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Skin Lesion Classification Using Convolutional Neural Network With Novel Regularizer

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ABSTRACT One of the most common types of human malignancies is skin cancer, which is chiefly diagnosed visually, initiating with a clinical screening followed by dermoscopic analysis, histopathological assessment, and a biopsy. Due to the fine-grained differences in the appearance of skin lesions, automated classification is quite challenging through images. To attain highly segregated and potentially general tasks against the finely grained object categorized, deep convolutional neural networks (CNNs) are used. In this paper, we propose a new prediction model that classifies skin lesions into benign or malignant lesions based on a novel regularizer technique. Hence, this is a binary classifier that discriminates between benign or malignant lesions. The proposed model achieved an average accuracy of 97.49%, which in turns showed its superiority over other state-of-the-art methods. The performance of CNN in terms of AUC-ROC with an embedded novel regularizer is tested on multiple use cases. The area under the curve (AUC) achieved for nevus against melanoma lesion, seborrheic keratosis versus basal cell carcinoma lesion, seborrheic keratosis versus melanoma lesion, solar lentigo versus melanoma lesion is 0.77, 0.93, 0.85, and 0.86, respectively. Our results showed that the proposed learning model outperformed the existing algorithm and can be used to assist medical practitioners in classifying various skin lesions.

INDEX TERMS Convolutional neural network, skin lesion, novel regularizer, AUC-ROC.

I. INTRODUCTION

In the present era, computer-aided diagnosis (CAD) systems have become a necessity to diagnose and evaluate medical images [1]. For instance, CAD has become an essential component of a mammogram for detecting breast cancer in the United States (US) [2]. In addition, CAD is important for medical research specifically for diagnostic and imaging radiology. When used accurately, the CAD system could lead to the early detection of diseases, leading to early treatment options, thereby possibly saving lives [3]. For instance, the effective identification and treatment of a type of cancer are directly related to the ability to detect it during its initial stages [4]. Due to widespread interest, the early detection and treatment of cancer are important, as it is an amalgamation of multiple diseases [5]. Over 14 million new cases with over 8.2 million deaths due to cancer were reported in 2012 worldwide. These statistics make cancer the leading cause of death in humans [6]. For instance, skin cancer is a common type; it typically occurs in skin that has been constantly exposed to sunlight, although cancer could be present on any part of the body [7]. As skin cancer initiates from the epidermis, which is the topmost skin layer, it is quite visible [8]. This indicates that the CAD system has the capacity to utilize the images of skin lesion without assessing any other relevant information to reveal the preliminary diagnosis.

The most lethal type of skin cancer found in the humans is melanoma, which causes pigmented marks on moles onto the skin [9], [10]. The reason for melanoma is any abnormality in the melanin-producing cells (also known as melanocytes), which give coloration to the skin. Melanoma has certain risk factors, such as a sunburn history, weakened immune system, fair skin, hereditary factors, unnecessary exposure to ultraviolet (UV) light, and the use of tanning beds [11], [12]. According to [13], approximately 91,270 new kinds of melanomas are predicted to be identified in 2019, while 9,320 humans are estimated to die due to melanoma. Moreover, white people are 20 times more likely to be diagnosed with melanoma than African-Americans. Generally, 2.6 percent (1 out of 38) white people are likely to suffer from melanoma, while the lifetime risk for the blacks in 0.1 percent (1 in every 1000) and 0.58 percent (1 in every 172) among Hispanic people.

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Furthermore, the chance of getting melanoma increases with age. On average, 63 is the ideal age for people to be diagnosed with melanoma. Nevertheless, it is also common in people younger than 30 years of age. Additionally, melanoma has become one of the most commonly occurring cancers in young women.

If undiagnosed, melanoma starts to grow and continues to spread throughout the outer skin layer before penetrating the deep layers, where it finally connects with the blood and the lymph vessels. There is a high probability of treatment if the skin cancer is detected during the early stages compared to when it is diagnosed in the advanced stages. Nonetheless, it is expensive to detect skin cancer during the initial stages. Since the lesions on the skin look similar to one another, it is difficult to analyze whether the lesion is malignant or benign. A normal mole is commonly the same color as the skin, like brown, black, or tan, with a distinctive border segregating it from the adjacent skin. The moles are generally round or oval and smaller than 0.25 inches (approximately 6mm) in diameter, which is the same size as a pencil eraser. To detect unusual mole characteristics that could indicate skin cancer or melanoma, a search for moles with irregular borders, shapes, colors, and moles with more than 6mm diameter is done. To assess the soreness of the skin and classify it either as melanoma or benign, numerous techniques, including genetic algorithms, artificial neural networks (ANNs),CNNs, ABCDE rule, and support vector machines (SVMs), have been proposed [14]–[25]. All these techniques have been verified as cost-effective, highly efficient, and less painful than conventional medical techniques. However, in many computer vision problems, it becomes undeniable that both CNNs and deep learning are the technique of choice [26]. The latest research conducted at the Stanford University [14] created a deep CNN that outperformed dermatologists in terms of categorizing the keratinocyte carcinoma against the benign seborrheic keratosis and benign nevi vs. malignant melanomas. In this paper, we propose a new prediction model based on a new regularizer technique.

This research assesses the classification accuracy of a developed deep CNN based on a new regularizer technique. The CNN is designed in such a manner to differentiate melanoma from solar lentigo and seborrheic keratosis, which is oftentimes difficult [27], [28]. To this end, this paper establishes new test outcomes for the newly proposed technique. This is significant since the method needs to differentiate between multiple malignant and benign lesions to offer an accurate medical diagnosis. Hence, we intend to compare and report the accuracy and performance of our new method in comparison to other methods.

II. BACKGROUND

A. SKIN CANCER

Cancer is defined as a combination of multiple disease states in which the cells in the body begin to replicate, divide, and spread across the surrounding tissues [29]. There are different forms of cancer, of which skin cancer is one of the most common with a high risk of malignancy [30]. Skin cancer commonly occurs due to exposure to UV rays from the sun, which damages the DNA of the skin cells. Damage in the DNA triggers gene mutations leading to the multiplication of the skin cell to form tumors. Genetic defects are also a common cause of skin cancer [31]. Skin cancer is classified into different kinds, including basal, melanoma, and squamous cell carcinoma; melanoma is lethal [32]. Squamous and basal cell carcinoma hardly spread across the actual tumor site [7]. Melanoma skin cancer merely represents 4% of all skin cancer types, yet it is responsible for 75% of all the deaths caused by skin cancer [32]. Compared to other types of skin cancer, melanoma is aggressive and has the potency to spread across adjacent cells [7]. It is critical to detect melanoma during the early stages since the predicted five-year rate of survival decreases from 99% to 14% if detected during the advanced stages [14]. Currently, the diagnosis of skin cancer is made visually. The preliminary test is a clinical screening, which is then followed by biopsy, histopathological assessment, and dermoscopic analysis [14]. Characteristics play an integral role in classifying the skin lesions [33]. Different characteristics are considered with respect to the skin. These classifications are based on dermal features, contour features, color features, texture features, geometric features, histogram features, and the ABCDE rule features that assess the variation in color, diameter, border irregularity, and asymmetry [33].

B. CONVOLUTIONAL NEURAL NETWORKS

A CNN tries to mimic the process of recognition of images by the visual cortex in the brain. For better results in image classification, feature extraction is used according to machine learning tasks [34]. Different experts used handcrafted feature-extraction tools for digital image processing before the discovery of CNNs. Now CNNs perform the respective task of feature extraction automatically during the training phase using a stack of convolution layers and pooling layers. In the convolution layer, different types of dynamic filters are used that are trained according to the classification task during the training phase. Similarly, pooling layers retain the size and shape of invariant features by reducing the dimension of the input image while downsampling the neighboring pixels into a single pixel [34]. The standard structure of the CNN model was proposed by LeNet5 [35]. According to LeNet5, in CNN architecture there are multiple convolution layers followed by a stack of pooling layers, then contrast normalization layers. In the end, there is at least one fully connected layer. Compared to the feed-forward network, a CNN is less dense and can easily be trained. However, in theoretical terms, the best performance of CNNs is slightly lower and more computationally heavy on high-resolution images than the feed-forward network [35]. Nevertheless, the discovery of GPUs in 2012 and optimized 2-D convolution versions have made CNNs able to yield promising results with limited computational cost [35]. Hence, they can be

used to achieve effective results by incorporating additional intelligence.

III. RELATED WORK

In this section, the emphasis is on applying various techniques for skin cancer detection and diagnosis, with more focus on the recent studies that have used deep learning for the same purpose. A computer-aided approach to the detection of skin cancer is proposed in [36]. Using CNNs as the future scope has been encouraged by the in Dubal *et al.* [37] to distinguish the affected skin images without conducting feature extraction and segmentation independently [37]. A custom designed automated segmentation was used in [38] as a novel technique for applying the CNN methodology. The authors used CNNs for feature extraction and ANNs for the classification of the extracted features. Noteworthy, no additional classifier, such as a k-nearest neighbors (KNN) or SVM, was necessary for the CNN, as three fully-connected layers were utilized to train the classification model. Ali and Al-Marzouqi [39] used transfer learning to modify the architecture of the CNN within the LightNet pre-trained model to attain better accuracy [14]. The retention of Google Inception v3 through transfer learning alongside labeled images of the skin lesions was studied in a recent study at Stanford University [14]. In addition, Esteva *et al.* [14] compared the performance of their proposed CNN to 21 different board-certified dermatologists with respect to biopsy-proven clinical images in addition to two critical binary classification use cases. The deep learning CNN outperformed the dermatologists in terms of classifying the skin cancer through dermoscopy and photographic imaging. In the same context, Nylund [15] made use of a common CNN for the classification of the image known as AlexNet. The outcomes of this study were close to the results obtained in Esteva *et al.* [14]. Furthermore, Ridell and Spett [16] performed a study in which CNN was trained based on Google Inception v3 to identify skin cancer. They investigated how the precision of categorizing malignant melanoma and benign nevus was influenced based on the training dataset size. Mahbod *et al.* [40] proposed an automatic computerized method that achieved competitive results to an experienced dermatologist, and their method employed ensembles learning and pre-trained CNN for the classification of skin lesions. Moreover, they used 2000 images from ISIC 2017 and achieved an accuracy of 93.6% and 84.8% for seborrheic keratosis and melanoma, respectively. A semi-supervised, self-advised learning model proposed in [41] to recognize melanoma employed a dermoscopic approach. An investigation conducted in [42] on three different thin artefacts removal methods. The authors used two different skin lesion segmentations to compare their results. Similarly, Demyanov *et al.* [43] investigated the feasibility of using a deep CNN to detect dermoscopic patterns. On top of the above proposed methods, Nasr-Esfahani *et al.* [44] proposed a CNN for the classification of suspicious skin lesions. They also stated that their CNN could be a useful tool for the automatic extraction of discriminative features. A neural network based on classifiers and a CNN was proposed in [45] for detecting the border of skin lesions. An effective and simple technique for classifying melanoma was proposed, where Yoshida *et al.* [48] utilized the cytological properties of melanomas. As a result of their technique, there was an improvement in terms of the classification performance of melanoma. To achieve a high classification accuracy of dermoscopy images, Harangi [49] proposed an ensemble framework of CNNs for skin lesion classification. In their method, they fused the outputs of the classification layers of four different deep neural network architectures. Finally, they reported that their method outperformed the accuracy of the individual CNNs. In this work, we presented a new CNN model based on a novel regularizer. This CNN model performed better than the state-of-the-art methods in terms of accuracy, the AUC-ROC curve, and sensitivity. Moreover, the proposed CNN model has many advantages, such as lesser computational complexity and better generalization capability than other models.

IV. PROPOSED REGULARIZER

Regularization is a technique through which the classifier complexity is controlled. There are multiple ways to achieve this task, for example, using dropout in neural networks or using L1 and L2 regularizers. Here, in this work we have proposed a novel regularizer based on the standard deviation of the weight matrix of the classifier. In other words, we are controlling the complexity of the classifier by putting a penalty on the dispersion of the weight matrix values. Therefore, the weights values will lie closely, and similarly we are taking in account the correlation of these values. The mathematical formulation of the proposed regularizer is given below:

$$\lambda \sum_{i=1}^{k} \sigma(w_i) \tag{1}$$

λ is a regularization parameter that penalizes the weight matrix from getting large and disperse values. k is the number of filters in a convolutional layer, and n is the number of parameters in a single convolution filter that depends on the dimension of the filter. For example, in Figure 2, in the first convolutional layer there are 32 filters, and each filter is of size 3×3. Therefore, k corresponds to 32 and n is equal to 9, where σ represents the standard deviation as given below:

$$\sigma(w) = \sqrt{\frac{1}{n}\Big\{\sum_{i=1}^{k} w_i^2 - \frac{1}{n}\Big(\sum_{i=1}^{n} w_i\Big)^2\Big\}} \tag{2}$$

V. DATA SET

To test our proposed method, we trained the CNN model on skin lesion images. The dataset was taken from ISIC archives [51]. It is a benchmark dataset used by Pomponiu [24] and Harangi [49], consisting of skin

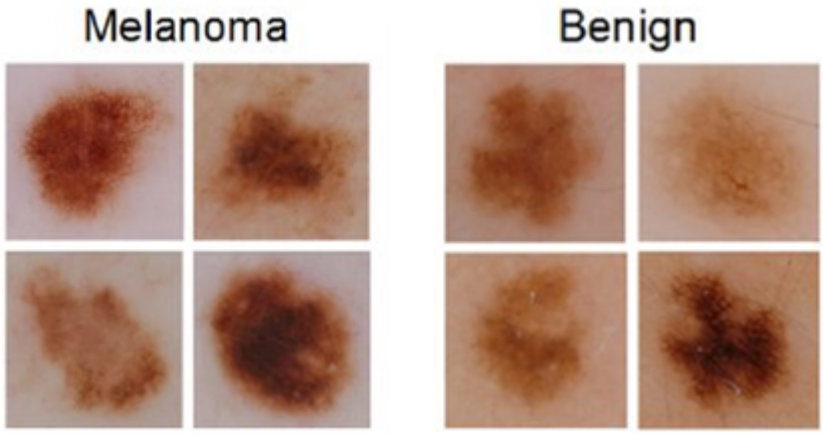

FIGURE 1. Some melanoma and benign images from data set.

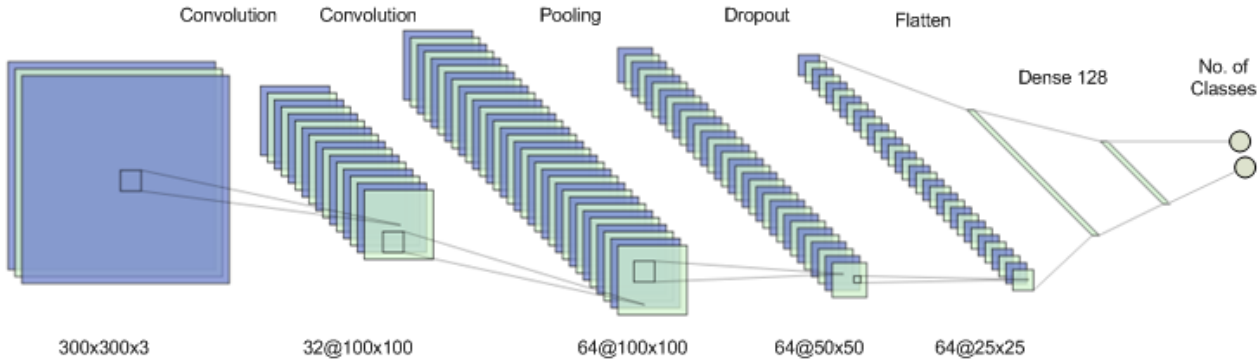

FIGURE 2. CNN architecture with embedded novel regularizer.

melanoma images of benign and malignant lesions. There are 23906 images of different classes available. We divided the dataset into three equal parts of around 8000 images of benign and malignant categories of approximately 600x600 resolutions. The proposed model was trained on each part, and the average validation accuracy was computed accordingly. Sample images from the dataset are shown in Figure 1.

A. NUMBER OF IMAGES USED IN THE TRAINING AND TEST SETS

The CNN model given in Figure 2 was trained on 70% and validated on 30% for each part explained in the previous section. Consequently, 5600 images were used for the training set and the remaining 2400 for the validation set in each part. The ratio of malignant to benign images in the overall dataset was 19%. Therefore, there were 4533 malignant and 19373 benign skin lesion images.

VI. CNN MODEL WITH NOVEL REGULARIZER

The CNN architecture used for this experiment is shown in Figure 2. In this architecture, we have two convolution layers followed by a pooling layer and dropout. After dropout, the 2-D outputs are flattened in a 1-D array and fully connected with the next layer having 128 neurons. In the last layer, there is one output neuron per class. In each convolution layer, the novel regularizer is embedded. The reason is since weight matrices are the filter values applied on each input. Therefore, embedding the novel regularizer controls the values of filter or kernel matrix values.

A. SETTING UP THE CNN AND TRAINING PROCESS

Before training the CNN model, all images in the dataset were re-sized to 300x300 pixels to retain the information in the image and reduce the computational cost for processing. In the next phase, all the images were transformed using power law transformation, as given in the following equation.

$$s = c.r^{gamma} \tag{3}$$

where for different *gamma* values and input pixel values r, the plot in Figure 3 shows different output results s. Hence, the input shape of the CNN is $300 \times 300 \times 3$ where 3 represent the number of RGB channels in the image. In the next layer, 32 convolution filters were applied with a size of 3×3 producing 32 channels of size 298×298. In the second convolution layer, 64 convolution layers were applied of the same size, which producing 64 channels that were 296×296. As stated

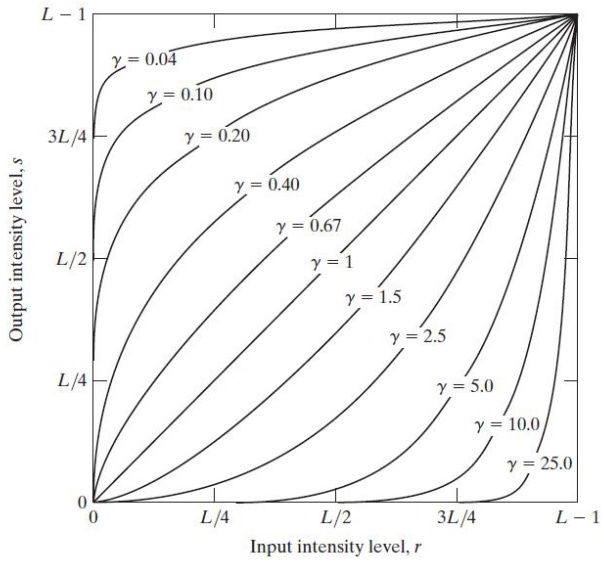

FIGURE 3. Power law transformation for different gamma values.

earlier, in each convolution layer the novel regularizer is embedded in it to reduce the complexity of the CNN model while penalizing the filter (kernel) values. After applying two convolution layers on input images, in the next layer the max pooling of size 2×2 was applied to maintain the translation invariant features in the output results. Before flattening the 2D output results, the dropout layer was applied, which helped in producing a high accuracy value. After the dropout, the outputs were flattened and fully connected with 128 neurons in the next layer, which were then followed by the last output layers of one neuron per class value. After finalizing the architecture, the model was trained for 100 epochs for 5600 images and validated on 2400 images. The validation phase is explained in the following sections.

VII. RESULTS

A. VALIDATION AND TEST PROCESS

The CNN model was validated on 2400 images during the training process. Before giving the images as an input to the model, all these images were pre-processed as explained earlier. During the training process, the parameters of the convolution layers were set according to the output results. Furthermore, during the validation process the parameters remained the same, but the test image was passed through the model to check whether the pre-set parameters were correct or needed fine tuning. During this process, the maximum average accuracy achieved was 97.49% for 100 epochs. Here, to tackle the imbalanced dataset, we used the weighted accuracy, which was defined as the average of the true positive rate obtained for each class [50]. The variations in the test and train accuracy during the training process are shown in Figure 4. For $\lambda = 0.02$, the following results were obtained. A Receiver Operating Characteristic (ROC) curve is a basic tool for analyzing the test evaluation of the classifier. In this curve, a plot between sensitivity (true-positive rate) as

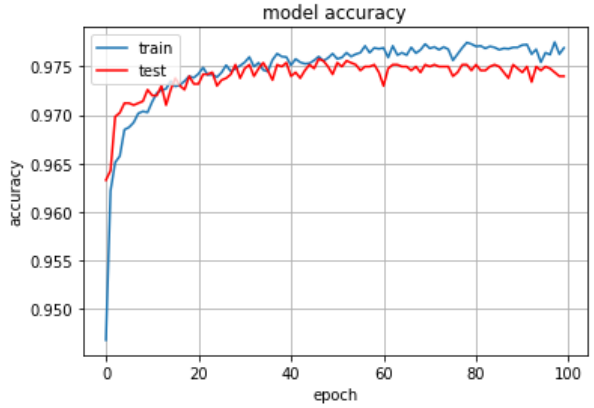

FIGURE 4. Training and validation accuracy of CNN with embedded novel regularizer for 100 epochs.

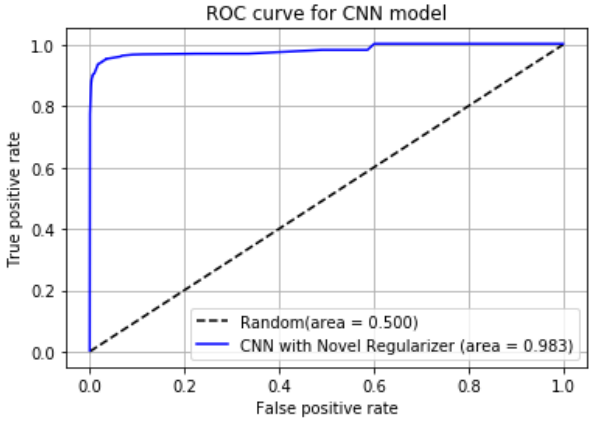

FIGURE 5. ROC for 97 images of nevus and 33 images of melanoma.

a function of the specificity (false-positive rate) is shown for different threshold values of the parameter. In the ROC plot, each point on the graph is a pair of FPR and TPR values for a specific threshold point. Hence, the AUC represents how a classifier distinguishes between a diseased or normal class-in our case the malignancy of benign lesions. The ROC curve of the novel regularizer embedded in the CNN is shown in Figure 5. The AUC for our proposed model achieved was 98.3% during the validation process, illustrating that our model distinguished well between malignant and benign lesions. To test the differentiation power of the proposed algorithm, we have tested it on some similar lesion images of different sub-classes, as explained by Boman and Volminger [47]. The results computed through the proposed model are explained below.

Figures 6, 7, 8, and 9 show the ROC curves for the CNN tested on four different binary comparisons. For each case, the following numbers of images are tested on the trained CNN model with the embedded novel regularizer.

Figure 6 represents the ROC of 97 images of nevus and 33 images of melanoma.

Figure 7 represents 70 images of seborrheic keratosis and 65 images of basal and squamous cell carcinoma.

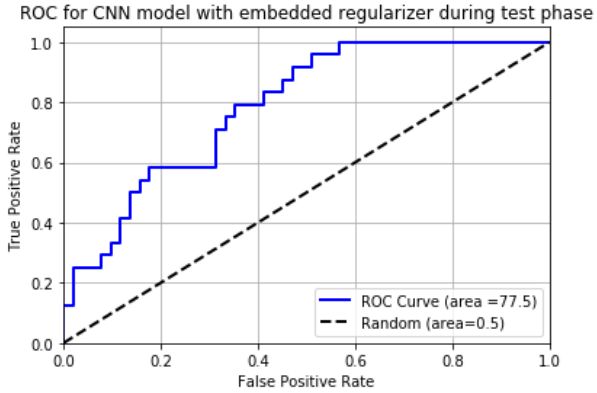

FIGURE 6. ROC for 97 images of nevus and 33 images of melanoma.

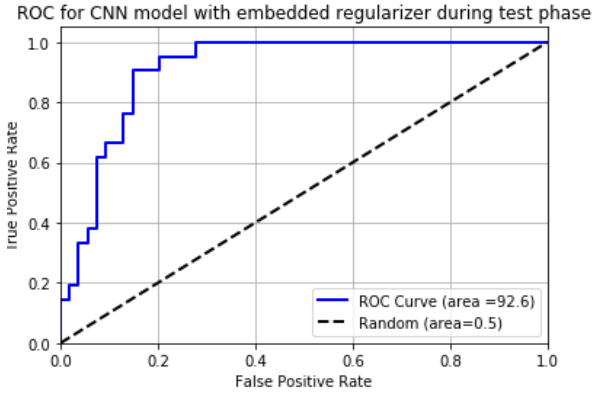

FIGURE 7. ROC for 70 images of seborrheic keratosis and 65 images of basal and squamous cell carcinoma.

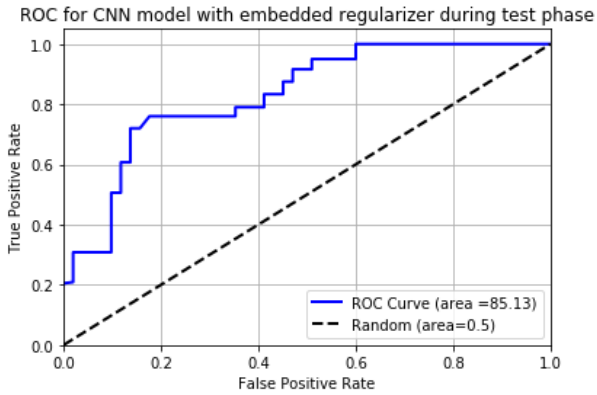

FIGURE 8. ROC for 97 images of seborrheic keratosis and 33 images of melanoma.

Figure 8 represents 97 images of seborrheic keratosis and 33 images of melanoma.

Figure 9 represents 20 images of solar lentigo and 20 images of melanoma. Table 1 represents the AUC for each test case explained above. Based on our analysis of Table 1, our CNN with a novel regularizer achieved a higher AUC-ROC when compared to the method in [47]. For nevus vs. melanoma, we achieved a 6.5% increase in AUC-ROC. Similarly, for seborrheic keratosis vs. basal and squamous

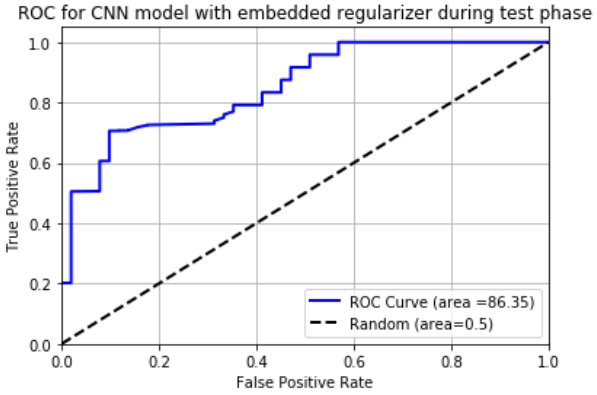

FIGURE 9. ROC for 20 images of solar lentigo and 20 images of melanoma.

TABLE 1. AUC for the ROC curves in Figures 6, 7, 8, and 9.

Test Case	AUC
Nevus vs Melanoma	0.77
Seborrheic Keratosis vs Basal and Squamour cell carcinoma	0.93
Seborrheic Keratosis vs Melanoma	0.85
Solar Lentigo vs Melanoma	0.86

cell carcinoma, there was a 1.6% rise observed in AUC-ROC. For seborrheic keratosis vs. melanoma, our classifier also performed well and resulted in a 1.13% increase in AUC-ROC. Likewise, for the classification of melanoma against solar lentigo, the AUCROC achieved was 86.35%, 3.35% higher than the previous results reported by [47].

B. COMPARISON TO OTHER STATE-OF-THE-ART METHODS

The intent was that the CNN in this study would classify the binary comparisons of nevus vs. melanoma and seborrheic keratosis vs. basal and squamous cell carcinoma with higher accuracy than other methods. Esteva *et al.* [14] reported 72.1% accuracy using three-way classification with a 0.9% standard deviation. Obviously, the maximum accuracy in the literature is 93.64%, which was reported by Pomponiu [24]. In comparison to these results claimed by different authors, our proposed model produced a maximum average accuracy of 97.49%. Different values of the regularizer were tested, including $\lambda = 0.2, 0.02$ and 0.002, but the maximum accuracy was achieved with $\lambda = 0.02$, i.e., 97.49%. Table 2 shows the comparison of our work with other methods. Based on our results, our proposed model outperformed the existing models.

C. LIMITATIONS OF THE PROPOSED REGULARIZER

There are multiple regularization algorithms used by different authors. Among these regularization algorithms, ridge regression and lasso regularizations are very common. These regularizations have some disadvantages; for example, when the dimensionality is very high and the number of instances is very low, the use of these regularizations is pointless. Likewise, our regularization algorithm has also several

TABLE 2. Comparison to existing literature.

Ref.	Method	Application	Acc (%)	AUC	Sen (%)	Spe (%)
[24]	CNN	Skin mole lesion classification	93	-	92.10	95.18
[14]	CNN	Skin cancer classification	91.0	-	-	-
[40]	CNN	Skin lesion classification	84.7	0.89	-	-
[41]	DBN	Skin lesion classification	89.0	-	90	88.3
[43]	DBN	Dermoscopy patterns classification	88.0	-	-	-
[48]	CNN+Cytological Findings	melanoma classification	-	0.84	80.9	88.1
[49]	An ensemble based CNN framework	dermoscopy image classification	86.6	0.89	55.6	78.5
[46]	FCRN	Melanoma recognition	85.5	0.78	54.7	93.1
Our Work	CNN+Novel Regularizer	Skin Lesion Classification	97.49	0.98	94.3	93.6

*- *indicates that the information is not reported by the author(s).*

limitations, as given below:

1) It cannot be used for feature selection or feature reduction.
2) Choosing a suitable value of λ is difficult, as it is a continuous value and attempting a million times to select a single suitable value is computationally expensive and time intensive.

VIII. CONCLUSION

Due to the consequences of inadequate detection and the necessity of excellent detection accuracy, the detection of skin cancer has been deemed challenging. The implications of artificial intelligent methods and the efficient utilization of soft computing skills would negate the issues related to detection inaccuracy. Numerous techniques highlighting the classification and detection of skin cancer were discussed in this study. A new prediction model based on a new regularizer was presented in this study. Based on our results, the newly proposed model defeated other state-of-the-art detection methods in terms of accuracy. Moreover, the proposed CNN model was tested on different use cases and produced better AUC-ROC results than other methods. Hence, our proposed model produced the best results and outperformed the existing literature.

Acknowledgment

Data Availability Statement: Data are publicly available through ISIC (https://www.isic-archive.com/#!/topWithHeader/onlyHeaderTop/gallery).

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