**Classification Of Skin Lesions and Detection Of Cancer Using Deep Learning Technique**

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**Abstract.** Cancer is a deadly condition brought on by the unchecked growth of body cells. Cancer has been described as the most serious problem affecting public health because a large number of people die from it each year. Any part of the human body, which may contain trillions of cells, can become infected with cancer. Skin cancer will widespread at a particular time. The best solution for this is deep learning. Previously, features sequences and various imaging modalities were used in conjunction with machine learning. It is proven that the existing deep-learning architectures like DeepConvNet is suitable for automated extraction of complex features. An ensembled network depending on the integration of DeepConvNet and handcrafted features based on multi-layer feature is proposed in this work to further enhance the efficiency of the DeepConvNet models. a skin lesion segmentation Multi-Scale Attention U-Net (MSAU-Net) is used in this paper.

**Keywords:** Machine learning, Deep learning, skin lesion, ConvNet, lesion segmentation, feature.

**1 Introduction**

Melanoma, also known as cutaneous carcinoma, is the most lethal infection. In 2000, the World Health Organization (WHO) estimated that approximately 65000 people worldwide died from melanoma. The number of deaths is rising; Over the past ten years, melanoma incidence rates have been rising at an annual average rate of 2.6%. Cancerous tissue with 98% five-year survival rate, if detected early by the time cancer is localized. surface. Melanocytes are the cells that make the UV-absorbing pigment melanin and are found at the base of the epidermal layer.Even though Skin cancer is spreading more and more, it is treatable when diagnosed early. Colour, shape, and texture were among the features that were extracted. In automatic skin image analysis, there are typically three stages: 1) segmenting an image; 2) selection and extraction of features; and 3) classification of lesions.

Digital images of melanoma skin lesions have been studied in an effort to develop an efficient method for detecting skin cancer in its earliest stages without necessitating any unnecessary skin biopsies. In order to properly analyze an image, feature extraction is regarded as an essential tool. Unsupervised or automatic segmentation techniques were used to analyze a variety of digital images in this thesis. On these segmented images, feature extraction methods are then applied. Following this, a comprehensive discussion based on the results has been conducted.

**2 Related Paper**

High-performance automated feature extraction and classification have been made possible by recent DCNN model development efforts. T. Y. Satheesha and others [1], patients with skin cancer have the highest mortality rates from melanoma. Here we have presented computerized mammogram platform that deals with the diagnosis lesions based on their estimated depth. To get accurate results, you need to extract features. The proposed method is intended to diagnose blue nevus, dermatofibroma, seborrheic keratosis, haemangioma, basal cell carcinoma and normal mole lesions in addition to in-situ melanoma.

Gessert, N., et al. [2], proposed high-resolution patches to use high-resolution images. Patch-based attention's efficacy is investigated through the modification of three pretrained architectures. We compare class-specific loss weighting, balanced batch sampling, and oversampling to combat imbalance issues in classes.As a result, pretrained architectures can use high-resolution images without having to down sample. When dealing with class imbalance, the new diagnosis-methods will makes it possible to train effectively.

Y. T. Xie and others [ 3], In computer-aided skin cancer diagnosis, the two most important and related tasks are automated skin lesion partition and separation. For skin lesion classification, we have proposed MB-DCNN model in this paper. Enhanced-SN, Mask-CN and coarse-SN all make up this model.By mutually exchanging knowledge the issues that was brought on by hard-easy pixel imbalance and class in segmentation networks, and have also developed a novel rank loss and we have used it in with the dice loss.

Yuan, Y. D., et al. [4], The contrast that is between the skin and the lesion surroundings, fuzzy borders of the lesion, various artifacts presence, and a variety of acquisition imaging conditions make automatic lesion segmentation of dermoscopic images difficult. By use of 19-layer CNNs, we developed an approach to lesion segmentation and is trained from beginning to end.Our approach can be used for a large range of medical image segmentation tasks because it is sufficiently broad and requires minimal pre- and post-processing.

L. Yu and others [ 5], Because of less variants of lesion, striking visual similarity of lesional and non-melanoma lesions, high intraclass variation of melanomas and presence of numerous artefacts in the image, carcinoma diagnosis in medical imagery is automated. To address these issues, we recommend a method for detecting melanoma based on CNNs Finally, by seamlessly combining the recommended FCRN for segmentation with deep residual networks for categorisation, two-stage network is created. The framework that is classified can now use segmented results rather than the entire dermoscopy image to extract features.

M. A. Kassem and others [ 6], Cutaneous Melanoma is a kind of cutaneous cancer that kills a lot of people. Because of their striking resemblance, the various types of lesions on the skin make it difficult to accurately diagnose them. Dermatologists are able to by accurately classifying lesions of skin in early stages, you can give treatment to patients and it is possible to their lives. A highly accurate model skin lesions classification is proposed in this paper.

Yang, J., et al. 7], a novel dermoscopy-based convolutional neural network-based melanoma classification method is presented in this work. The feature extraction process can now concentrate on the area of interest thanks to the introduction of the region average pooling (RAPooling) method. The segmented lesion region is used to guide the classification by RAPooling in an end-to-end classification framework that incorporates segmentation data. To optimize and obtain the final classification result, a linear classifier named RankOpt that is based on the area under the ROC curve is utilized. By optimizing RankOpt, the proposed method improves classification performance for an imbalanced dermoscopy image dataset and incorporates segmentation information into the classification task. Experiments on the ISBI 2017 skin lesion analysis dataset for the melanoma detection challenge dataset demonstrate our method's efficacy in comparison to other cutting-edge techniques.

Yang, J., et al. 8], In many classification tasks, class imbalance is a challenging issue. Because there are fewer training samples in minority classes than in other classes, this leads to biased classification results. The majority and minority classes were resampled in accordance with the unbalance number. We suggest SPBL algorithm as a solution. By achieving a balance complexity of each pace, network can learn discriminative representations iteratively.

Z. Yu and co. 9], a novel framework for machine vision in microscopy employing both a local descriptor encoding strategy and deep learning is presented. Specifically, ResNet that was based on large set of natural images. It is used to first obtain representations of medical picture that has been rescaled.. Using ISBI 2016 skin lesion difficulty dataset, we show that our model performs existing methods.

H. C. Shin and co. 10], in this paper, we make use of three significant, but unexplored, aspects of applying to utilise deep convolutional neural networks problems in machine-assisted detection. The two specific CADe issues we investigate are interstitial lung disease (ILD) thoracic-abdominal lymph node (LN) detection. Our extensive, CNN model evaluation, empirical evaluation and in addition to useful insights could help in designing high-performance CAD systems in medical image activities.

**3 Proposed Method**

MSAU-Net, a consideration-incorporated U-Net network is suggested for lesion segmentation.

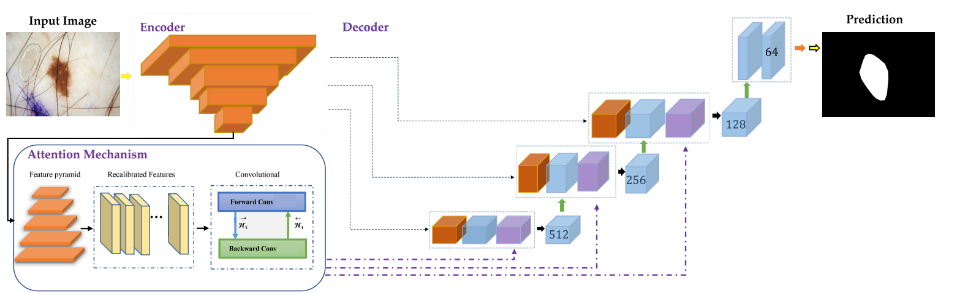


Fig. 1. The proposed skin lesion segmentation.

## 3.1 Encoder

The segmentation issue is represented by a MSAU-Net structure in the approach we propose. Encoder and decoder modules are used by the Net model, which has a symmetric structure, to learn the segmentation map. Albeit the U-Net model is equipped for catching nearby data, its design doesn't focus closer on the limit region, hence, it is less exact in isolating skin sores from the covered foundation. To put it another way, the training process should teach the trainee both the local appearance and the entropy of the area in order to accurately distinguish the skin lesion from the rest of the body. On top of the encoder blocks, we include an attention mechanism to model this region-sensitive representation. Modelling the multi-scale representation and highlighting the significance of each activated feature map during the recognition process are the goals of the attention layer. For skin lesion segmentation tasks involving multiple scales on the lesion patterns, the attention module's feature map can provide rich, scale-dependent descriptions.

## 3.2 Feature Recalıbratıon

The use of a series of consecutive max-pooling and down-sampling functions significantly reduces the spatial feature's resolution in conventional CNN networks. Additionally, images may contain objects of various sizes. We propose utilizing multi-scale representation results from each encoder module block to lessen this issue. A multi-scale representation is created by combining the various feature maps produced by the encoder block in our design. An Atrous convolution is used to transform the various feature maps into a single shape. In order to accomplish this, we up-sample the representation filters using the Atrous operation on top of the final convolutional layer of each encoder block. A hole convolutional filter is applied to the full-resolution image for up-sampling the filters, putting zeros in between their values. Because only the values of non-zero filters are taken into account in the calculations, the number of parameters used in this operation does not change.

(1)

where w is a convolution filter, x is the input feature map, i is a spatial location on y, and x is the output feature map. The network employs this tactic by selectively empathizing informative features and suppressing less useful ones using the global information of the input data.

## 3.3 Decoder

The decoder is implemented in accordance with standard U-Net in the model we propose. Along with the multi-scale representation derived from the attention module, the features that were up-sampled from the previous decoder layer are concatenated with features that were directly imported from the encoder. In order to learn the semantic representation, we employ two Convolutional layers followed by a batch-normalization and activation layer in each block of the decoding path. Finally, a softmax activation is used in the final decoding block to generate the segmentation.

## 3.4 Input Image Pre-Processing

Visual evaluation becomes more difficult when dealing with digital images because of their complexity.[9] To help doctors correctly diagnose skin lesion efficient image processing methods are required.As a result, these pictures are automatically refined and cropped prior to being used in the classification algorithm

## 3.5 Data Augmentation

The data augmentation method is used in this step. This is similar to cropping, flipping, and rotating the image for image classification purpose. To maximise the profits of training samples and boost the precision of model, a number of random modifications were added to the ISIC dataset.[7]

## 3.6 Segmentatıon And Features Extractıon Usıng U-Net & Resnet

Algorithms currently in use only calculate numeric values and necessitate manual feature extraction and pre-processing. [6] We employ the transfer learning algorithm Attention U-NET and ResNet, which is a variant of CNN, to bypass these time-consuming steps and enable them to perform extraction of features itself.

## 3.7 Predıctıon Output

The DeepConvNets framework, which employs a local, interpretable model to explain individual predictions, is utilized in this step.[8] The initial data points were perturbed, fed into a segmentation and feature model, and the results were observed. The additional data points are then weighted according to their extent from the initial destination by the method. Lastly, it trains a alternate model on the dataset using those sample weights, such as linear regression.

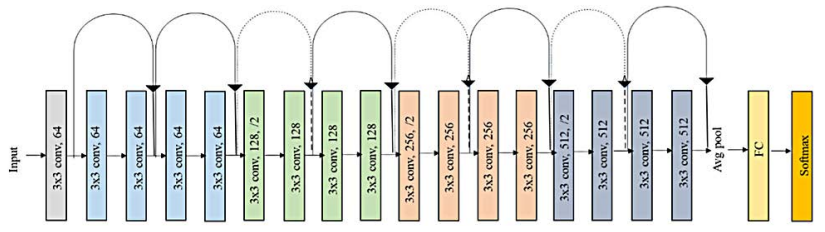


Fig. 2 ResNet transfer learning algorithm layer

**4 Implementation Result**

We recommend(i) detailing’s about dataset, (ii) the metrics we used to calculate the method (iii) a interpretation of each output of experimental calculation in this section.

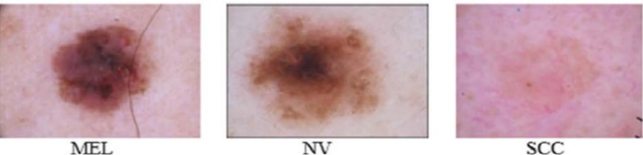


Fig. 3 An image of ISIC 2019 skin lesions dataset with name

## 4.1 DataSet

Using the ISIC 2019 dataset, the developed model is evaluated with regard to the classification of skin lesions. There are 1000 RGB images in this dataset, which is accessible to the general public. There are eight classes, including: benign keratosis (BKL), squamous cell carcinoma (SCC), melanoma (MEL), and melanocytic nevus (NV). The images are split up into NV: 200, MEL: 200, BKL: 200, BCC: SCC and 200: 200. One kind of skin lesion is labelled on each image in the dataset. In Fig. 6, we illustrate various types of skin cancer. This dataset is one of the most difficult to divide into five classes because each class has different numbers of images.

## 4.2 Performance Measures

Accuracy shows the percentage of correct prediction,

(1)

Specificity measures the proportion of FP that are correctly identified by model,

(2)

Sensitivity measures the proportion of predicted TP that are correctly identified by model,

(3)

F1 score also known as balanced F-score or F-measure, is a weighted average of the precision and recall, (4)

TP, TS, FP, TN, and FN stand for true positive, total samples, false positive, true negative, and false negative, respectively.

**4.3 Result**

Using the ISIC 2019 dataset, the evolved model is calculated with regard to the classification of skin lesions.[3] There are 1000 RGB images in this dataset, which is accessible to the general public. One kind of skin lesion is labelled on each image in the dataset.

**Table 1.** Prevailing Papers on Skin Lesion Classification

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
| **S.No** | **Paper Name** | **Author Name** | **Methodology used** | **Advantage** | **Disadvantage** |
| **1** | Melanoma Is Skin Deep | T. Y. Satheesha, D. Satyanarayana, M. N. G. Prasad, and K. D. Dhruve | 3D reconstruction technique | Improved accuracy and Robustness | Inadequate data |
| **2** | Skin lesion classification using CNNs with patch-based attention | N. Gessert et al | CNN | Improved performance | Required more data |
| **3** | Mutual Bootstrapping Model for Automated Skin Lesion Segmentation and Classification | Y. T. Xie, J. P. Zhang, Y. Xia, and C. H. Shen | Deep learning | Reduced variance | Difficulty in interpretation |
| **4** | Automatic Skin Lesion Segmentation Using Deep Fully Convolutional Networks with Jaccard Distance | Y. D. Yuan, M. Chao, and Y. C. Lo | CNN | Automated feature extraction | Need for large amounts of labelled data |
| **5** | Automated Melanoma Recognition in Dermoscopy Images via Very Deep Residual Networks | L. Yu, H. Chen, Q. Dou, J. Qin, and P. A. Heng | CNN | Ability to capture spatial and temporal relationships | High computational complexity |
| **6** | Skin lesions classification into eight classes for ISIC 2019 using deep convolutional neural network and transfer learning | M. A. Kassem, K. M. Hosny, and M. M. Fouad | CNN and Transfer Learning | Consideration of complex relationships | Data quality |
| **7** | Classification for dermoscopy images using convolutional neural networks based on region average pooling. | J. Yang, F. Xie, H. Fan, Z. Jiang, and J. Liu | CNN | Handles non-linear relationships | High computational cost and the need for large amounts of data |
| **8** | “Self-Paced Balance Learning for Clinical Skin Disease Recognition | J. Yang et al | Self-Paced Balance Learning | robust prediction | overfitting |
| **9** | Melanoma Recognition in Dermoscopy Images via Aggregated DeepConvolutional Features | Z. Yu et al | Deep learning and CNN | Reduced overfitting | Sensitivity to noisy data |
| **10** | Deep Convolutional Neural Networks for Computer-Aided Detection | H. C. Shin et al | CNN and Deep Learning | Automatic feature extraction | Increased complexity |

**5 Conclusion**

A MCA attention technique for learning a stratified representation is proposed in this paper. Our attention module uses a channel wise normalization technique to rebalance feature vectors based on benefaction to object recognition level after receiving multi - level feature maps from encoding model. In all cases, image pre-processing is required prior to feeding any deep neural learning algorithm. In accordance to resolve the difficulty of classifying skin lesions, we conducted numerous experiments and tried various methods. When images are reduced in size, some helpful data from the lesions may be lost. The classifier's work process may also be simulated on reducing the data samples available for training and validation in order to balance the dataset. The dermatologist can use an optic rationale to recognize advanced classes and add good examples to the existing datasets using the proposed method, which combines the DL model with AI, for improved performance in early prediction of lesions of the skin. It is a significant contribution to both increasing the accuracy of skin cancer detection and identifying the new classes.

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