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U-Net-RCB7: Image segmentation algorithm

U-Net-RCB7: Görüntü bölütleme algoritması

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U-Net-RCB7: Image Segmentation Algorithm

Highlights

- *The incidence of skin cancer is increasing.*
- *There is no avaliable noise dataset in current literatüre*
- *Properly segmented images can help doctors predict the type of skin cancer.*

Graphical Abstract

U-Net-RCB7 contains EfficientNetB7 as the encoder and ResNetC before the last layer. This paper uses a modified U-Net model. Images were divided into 36 layers to prevent loss of pixel values in the images. As a result, noise removal and lesion segmentation were 96% and 98.36% successful, respectively.

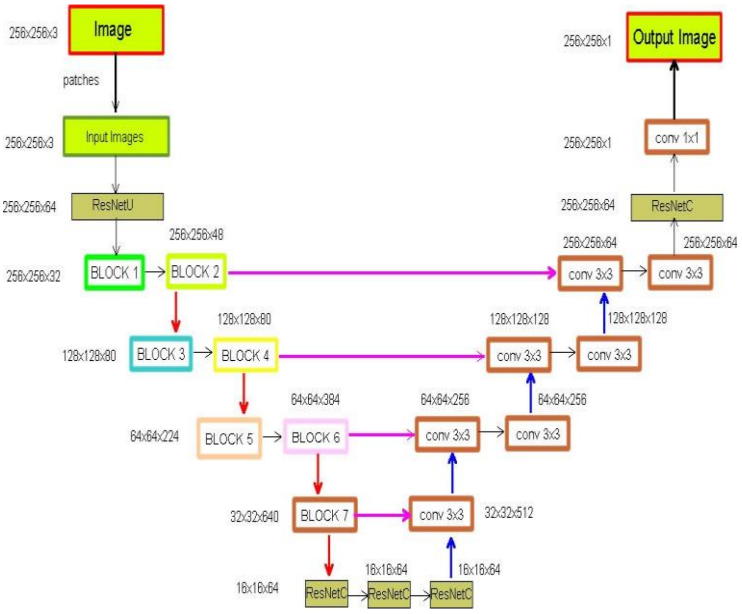

Figure. U-Net-RCB7 architecture

Aim

Model proposition for noise removal and lesion segmentation on skin cancer images.

Design & Methodology

Deep learning trainings have been completed with the proposed UNet-RCB7 and image processing algorithms.

Originality

A noise data set consisting of 3000 masks was created. High success values were obtained with the proposed model.

Findings

Noise removal and lesion segmentation were 96% and 98.36% successful, respectively.

Conclusion)

It has been observed that image processing algorithms are not sufficient for noise cleaning and segmentation. Learning trainings that are structured with a correctly created noise data set have shown success in noise cleaning.

Declaration of Ethical Standards

The author(s) of this article declare that the materials and methods used in this study do not require ethical committee permission and/or legal-special permission.

U-Net-RCB7: Image Segmentation Algorithm

Araştırma Makalesi / Research Article

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ABSTRACT

The incidence of skin cancer is increasing. Early detection of cases of skin cancer is vital for treatment. Recently, computerized methods have been widely used in cancer diagnosis. These methods have important advantages such as no human error, short diagnosis time, and low cost. We can segment skin cancer images using deep learning and image processing. Properly segmented images can help doctors predict the type of skin cancer. However, skin images can contain noise such as hair. These noises affect the accuracy of segmentation. In our study, we created a noise dataset. It contains 3000 images and masks. We performed noise removal and lesion segmentation by utilizing the ISIC and PH2. We have developed a new deep learning model called U-Net-RCB7. U-Net-RCB7 contains EfficientNetB7 as the encoder and ResNetC before the last layer. This paper uses a modified U-Net model. Images were divided into 36 layers to prevent loss of pixel values in the images. As a result, noise removal and lesion segmentation were 96% and 98.36% successful, respectively.

Keywords: Decision support systems, deep learning, image processing, skin cancer, UNet.

U-Net-RCB7: Görüntü Bölütleme Algoritması

ÖZ

Cilt kanseri insidansı artmaktadır. Cilt kanseri vakalarının erken tespiti tedavi için hayati önem taşır. Son zamanlarda kanser teşhisinde bilgisayarlı yöntemler yaygın olarak kullanılmaktadır. Bu yöntemlerin insan hatası olmaması, kısa teşhis süresi ve düşük maliyet gibi önemli avantajları vardır. Derin öğrenme ve görüntü işlemeyi kullanarak cilt kanseri görüntülerini segmentlere ayırabiliriz. Düzgün şekilde bölümlere ayrılmış görüntüler, doktorların cilt kanseri türünü tahmin etmesine yardımcı olabilir. Bununla birlikte, cilt görüntüleri saç gibi gürültüler içerebilir. Bu sesler, segmentasyonun doğruluğunu etkiler. Çalışmamızda bir gürültü veri seti oluşturduk. 3000 resim ve maske içerir. ISIC ve PH2'yi kullanarak gürültü giderme ve lezyon segmentasyonu gerçekleştirdik. U-Net-RCB7 adlı yeni bir derin öğrenme modeli geliştirdik. U-Net-RCB7, kodlayıcı olarak EfficientNetB7'yi ve son katmandan önce ResNetC'yi içerir. Bu yazıda değiştirilmiş bir U-Net modeli kullanılmaktadır. Görüntülerde piksel değerlerinin kaybolmaması için görüntüler 36 katmana ayrılmıştır. Sonuç olarak, gürültü giderme ve lezyon segmentasyonu sırasıyla %96 ve %98.36 başarılı olmuştur.

Anahtar Kelimeler: Cilt kanseri, derin öğrenme, görüntü işleme, karar destek sistemleri, UNet.

1. INTRODUCTION

It is predicted that in 2040, about 16 million people will die from cancer [1]. The incidence of skin cancer is increasing due to increased sun exposure. Melanoma represents a lethal type. About 63% of deaths are due to melanoma. In the United States, 115320 new cases were counted in 2021. 11540 of these cases ended in death [2].

Melanoma is curable in about 95% of cases if detected early [3]. Melanoma is multicolored, asymmetric and contrasting [4]. The ABCD rule is the classic method used by dermatologists [5]. Another method is dermoscopy. Dermatologists evaluate the images of dermoscopy. This procedure costs a lot of time and money [6]. The success is directly proportional to the experience of the examiner. Using visual examination and dermatoscopic images together, dermatologists can predict melanoma with about 75% accuracies [7].

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Cleaning the lesion of hair-like noise is critical for correct segmentation [8]. Deep learning models can help decision makers in disease diagnosis. Using deep learning models, especially in the model component of decision support systems, will enable the diagnosis process to be faster and more successful.

Within the scope of the study, an algorithm that can also be used in the model component of decision support systems has been proposed. This algorithm is presented for noise removal and lesion segmentation stages in skin cancer images. Deep learning and image processing can eliminate human fault and achieve successful results. In summary what we did:

1. The images are divided into 36 layers (256x256x3). So the total size of the image becomes 1536x1536. This minimizes the pixel loss.

2. A new model called U-Net-RCB7 is developed.

3. A noise dataset with 3000 images and masks is created, which includes hair, patches, black frames, water bubbles, etc.

The second section contains related work. The third and fourth sections deal with the material and method. The fifth and sixth sections present results and conclusions.

1.1. Related Works

DullRazor is an ancient hair removal method. It removes hair noise from images using image processing. In this method, hair noise in the image is tried to be determined by using morphological operations. It is ineffective in detecting fine hair noises. It can be preferred in studies due to its fast and simple structure [9]. Ünlü and Çınar showed that using deep learning and image processing together is useful for hair removal. 85% accuracy was obtained. In the study, the Unet model was preferred for lesion segmentation. The Unet model is supported by image processing algorithms. Gaussian filter is used as image processing algorithm. With this filter, it is aimed to reduce the noise in the image [10]. Most of the studies use ISIC and PH2 datasets. Tardi et al. proposed a model for hair removal. In this study, a noise dataset was created that included 306 images and masks in ISIC2018. In this study, the UNet model was preferred. UNet decoder is frequently preferred in segmentation of medical images due to its structure and efficiency [11]. Thapar et al. presented a hybrid model for segmentation. They achieved 94.8% dice accuracy with the ISIC2018 dataset. A hybrid method is proposed by using basic CNN and K means algorithms together [1].

The use of coders such as efficientNet and ResNet increases the accuracy of the models. There are several examples in the literature. Waris et al. chose ResNet as an encoder. In lesion segmentation, they obtained a dice coefficient of approximately 86% with the ISIC 2017 dataset and a dice coefficient of approximately 92% with the PH2 dataset. In this study, When noise cleaning was performed, it was observed that the segmentation success increased by 1% [12].

Shen et al. have developed DSM model. In this study, the hair removal step is used. They used image contrast enhancement to improve accuracy. 94.3% training success was achieved in the study [13]. Dahal et al achieved an accuracy of 87% using U-Net and FCN. Noises may cause low accuracy. In this study, it was observed that the noise on the images can reduce the success [14]. Akyel and Arıcı presented a study based on U-Net. This study achieved 88,580% success in noise cleaning and 92.6% in segmentation. A dataset of noise with 1534 images and masks was used [15]. Wang et al. proposed FAC -Net. Using the ISIC2018 dataset, an dice accuracy of 91.19% was achieved in the study [16].

Alpaslan et al. presented a study on segmentation with Seg-Net architecture. The study proves that the DullRazor is insufficient for thin hairs. About 88% dice coefficient was observed in this study [17]. Rajan et al. proposed a study using Seg-Net. In this study, the dice accuracy is 85.16% on PH2 dataset. Segnet has an encoder-decoder architecture like unet. With this structure, it can be an effective model in image segmentation [18]. In another study, an algorithm based on U-Net was used in the lesion segmentation stage. The encoder used is DenseNet. A dice accuracy of 94% was obtained with this model in training stage [19]. Bagheri et al. used Mask R-CNN algorithm. About 89% dice accuracy was observed on the PH2 dataset. As a result of the segmentation obtained as a result of the model, corrections were made with the geodetic method [20]. Akyel and Arıcı proposed LinkNet-B7. A noise dataset was created, which included 2500 images. They achieved about 95.72% in noise cleaning and 97.80% in the segmentation. Linknet is a deep learning model with an encoder-decoder architecture like Unet [21].

Tang et al proposed a segmentation model with U-Net. They achieved 86 % dice accuracy with ISIC2017 dataset. In this study, it was stated that low contrast difference makes segmentation difficult [22]. In the study of Akyel and Arıcı, FCN8-ResNetC was used. They created 3000 hair noise masks. They used ISIC2018 and PH2 datasets. They achieved 89.380% dice accuracy in noise removal and 97.050% dice accuracy in segmentation stage [23].

EfficentB7 has a short epoch time and high accuracy in training stages [24]. Eff-U-Net was introduced by Innani et al. EfficientNet-B7 is used as an encoder. EfficientNet has the highest accuracy among ResNet18, 34, 50, 101, and EfficientB5 [23]. EAR -U-Net was presented in image and video processing. They achieved 95.2% dice accuracy on a liver dataset. In this study, efficientnetB4 is used to increase the success of the encoder blocks of the U Net model [26].

2. MATERIAL AND METHOD

80% of the images were reserved for training, validating (10 percent for validate) and 10% for testing.

2.1. Datasets

We used two datasets that belong ISIC 2018 datasets. The first one has 10015 RGB images [27]. From this dataset, 3000 images that contain noises were selected randomly. 3000 noise masks from these images were created. This dataset was created in our previous study [21]. We used the second ISIC dataset (13000 images and masks) [28] and PH2 dataset (200 images and masks) [29] in lesion segmentation. These datasets were cleaned of noise using the model trained in the noise removal stage. Figure 1 shows our cleaned dataset. These datasets are collected from many different health institutions and made available to the public. This data set is preferred because it is valid in many studies.

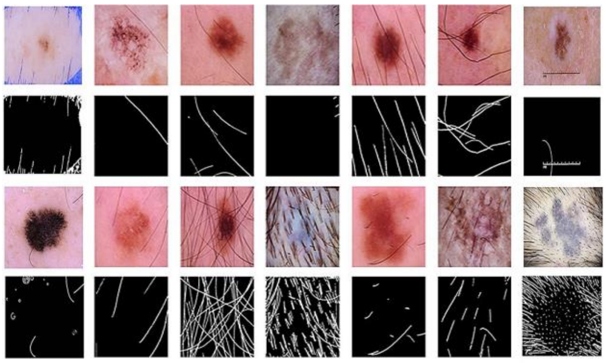

Figure 1. Cleaning dataset samples [21]

2.2. Image Preprocess

2.2.1. Contrast enhancement

Contrast enhancement was performed on the image to extend the intensity range (Figure 2).

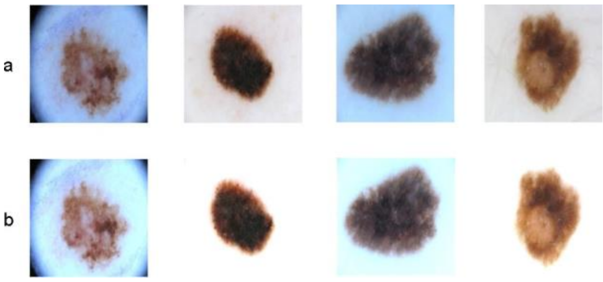

Figure 2. A sample for contrast enhancement

2.2.2. Data augmentation and image slices

To increase learning and prevent overfitting, data were increased. We used horizontal and vertical flips, width and height shifts. The data augmentation increased the cleanup dataset to 12000 and the segmentation dataset to 52800. All images are divided into 36 slices (256x256x3). Thus, images with a total size of 1536x1536x3 can be used as input. This helps to improve the accuracy. The cleanup dataset is 384000 images and the segmentation dataset is 1696000 images, as shown in Figure 4.

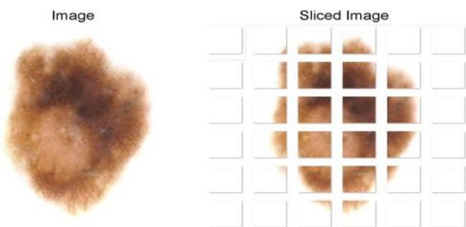

Figure 3. Sample of sliced image

2.3. UNet

U-Net is useful for segmentation of medical images. U-Net is a deep learning algorithm that has high accuracy. In U-Net, input images are obtained as output maps. Figure 4 demonstrates the structure of U-Net. U-Net uses the activation function Relu, 3x3 convolutional layers. In the last layer, 1x1 convolution is used. 23 convolutional layers are used in the model [30].

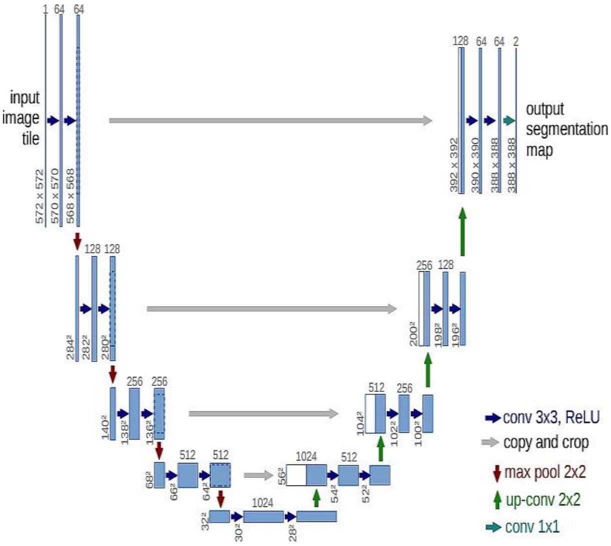

Figure 4. U-Net architecture [30].

2.4. EfficientNet

Mobile Inverted Bottleneck Convolution (MBConv) is the main block in this model [31]. EfficientNetB7 is the most powerful model among the EfficientNet models [24]. EfficientNetB7 has 7 blocks. The model can be seen in Figure 5 [25].

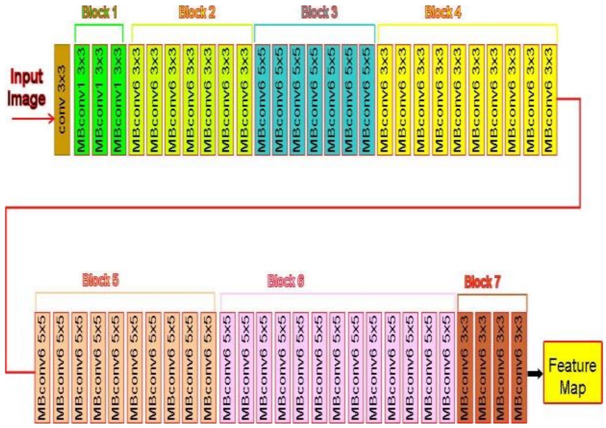

Figure 5. EfficientNet-B7 architecture [21]

2.5. ResNet and ResNetC

The residual structure brings solutions to the disappearance of the gradient and the explosion [26]. Shortcut links are those that skip one or more layers. With blocks, inputs can now propagate faster over the remaining connections between layers [32]. ResNetC is used it in the proposed U-Net-RCB7 algorithm. ResNetC includes four ResNet blocks. The ResNet and ResNetC networks can be seen in Figure 6. ResNetC has almost 2% higher dice accuracy than the basic ResNet architecture in PH2 dataset [23].

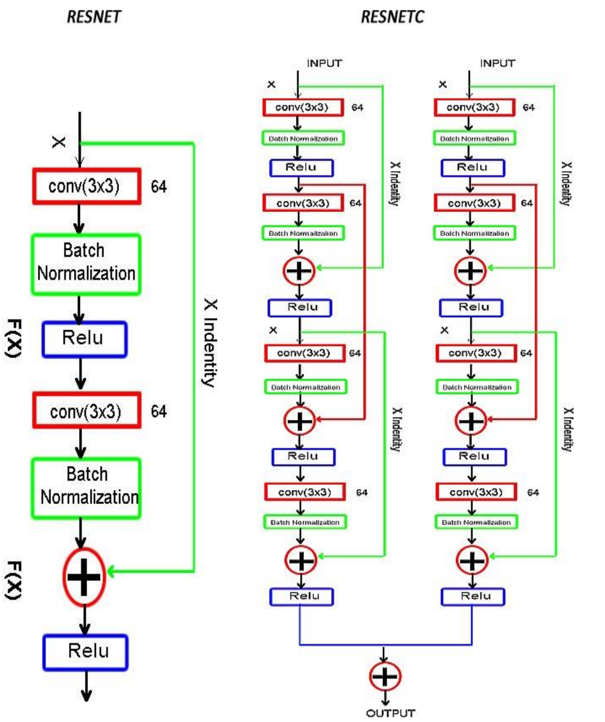

Figure 6. ResNet and ResNetC architecture [23]

2.6. U-Net-RCB7

The U-Net-RCB7 model was developed in this study. Due to its decoder structure, different models can be added to UNet as encoders. According to the added encoder models, an increase in success can be achieved. In this study, the efficientnetB7 model offered by google is added as an encoder. Because it has the highest performance compared to others [21]. In our model, a single ResNetC layer is used before the last layer. ResNetC has higher accuracy than ResNet. Also in our study, a middle block is used. This block includes three conv3x3 layers. In this way, more features can be obtained before the decoder blocks. In Figure 7, the structure of U-Net-RCB7 can be seen.

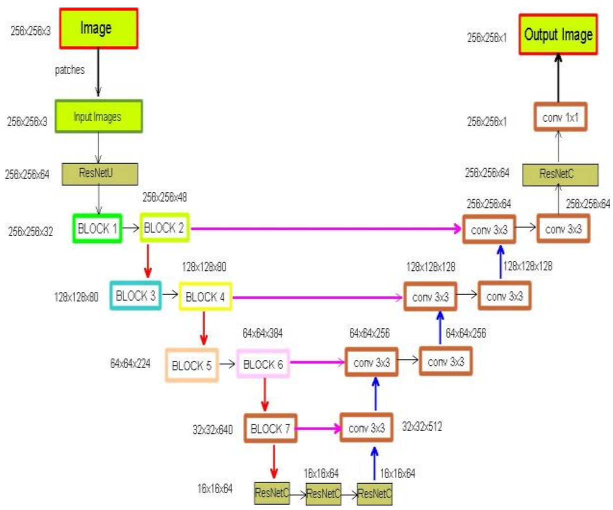

Figure 7. U-Net-RCB7 architecture

You can see the parameters in Table 1. The structure of the encoder can be seen in Table 2.

Table 1. Hyperparameters applied in models

Parameter	Noise Removal Stage	Lesion Segmentation Stage
Batch Size	36	36
Input	256	256
Learning Rate	0.001	0.001
Number of Epochs	5000	5000
Optimizer	Adam	Adam
Loss Function	Dice Loss	Dice Loss

Table 2. Layers of the encoder.

Step	Operator	Size	Channel	Layer
1	ResNetC	256 x 256	64	2
2	Block 1-MBconv1 3x3	256 x 256	32	3
3	Block 2-MBconv6 3x3	256 x 256	48	7
4	Block 3-MBconv6 5x5	128 x 128	80	7
5	Block 4 - MBconv6 3x3	128 x 128	80	10
6	Block 5 - MBconv6 5x5	64 x 64	224	10
7	Block 6 - MBconv6 5x5	64 x 64	384	13
8	Block 7 - MBconv6 3x3	32 x 32	640	4

2.7. Parameters

Parameters that were used in the study can be found below.

•Dice coefficient: The total number of pixels is 2 times the divided overlap area in both images (predicted and correct image) (ground truth: Y and predicted segmentation: X) [33].

$$\text{Dice coefficient} = (2*|X \cap Y|)/(|X|+|Y|) \qquad (1)$$

•Loss function: Dice loss was used in study [16]. The Dice loss can be written as (1 – Dice coefficient).

•Optimizer: The Adam optimizer is used. Gradient descent suggested by combining the advantageous aspects of rmsprop and momentum methods is the algorithm [34].

•MIoU: The Mean IoU average evaluates the overlap among the found and the true regions [35]. We used the mean IoU.

2.8. First Stage: Noise Removal Stage

Dataset are divided into 268800 training, 76800 validation, and 38400 test set.

• Step 1: U-Net-RCB7 was run for 5000 epochs.

• Step 2: Testing. Remove noises from results with morphological operations (opening, closing, dilating).

INPAINT is used to create a clear image according to the mask [36]. Training was performed on the same data set and parameters. The results can be seen in Table 5.

2.9. Stage 2: Lesion Segmentation

Noises are removed with algorithm we proposed. The noise affects the performance of lesion segmentation. The accuracy increased by about 2% with the cleaned data set.

• Step 1: Dataset are divided into 1187200 training, 339200 validation, and 169600 test set.

• Step 2: U-Net-RCB7 was run for 5000 epochs.

• Step 3: Testing. Remove noises from results with morphological operations (opening, closing, and dilating). Clearing the segmentation results with post-processing. shows results. Results can be seen in Table 6.

3. RESULTS

In this section, results that were obtained in noise removal and lesion segmentation stages were presented. We compared our model with some other popular models. In these comparisons, we used the same number of images. And in the noise removal stage, there are a few studies that are using deep learning. There is no accuracy rate in studies that are not using a deep learning algorithms. So we have compared fewer studies in the noise removal stage. Therefore, we have compared fewer studies in the noise removal stage. EffientNetB7 is chosen, since it has more accuracy than other EfficientNet types. We compared EfficienNet types in our model. Abbreviations used in the tables in section 3 and section 4: Accuracy:Acc, Validation: Val, Proposed Method: PM.

Figure 8 shows results. U-Net-RCB7 was run for both stages. The results of noise removal can be found in Table 3 and Figure 9. The results of lesion segmentation can be found Table 4 and Figure 10. Table 3 shows that the proposed model provides the highest success in all parameters in the noise cleaning stage. Table 4 represents the results obtained in the lesion segmentation stage.

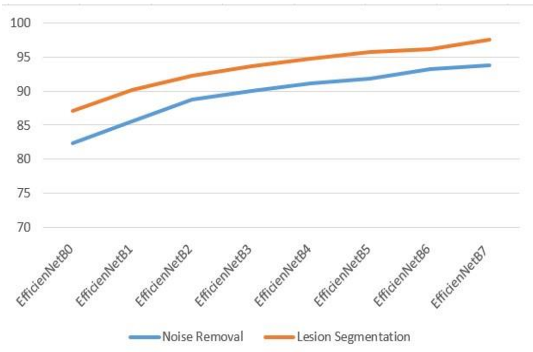

Figure 8. Comparison of EfficientNet types in our model

Table 3. Noise removal stage training results with different models.

Parameter (%)	U-Net	LinkNet	EAR-U-Net	U-Net-RCB7
Training Acc	87.35	90.27	95.30	96
Val Acc	84	91.02	94.50	94.75
MeanIoU	86.32	89.60	93.95	94.60
Dice	86.80	89.10	92.90	93.72
Dice on Test Data	85.50	87.75	91.80	92.60
Acc on Test Data	86.10	89	94.20	94.82

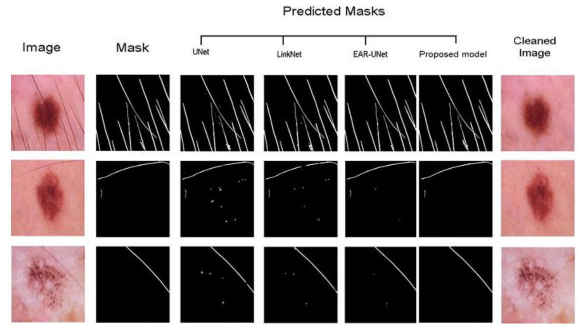

Figure 9. Noise removal results of five models

Table 4. Lesion segmentation stage training results with different models

Parameter (%)	U-Net	LinkNet	EAR-U-Net	U-Net-RCB7
Training Acc	89.40	94.05	98	98.36
Val Acc	90.02	93.95	95.65	97.05
MeanIoU	88.20	93	96.35	97.04
Dice	86.62	91.70	96.85	97.52
Dice on Test Data	86.40	91.400	96.70	97.30
Acc on Test Data	89.10	93.500	97.80	98.20

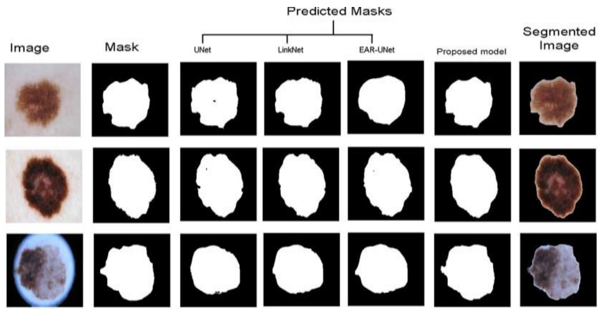

Figure 10. Segmentation results of five methods

3.1. Ablation Studies

We selected U-Net as baseline model. Then we add EfficientNetB7 and ResNetC models to the basic model and see their effects on the basic model. We used Accuracy, Validation Accuracy, MeanIoU and Dice Accuracy with the test results shown in Tables 5 and 6. These tables shows effect of EfficientNetB7 and ResNetC with different parameters.

Table 5. Ablation Study in Noise Removal Stage

Parameter	Acc	Val Acc	Mean IoU	Dice Acc
Baseline model	87.35	84	86.32	86.80
Baseline model + EfficienNetB7	95.10	93.25	93.20	92.60
Baseline model + ResNetC	94.05	92.55	92.30	91.15
Baseline model + ResNet	92.20	90.45	90.50	89.35
Baseline model + EfficienNetB7 + ResNet	94.45	92.85	92.90	91.80
Baseline model + EfficienNetB7 + ResNetC	96	94.75	94.60	93.72

Table 6. Ablation Study in Lesion Segmentation Stage

Parameter	Acc	Val Acc	Mean IoU	Dice Acc
Baseline model	95.40	92.35	91.80	93.70
Baseline model + EfficienNetB7	97.40	93.65	93.80	96.65
Baseline model + ResNetC	96.10	92.45	92.20	95.08
Baseline model + ResNet	94.30	90.65	90.70	93.20
Baseline model + ResNetC + EfficienNetB7	96.50	95.65	95.10	96
Baseline model + ResNetC + EfficienNetB7	98.36	97.05	97.04	97.52

As seen in the tables, the highest success values are obtained when EfficientNetB7 and ResNetC were added to the basic model together.

3.2. Comparison Results

U-Net-RCB7 was compared with other studies that used different deep learning algorithms. Architecture of U-Net-RCB7 can be seen in Figure 5. Tables 7, 8 and 9 demonstrate results. Tables include method, stage, number of images, dice accuracy and accuracy. We used same number of images and same parameters with other studies in comparison.

We used PH2 and ISIC datasets as test data on training models. Tables 9 shows cross training results.

Table 7. Testing of the five models in noise removal stage

Study	Method	Stage	Number of images	Dice Acc	Acc
[11]	U-Net	Hair cleaning	306	87.42	-
[15]	U-Net	Hair cleaning	1534	-	88.580
[21]	LinkNet B7	Hair cleaning	160000	95.72	-
[23]	FCN8-ResNet C	Hair cleaning	3000	-	90.300
PM	U-Net-RCB7	Hair cleaning	306	98.10	99.12
PM	U-Net-RCB7	Hair cleaning	1534	96.20	97.05
PM	**U-Net-RCB7**	**Hair cleaning**	**384000**	**95.85**	**96.42**

Table 8. Lesion segmentation stage training results with PH2 dataset.

Study	Base	Dataset	Image Number	Dice Acc
[1]	K Means with Goa	ISIC2018	3.200	94.89
[16]	U-Net	ISIC-2018	2594	91.19
[12]	U-Net	ISIC-2017	unspecified	85.8
[13]	U-Net	ISIC-2017	2750	94.3
[14]	U-Net	ISIC-2017	2750	87.53
[15]	U-Net	ISIC-2018	13,000	92.6
[17]	Seg-Net	ISBI-2016	900	88.43
[21]	LinkNetB7	ISIC2018	844.800	96.75
[22]	U-Net	ISIC2017	unspecified	86
[23]	FCN8-ResNetC	ISIC2018	13200	96.50
PM	**U-Net-RCB7**	**ISIC 2018**	**1696000**	**97.52**

Table 9. Lesion segmentation stage training results with ISIC Datasets

Study	Base	Dataset	Image Number	Dice Acc
[1]	K Means with Goa	ISIC2018	3.200	94.89
[16]	U-Net	ISIC-2018	2594	91.19
[12]	U-Net	ISIC-2017	unspecified	85.8
[13]	U-Net	ISIC-2017	2750	94.3
[14]	U-Net	ISIC-2017	2750	87.53
[15]	U-Net	ISIC-2018	13,000	92.6
[17]	Seg-Net	ISBI-2016	900	88.43
[21]	LinkNetB7	ISIC2018	844.800	96.75
[22]	U-Net	ISIC2017	unspecified	86
[23]	FCN8-ResNetC	ISIC2018	13200	96.50
PM	**U-Net-RCB7**	**ISIC 2018**	**1696000**	**97.52**

Table 10. Cross-training test results of lesions segmentation stage

	TRAIN DATASETS					
	PH2			ISIC 2018		
Test Dataset	Acc	MIoU	Dice	Acc	MIoU	Dice
PH2	–	–	–	97.400	96.200	97.300
ISIC 2018	**97.650**	**96.700**	**97.550**	–	–	–

In the noise cleaning stage, the model proposed with the ISIC2018 dataset achieved 95.85% dice accuracy, which is higher than the other models compared. In the segmentation phase, 97.52% dice accuracy was obtained with the ISIC2018 data set.

4. CONCLUSION

In study, the images were divided into 36 slices (256x256x3). Therefore, in total, an image size of 1536x1536x3 can be used as input. Thanks to this, no pixel values are lost. By using slices and data expansion, the training accuracy has increased by almost 4%. There is a black frame and plaster noise in the ISIC datasets. These were also cleared.

The use of deep learning and image processing algorithms in the medical field shortens the diagnosis time and increases success. Deep learning structures find their place in the model component of decision support systems used especially for clinical purposes. With this use, more successful and faster decision support systems will be able to be used in disease diagnosis.

Five models were run on the same data set in the study. As we can see, U-Net-RCB7 has more successful results than the other models for both stages. It has been seen in the study that the use of EfficientNetB7 as an encoder increases the success of UNet. The results obtained have the highest values among the compared studies. As a result of the study, it has been seen that the proposed UNet-RCB7 model is an effective and suitable solution for noise removal and segmentation stages in skin cancer images.

DECLARATION OF ETHICAL STANDARDS

The authors of this article declare that the materials and methods used in this study do not require ethical committee permission and/or legal-special permission.

AUTHORS’ CONTRIBUTIONS

Cihan AKYEL: Created the model and completed the training processes. And performed the experiments

Nursal ARICI: Analyse the results.

CONFLICT OF INTEREST

There is no conflict of interest in this study.

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