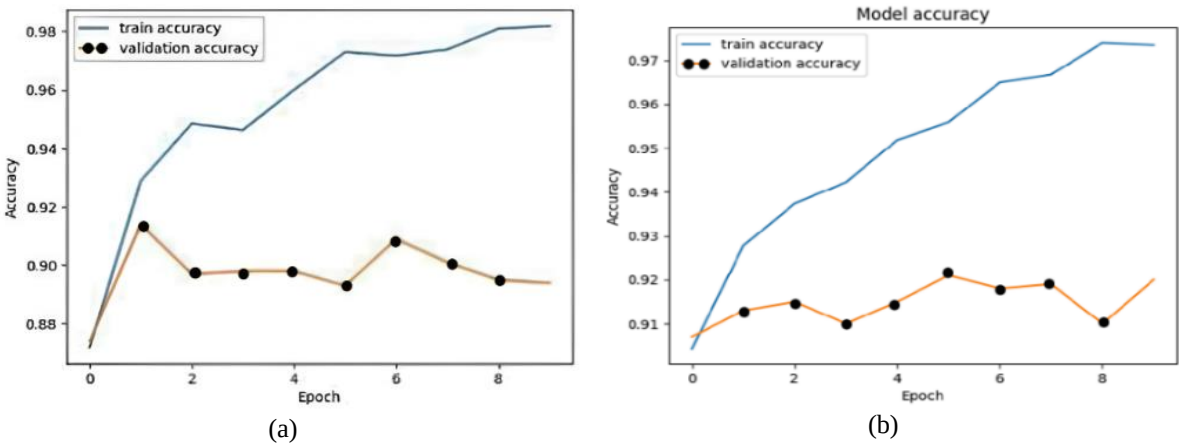

Figure 3. Accuracy on (a) HAM10000 subset and (b) full dataset

Table 1. Accuracy of models on the first dataset

Model	Training	Testing
CNN	78.5%	69.53%
ResNet50	96.92%	82.88%
InceptionV3	93.45%	86.7%
Xception	97.84%	86.9%

Table 2. Model accuracy on a subset of the HAM10000 dataset

Model	Training	Testing
InceptionV3	94.51%	86.9%
Xception	97.85%	89.4%

Table 3. Comparison of models based on accuracy

Source	Dataset used	Accuracy	Whether generalized?
Mridha *et al*. [16]	HAM10000	82.0%	No
Huang *et al*. [17]	ISIC	79.2%	No
Tajerian *et al*. [18]	HAM10000	84.3%	No
Ali *et al*. [26]	HAM10000	91.93%	No
Proposed	HAM10000	92.93%	Yes

4. CONCLUSION

This research evaluated multiple DL models on a balanced dataset, with the top-performing model further trained on a larger dataset to assess generalization. To improve computational efficiency, a subset of this larger dataset was used for evaluation, excluding less effective models. The Xception model excelled, achieving 99% accuracy in training and 93% in testing. Despite using only a few training epochs, the model's performance could potentially be improved with hyperparameter tuning. Comparisons suggest this model outperforms other recent studies. The results of this model are likely to enhance standardization and regularization activities. Standardization in skin cancer detection is guided by dermatology and medical imaging initiatives. Key efforts include developing protocols, guidelines, and benchmarks to advance technology. The ISIC organization contributes by offering a database of clinical and dermoscopic images and organizing research challenges. Regulatory bodies like the European Medicines Agency and the Food and Drug Administration (FDA) establish standards for medical devices and testing to ensure compliance and effectiveness.

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