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Skin Cancer Recognition Using Compact Deep Convolutional Neural Network

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Abstract

Skin cancer is a common form of cancer that affects millions of people worldwide. Early detection and accurate diagnosis of skin cancer are crucial for effective treatment and management of the disease. There has been a growing interest in using deep learning techniques and computer vision algorithms to develop automated skin cancer detection systems in recent years. Among these techniques, convolutional neural networks (CNN) have shown remarkable performance in detecting and classifying skin lesions. This paper presents a comprehensive study using CNN and deep learning techniques for skin cancer detection using the International Skin Imaging Collaboration (ISIC) dataset. The proposed architecture is a compact deep CNN that is trained using a dataset of benign and malignant skin lesion images. The proposed architecture has achieved 84.8% accuracy, 83.8% TPR, 83.7% TNR, 81.6% F1-score and 80.5% precision for performance evaluation. The experimental results show promising results for the accurate and efficient detection of skin cancer, which has the potential to improve the diagnosis and treatment of this life-threatening disease.

Keywords: Skin cancer, Convolutional neural network, Deep learning, Isic dataset, TensorFlow

Özel Derin Konvolüsyonel Sinir Ağı Kullanarak Cilt Kanseri Tanıma

Öz

Cilt kanseri, dünya genelinde milyonlarca insanı etkileyen ciddi ve yaygın bir kanser türüdür. Cilt kanserinin erken teşhisi ve doğru tanısı, hastalığın etkili bir şekilde tedavi edilmesi ve yönetilmesi için önemlidir. Son yıllarda derin öğrenme tekniklerinin ve bilgisayarlı görü algoritmalarının otomatik cilt kanseri tespit sistemleri geliştirmek için kullanılması konusunda büyük bir ilgi bulunmaktadır. Bu teknikler arasında konvolüsyonel sinir ağları (CNN), cilt lezyonlarını tespit etme ve sınıflandırmada dikkate değer bir performans göstermiştir. Bu makalede, Uluslararası Cilt Görüntüleme İşbirliği (ISIC) veri seti

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kullanılarak cilt kanseri tespiti için CNN ve derin öğrenme tekniklerinin kapsamlı bir çalışmasını sunmaktayız. Önerilen mimari, özelleştirilmiş derin CNN kullanılarak eğitilmiş olan, benign ve malign cilt lezyonu görüntülerinin bir veri setini kullanmaktadır. Önerilen mimari, performans değerlendirmesi için 84.8% doğruluk, 83.8% TPR, 83.7% TNR, 81.6% F1-skoru ve 80.5% hassaslık elde etmiştir. Deneysel sonuçlar, cilt kanserinin doğru ve verimli bir şekilde tespiti için umut verici sonuçlar göstermektedir ve bu yaşamı tehdit eden hastalığın teşhis ve tedavisini iyileştirme potansiyeline sahiptir.

Anahtar Kelimeler: Cilt kanseri, Konvolüsyonel sinir ağı, Derin öğrenme, Isic veri sesti, Tensör Akışı

1. INTRODUCTION

Skin cancer is one of the most common types of cancer globally, and its incidence rate is increasing every year. Early skin cancer detection is crucial for successful treatment and improved patient outcomes [1,2]. Skin cancer happens when skin cells grow abnormally. It starts as a small, dark spot or bump and can spread if not treated in the early stages [3]. The categorization of skin cancer is based on its histopathological features, and it is broadly classified into four types: basal cell carcinoma (BCC), melanoma, actinic keratoses (AK), and squamous cell carcinoma (SCC), as documented in the literature [4-7]. The American Cancer Society claims that there were 9.5 million cancer-related deaths and 17 million new cancer diagnoses recently [8].

Skin cancer can be diagnosed using a variety of methods [9,10]. Visual inspection is the most common method of skin cancer diagnosis. A dermatologist or physician examines the skin using a magnifying glass or a dermatoscope to look for any abnormal growths, lesions, or moles. In addition, biopsy and dermoscopy can be performed during the visual inspection. However, traditional skin cancer diagnostic methods are based on dermatologists' visual inspection, which can be time-consuming and prone to inter-observer variability [11]. Molecular testing involves analysing the DNA or RNA of skin cells to detect genetic mutations associated with skin cancer. Molecular testing can be used to identify high-risk patients and guide treatment decisions. Computer-assisted diagnosis involves the use of specialized software that analyses digital images of skin lesions to detect signs of cancer. This method can help increase the accuracy of diagnosis and reduce the need for unnecessary biopsies. Thus, recently, machine learning algorithms and computer vision techniques have shown promising results in automated skin cancer detection [12].

Convolutional Neural Networks (CNNs) are a type of deep learning algorithm that has shown remarkable performance in image classification tasks [13]. CNNs are the most popular deep-learning technology used in computer vision for efficient medical diagnosis, particularly for skin cancer [14]. CNN can learn to extract features autonomously, making it a more effective approach for medical diagnostics compared to typical machine learning algorithms [15,16]. In addition, an effective deep-learning model for skin cancer diagnosis can increase the chances of survival by 99% [17].

CNNs can learn and identify complex patterns in images, making them an ideal choice for skin cancer detection. CNNs have been shown to be highly effective in classifying skin lesions for the purpose of skin cancer diagnosis [18]. These deep learning algorithms are designed to recognize patterns in images and can learn to differentiate between different types of skin lesions based on their visual features. A dataset of labelled images is needed to train a CNN for skin lesion classification. This dataset is typically divided into a training set, a validation set, and a test set. The CNN is trained on the training set, and the validation set is used to monitor its performance and adjust its parameters. The test set is then used to evaluate the final performance of the CNN [19]. CNNs can be trained to classify skin lesions into different categories, such as benign and malignant, or to identify specific types of skin cancer, such as melanoma or basal cell carcinoma. The CNN learns to recognize patterns in the images that are associated with each category and can make predictions on new, unseen images

based on these patterns. Several studies have shown that CNNs can achieve high levels of accuracy in skin lesion classification, often outperforming human experts [20].

Thus, we propose a compact custom design CNN-based approach for skin cancer detection using the International Skin Imaging Collaboration (ISIC) dataset in this paper. ISIC is one of the most widely used datasets for skin cancer detection [21]. It is a publicly available dataset that contains over 23,000 images of skin lesions, including benign and malignant cases, along with their corresponding labels. We trained and evaluated our model using the TensorFlow deep learning framework.

The main contribution of this work is the development of an accurate and efficient skin cancer detection system that contains fewer parameters, can yield a fast inference time, and can be used in small devices such as smart phones that can aid patients in making early decisions before contacting dermatologists. This type of application can be especially useful when people are stuck at home.

The rest of the paper is organized as follows: Section 2 provides a brief overview of related work in the field of skin cancer detection using deep learning. Section 3 describes the methodology used in this work, including the dataset preparation, model architecture, and training process. Section 4 presents the experimental results and a comparative analysis with state-of-the-art methods. Finally, Section 5 concludes the paper and discusses future directions for research in this area.

2. RELATED WORK

Skin cancer recognition with the use of a convolutional neural network has gained more attention over the past years. Several studies have been conducted in this area, including face recognition [9], object detection [11], and image classification [22] using CNN networks. From literature studies on skin cancer recognition, a lot of CNN pattern recognitions have been suggested. Pre-processing and pro-processing phases are typically combined in algorithms.

The study in [6] introduces a novel deep transfer learning model using MobileNetV2 to classify melanoma. The ISIC 2020 dataset, with a severe class imbalance, was used, and various data augmentation techniques were applied. Results show that the proposed model outperforms existing methods in accuracy and computational efficiency, offering promise for enhancing melanoma diagnosis and patient outcomes. A deep spiking neural network with the surrogate gradient descent method to classify skin lesion images (3670 melanoma and 3323 non-melanoma) from the ISIC 2019 dataset is used in [19]. The proposed spiking VGG-13 model outperforms VGG-13 and AlexNet with fewer parameters. This highlights the potential of spiking neural networks to improve skin cancer diagnosis and reduce related deaths.

In [23], a deep learning-based methodology was described in which the skin lesions were first pre-processed using the decorrelation formulation method and then further segmented using MASK-RCNN. DenseNet was used to extract features from the segmented image. The entropy-controlled least squares-based SVM approach is then used to identify the best features. The HAM10000, ISBI2016, and ISBI2017 datasets were used to conduct the experiment. This dataset's respective accuracy percentages were 96.3%, 94.8%, and 88.5%.

In addition, a new deep learning-based system for segmenting and categorising skin lesions was proposed in [24]. The segmentation was carried out using the mask recurrent neural network (MRNN). In addition, the Pyramid Network function was utilized using Resnet-50 for the feature extraction process, while the SoftMax classifier was also utilized for the lesion classification process [25]. Therefore, deep learning methods were assessed using the HAM10000 dataset, which had an accuracy of 86.5%, to produce consistent performance. In [26], the authors investigated how image scaling affected the categorization of skin lesions by a CNN network. The authors scaled the images to six different sizes. Hence, three CNN architectures, such as EfficientNetB0, EfficientNetB1, and SeReNeXt-50, were used in classifying the images. An ensemble-based

technique for multiscale multi-CNN fusion (MSM CNN) was proposed and evaluated. This approach made use of three different CNN models. The proposed approach was developed using a variety of cropped image sizes. Using the ISIC2018 dataset, the MSM CNN method produced an accuracy of 86.2%. They also discovered that cropping images gave better results than enlarging them.

In addition, an integrated diagnostic framework that comprises a step for segmenting the boundaries of skin lesions and a stage for classifying numerous skin lesions was proposed in [27]. First, the authors used a deep learning full-resolution convolutional network (FrCN) to separate the borders of the skin lesions from all of the dermoscopy images. The segmented skin lesions were then subjected to a convolutional neural network classifier (ResNet-50) for classification. The International Skin Imaging Collaboration (ISIC) 2018 dataset, which contains seven different types of skin lesions, was used to assess the suggested deep-learning model independently. The total weighted prediction accuracy of the ResNet-50 model, which measures its performance, is 89.28%. The effectiveness of employing 17 frequently pre-trained CNN architectures was investigated in [28] as feature extractors. In addition, 24 machine learning classifiers were employed to evaluate the classification of skin lesions from the ISIC 2019 dataset and recommend DenseNet201+Fine KNN. The authors then obtained the greatest accuracy score for the ISIC 2019 dataset at 92.34% using a DenseNet201 and Fine KNN combination.

However, the present research shows that there is still a need for improvement in both the classification and recognition of skin cancer, despite the fact that much work has been suggested in the automated recognition of skin cancer. By using splitting methodologies as part of cancer recognition research, this paper will focus on skin cancer recognition using a deep convolutional neural network.

3. MATERIALS AND METHODS

A dataset of labelled skin lesion images is needed to train and test the proposed custom CNN model. Hence, the ISIC dataset is a commonly used dataset for skin lesion classification and is also used in this paper.

The skin lesion images are pre-processed before they can be used for training. This may include resizing, cropping, or normalising the images. Therefore, a custom CNN architecture is designed and implemented using a deep learning framework such as TensorFlow. The architecture typically consists of several layers of convolutional and pooling layers, followed by one or more fully connected layers. After that, the CNN is trained on the labelled skin lesion images using a loss function and an optimisation algorithm. The goal is to minimise the loss function by adjusting the parameters of the CNN. The performance of the CNN is evaluated using a validation set of images that are not used in training. The accuracy, precision, recall, and F1-score of the CNN are typically calculated to assess its performance. Then, the final performance of the CNN is evaluated using a test set of images that are not used in training or validation. The accuracy and other performance metrics are calculated to assess CNN's ability to classify new, unseen images.

3.1. Datasets

The ISIC has created a publicly available skin disease dataset for the computer vision community worldwide to help reduce skin cancer mortality and support digital skin imaging. Kaggle is an accessible solution for this ISIC dataset [21,29]. This dataset is made up of 3,297 skin cancer (both malignant and benign) images. A malignant class contains 1,497 images, in contrast benign class contains slightly more images, that is 1,800.

3.2. Network Model Architecture

In this paper, a custom CNN framework is utilised for the automatic recognition of skin cancer images. The proposed architecture uses convoluted filters to analyse various image input structures and retrieve necessary information from the images. Figure 2 shows the proposed network architecture.

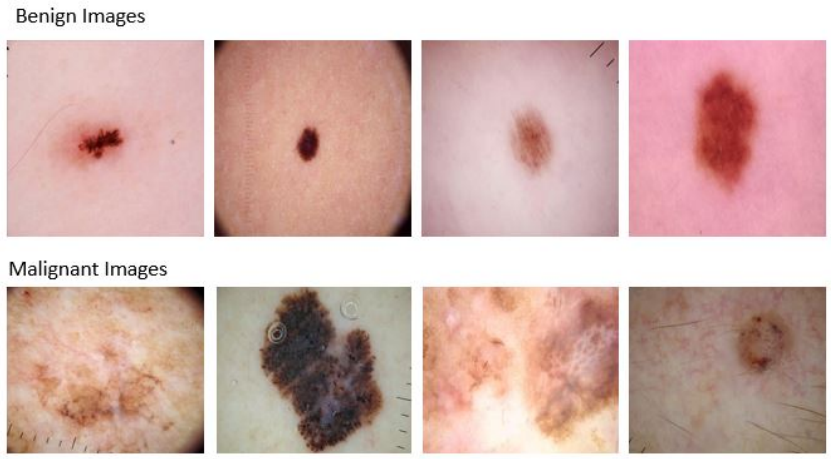

Figure 1. Samples of skin-cancer images of both Benign and Malignant in the dataset

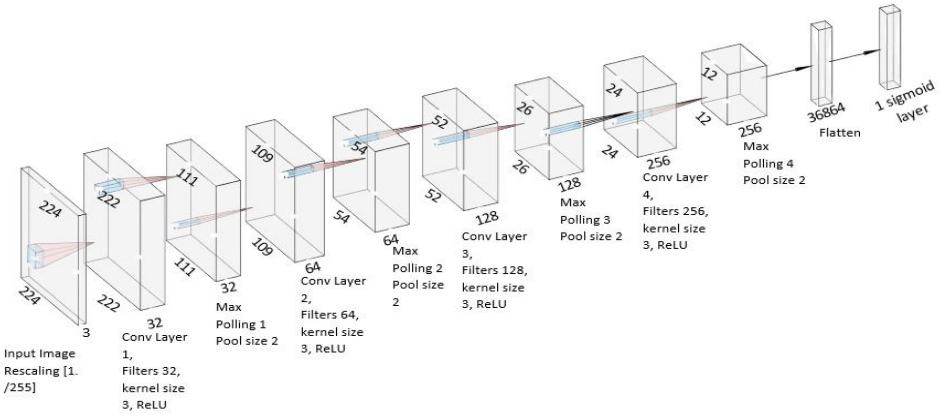

Figure 2. Proposed CNN model

The input to the proposed network is images measuring [224x224] by 3, where the length, breadth, and channel size are represented by these values. The proposed model has six convolutional layers, each followed by batch normalisation and ReLU activation. The model takes in an input image of size [224x224x3] pixels, which is rescaled to a range of (0,1). The first convolutional layer has 32 kernels of size 3, and the output dimensions are [222x222x32]. The first max-pooling layer reduces the output dimensions to [111x111x32] with a pool size of 2. The subsequent convolutional layers have 64, 128, 256, 512, and 1024 kernels of size 3, respectively. The output dimensions for each layer decrease with the use of max-pooling, resulting in [109x109x64], [52x52x128], [24x24x256], [10x10x512], [3x3x512], and [1x1x1024], respectively. After the final convolutional layer, the output is flattened, and a binary output layer with a sigmoid activation function is connected for the final classification.

The model's architecture enables it to capture increasingly complex features in the input image as

it progresses through the layers, allowing for the accurate detection of skin cancer. The pool size for the sixth max-pooling layer, which has dimensions of [1x1x1024], is 2.

3.3. Convolutional Neural Network Training

The skin cancer recognition model architecture and training environment involve a two-stage process: the forward step of sending input data through the network and the backpropagation process of adjusting weights based on training data. The weight adjustments are comprised of a forward pass, loss function, backward pass, and weight update. Various training choices, such as initial learning rate, batch size, maximum epochs, and training plot, are specified in the study.

An epoch is a complete pass over the training dataset, and the maximum epoch is a user-defined variable that controls the number of times the algorithm loops over the data. The maximum epoch value is determined by balancing model performance and computing time. Hence, it is often determined through testing. In addition, the learning rate is a critical hyperparameter in deep learning models trained using stochastic gradient descent. Low learning rates lead to more reliable training but slower optimisation, while excessively high rates can cause weight fluctuations and divergence. Depending on the historical gradient data, RMSprop adjusts the learning rate for each weight (model parameter). In order to do this, the learning rate is divided by an exponentially decaying average of the sum of squares, which helps eliminate instabilities and speeds up integration [30,31]. RMSprop has been utilised in a range of applications, including language modelling, image classification, and machine translation, and has been proven to be particularly successful at training DNNs on big and noisy datasets [32-34]. Furthermore, batch size refers to the number of samples processed in one iteration during training, allowing the use of stochastic gradient descent. This hyperparameter affects both training time and model performance by regulating the amount of data used in each iteration. A larger batch size speeds up training but requires more memory, while a smaller batch size reduces memory usage but may require more iterations. Choosing the optimal batch size requires balancing. Therefore, Table 1 provides an overview of the CNN training parameters used for the proposed model in the experiments.

Table 1. CNN model's training parameters

Parameter	**Description/Value**
Optimization algorithm	RMSprop
Batch size	32
Initial Learning Rate	0.0001
Maximum epoch	30

3.4. Performance Evaluation Metrics

ISIC dataset images of malignant and benign skin cancers were used to train the proposed network. The effectiveness of the proposed DCNN was measured by performing a statistical analysis of network prediction on the test dataset. The statistical tests used in the confusion matrix performance evaluation are accuracy (ACC), F1 score, true positive rate (TPR), true negative rate (TNR), and precision (P). These assessment metrics are described as follows: TP, TN, FP, and FN represent the total number of true positives, true negatives, false positives, and false negatives, respectively, of the test datasets.

$$ACC = \frac{TP+TN}{TP+TN+FP+FN} \quad (1)$$

$$TPR = \frac{TP}{TP+FN} \quad (2)$$

$$TNR = \frac{TN}{TN+FP} \quad (3)$$

$$P = \frac{TP}{TP+FP} \quad (4)$$

$$F1 = \frac{2TP}{2TP+FP+FN} \quad (5)$$

4. EXPERIMENTAL RESULTS

In this section, we present the experimental results obtained from our proposed CCN model on skin cancer diagnosis using CNN and deep learning methods using the ISIC dataset.

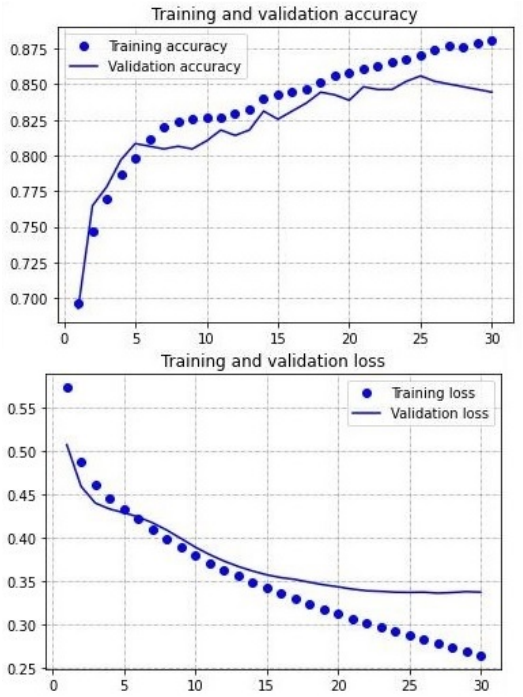

Figure 1. Training and validation loss and accuracy

K-fold cross-validation was performed to determine the performance of the custom-designed deep network by using various numbers of convolutional layers. To do this, all images into the database (3,297 images) were used for K-fold cross-validation process. To perform K-fold cross-validation, the training dataset was first randomised and then split into 10 equal folds (that is, K=10), where each fold contained the same number of images from both classes (benign and malignant). During training, K-1 folds were used to train a model from scratch, and the model performance was verified on the rested fold. This process was repeated 10 times (because K=10) using each fold as a test dataset. Statistical measurements (ACC, P, TPR, TNR, and F1 score) were also stored after each model was tested on the test fold.

Table 2 displays the performance of the compact model on various layers of the CNN. The mean and standard deviation of the related measures across 10 training sessions are represented by the values in the table. In addition, Table 2 can be used to compare how well our proposed compact model performs on various convolutional layers and to choose the number of layers that perform the best for the classification. As a result, using four convolutional layers performed the best, where the F1 score was 0.8326 which is the highest value.

Table 2. K-Fold cross-validation performances of the custom deep network model by using various convolutional layers

Layers	ACC	P	TPR	TNR	F1
Layer1	0.8179±0.0061	0.7846±0.0158	0.8276±0.0217	0.8099±0.0227	0.8055±0.0063
Layer2	0.8307±0.0071	0.7732±0.0110	0.8882±0.0109	0.7827±0.0145	0.8267±0.0066
Layer3	0.8211±0.0046	0.7656±0.0072	0.8742±0.0106	0.7769±0.0103	0.8163±0.0048
Layer4	0.8354±0.0065	0.7749±0.0119	0.8996±0.0180	0.7818±0.0181	0.8326±0.0068
Layer5	0.8266±0.0069	0.7729±0.0144	0.8769±0.0230	0.7846±0.0236	0.8216±0.0068
Layer6	0.8483±0.0048	0.8057±0.0153	0.8503±0.0142	0.8266±0.0188	0.8274±0.0033

Table 3. Performance of the four-layered custom deep network when increasing or decreasing the training dataset. The test ratio is kept fixed and always same test images are always used for the reliability of the experimental result

Train | Validation | Test ratio	F1-Score
40% | 30% | 30%	0.7897
50% | 20% | 30%	0.8012
60% | 10% | 30%	0.8160

Table 4. Comparison between the Custom model and some existing studies. Unreported findings are represented by the symbol "-"

Method	Datasets	Sample number	ACC (%)	F1 (%)	P (%)	TPR (%)	TNR (%)	Param. (millions)
Mask-RNN[25]	HAM10000	10,015	86.5	86.28	87.01	85.57	-	63.7
MSM-CNN[26]	ISIC 2018	2,912	86.2	-	-	-	-	25.7
ResNet-50[27]	ISIC 2018	11,720	89.28	81.28	-	81.00	87.16	23.54
DenseNet201 + Fine KNN[28]	ISIC 2019	25,331	92.34	86.96	85.22	92.75	96.38	20.2
IGR0235 Model[32]	ISIC 2017	2000	83.0	-	-	-	-	322.5
DCNN [33]	ISBI 2016	4867	76.5	-	-	89.5	96.3	62.3
VGG[34]	ISIC 2016	1,279	-		72.3	76.0	-	138
Compact-DCNN Model	ISIC Archive	3,297	84.8	81.6	80,5	83.8	83.7	6.2

After determining the number of convolutional layers on the custom CNN, the four-layered CNN was trained from scratch using all the images from the database. In addition, the optimal splitting ratio for the training process was determined; therefore, we tested three different training-validation ratio combinations. It is important to note that the test images are always the same, which is determined by using the test ratio, which is fixed at 30% of the entire database. The remaining 70% of the images were split into the following training-validation ratio combinations: 40%–30%, 50%–20%, and 60%–10%. The experimental results showed that a 60%–10% training–validation ratio split yielded the best result for this specific database. Table 3 presents the performance of the four-layer custom CNN on the test images by splitting the training and validation sets with different ratios. Generally, a deep neural network requires more images, which provides better generalization performance on unseen input images. As a result, when 60% of the images are used in the training process, the performance of the network improves. It is also important to keep some images in the validation set to adjust the hyperparameters of any deep network architecture to prevent overfitting and underfitting problems.

The final trained model (using a train-validation-test split ratio of 60%–10%–30%) was verified on the test dataset by reporting the final unbiased performance of the proposed CNN. The results show that the proposed compact model performs with a classification accuracy rate of 84.8%, a precision of 80.5%, a TPR of 83.8%, a TNR of 83.7%, and an F1 score of 81.6% when recognising skin cancer images. Figure 3 shows the training and validation losses and accuracy during 30 epochs of training. In comparison to other difficult methods and deep learning systems, our suggested technique performs better. The proposed compact network and other relevant models mentioned in [25], [26], [27], [28], [32], [33], and [34] were compared in this paper in order to show the effectiveness of the proposed model.

Research using the ISIC ARCHIVE database, which is a database comparable to the one employed in this paper, the skin cancer database, and other self-acquired datasets were the subject of the comparative evaluation. The proposed technique in this paper has done remarkably well when compared to other algorithms stated in Table 4, which summarises the comparative research. This data will also be used to calculate the required number of convolutional layers of the custom DCNN model. The accuracy of this study's findings is compared to existing studies in Table 4. As demonstrated, the performance and accuracy of our proposed method are promising.

The methods are examined in Table 4 and evaluated on different datasets. Each dataset represents a different collection of images for skin lesion classification. The number of samples varies across the datasets, ranging from 1,279 to 25,331. Please

note that this difference in sample size can influence the model's performance and generalizability. The accuracy metric indicates the overall correctness of the classification models. As clearly seen from the table the proposed model performs well with the considered sample size. It is worth noting that not all methods provide all the performance metrics. Some methods lack certain metrics, such as F1-Score, Precision, TPR, or TNR, making it difficult to make direct comparisons in those cases.

In summary, the given data showcases different methods for skin lesion classification, evaluated on various datasets. The methods differ in terms of the dataset used, the number of samples, and the reported performance metrics. By comparing the metrics, we can gain insights into the relative performance of these methods in classifying skin lesions.

5. CONCLUSION

In this study, we proposed a new compact model using CNN in order to test its effectiveness in classifying skin cancer. The recognition of skin cancer is important because a good classification method can save time when searching for and diagnosing skin cancer in databases. The ISIC-Archive database contains 3,297 images of both benign and malignant skin, with dimensions of [224x224] pixels. The dataset was first checked for structural integrity and then normalized to improve the performance of learning algorithms. It was then split into three parts: a training set (60% of the images), validation set (10%), and testing set (30%) by determining the impact of the training set ratio beforehand (see Table 3).

Our proposed model achieved a classification accuracy rate of 84.8%, precision 80.5%, TPR 83.8%, TNR 83.7% and F1-score 81.6%, respectively compared to other studies. When a skin image is provided, the pre-processing phase is applied, and the trained CNN extracts features from the image and classifies the label based on the filters learned during training.

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