A Review On Various Deep Learning Techniques Used For Melanoma Detection

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Abstract—Melanocytes, which produce melanin, the pigment that gives your skin its colour, are the source of carcinoma, one of the most life-threatening types of skin cancer. Although there is no confirmed cause for all tubercles, exposure to ultraviolet (UV) rays from the sun, tanning lamps or prolonged exposure to sunlight increases the risk of developing the condition. If cancer is not treated at early stages of development, there is a high probability of mortality. The probability ratios of the case surviving can be improved with a timely and precise opinion. Initial identification of skin cancer can save the lives of those affected. Because of this, it is vital to develop a computer-based support system for the detection of carcinoma. In order to determine whether the specimen skin lesions are benign or malignant, this paper discusses various novel deep transfer learning methods for early melanoma diagnosis. Deep convolutional neural networks are used to determine if these particular skin lesions are malignant or benign. The use of various datasets to evaluate the viability of the deep learning architecture is discussed as well. According to the findings of the experiments, the deep learning strategy performs better than many of the traditional deep learning algorithms in terms of computational efficiency and precision.

Index Terms—Deep learning, Melanoma, CNN

I. Introduction

Skin cancers such as melanoma, which is a type of skin cancer, may develop from melanocytes, cells that produce pigmentation in the skin. This dark pigment melanin is in charge of giving the skin color. Melanomas are typically brown or black in color [1]. However, some melanin are pink or flesh-colored. One of the most prevalent cancers in people under the age of 40, especially young women, is melanoma. Rarely, melanomas can also develop in the eyes, intestines, or other organs apart from skin.

Incidence of melanoma has increased dramatically during the past 30 years. Although the exact aetiology of melanoma is unknown, it is widely accepted that prolonged exposure to ultraviolet (UV) rays is one of the primary cause for the rise in melanoma instances [2]. Fair skin, a history of sunburns, excessive UV exposure, having many moles or odd moles, a weakened immune system, a family history of melanoma etc. are some of the factors that might increase the risk of developing melanoma. two lowest layers of skin, dermis and subcutaneous tissue, are mostly affected by invasive melanoma. Lymph nodes and the gastrointestinal system are frequently affected when melanoma spreads to other parts of the body. However, any organ in the body could be affected. With early diagnosis, the cure rate is 99%. Since the depth of tumor development directly impacts the efficacy of treatment, early diagnosis is of the utmost scientific relevance. Melanoma can be lethal despite only being present in about 1% of cases. The only certain approach for a doctor to diagnose melanoma involves performing biopsy [3] of the skin lesion that is suspected. If the pathology report indicates primary melanoma tumor, additional testing may be required. Such testing involves tests for for high-risk or later-stage melanoma involving ultrasound, Computed Tomography (CT) scan, Magnetic Resonance Imaging (MRI), Positron Emission Tomography (PET), or PET-CT scan . Due to human error, even a trained dermatologist could misdiagnose a patient, which can be a serious and even fatal problem. Several scholars have suggested Computer Aided Diagnostic (CAD) systems as a solution to this issue. The CAD system serves as a tool in research that frequently employs image processing and machine learning techniques to analyse dermoscopic images [4]. This supports dermatologists in reaching judgements quickly and eliminates inaccurate diagnosis. The rest of this paper gives an overview to the various techniques used for the detection of melanoma and a detailed comparison of the same

II. Melanoma Detection Techniques

The idea of using image processing to find skin cancer lesions on digital image had started in the late 20th century. Waghulde et. al in [1] proposed an approach based on Probabilistic Neural Networks [PNN] and the feature extraction algorithm GLCM. The PNN classifier not only aids in classifying the lesions but also identifies the cancer type. Using this method, skin cancer can be automatically diagnosed. However it classifies new cases more slowly than some other networks like the multilayer perceptron network and also takes up more storage space while storing the model. A deep learning-based approach for automatically detecting melanoma was presented in [5] that used a fully automated method to find the condition using dermoscopic images. The Softmax classifier is used in this method to classify melanoma lesions at the pixel level using a multistage, multiscale strategy. It is a potent system capable of doing real-time medical diagnosis duties while utilizing the least amount of computer resources. Sreedhar et. al presented an assessment of the diagnosis of melanoma skin cancer utilizing

traditional and modern image processing techniques in [6]. The technique employed image classification using Convolutional Neural Network (CNN) Support Vector Machine (SVM)-based deep learning and machine learning algorithms. The method has shown to outperform the conventional image processing algorithms based on image classification. The Deep Convolutional Neural Network (DCNN) was used to detect melanoma was proposed in [7]. However the method proved to have low accuracy A skin classification method based on transfer learning and VGG19 is proposed in [8]. The dataset used is $HAM10000$ The autonomous feature extraction capacity of $VGG19$ is exploited in this work. It is a powerful tool that diagnoses skin cancer with exceptional precision. However, additional pre-processing steps to boost accuracy increases the computational complexity. A study using $YOLOv4 - Darknet$ and acuive contour to recognize and segment melanoma lesions was presented in [9]. The approach involved brightening the image regions and applying morphological procedures to eliminate artifacts from the dermascopic images. The $YOLOv4$ object detector is then tuned for melanoma detection to be able to distinguish among closely interconnected infected and non-infected regions, which enables the identification of the diseased region. Finally, the troubled melanoma patches were obtained using active contour segmentation for texture extraction. The segmentation resulted in developing a clinical assistance system for melanoma detection. One disadvantage of $YOLOv4$ is the increased localization inaccuracy. Machine learning algorithms for skin cancer detection may were also exploited alongwith feature extraction for the early diagnosis of skin lesions as in [10]. Pre-processing includes noise removal using median filter followed by hair removal using region filling morphology. Segmentation was done using Geodesic Active Contour (GAC).The GAC monitors variations in the total number of skin abnormalities. The lesions were segmented which was followed by feature extraction by ABCD scoring method. The features were extracted on the basis of symmetry, border, color and diameter. Gray Level Co-occurence Matrix (GLCM) was utilized for extracting textural features which was followed by the process of classification. The K- Nearest Neighbour Algorithm (KNN),SVM and Naive Bayes were employed for feature extraction and classification. Though it has an increased accuracy, heavy computational ambiguity seems to be a disadvantage.In [11] Rowinet. al introduced a method based on neural networks on an implanted device to quickly identify skin cancer. The procedure was created to offer real-time skin cancer screening on a smartphone, enabling users to scan multiple tumors at once. Artificial intelligence and embedded technologies were employed to detect skin cancer. The accuracy of these methods suffers greatly from the lack of bodily information, including the age or the position of tumors. A classification of melanoma based on feature similarity assessment for codebook learning in the bag-of-features model was analysed in [12], that focused exclusively on Bag-of-features (BoF) model based melanoma classification methods. Dermatologists might have been able to diagnose skin conditions more successfully with the help of this method. The K-means clustering approach is frequently utilized to learn a codebook. Codebook learning is a crucial stage in the BoF model. To successfully quantify the original features of melanomas, it presented a new codebook learning technique based on Feature Similarity Measurement (FSM) and used a mix of the linearly independent and Linear Prediction (LP) algorithms to assess feature similarity. In [13], a deep learning network has been chosen and trained for the evaluation of more than 24000 melanoma images by Convolutional Neural Network ($ConvNet$) model applying with the models ($InceptionV3$, $ResNet$, and $VGG19$) with many metrics to identify the best classification method; and classifying the cancer type as benign or malignant with high accuracy. The dataset used were high-resolution images from the ISIC archive between 2019 and 2020. After all the performance metrics were evaluated the best architecture is $InceptionV3$. Any worrisome lesions were looked at using a $MobileNetV2$ based transfer learning approach for melanoma and benign skin lesions diagnosis in [14]. To identify whether a condition is benign or malignant, it is implemented on an $ISIC2020$ challenge dataset of skin cancer disease images. To expand the dataset and boost $MobileNetV2$ precision, data augmentation strategies were applied.

A research on the categorization of skin cancer based on Convolutional Neural Networks (CNN) was analysed in [15]. Based on historical information from clinical imaging, a CNN was utilized to identify and categorize the type of malignancy. This methodology has a number of benefits, including the ability to automate the diagnosis process and reducing manual errors, as well as accuracy rates of over 80%. One of its drawbacks has been that the dataset it utilized skewed and needed a lot of augmentation. In [16] skin cancer diagnosis depending on Extreme Learning Machine (ELM) and an established variant of Thermal Exchange Optimization (TEO) algorithm. ELM may be used for regression and classification right away and have a high learning rate, but training takes a long time because of several soft approaches. In order to identify melanoma from dermatoscopic images, a study in [17] provided two applications of multi-network systems (assemblages of effective neural networks) with good performance. The first model was built by combining the judgments of various neural networks while taking the weights of the different networks into account. The second model was a horizontal casting votes model that was based on the of various network models that were obtained from the fundamental networks over a range of epochs. Both models had reasonably acceptable results, meanwhile the second model based on horizontal voting had a melanoma detection accuracy of 94.06%. Using $MobileNet$ and the CNN algorithm, an original analysis of the prediction of melanoma skin cancer was conducted. In order to forecast melanoma skin cancer, a comparison between $MobileNet$ and CNN Algorithm was conducted in [18]. The $MobileNet$ architecture was used in Group 1 with a sample size of 10, and the CNN method was used in Group 2. The $MobileNet$ architec-

ture algorithm's accuracy (75%) is considerably higher than the Convolutional Neural Network's (60%). The $MobileNet$ architecture technique outperformed convolutional neural networks in the detection of melanoma skin cancer and has a high significance level. An ensemble model for the detection of skin cancer was proposed utilising Consolidated Decision of Deep Learners in [19]. It was created by fusing the three deep learning models, $ResNet$, $Caps - Net$, and Visual Geometry Group (VGG). From the findings, it can be shown that the proposed ensemble had a categorization training time of $106s$ and an average accuracy of 93.5% [19]. In terms of sensitivity, accuracy, F-Score, specificity, false positive, and precision, the suggested model outperforms individual learners. A method for detecting skin lesions in extremely unbalanced datasets utilizing deep clustering was developed in [20]. A unique Center Oriented Margin free triplet loss ($COM - Triplet$), enacted on image embedding from a CNN backbone, was used to achieve clustering. It was less susceptible to class imbalance since the suggested strategy attempts to create cluster centers that are as far apart as possible rather than minimizing classification error. According to [21], Convolutional Neural Networks (CNN) outperformed all other neural networks in tests for object detection and classification. The $MNIST : HAM10000$ dataset, which has a sample size of 10015 and includes seven different types of skin lesions, was used for the experiment. The model was trained using transfer learning approaches like $DenseNet169$ and $ResNet50$, and the results were obtained using a variety of data pre-processing techniques such sampling, dull razor, segmentation using autoencoder and decoder, and sampling. A deep learning strategy for melanoma early diagnosis was put forth in [22]. The architecture employed was called $VGG - 16$, or octal architecture, after the VGG. Through using the layers of the architecture, the various properties of the incoming data were retrieved and used for categorization. The training set included more than 1697 images. 510 photos were used to train the random forest model, and testing was done using the random forest approach as well. The effective strategy was selected based on accuracy. A structure for automated initial melanoma diagnosis utilizing sequential dermoscopic images was put forth in [23].

A. VGGNet model-based FCN Layer Architecture

The $FCNLayer$ technique based on $VGGNet$ was utilised to identify the lesion site in the improved dermoscopy pictures. This design is based on semantic segmentation using a pixel-based fully convolutional network [23]. The suggested segmentation as well as classification models were evaluated using the $HAM10000$?? dataset. This dataset contains 10015 dermoscopic pictures from seven different types of skin cancer: melanoma, melanocytic nevi, basal cell carcinoma, vascular lesion, benign keratosis, dermatofibroma, and actinic keratosis. Furthermore, it is an imbalanced dataset, with a variable amount of photos for each type. In the current study, 1113 melanoma photos and 8902 non-melanoma images were subjected to experimental tests. An imbalance in data between these two groups might result in overfitting throughout the training phase. To equalise the data numbers, the data enhancement method, a rotation, flip, contrast, and exceptional were utilised. The raw data set was separated into training and test datasets, and the data was balanced utilising techniques for data enhancement for these two different datasets. Following these procedures, the number of melanoma photos was raised by 8904, giving the collection of data a total of 17806 images. One of the limitation of $VGGNet$ model-based FCN Layer architecture is that it consumes so much of time for training and the increase in number of parameters lead to exploding gradients problem.

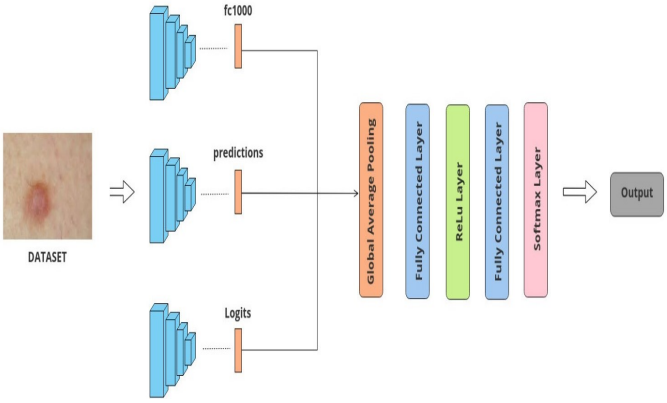

Fig. 1. The structure of the classifier model

Based on the pretrained $VGG16$ architecture presented in Fig. 1, the $VGGNetFCN8s$, $VGGNetFCN16s$, and $VGGNetFCN32s$ models were employed for lesion segmentation.These techniques were trained using deep settings that included epoch size 200, batch size a value of 1, as well as the Adam optimisation algorithm. The dermoscopic changes from aligned lesion images and the corresponding difference images was captured with a spatio-temporal network. The sequential dermoscopic images of skin lesions were integrated using approximate Euclidean transformations. The lesion growth region was extracted by computing image differences among the consecutive images. The model was seen to have high diagnostic performance compared to the detection by those of skilled dermatologists.

B. $DenseNet - II$ Architecture

$DenseNet - II$ is based on deep learning models such as $DenseNet$,$VGG - 16$, $InceptionV3$, and $ResNet$. It takes the essential elements of each method and combines them to build a robust classifier. The complete melanoma detection process may be divided into many sub-phases utilising various established models. The dataset is examined statistically. It is further pre-processed. The dataset is then partitioned to recover the training and testing set. The data is then trained and finally tested for assessing the effectiveness of our models.The layers utilised to build the $DenseNet - II$ model are summarised as $Conv2d$ Layer, $ConvMaxpool2d$ Layer, Flatten Layer, and Dense Layer [24]. The $DenseNet$ algorithm is a

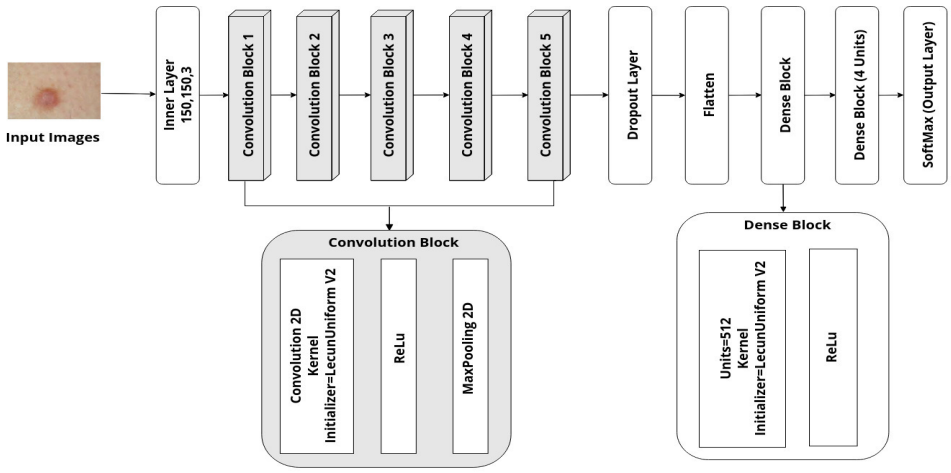

Fig. 2. Architecture of $DSCC\_Net$ used to classify skin cancer diseases.

combination of convolution, normalisation, and ReLU functions. The $ReLU$ function then turns the negative numbers to zero.

The $HAM10000$ dataset was used for the investigation. The dataset contains a diverse array of dermatological photos. The dataset has around 10000 records. The dataset contained information such as the lesion id, picture id, position of the mole, the gender and age of the infected individual, diagnosis type, and method of diagnosis. The model was evaluated via the confusion matrix, which was best suited for categorisation and accuracy computations. To provide a better overall perspective of how the model performed, the degradation of both validation and training of the data while training are also visualised for different epoch values. It might deliver significantly higher performance and more encouraging performance metric data. The $DenseNet-II$ neural network, however, had issues with overfitting. One of the limitation of this model is that the feature maps of each layer are spliced with the previous layer, and the data is replicated multiple times. As the number of network layers increases, the number of model parameters grow linearly, eventually leading to explosive growth in computation and memory overhead during training.

C. Deep learning based Skin Cancer Classification Network ($DSCC\_Net$)

The $DSCC\_Net$ was built on a CNN (Convolutional Neural Network) and was tested on three publicly accessible datasets (ISIC 2020 ??, DermIS [?], and $HAM10000$).The four types of melanoma was detrmined using the $DSCC\_Net$ model in Fig. 2. It consists of 5 convolutional blocks, a ReLU (Rectified Linear Unit) activation function, one dropout layer, two dense layers, and a classification layer using softmax function [25]. The convolutional block was made using many layers.The use of the convolutional block was to identify early skin cancers. The samples were created using the SMOTE Tomek method as it could tackle dataset disparity problems and keep the amount of specimens for each class balanced. The $DSCC\_Net$ model can be an invaluable resource for medical professionals.

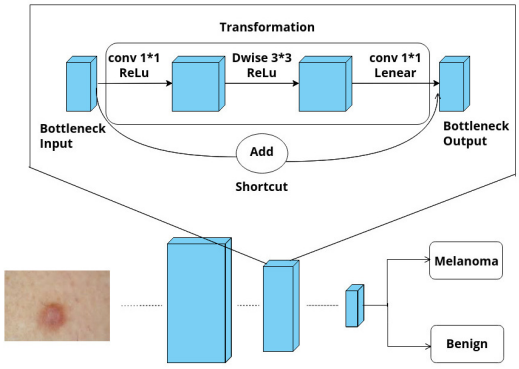

Fig. 3. Classifier based on MobileNetV2

TABLE I
Parameters Used in the Experiment

Architecture Used	MobileNetV2
Optimization Algorithm	Adam
Learning rate	Default Alpha Rate
Activation Function	Sigmoid & ReLu
Batch Size	64
Epochs	100

D. $MobileNetV2$ Architecture

The $MobileNetV2$ design will address the challenge of melanoma categorization. Several variables affected the $MobileNetV2$ model's selection. The dataset used to train a model was rather small, rendering it prone to over-fitting, and utilising a smaller yet more expressive system, such as $MobileNetV2$, considerably decreased this effect [14]. The performance of the model was evaluated using the ISIC 2020 dataset. $MobileNetV2$ is an architecture that optimises processing speed and memory usage while incurring the least amount of error.

Because of the fast execution speed, parameter adjusting and experimentation are much easier to handle, and the low memory usage is an added bonus. $MobileNetV2$ structure is based on $MobileNetV1$. The depthwise separable convolution, linear bottleneck, and inverted residual are two key concepts that describe the $MobileNetV2$ framework. The classifier used is shown in Fig. 3. The training set was used to train the $MobileNetV2$ model, while the validation and testing datasets were employed to assess the model's efficiency. The parameters used for study are given below in Table I.

III. Results & Discussion

A number of automated techniques were mentioned in the previous sections. Before applying it in clinical diagnosis it is necessary to ensure that the algorithms are fully capable of melanoma detection. To quantify the results it is necessary to use some performance metrics. The following sections explains the different parameters for evaluating an automated algorithm for melanoma detection.

A. Performance Matrices

1) Confusion Matrix: A confusion matrix presents the evaluations of the different results of a classification problem in a tabular form and helps visualize its outcomes. Fig. 4 shows a sample confusion matrix [26]. Here,

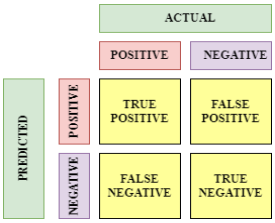

Fig. 4. Confusion Matrix

2) True Positive (TP): A true positive is a test result where the model correctly indicates the positive category.

3) True Negative (TN): A true negative is a test result where the model correctly indicates the negative category.

4) False Positive (FP): A false positive is a test result where the model wrongly indicates the positive category.

5) False Negative (FN): A false negative is a test result where the model wrongly indicates the negative category.

B. Sensitivity

Sensitivity analyses a model's capability to predict true positives of each given class.

$$Sensitivity = \frac{TP}{TP + FN} \tag{1}$$

1) Accuracy: The classification accuracy is the proportion of the number of correct evaluations to the total number of input cases [27].

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \tag{2}$$

2) Precision: Precision evaluates the ratio of units the model says are positive to how many are actually positive [26].

$$Precision = \frac{TP}{TP + FP} \tag{3}$$

3) Recall: Recall measures the ability of the model to find all the positive units in the dataset [26].

$$Recall = \frac{TP}{TP + FN} \tag{4}$$

4) $F1 - score$: The $F1 - score$ is a weighted average between precision and recall. The best value is 1 and worst is 0 [26]. its best value at 1 and worst score at 0.

$$F1 - score = \frac{2 * (Precision * Recall)}{Precision + Recall} \tag{5}$$

TABLE III
Performance Evaluation of $VGGNet$ [23] Model

	Accuracy	Precision	Sensitivity
$VGGNet - FCN8s$	93.61	92.59	98.99
$VGGNet - FCN16s$	96.99	97.65	98.41
$VGGNet - FCN32s$	96.11	96.71	98.17

Though a large number of methods were reviewed in the previous sections. Various recent deep learning based techniques such as $VGGNet$ model [23], $DenseNet - II$ [24], $DSCC\_Net$[25], $MobileNetV2$ [14] have been evaluated below in terms of the above performance metrics. The confusion matrices for $VGGNet$ [23] and $MobileNetV2$ [14] have been evaluated in Table II and Table VI respectively. Similarly performance evaluation based on accuracy, sensitivity and precision have been done in Tables III, IV, V and VII respectively.

TABLE IV
Performance Evaluation of $DSCC\_Net$[25] Model

Classifiers	Accuracy	Precision	Recall	F1-Score
$DSCC\_Net$	94.17 %	94.28 %	93.76 %	93.93 %

TABLE V
Performance Evaluation of $DenseNet - II$ [24] Model

Model	Accuracy
$DenseNet - II$	96.27 %

TABLE VI
Confusion Matrix for $MobileNetV2$ [14] Model

	TP	FP	FN	TN
$MobileNetV2$	1721	29	34	1716

TABLE II
Confusion Matrix for $VGGNet$ [23] Model

	TP	FP	FN	TN
$VGGNet - FCN8s$	4596975	3681826	466798	14797339
$VGGNet - FCN16s$	44483463	1168338	782699	14481438
$VGGNet - FCN32s$	48019878	1631923	896535	14367602

TABLE VII
Performance Evaluation of $MobileNetV2$ [14]

Performance measure	Malignant	Benign
Accuracy	98.1 %	98.4 %
Recall	98.3 %	98.0 %
$F1 - Score$	98.1 %	98.1 %
Precison	98.0 %	98.3 %

IV. Conclusion

Melanoma is a dangerous type of skin cancer. However if detected and treated early, it may not be fatal. Hence, it is important to apply different imaging modalities to improve diagnosis. Recent research approaches provide a deep transfer learning system for classifying malignancies of the skin. Hence, in this paper, to explore any worrisome lesion, various deep learning models were reviewed and studied for melanoma and benign skin lesions diagnosis. The use of different types of datasets to evaluate the viability of the deep learning architecture is also discussed.The evaluation metrics used to validate the models reviewed in this paper include accuracy, precision, recall and $F1$ score. Through this study, it was observed that $MobileNetV2$ model obtained a diagnostic accuracy of more than 98% compared to various other models like $DenseNet - II$, $DSCCNet$ and $VGGNet$ model. The suggested architecture was found to provide outstanding classification accuracy and precision which improved the overall model efficiency.

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