DL-SCDDS: Accurate Skin Cancer Detection and Diagnosis Scheme Based on An Improved Convolutional Neural Networks Model

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Abstract. One of the worst types of cancer is skin cancer. Unrepaired deoxyribonucleic acid (DNA) in skin cells results in genetic errors or mutations on the skin, which is the cause of skin cancer. Skin cancer is best diagnosed early because it is more treatable in its early stages and tends to spread gradually to other body areas. Early diagnosis of skin cancer signs is imperative due to the disease's rising incidence, high death rate, and cost of care. The accuracy of traditional skin cancer diagnostic techniques, especially those that depend on visual examinations, is limited and not accurate, which could endanger the patient. As a result, the use of Deep Learning (DL) has aided researchers in creating a variety of early detection methods for skin cancer. These methods employed characteristics of the lesion, such as color, size, shape, symmetry, etc., to identify skin cancer and differentiate it from melanoma. This paper proposes a new DL-based skin cancer detection and diagnosis scheme (DL-SCDDS) that uses the Human Against Machine 10,000 (HAM10000) dataset, a large and diverse dataset, to ensure an accurate yet effective diagnosis through the implementation of DL techniques, specifically Convolutional Neural Networks (CNN). Before testing, the suggested CNN model underwent training, and it achieved remarkable results, accurately diagnosing seven different types of skin lesions with 96.9% accuracy. Additionally, the results obtained were contrasted with those of other studies that suggested a slightly different methodology; in these comparisons, the suggested model proved to be superior.

Keywords: Skin Cancer Detection, Deep learning, CNN, Diagnoses, Normalization. Augmentation

1 Introduction

Globally, skin cancer is the most prevalent type of cancer. According to estimations from the World Health Organization (WHO), skin cancer accounts for one out of every three cancer diagnoses [1]. Over the past few decades, there has been a relatively steady increase in the frequency of skin cancer diagnoses in nations including the USA, Canada, and Australia [2], [3] . Melanoma is the worst kind of skin cancer, and patients have a far better prognosis if it is discovered early [4]. However, there are insufficient medical resources and trained personnel to support the populace, particularly in developing nations and rural areas [5]. Various computer-aided diagnosis

(CAD) systems have been presented during the past few decades to address the issue of skin cancer detection. With these systems, conventional computer vision techniques are mostly used to extract different features, such as shape, color, and texture, and feed them into a classifier [6], [7].

One of the most significant methods for handling this problem is deep learning (DL), which has been the subject of numerous studies published recently. CNN in particular has achieved outstanding success in this field. In a study published by [8], the authors used CNNs to construct a system that can distinguish between benign and skin cancer. The CNN method, using random regulators, achieved a 97.49% accuracy in this study and was able to distinguish certain skin lesions, such as nevus lesions, carcinoma, and melanoma. The ISIC dataset's augmentation data is used in this investigation. This dataset is used to distinguish benign cancer from skin cancer lesions. In their model, there were three hidden layers and an output channel; the model is also built with several optimizers, including Adam, SGD, RMSprop, Nadam, etc. The CNN model with the Adam optimizer achieved the best results in dataset classification, with a 99% accuracy rate. The performance outcome guarantees that medical professionals can utilize the suggested model as a tool for diagnosing skin cancer.

In contrast, a study employing automatic skin cancer detection was suggested by Hasan et al., 20197 where CNNs were employed to categorize cancer images as benign or malignant. In this study, feature extraction techniques are used to extract features of skin cells impacted by cancer while CNNs are used in the next stage to sort the extracted features. Using the publicly available data set, this method yields an accuracy of 89.5% and a training accuracy of 93.7%. The method can be regarded as a standard for the detection of skin cancer based on the experiments and evaluations in this work [9].

In a different study [10], the authors suggested a novel hybrid CNN-NLP (Natural language processing) method in which accuracy and efficiency were improved using dense layers, in addition to four convolutional layers. To cut down on extraneous data, two max-pooling layers are also employed. In the proposed approach, the images of skin lesions are uploaded to the system, then, the application categorizes the lesion, and the Chabot engages the patient. The proposed system recorded a 99.35% accuracy rate with a 2.25 % training data loss. Also, an accuracy of 83.93% and a testing data loss of 66.48% were observed. Hence, the image identification capability of the new CNN model was accurate and efficient. Patients can easily interact with the application via a user-friendly environment created using NLP.

To determine the ability of an algorithm to automatically identify a suspected skin cancer location and classify it as malignant or benign, Authors in [11] proposed a model that extracts benign lesions from images using region-based CNNs that was created using 924,538 potential lesions. These lesions were either manually or automatically annotated in the next step. CNN was trained on 1,106,886 images for skin cancer location identification. A data collection of benign and normal images was also created using R-CNN technology; the acquired dataset was used to train the disease classifier and fine-image selector for the successful identification of malignant facial melanoma.

A study published in 2021 [12], reported a study that employed CNNs to identify and categorize skin cancer based on historical clinical imaging data. The primary goal of the study is to create a CNN model with a precision level of more than 80%, an accu-

racy of more than 80%, and a false negative rate of less than 10%. Dermatoscopic images of skin lesions make up the HAM10000 data set, which was employed in the investigation. There were 10,015 colored images in the dataset, with the majority having a resolution of 600 x 450. Several research articles and techniques were examined and tested. Using the HAM10000 dataset, an accuracy of at least 80% was attained. The result demonstrated that the most effective method for detecting skin cancer is the standard CNN.

Rezaoana et al., (2020) suggested an automated method for skin cancer identification and categorization that comprises the classification of nine different forms of skin cancer in addition to observing and assessing the behavior and capabilities of deep CNNs. The dataset used in this work contains 9 types of skin cancer which are nevus, actinic keratosis, benign keratosis, basal cell carcinoma, squamous cell carcinoma, seborrhoeic keratosis, melanoma, and vascular lesions; hence, this work aims to build a model that uses CNNs for skin cancer identification and categorization into any of the nine types. Image processing and deep learning methods are used in skin cancer diagnosis and for this process, the number of images is increased by applying different image segmentation techniques; the accuracy and efficiency of categorization tasks were also improved by introducing a transfer learning strategy. The CNN-based approach in this study recorded an overall accuracy of 79.45 % [13].

In their study, Pham et al. (2018) made a significant contribution by using CNNs and data augmentation to build a classification model for improving performance during skin cancer classification; the study also showed how to employ image augmentation to address the limited data problem. The impact of several augmented samples on the performance of different classifiers was also studied using image augmentation; a public dataset comprising 6,162 training and 600 testing images was also used to train and test the model. Also investigated in this study is the impact of each enhancement on 3 different classes; the results showed differences in the impact of each augmentation on the behavior and capabilities of each classified ID. Hence, data augmentation is considered a possible way of improving the performance of models in skin cancer categorization [14].

This study aims to expand the published literature works by developing a new, accurate skin cancer classification model that can identify and differentiate 7 different types of skin cancer.; the proposed model was named DL-SCDDS. The model involves three main phases, (i) pre-processing, (ii) building a CNN classifier model, and (iii) evaluation process. The proposed DL-SCDDS model uses a large and diverse dataset called the HAM10000 dataset. In this study, a CNN model was developed for this specific task; the imbalance data was handled, and GPU-accelerated training was used.

This study is organized as follows: Section 2 lists the proposed methodology that aims to solve the research problems defined in this paper. Section 3 expresses the results achieved using the proposed methodology. This study is concluded in section 4 and future work related to the current study is mentioned.

2 Methodology

DL technology has been chosen for the task of detection and diagnosing skin cancer in this study due to its capabilities in learning complex features and patterns and creating relationships between the data which make it possible to generalize the acquired knowledge into new unseen data to generate accurate results. For this reason, CNN has been selected. The HAM10000 dataset was chosen for training and testing the utilized CNN model. The details of the steps of the preparation and implementation of the proposed DL-SCDDS mode are presented in Figure 1.

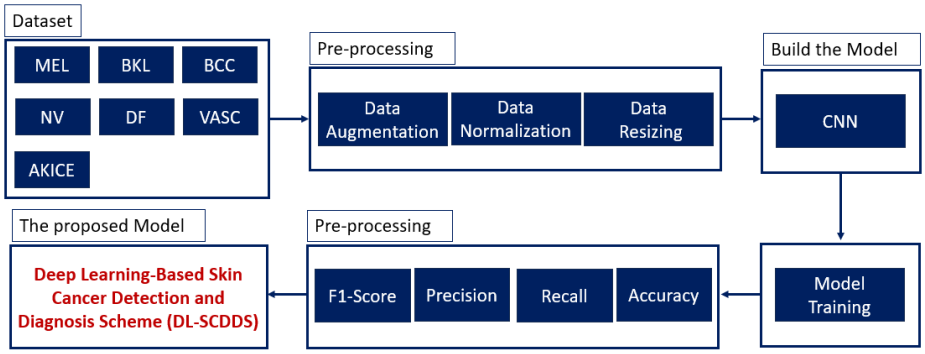

Fig 1. The workflow of the proposed DL-SCDDS model

Initially, the HAM1000 dataset is acquired, containing 7 different classes of skin cancer, namely "MEL", "BKL", "BCC", "VASC", "AKIEC", "NV", and "DF". Before feeding the acquired data to the proposed DL-SCDDS model, data pre-processing was performed which involved many procedures; the first one is data augmentation [14], data normalization [12], and The last process is data resizing [14] (See section 2.2.). After the data pre-processing stage, the proposed DL-SCDDS model is fed with the processed dataset which it uses for training and learning features of various skin cancer legions; this will enable the model to recognize these features in the testing stage. During the testing stage, the trained DL-SCDDS model is challenged with new previously unknown datasets to perform classification on them; this is a way of evaluating the classification performance of the proposed DL-SCDDS model. The evaluation takes into consideration several factors such as precision, recall, accuracy, and F1 score.

2.1. Dataset

For the classifier to be able to classify skin cancer types, it must already know the special features of each type through prior training on a suitable dataset. In this study, the chosen dataset is the HAM10000 dataset which originally contained 10000 images [12]. The HAM10000 dataset was developed by the Department of Dermatology at the Medical University of Vienna, where 10,000 high-resolution images of skin can-

cer were collected. In fact, the dataset now comprises 10015 images of pigmented skin cancer tissues, as 15 new images were added to the original dataset. The images within the dataset were collected through multiple dermo scopes, and they cover seven different types of pigmented skin cancer. Furthermore, each image within the dataset also shows metadata including the gender of the patient from whom it was taken, as well as their age, and the annotation relative to the skin cancer type. The seven different types/classes of skin cancer are vascular lesions “VASC” such as pyogenic granulomas, angiokeratomas, angiomas, and hemorrhage, melanoma “MEL”, benign keratosis-like lesions “BKL”, melanocytic nevi “NV” (commonly known as moles), melanoma “MEL”, actinic keratoses “AKIEC”, basal cell carcinoma “BCC”, and dermatofibroma “DF”. To show samples from the dataset of all the skin lesion types, Figure 2 presents 16 images that were randomly selected from the HAM10000 dataset.

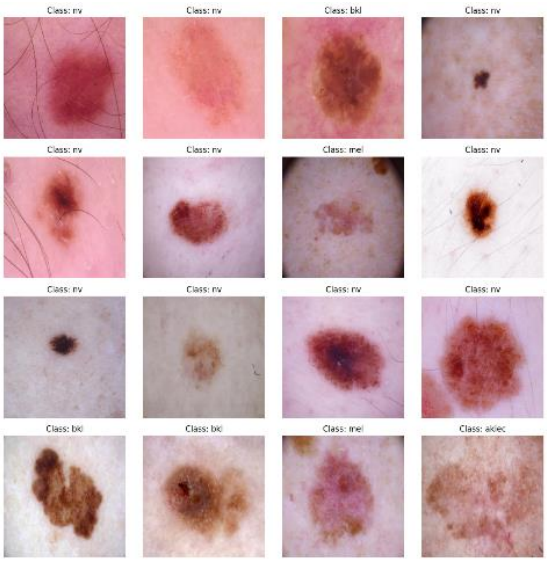

Fig. 2. Randomly Selected Samples of Images from HAM10000 Dataset [12]

2.2. Data Pre-Processing

Pre-processing phase of the data to be input into any image diagnosing and classifying system is an essential step; it improves the quality of the images such that they become free of distortions and with enhanced features so that it becomes easier for the scheme identify the features and use them for classification. Aside from ensuring the high quality of the images in the dataset, data pre-processing also helps in identifying important features to be learned through analysis and creating correlations between the features. As mentioned earlier, data pre-processing in this paper involves data normalization, data augmentation, and data resizing.

In the HAM10000 dataset, data augmentation took place through random transformation of the images in the training dataset, such as rotation_range, width_shift, and height_shift as means of random rotations and random translations, respectively; shear_range and zoom_range were used as means of random shearing transformations and random zooming, respectively (See equations no. 1,2,3,4, and 5). In addition to data augmentation, a data normalization step took place, where the data was transformed into values ranging between 0 and 1. Data normalization serves to avoid feature dominance so that the learning process is not dominated by one feature as a result of its scale (See equation no. 6). In addition, data normalization promotes convergence and enhances the model's performance. After that, the size of the augmented dataset is allocated as $244\ x\ 244$ pixels, which is the data resizing step. Data resizing ensures that all the input data has the same uniform size since CNN models require that the input data has a fixed size which enables efficient batch processing and compatibility (See equation no. 7).
Finally, the pre-processed images of the dataset were divided into 80% of the images assigned for the utilised CNN model training, and 20% assigned for model testing. This is to guarantee that there is sufficient data for training the model while keeping adequate data for testing the scheme's performance.

$$\begin{bmatrix} p' \\ q' \\ 1 \end{bmatrix} = \begin{bmatrix} -1 & 0 & 0 \\ 0 & 1 & 1 \\ 0 & 0 & 1 \end{bmatrix} \times \begin{bmatrix} p \\ q \\ 1 \end{bmatrix} \quad (1)$$

$$p' = -p, q' = q \quad (2)$$

$$\begin{bmatrix} p' \\ q' \\ 1 \end{bmatrix} = \begin{bmatrix} 1 & 0 & 0 \\ 0 & -1 & 1 \\ 0 & 0 & 1 \end{bmatrix} \times \begin{bmatrix} p \\ q \\ 1 \end{bmatrix} \quad (3)$$

$$p' = p, q' = -q \quad (4)$$

$$R = \begin{bmatrix} \cos(q) & \sin(q) & 0 \\ -\sin(q) & \cos(q) & 0 \\ 0 & 0 & 1 \end{bmatrix} \quad (5)$$

$$Normalized\ Pixel\ Value = \frac{Original\ Pixel\ vAlue}{255} \quad (6)$$

$$image\ resized = resize\big(image, (224, 224)\big) \quad (7)$$

2.3. The Proposed DL-SCDDS Model

For the skin lesion diagnosis task, CNNs [13] were chosen, being a DL architecture. CNNs are well known for their capabilities in image classification and recognition. The architecture of different CNNs may vary according to the task required, yet all of them have the same basic structures which are the convolutional layers and the pooling layers. Each of the multiple layers within the CNN architecture performs essential functions in extracting hierarchical features from input images.
The CNN model utilised in this work contained two Conv2D layers; these layers aid in extracting spatial features through convolutional operations; the convolutional layers in this study utilize 3x3 kernels, as well as the ReLU activation function to introduce non-linearity. The 'padding' parameter was set to 'same' to ensure consistent spatial dimensions of the feature maps. The next layers are the MaxPooling2D layers which aid in reducing the spatial dimensions of the feature maps while retaining the

important features; the aim of the pooling procedure is to help in achieving translation invariance; it also reduces computational complexity via feature maps down-sampling. To increase the number of filters, the Conv2D- MaxPooling2D layers sequence is repeated frequently to arrive at a hierarchical structure that allows the proposed model to capture intricate patterns at different scales; it also facilitates effective feature learning. In the proposed model, the role of the Flatten layer is to aid in the transformation of the 3D spatial information into a 1D vector; this prepares the data for the fully connected layers. These layers, represented by Dense, perform classification based on the learned features and introduce global dependencies. A Dense layer with 512 neurons is included in the proposed model, in addition to another Dense layer with 32 neurons; both layers are coded with the ReLU activation function. The Dense layer is the final layer; it consists of 7 neurons and is coded with the Softmax activation function; it generates the probability distributions across the 7 classes to enable multi-class classification.

CNNs are efficient because they can learn hierarchical features from raw pixel values; this implies that there is no need for manual feature engineering. This capability makes CNNs particularly effective in tasks related to images, such as skin cancer classification. The proposed scheme, with its stack of convolutional and pooling layers, is well-suited to capture intricate patterns within dermatoscopic images, thereby contributing to accurate and robust skin cancer classification.

Figure 3 illustrates the details of the layers within the proposed CNN model architecture, where convolutional and pooling layers are implemented to extract features, whereas fully connected layers are employed for classification. The introduction of non-linearity is achieved through the use of Rectified Linear Unit (ReLU) activation functions. In the output layer, the softmax activation function generates class probabilities for the multi-class classification task.

3. Results and Discussions

3.1. Training Environments

Google Colab was used as the training environment employing a Tesla T4 GPU with 15 GB of dedicated VRAM. Furthermore, the training process benefited from the system's 15 GB of RAM, which facilitated efficient utilization of resources. To develop and implement the DL model, the TensorFlow library, along with the Keras API, was utilized.

3.2. Testing Evaluation Metrics

After the development of the CNN architecture and its training, the proposed model is tested on 20% of the dataset to evaluate its performance. The evaluation process allows an objective assessment of the effectiveness and reliability of the tested model in performing the task, which in this case is classifying skin lesions. Different metrics can be used to assess how the model is performing during the training phase as well as the testing phase.

During training, the accuracy and loss metrics were utilized to assess the proposed model’s classification. The accuracy is a measure of how many incidents the model achieves compared to the total number of classification incidents. This means that the

accuracy metric directly determines how well the model classifies the different classes.

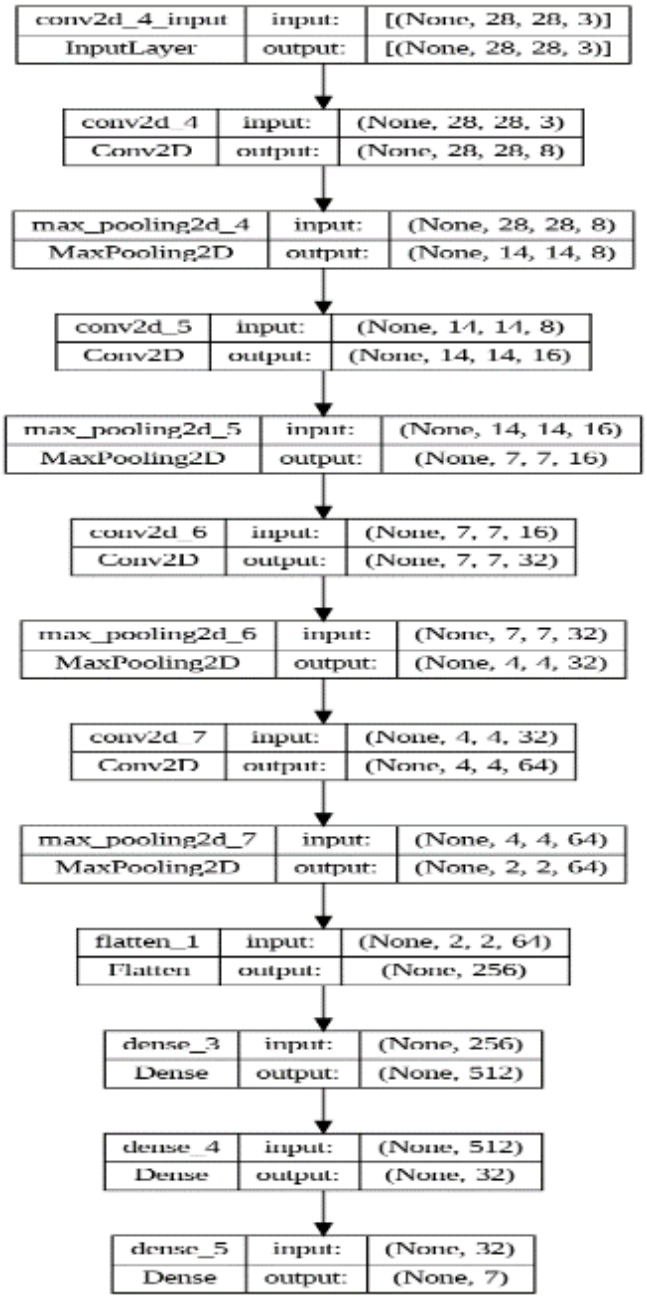

Figure 3. CNN architecture visual representation

On the other hand, the loss metric is a quantitative measure of the mismatches performed by the model. It also measures the fitting capabilities of the model. The accuracy and loss of the proposed CNN model are shown in Figure 4. According to the figure, the training and validation accuracy increases gradually as the ephocs number increases, until it reaches the maximum at 15 epochs, where the model reaches a peak training accuracy of approximately 100%, with a corresponding validation accuracy of around 97.9%.

On the other hand, the training and validation loss decreases gradually as the number of ephocs increases, until it reaches the maximum value at 15 epochs. The training was stopped early during epoch 26 due to minimal further improvement. The learning rate was reduced at specific points marked by vertical dashed lines, responding to plateaus observed in validation performance.

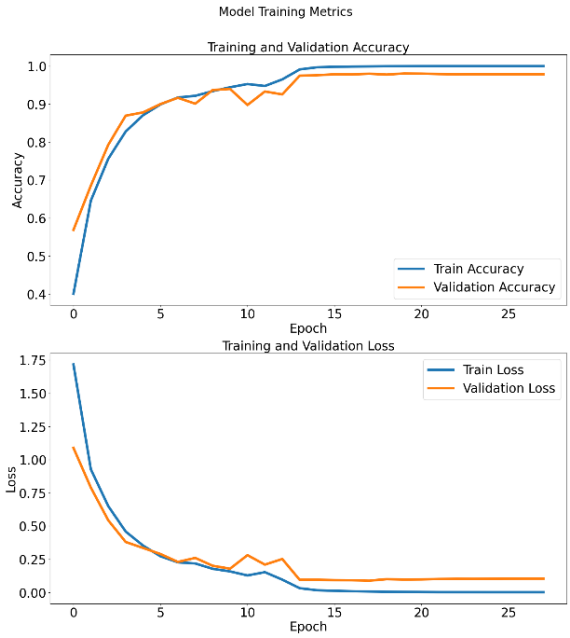

Figure 4. Accuracy and Loss evaluation during training and validation

In testing process, many metrics were be used to assess the proposed model's performance including recall, accuracy, f1-score, and precision [15], [16], [17]. All these metrics rely on True Positive (TP), True Negative (TN), False Positive (FP), and False Negative (FN). Equations 8,9,10,and 11 illustrate the utilized performance metrics.

$$Accuracy = \frac{TN + TP}{TN + TP + FN + FP} \quad (8)$$

$$Precision = \frac{TP}{TP + FP} \quad (9)$$

$$Recall = \frac{TP}{TP + FN} \quad (10)$$

$$f1-score = \frac{2\times(Precision \times Recall)}{Precision + Recall} \qquad (11)$$

The testing results in terms of recall, accuracy, f1-score, and precision are portrayed in Table 1, such that the accuracy of the proposed model was 96.955% indicating that out of all the instances or samples in the dataset, the CNN classifier accurately classified 96.9% of them correctly. Whereas the precision was 1.00 and the recall was 0.96. A precision of 1.00 indicates that all the positive predictions made by the classifier were correct. In other words, there were no false positives in the predicted positive instances, while a recall of 0.96 signifies that the classifier correctly identified 96% of the actual positive instances in the dataset. The achieved F1 score was 0.98, representing a high overall performance in classifying different skin lesions. An F1 score of 0.98 suggests that the classifier achieved a high level of accuracy in both correctly identifying positive instances (precision) and capturing a large proportion of the actual positive instances (recall). It indicates that the classifier is performing very well in terms of both lessening false positives and false negatives.

Table 1. Testing Accuracy, Precision, Recall, and F1 Score of the Proposed Scheme.

Metric type	Accuracy	Precision	Recall	F1-Score
Proposed model	96.955%	1.00	0.96	0.98

Additionally, a confusion matrix was generated, presenting a visual summary of the model's performance for each class. This matrix showcases the counts of false negatives, true negatives, false positives, and true positives. Figure 5 shows the confusion matrix of the performance of the Proposed DL-SCDDS model.

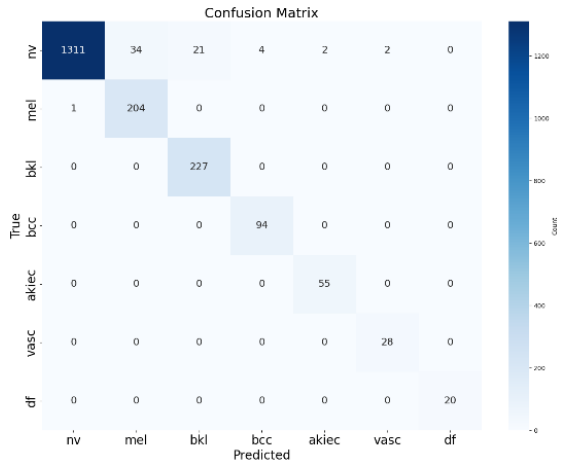

Fig. 5. Confusion matrix of the performance of the proposed model.

In Figure 5, the rows represent the true class labels, while the predicted labels are represented in columns. The numbers within each cell designate the number of in-

stances. The matrix is color-coded as a heatmap, where lighter shades represent higher counts. This matrix serves as a diagnostic tool, offering a clear overview of the classification accuracy and potential misclassifications across various classes. In more detail, the confusion matrix in Figure 5 shows the following classes were perfectly predicted by the model: DF, VASC, AKIEC, BCC, and BKL, where each class was always classified correctly as itself. Conversely, the MEL class was incorrectly classified once (1 time) as NV. However, NV was the class with the highest misclassification rate, where 1311 instances were correctly classified, 34 were incorrectly classified as MEL, 21 were incorrectly classified as BKL, 4 were incorrectly classified as BCC, 2 were incorrectly classified as AKIEC, and 2 others were incorrectly classified as VASC. The heatmap associated with the counts emphasizes and highlights them visually, allowing for a clear comprehension of the model's strengths and areas that need improvement. This visual tool is essential for evaluating the overall accuracy of the classification and identifying specific challenges in the model's predictive abilities.

3.3. Results and Discussion

In classifying various skin lesions, the proposed DL-SCDDS model achieved impressive results, scoring 96.9% classifying accuracy. The efficiency of the proposed model has also been backed up by the high precision, recall, and F1-score values during the testing stages. Notably, the model even achieves perfect scores in multiple class classifications, such as the DF class, VASC class, BCC class, and others. Whereas in the challenging classes such as the NV class, the model was able to achieve 1.00 precision and 0.96 recall, which also indicates the high capabilities of the CNN model in identifying the 7 different classes of skin lesions.

To gain a better overview of the performance of the proposed model, it is possible to compare its results with results achieved by other models in other studies. For instance, the study by [18]aimed to classify skin lesions using an incremental CNN model. Their approach relies on training the classifier by incremental method rather than being trained all at once. The process includes 4 different steps to ensure that the model is well-trained. To perform the classification task, their model was trained on the International Skin Imaging Collaboration (ISIC) 2018 challenge Dataset which also includes the seven skin lesion classes, similar to the HAM10000 dataset. Their approach with the incremental CNN model was able to achieve good results, which were better than the results of regular CNN using the same dataset. Their achieved accuracy was 90% compared to 64% achieved by the regular CNN model.

Another study by [19]also discussed the task of skin lesion classification using a CNN architecture and utilizing the HAM10000 dataset as well. The study aimed to classify all 7 seven types of skin lesions as well. Their developed CNN model was made up of 4 layers (4-CNN) with 2 max-pooling layers (Pool1, Pool2), 6 batch normalization layers, 4 dropout layers, and 4 fully connected layers. Their model was able to achieve good results overall with 93% accuracy.

In comparison to the results achieved by these two papers, the proposed DL-SCDDS model achieves much better results in terms of accuracy, precision, recall, and F1 score. The comparison of the results is shown in Table 2.

Table 2. Comparison of the performance of proposed model opposed to other models

References	Accuracy	Precision	Recall	F1-Score
Proposed model	96.955%	1.00	0.96	0.98
[18]	90%	0.88	0.87	0.86
[19]	93.6%	0.91	0.98	0.95

The model by [18]achieved 90% accuracy, 0.88 precision, 0.87 recall, and 0.86 F1-score, as opposed to the model by UdriȘtoiu AL et al. which achieved 93.6% accuracy, 0.91 precision, 0.98 recall, and 0.95 F1-score as shown in Table 3.

Table 2 shows that the proposed model performs better than the models of [18]and [19] in terms of precision, f1 score, Recall, and accuracy. It is clear that the proposed model achieved 96.9% accuracy, which is the highest accuracy followed by UdriȘtoiu AL model (93.6%), then the Ankir model (90%). Furthermore, the proposed model scored higher precision (1) compared to UdriȘtoiu AL (0.91) than Ankir (0.87). The recall values were slightly lower for the proposed model (0.96) as opposed to a higher score for the UdriȘtoiu AL model (0.98) followed by the lowest recall value scored by the Ankir model (0.87). Finally, the F1-score was highest for the proposed model (0.98) followed by the UdriȘtoiu AL model (0.95) then the Ankir model (0.86). Collectively, the proposed model performed better than most of the mentioned models in this study.

3.4. Conclusion

Timely detection and diagnosis of skin cancer is important for its proper management; it facilitates more efficient and faster treatment. CNNs have been discovered as advanced techniques for skin lesion diagnosis as they can learn complex patterns and features from skin images; they are mostly trained on large datasets for accurate skin lesion classification; the training enables automated and efficient screening of skin lesions, thereby assisting in reducing human error. A DL model, specifically the CNN model, was developed in this work for skin cancer classification using dermatoscopic images; the proposed DL-SCDDS scheme performed excellently by achieving 96.955% test accuracy on the HAM10000 dataset the comparative study with two referenced studies also showed the proposed model to record the best test accuracy; it also recorded better precision and recall across various skin lesion classes. The precision-recall balance achieved in our model highlights the potential for reliable and accurate skin cancer diagnosis.

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