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Accurate and Automated Deep Learning Solution for Skin Cancer Detection

Raj gaurang Tiwari[1], Sandeep Kumar[2], Gaurav Vishnu Londhe[3], Ambuj Kumar Agarwal*[4], Rajat Bhardwaj[5]

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Abstract*:* Cancer of the skin is a major health concern worldwide. In order to aid clinical decision-making, early categorization of skin lesions is essential. This can potentially increase the likelihood of a cure being found for the disease before it progresses to malignancy. However, automatic skin cancer classification is challenging due to the imbalance and scarcity of most skin disease training photos, as well as the model's ability to adapt and be resilient between domains. In this paper, an optimized deep neural network is proposed to enhance disease detection accuracy so that an accurate automated solution can be generated for practitioners. According to the findings of the comparison between the proposed model and other models, the proposed model outperforms the other models.

Keywords: *Convolutional neural network, deep learning, generative adversarial networks, , image classification, skin cancer.*

1. Introduction

The need for an efficient approach to automatically categorize skin cancer is critical with the growing frequency of the disease as well as the value of early diagnosis. The skin, the biggest one of the human body's organs [1], is responsible for safeguarding other bodily systems, making it more susceptible to illness [2]. Around 300,000 new instances [3] of melanoma were reported globally in 2018, making it the most prevalent malignancy in both men and women. In 2018, there were approximately 1 million occurrences of basal cell carcinoma (BCC), the second most widespread kind of skin cancer, and squamous cell carcinoma (SCC), the third most common type [4]. According to [5], the United States diagnoses more cases of yearly more cases of skin cancer than all other malignancies combined. Thankfully, the likelihood of recovery is significantly increased if the condition is caught early. When melanoma does not metastasize, [4] states that the 5-year survival rate is 99%. The likelihood is that even if the percentage falls to 20% if it spreads to other bodily organs. Diagnostic outcomes are frequently reliant on the dermatologist's competence, though, as early signs of skin cancer are not usually obvious [6]. An automated diagnostic system is a vital tool for less experienced practitioners to make more accurate diagnoses. Moreover, it is extremely subjective and infrequently generalizable to make a skin cancer diagnosis with just the naked eye [7]. Therefore, it is essential to create a skin cancer fully automated categorization system that is more precise, more affordable, and quicker to detect [8]. Additionally, employing such automated diagnostic methods can successfully reduce skin cancer mortality, benefiting healthcare systems and patients [9].

Although, it is difficult to achieve automated categorization of skin cancer due given skin diseases' richness and variety of pictures. To begin with, there are many similarities between various skin lesions, which might lead to a mistake [10]. For instance, SCC and other skin conditions might act as different BCC mimics in histological imaging [11]. In light of this, it may be difficult for current techniques of diagnosis to reliably differentiate between skin malignancies and their well-known imitators. Second, skin lesions may vary greatly in colour, appearance, structure, size, and location, even among members of the same class [12]. As an illustration, BCC and its subcategories have virtually entirely distinct looks. Several subcategories within the same category are therefore challenging to categorize. The kinds of camera equipment used to take the photographs also have a significant impact on the categorization algorithms. Performance is negatively impacted when test photos are from a different domain [13].

Traditional machine learning methods are not suitable for skin cancer classification. For skin cancer detection, features are collected from skin disease photos and categorised using classic machine learning [14]. The ABCD Rule [15], Menzies Method [16], and 7-Point Checklist [17]

[1]*Chitkara University Institute of Engineering and Technology, Chitkara University, Punjab, India. rajgaurang@chitkara.edu.in*
[2]*Department of Computer Science and Engineering,School of Engineering and Technology,Sharda University, Greater Noida, India*
[3]*Associate Professor and Head CSE IoT, Jain Deemed to be University, Bangalore, India. gauravlondhe@gmail.com*
[4]*Department of Computer Science and Engineering,School of Engineering and Technology,Sharda University, Greater Noida, India*
5School of Computer Science and Engineering, RV University, Bengaluru, India. rajatbhardwaj.x@gmail.com
** Corresponding Author Email:ambuj4u@email.com*

can analyse skin disease images. Support vector machines [18], XGBoosts [19], and decision trees [20] classify handcrafted items. Machine learning algorithms can only recognise certain skin cancers as diseases due to the restricted amount of characteristics [21]. Due to their heterogeneity, categorising cutaneous cancers by their specific features is futile [22].

2. Literature Review

Deep learning algorithms without domain expertise or feature extraction have considerably improved skin cancer classification. Deep learning algorithms outperform conventional machine learning methods in extracting key characteristics from big data sets [23]. Deep learning systems can analyse and assess data for physicians [24]. Deep learning systems match human dermatologists in diagnosis accuracy [25–27]. These algorithms are still far from being applied in a comprehensive diagnostic framework. First, a lack of balanced data and annotated photos has hampered deep learning skin cancer categorization [12]. These algorithms typically misdiagnose non-trained skin tumours [28]. Deep learning methods may need additional processing and training time for pathological images with millions of pixels [29]. Different situations will also make different sounds (such as various imaging equipment, and backdrops). Thus, these methods' robustness and generalizability should be considered [30].

Over the last several years, many studies have discussed diagnostic improvements in skin cancer classification, but none have fully examined the cutting-edge challenges in these occupations[31]. examined the latest dermoscopy image-based skin lesion categorization advancements [32]. analyzed CNN studies on skin lesion categorization [33]. CNNs consistently diagnose skin cancer [34]. presented an overview of numerous deep learning-based algorithms for skin cancer detection, including important challenges and restrictions, while [12] and [28] examined many machine learning approaches for dermatological diagnosis. [36] reviewed the latest melanoma categorization studies and compared their findings to human experts [35]. CNN-based approaches for identifying skin lesions using patient and imaging data were examined [37].

3. Material and Methods

3.1. Dataset

To reduce the number of deaths caused by skin cancer throughout the world, the International Skin Imaging Collaboration (ISIC) has launched the Melanoma Project, which use digital skin imaging. There are both for-profit businesses and academic organisations taking part. The many types of datasets are shown in Fig. 1.

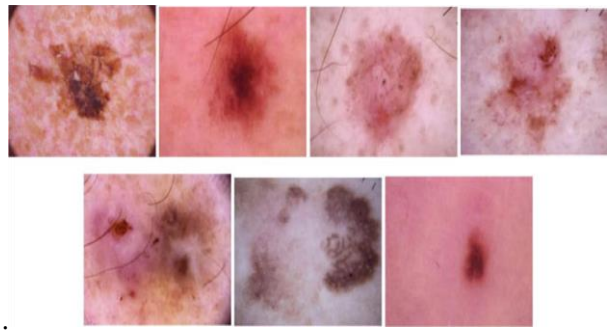

Fig. 1. Skin Cancer Classification.

The initial dataset, "ISIC 2018," comprises 10,015 photos of skin lesion disorders such benign keratosis, dermatofibroma, vascular lesion, melanoma, melanocytic nevus, basal cell carcinoma, and actinic keratosis. The Medical University of Vienna and University of Queensland granted permission for these photos. JPEG images typically have 600450 pixels [38, 39].

3.2. Proposed Methodology

3.2.1. Data Augmentation

Give deep learning models a lot of data to work with during training. Datasets for model training are improved through data augmentation. It is usual practise to enhance the datasets when dealing with big neural networks by cropping, padding, adding noise, altering brightness, and turning the data horizontally [40].

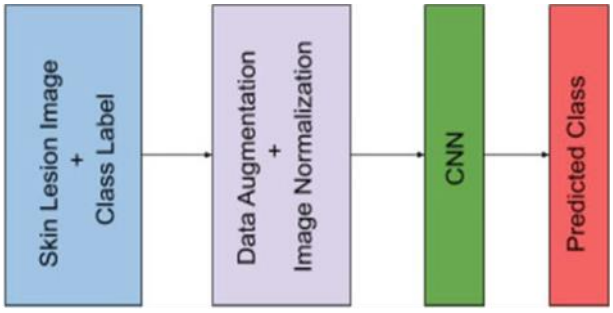

Fig 2. Proposed Methodology.

3.2.2. Optimized Deep Neural Network

3.2.2.1 Convolution

Extracting useful characteristics from input photos is the job of the convolution technique. Fig. 3 depicts these processes. The outcome of the convolution operation is a feature map as given in fig. 3 which shows how the convolution operation happens.

Although some information is lost during the convolution process, the goal here is to decrease the file size while simultaneously gaining access to the essential data. Image processing activities such as sharpening, edge detection, and blurring may all benefit from convolution performed with various filters.

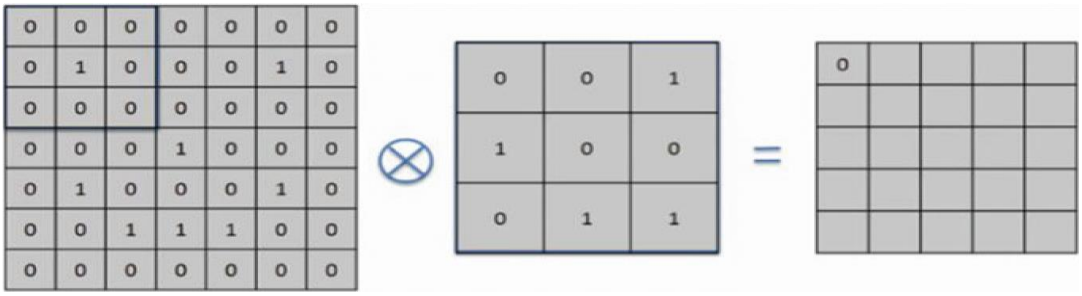

Fig. 3. Convolution Operation.

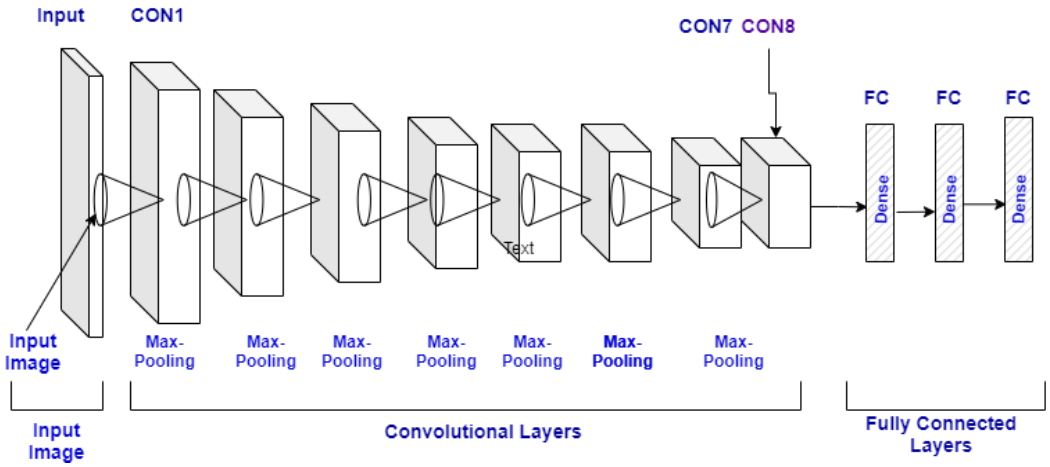

Fig. 4. CNN Model Architecture.

Table 2. DNN Tuning Parameter

Parameter	Description
Convolution Layer	10
Max Pulling Layer	10
Drop out rate	0.25
Network Weight Assigned	Uniform
Activation Function	Relu
Learning rates	0.0001, 0.001,0.01
Epchos	50, 100, 150
Batch Size	36, 64, 110

The problem here is that CNN's understanding of translation invariance is inadequate. The CNN includes numerous layers/processes, including Convolution, Pooling, Flattening, and Full Connection.

3.2.2.2 Pooling

When working with a very big picture, it might be helpful to reduce the amount of parameters by using a pooling technique. Reduce the number of dimensions in each feature map while maintaining critical information through subsampling, also known as spatial pooling. There are three primary types of pooling: maximum, total, and average.

The method of Max pooling is a kind of discretization that relies on a sampling strategy. On create the feature map, we apply a N X N max filter to the picture, picking the pixel with the greatest value after each iteration. Similarly, with average and sum pooling, the feature map incorporates the average and sum of pixel values. In Fig. 2, we see the Max Pooling procedure in action.

3.2.2.3 Flattening

The feature maps used as input by the artificial neural network must be in the form of a columnar vector of picture pixels. Our feature maps are "flattened" in the sense that they are transformed into a vector with a columnar layout. The procedure of flattening is shown in Fig. 6.

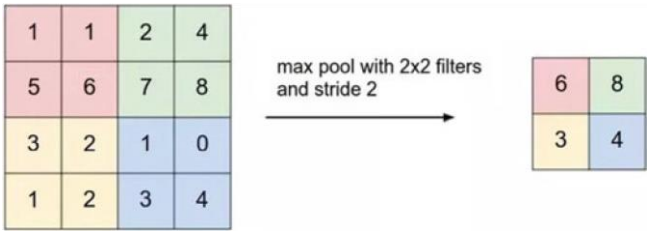

Fig. 6. Example of Max pooling

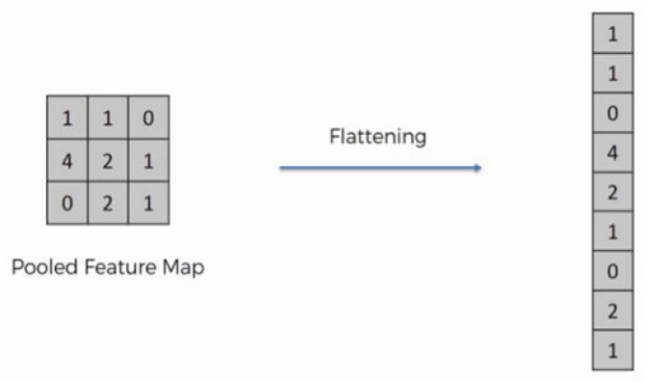

Fig. 7. Flattening example

3.2.2.4 Full Connection

The complete connection layer generates an N-dimensional vector containing the total number of classes recognised based on the previous convolution/pooling layer. Therefore, the layer takes advantage of the probabilities associated with the neurons to determine which characteristics are most strongly linked to a given class.

4. Result Analysis and Discussion

The recent success of deep learning models can be traced back in large part to studies conducted using Co-GPU Lab's and the karas libraries written in Python. Experiments using different batch sizes, learning rates, and epoch lengths are conducted in this study. The experiment is run using two different epoch sizes (50 and 100) and three different learning rates (0.1,.001, and.0001). The findings are presented in Section 4.1:

The effectiveness of the model is evaluated using a variety of performance metrics, which are as follows:

$$\text{Accuracy } (Acc) = \frac{TP+TN}{TP+TN+FP+FN} \quad (a)$$

$$\text{. Precision } (Pre) = \frac{TP}{TP+FP} \quad (b)$$

$$Recall.(Re) = \frac{TP}{TP+FN} \quad (c)$$

$$F1\text{-}Score = \frac{P.R}{P+R} \quad (d)$$

It is important to keep in mind that the abbreviations TP, TN, FP, and FN stand, respectively, for true positive, true negative, false positive, and false negative.

4.1. Epochs Test

The purpose of this experiment is to study how Epochs influence gadget performance. An epoch is a comprehensive data set introduction for a machine learning algorithm. The experiment sizes used in this study are 50 and 100 epochs. Fig. 8 depicts the experiment conducted over the course of 50 epochs, whereas Fig. 9 illustrates the same experiment conducted over 100 epochs with a 0.0001% learning rate. Both are very accurate, with a 98.02 and a 98 percent success rate, respectively.

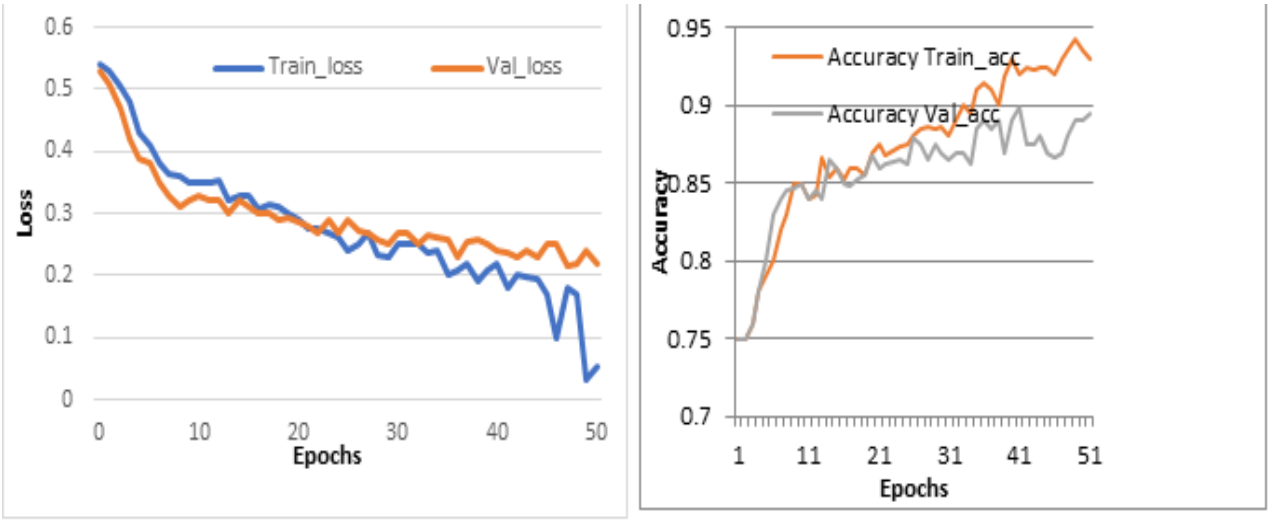

Fig. 8. Accuracy/loss with learning rate 0.0001 and epochs 50

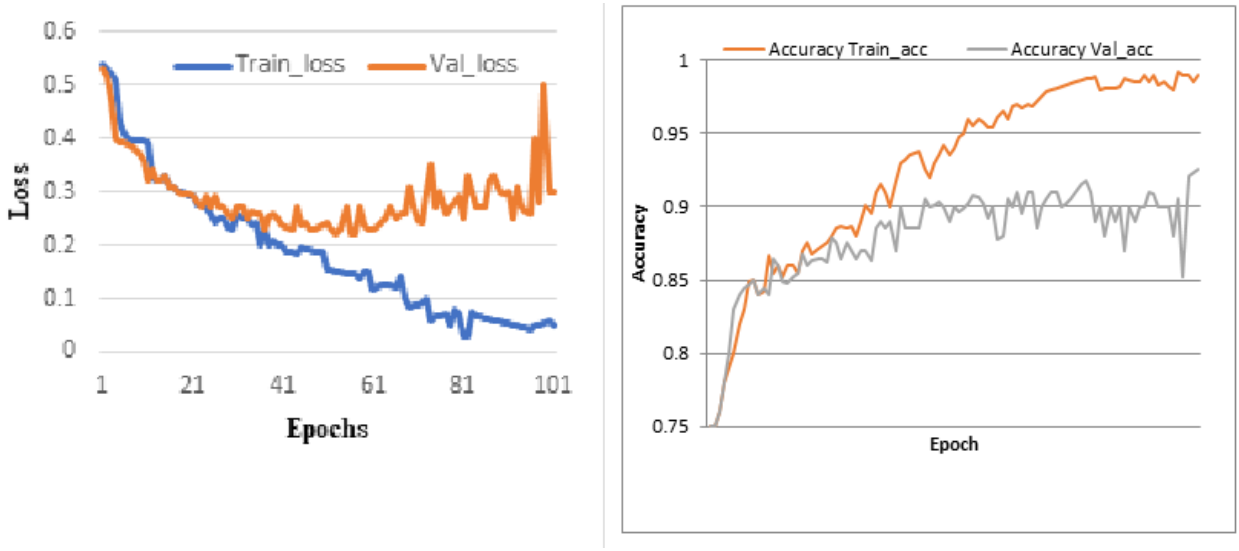

Fig. 9. Accuracy/loss with learning rate 0.0001 and epochs 100

Fig. 10. Accuracy/loss with learning rate 0.001 and epochs 50

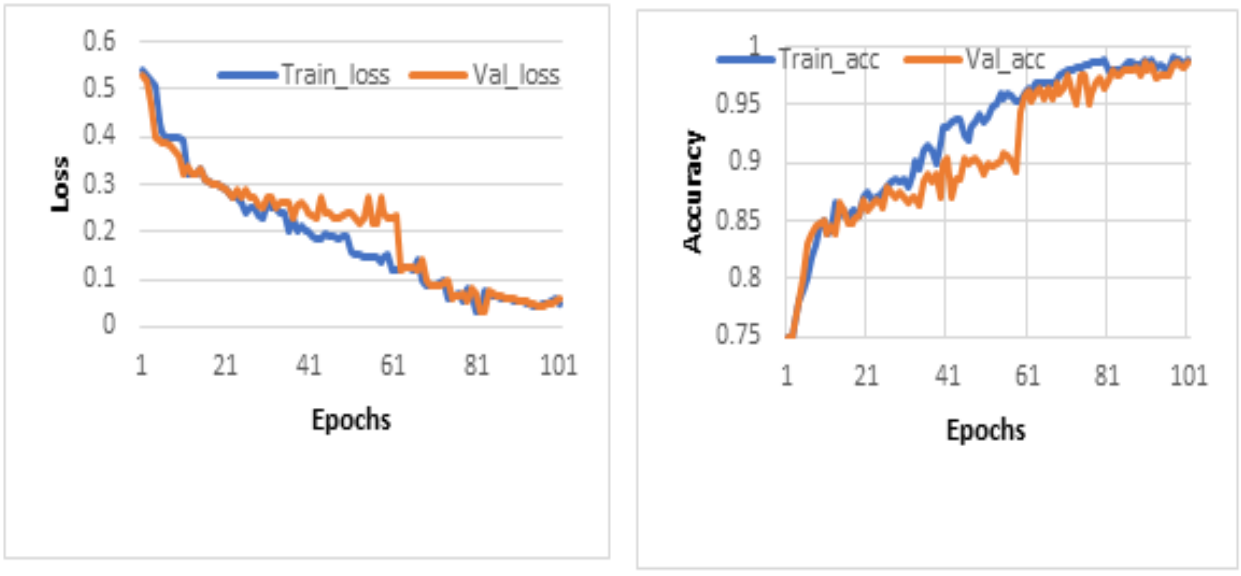

Fig. 11. Accuracy/loss with learning rate 0.001 and epochs 100

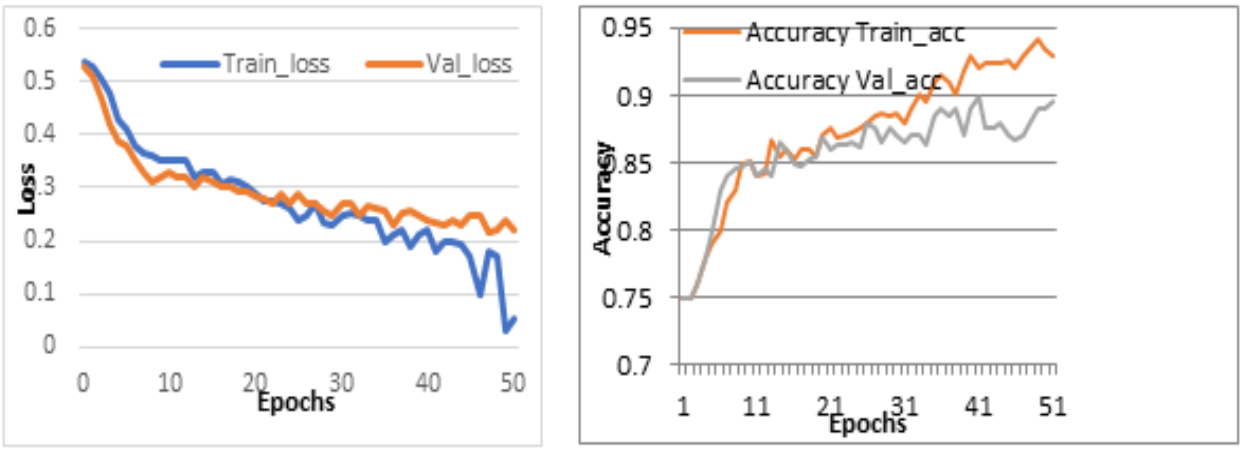

Fig. 12. Accuracy/loss with learning rate 0.01 and epochs 50

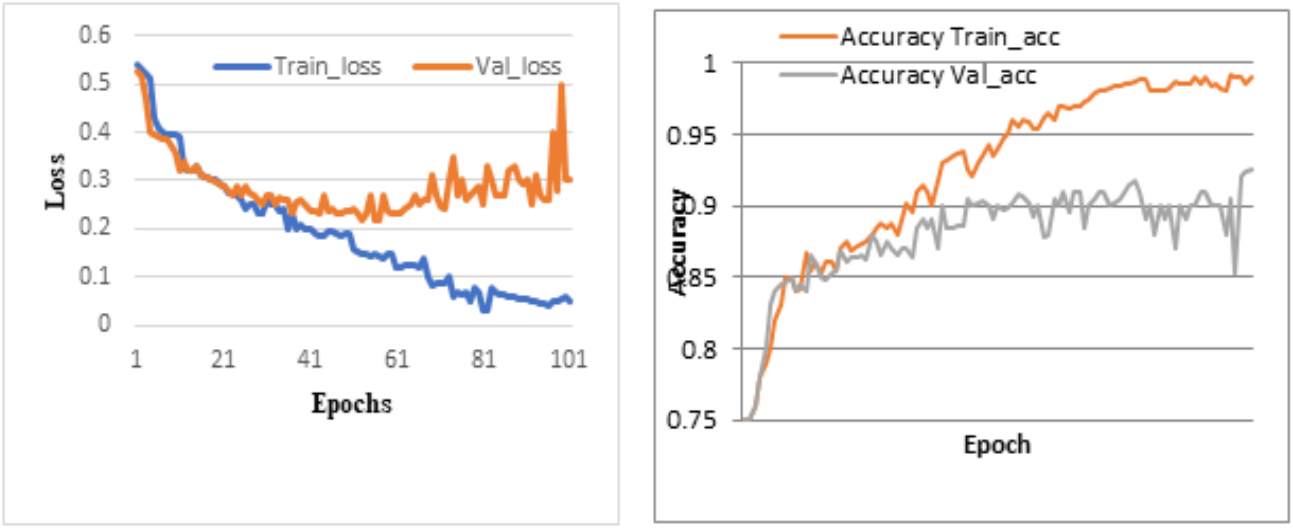

Fig. 13. Accuracy/loss with learning rate 0.01 and epochs 100

It is reasonable to anticipate that increasing the number of times the inquiry is carried out will result in an increased proportion of accurate results. However, the number of epochs is increasing since the training phase is taking a greater amount of time.

In this section, the experiment is carried out with a size of either 50 or 100 epochs. "Fig. 10: displays the test with 50 epochs," and "Fig. 11 shows 100 epoch sizes with a learning rate of 0.001." "Fig. 10: shows the test with 50 epochs." Both have an accuracy percentage that is between 98.07 and 98.25 percent, respectively.

In this case, we run the experiment with two different epoch sizes: 50 and 100. Fig. 12 depicts the 50-epoch test, and Fig. 13 illustrates the 100-epoch size with a 0.01-rate of learning. The two have a similar accuracy of 98.12%.

A more accurate data measurement with a faster learning rate may be assessed based on the evaluation process carried out. Analyses of experimental results are shown in Table 3.

Table 3. Experiment Results

Dataset Size	Epoch	LR	Accuracy (%)
2000	50	0.0001	98.02%.
	50	0.001	98.07%.
	50	0.01	98.12%.
	100	0.0001	98.00%
	100	0.001	98.25%
	100	0.01	98.12%.

Tables 4 and 5 provide a detailed look at the outcomes of the expected model's comparison to other models. The suggested model is compared to another deep learning model in Table 4 and Fig. 14. As a result, it may be

concluded that the suggested model is more precise than the alternatives. The suggested method has the lowest space complexity compared to other approaches.Tables 4 and 5 provide a detailed look at the outcomes of the expected model's comparison to other models. The suggested model is compared to another deep learning model in Table 4 and Fig. 14. As a result, it may be concluded that the suggested model is more precise than the alternatives. The suggested method has the lowest space complexity compared to other approaches.

Table 4. Comparison with Other Models

Model	Accuracy Rate	Space	Training Parameter's	Non-Trainable
Mobinet	70.46	82,566	180,20,552	4,55,262
InceptionV3	78.80	90,255	225,46,862	6,58,644
VGG16	79.52	85,245	210,00,254	5,32,654
Proposed	98.00	22,565	14,22,542	0

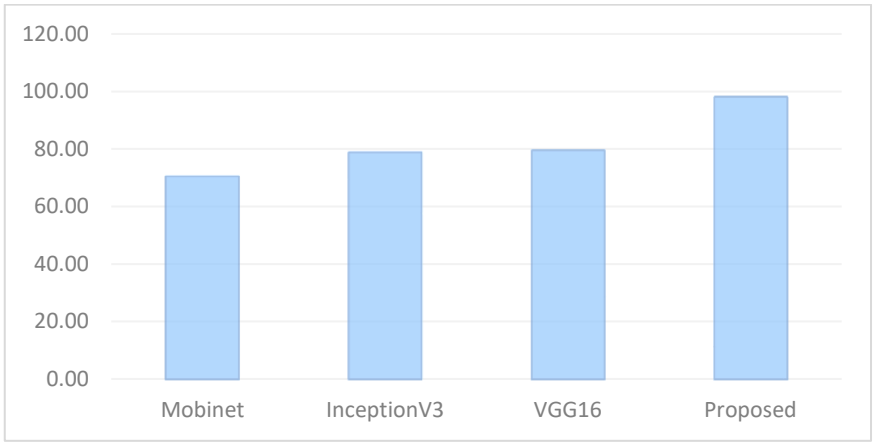

Fig. 14. Proposed Model Against the Current State of the Art

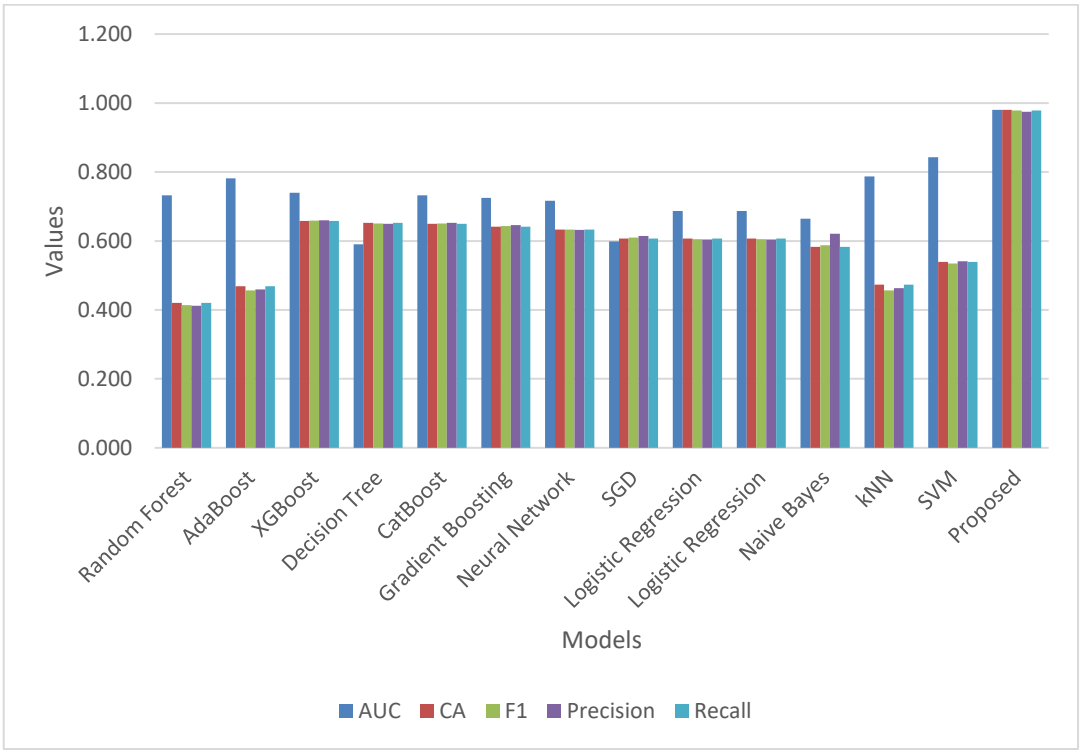

Fig. 15. Model Comparison: Proposed vs. State-of-the-Art.

Compared to previous models, the suggested model has superior accuracy, F1-score, precision, and recall, as shown in Table 5 and Fig. 15.

Table 5. Comparison with Other Models

Model	AUC	CA	F1	Precision	Recall
Random Forest	0.733	0.421	0.413	0.412	0.421
AdaBoost	0.782	0.469	0.457	0.459	0.469
XGBoost	0.740	0.658	0.659	0.660	0.658
Decision Tree	0.590	0.652	0.650	0.650	0.652
CatBoost	0.732	0.649	0.650	0.652	0.649
Gradient Boosting	0.725	0.641	0.643	0.646	0.641
Neural Network	0.717	0.633	0.633	0.632	0.633
SGD	0.598	0.607	0.610	0.615	0.607
Logistic Regression	0.687	0.607	0.605	0.604	0.607
Logistic Regression	0.687	0.607	0.605	0.604	0.607
Naive Bayes	0.664	0.583	0.588	0.621	0.583
kNN	0.787	0.473	0.456	0.463	0.473
SVM	0.843	0.539	0.535	0.541	0.539
Proposed	0.980	0.980	0.978	0.975	0.978

5. Conclusions

Some of the worst cancers are those of the skin. Classifying skin lesions early on may aid in clinical decision-making by giving an accurate diagnosis of the problem. There may be a better chance of finding a cure for the condition before it becomes terminal if this is done. However, automated skin cancer classification is difficult since most skin disease training photographs are imbalanced and scarce, and the model must be able to adapt and be adaptable across domains. This study recommends utilizing a deep neural network that has been trained with the best possible settings to increase confidence in medical diagnoses. The proposed model was found to be better than competing ones (with 98 percent accuracy).

Conflicts of interest

The authors declare no conflicts of interest.

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