# Skin Lesion Image Segmentation using Modified UNet Architecture.

**Muhammad Mahfuz Alam**
**ID: 181-15-11336**

**Dewan Sabiha Nabi**
**ID:181-15-11091**

**Md. Mamun Sikder Farid**
**ID: 181-15-11075**

This Report Presented in Partial Fulfillment of the Requirements for the Degree of Bachelor of Science in Computer Science and Engineering

Supervised By

**Aniruddha Rakshit**
Senior Lecturer
Department of CSE
Daffodil International University

Co-Supervised By

**Md. Abbas Ali Khan**
Senior Lecturer
Department of CSE
Daffodil International University

**DAFFODIL INTERNATIONAL UNIVERSITY**

**DHAKA, BANGLADESH**

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## APPROVAL

This Project titled "**Skin Lesion Image Segmentation Using Modified UNet Architecture**", submitted by ***Muhammad Mahfuz Alam*** , ***Dewan Sabiha Nabi*** **and** * **Md. Mamun Sikder Farid** * to the Department of Computer Science and Engineering, Daffodil International University, has been accepted as satisfactory for the partial fulfillment of the requirements for the degree of B.Sc. in Computer Science and Engineering and approved as to its style and contents. The presentation has been held on ***Wednesday 05 January 2022***

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Daffodil International University

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LICT Project, ICT Division, Bangladesh

# DECLARATION

We hereby declare that, this project has been done by us under the supervision of **Aniruddha Rakshit, Senior Lecturer, Department of CSE,** Daffodil International University. We also declare that neither this project nor any part of this project has been submitted elsewhere for award of any degree or diploma.

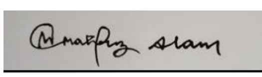
**Supervised by:**

**Mr. Aniruddha Rakshit**
Senior Lecturer
Department of CSE
Daffodil International University

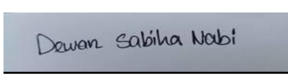
**Co-Supervised by:**

**Md Abbas Ali Khan**
Senior Lecturer
Department of CSE
Daffodil International University

**Submitted by:**



**Muhammad Mahfuz Alam**
ID: 181-15-11336
Department of CSE
Daffodil International University




**Dewan Sabiha Nabi**
ID: 181-15-11091
Department of CSE
Daffodil International University

**Md. Mamun Sikder Farid**
ID: 181-15-11075
Department of CSE
Daffodil International University

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# ABSTRACT

One of the most dangerous types of skin cancer is malignant melanoma. Early diagnosis, according to modern dermatology, is critical for lowering mortality rates and ensuring that patients receive less invasive therapies. For the early identification of skin lesions, computer-aided diagnostic (CAD) systems are becoming more popular. These systems are made up of various phases that must be selected based on the properties of digital images in order to produce a correct diagnostic. Acquisition, pre-processing, segmentation, feature extraction and selection, and finally classification of dermoscopic images all provide problems that must be met and conquered in order to improve automatic diagnosis of deadly tumors like melanoma. The categorization phase is particularly delicate, and a number of machine learning techniques have been presented over time to address this problem more effectively. The many machine learning approaches that have been proposed and that provide inspiration for the creation of effective frameworks are discussed in this study.

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# Chapter- 1

# Introduction

## 1.1 Introduction

Nowadays, Melanoma is the most deadly form of skin cancer, But it is also proved that a prompt diagnosis can lead to a very high probability of survival. As it is consider that it can quickly spread to other parts of the body. Each year, more than 1 million non-melanoma skin cancers and more than 250.000 melanoma skin cancers develop. Melanoma ranks fifth in terms of projected new cases in 2019 in both males and females in the United States [28]. It was expected that by 2021, 106110 new melanoma cases will be diagnosed in the United States resulting in 7180 deaths. The estimated five-year survival rate for melanoma is over 99% when diagnosed early, and ~14% when detected at an advanced stage. Therefore, early detection is essential for treatment and prevention of metastasis, which improves prognosis [28]. As indicated by The American Cancer Society's assessments for melanoma in the United States around 7,180 individuals are relied upon to pass on of melanoma (around 4,600 men and 2,580 ladies. On other aspect, Melanoma causes 55,500 cancer deaths annually which is 0.7% of all cancer deaths. Melanoma is an especially destructive type of skin disease and despite the fact that it represents just 4% of all skin malignant growths it is liable for 75% of all skin disease passings [14]. Melanoma has an incidence rate that is characterized by a favorable trend among the cancers that cause the most deaths in the United States. Despite the fact that cutaneous melanoma is still incurable, early excision of the skin lesion proves to be a critical event [4]. Melanoma is difficult to identify in the early stages since it is nearly indistinguishable from common nevi or benign dysplastic tumors. Even competent dermatologists face challenges in identifying melanoma and dealing with its aggressiveness, leaving them to decide how to continue. The specialist's sensibility and experience will determine whether the lesion is ignored or a biopsy is ordered. Melanoma has the ability to invade deep into the body. , statistics shows that the 5-year relative survival rate for people who has been diagnosed with melanoma in an early stage is about

98%. However, about 20% to 50% of people having melanoma in advanced stage will be alive 5 years after diagnosis [22]. Melanoma's most deadly feature is its ability to spread widely throughout the body via lymphatic and blood arteries. As a result, it is critical to support early diagnosis by specialists and to encourage direct self-diagnosis by the general public.

### 1.2 Motivation

Convolutional Neural Networks gave decent results in easier image segmentation problems but it hasn't made any good progress on complex ones. That's where Unet comes in the picture. UNet was first planned particularly for clinical picture division. It showed such a good results that why it was used in many other fields. Image segmentation is an important problem and every day some new research papers are published. UNet contributed significantly to such research. Many new architectures are inspired by UNet. But still, there is so much to explore. There are so many variants of this architecture in the industry and hence it is necessary to understand the first one to understand them better. The UNet is convolutional network design for quick and exact division of images. UNet architecture (example for 32x32 pixels in the most minimal goal). Each blue box compares to a multi-channel highlight map. The number of channels is signified on top of the container. Convolutional Neural Networks gave decent results in easier image segmentation problems but it hasn't made any good progress on complex ones. UNet was first planned especially for medical images segmentation. It showed such a good results that it was used in many other fields. UNet is one of the most used method.

### 1.3 Estimate of new cancer patient and Death

Every year, the American Cancer Society gauges the quantities of new disease cases and passings that will happen in the United States and gathers the latest information on malignant growth occurrence. In this bar chart, we presents the assessed quantities of new instances of obtrusive disease expected in the United States in 2017-2021 by sex. The general gauge of new cancer from 2017 to 2021 is about 481320. In the graph death rate is high in 2017.This rate is decreasing in 2018 and 2019. But in 2021 death rate is increase from 2020.there is also a noticeable thing is new cancer case rate is huge in male than female.The rate of new melanoma cancer is increasing continuously day by day. Melanoma is the most invasive skin cancer with the highest risk of death. While it's a serious skin cancer, it's highly curable if caught early.

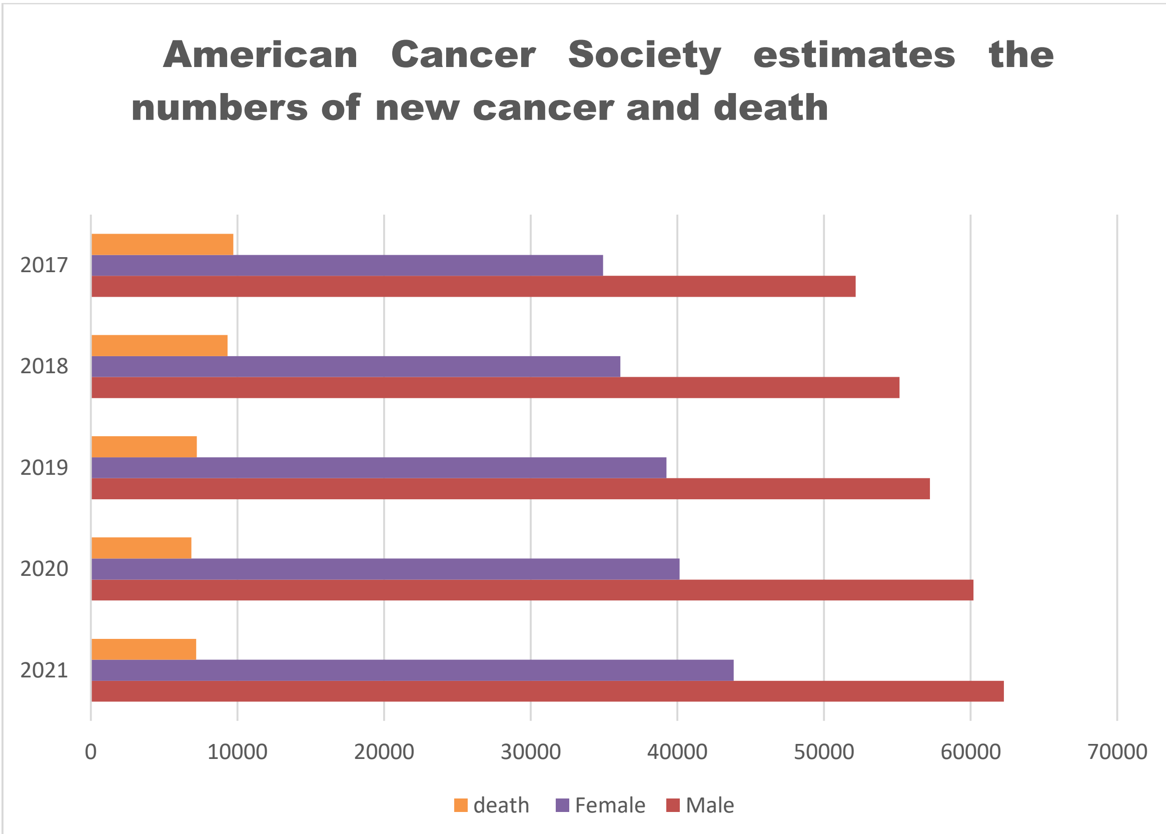



Figure 1: Estimate of new cancer patient and Death (According to Amrican cancer society 2021).

# Chapter 2

# Literature review

## 2.1 Introduction

A writing audit reviews books, insightful articles, and some other sources pertinent to a specific issue, space of exploration, or hypothesis, and thusly, gives a portrayal, rundown, and basic assessment of these works comparable to the examination issue being researched. Writing surveys are planned to provide perusers with an outline of the sources you utilized when concentrating on a specific issue and to show them how your exploration squeezes into a more extensive field of study.

## 2.2 Literature review

In this paper, they have compared melanoma skin cancer and lesion segmentation. The Gradient and Feature Adaptive contour (GFAC) model detect melanoma skin cancer. They used pre-processing, noise elimination technique multiple Gaussian distributed pattern. Lesion segmentation artifacts exclusion, efficient feature extraction and classifications are four types of dermoscopic images requires for the efficient diagnosis. The efficient classification of skin segmentation depends on the effective feature extraction and RIO extraction. Several existing methods namely k-mean algorithm, automated computed aided methods, saliency, convolution and deconvolution networks and fuzzy algorithm are presented [1]. In this paper, they have implemented a substantial improvement on most segmentation metrics tested on seven publicly available biomedical imaging datasets demonstrating the effectiveness of the proposed FANet. They used some methods such as Feedback attention learning, Iterative refining of prediction masks, Embedded run-length encoding strategy, Systematic evaluation, Efficient training. The method portion they used SE-Residual block, MixPool block, Proposed FANet architecture. In the dataset portion they applied Kvasir-SEG, CVC-ClinicDB dataset, 2018 Data Science Bowl, ISIC 2018 dataset, DCHASE-DB1 dataset, EM dataset. In the

Ablation study the also discussed Baseline (B1), Baseline + MixPool (B2), Baseline + MixPool(E1, D4) + Feedback (B3), Baseline + MixPool + Feedback (B4). They described four network configurations (B1-B4) like Effectiveness of MixPool block, Optimum position of Mixpool block in FANet architecture, Significance of feedback during evaluation. They also applied CNN, RNN [2]. In this paper, they have developed automated melanoma skin cancer detection using image segmentation. They used some methods like: preprocessing, segmentation. In preprocessing part tive methods used such as Resizing, Masking, Cropping, Hair Removal, Convert RGB to Grayscale image. In segmentation portion they applied some techniques like sigmoid mapping, principle component transform (PCT), Iterative Fuzzy c-means, Scoring system, Boundary Refinement [3]. In this paper, they have implemented segmentation. In the methodology portion they showed three block like Residual block, Dense net blocks, Encoder and decoder blocks in DRUNet. In Material and Network Parameter Settings also used ISIC 2018, Brain Data, Network Settings. They applied DCNN, FCN, Conv-ReLU, DenseNet, r UNet, RUNet, DU-net [4]. In this paper, they have implemented the particular case of skin cancer detection using Clan and Vase model. They focused on segmentation based on Total variation methods. They applied CAD systems for the decision of pathologists with only the input used by dermatologists. In segmentation portion used many techniques like fuzzy c-means, center split, multi goal, part and union, Pct/middle cut and versatile thresholding. The accuracy of detection of a image used ABCD rule [5].

In this paper, they have showed skin lesion segmentation, analysis and classification. They used some methods such as Strategy, Data, Experimental Design Tactics, Notable Novelties, Computational Resources. They applied ISIC 2018 Challenge, ISIC Archive, Interactive Atlas of Dermoscopy, Dermofit Image Library, and PH2 Dataset. For the experiments, they used NVIDIA GPUs available at RECOD Lab: two Titan X Pascal, six Titan Xp, one Tesla K40, and for Tesla P100. They also used the NC6 (Tesla K80) and ND6 (Tesla P40) virtual machines provided by the Microsoft Azure Cloud platform. TASK 1: LESION BOUNDARY SEGMENTATION, TASK 2: LESION ATTRIBUTE DETECTION, TASK 3: LESION DIAGNOSIS also used. They trained three different

CNN architectures: Inceptionv4 [18], ResNet-152 [19], and DenseNet-161 [20], all pretrained on ImageNet dataset [6].

In this paper, they have implemented skin lesion localization and segmentation. They used some methods such as Proposed Detector-SegMentor, Training Strategy. In the Proposed Detector portion they discussed Stage - 1 : Detector, Stage - 2 : SegMentor. In Stage - 2 : SegMentor also applied Encoder – Decoder, Hourglass Module. They compared result on SIC 2018, ISBI 2017 validation set with UNet+2HG and ISBI 2017 validation and PH2 dataset with UNet+2HG. In Stage - 1 : Detector portion discussed the base network, region proposal network(RPN), and the RCNN [7].

In this paper, they have compared skin cancer detection and lesion segmentation. They showed some methods for lesion segmentation such as region growing, fuzzy c-means, otsu's, Gaussian low-pass. For image preprocessing they used ABCD rule, feature extraction. They applied fast fourier transform and discrete cosine transform. Deep network based feature learning method had developed. For the implementation the implementation of deep network, the caffe framework with GPU Geforce GTX TITANX used [8]. In this paper, they have implemented Skin Lesion Segmentation and Melanoma Detection. They used some methods such as Dermoscopy Image Augmentation, Lesion Segmentation with UNet, Feature extraction with DCNN, Result Analysis. In the Lesion Segmentation with UNet portion they notice some layer like input, conv_block 1, pooling 1, conv_block 2, pooling 2, conv_block 3, pooling 3, conv_block 4, pooling 4, conv_block 5, pooling 5, conv_block 6, upsampling 1, concatenate 1, conv_block 7, upsampling 2, concatenate 2, conv_block 8, upsampling 3, concatenate 3, conv_block 9, upsampling 4, concatenate 4, conv_block 10, upsampling 5, concatenate 5, conv_block 11, conv 1×1. The conv_block consists of the sequence of operations Conv + BN + ReLU + Conv + BN + ReLU + Spatial Dropout layers with kernel size of 3×3 and stride 1. At the last layer, 1×1 convolution is applied and sigmoid enactment is utilized. They also applied Rectifier Linear Unit (ReLU), DCNN, CNN. They also used ISIC 2018 and $PH^2$ dataset [9]. In this paper, they implemented skin cancer detection using thresholding, region based and edge based segmentation algorithms. They used texure distinctiveness algorithm, k-means and TD algorithm. They applied MSIM, TDLS, feature extraction, SVM algorithms. In MSIM algorithm involved three steps like segmentation map, Illumination map, reflectance map. To classify segmentation lesion image used ANN, SVM classifier [10].

In this paper, they presented a methodological approach for classification of skin lesion and melanoma skin cancer. They used mean shift algorithm for detecting melanoma skin cancer. They applied KNN, decision tree, SVM classifier and ABCD rule. Some method also used such as preprocessing, hair removal, filtering hair removal image, image segmentation, feature extraction, feature selection and dimension deduction and classification. In image segmentation portion used segmenting lesion images, features of border. In feature extraction also used feature for asymmetry, feature for color variation, feature for diameter, classification and evaluation criteri [11].

In this paper, they have implemented melanoma skin cancer using pre-processing and post-processing methods. In preprocessing portion they used otsu/kapur based thresholding technique. Metrices were used to significance of the proposed tool such as jaccard's coefficient, dice's coefficient, false positive rate, negative rate, accuracy, sensitivity and specificity. The level set method increased the segmentation result compared to the adaptive thresholding, gradient vector flow, fuzzy based split and merge Technique. They also computed statistical parameters, namely precision, f-measure, sensitivity, specificity, balanced classification rate, balanced error rated accuracy. In preprocessing portion they used multi-level thresholding, SGO, TSU based thresholding, kapor based thresholding, image morphology operation. In post-processing portion applied level set, active contour Technique [12]. In this paper, they used encoder decoder model for skin cancer detection. They gave three scenario and three methods. The methods are comparison of different learning rate values, comparison of different testing type, comparison of different input size. They took different size and different values. Therefore they applied evaluation stage for highest score results from test model [13]. In this paper, they present a CAD technique for the identification of melanoma skin disease utilizing picture pre-processing instruments. They dissect picture utilizing a few boundaries like deviation, line, shading, measurement, abcd, by surface, size and shape examination for picture division and component stages.They used some steps like image acquisition of skin lession image, segmentation of the skin lesion from skin region, extraction of feature of the lession blob and feature classification. They also used image preprocessing, image segmentation, feature extraction and classification techniques [14].

In this paper, they have showed the preprocessing approaches can be used in skin cancer detection. The approaches are image preprocessing, segmentation, feature extraction and classification. They applied image enhancement, image restoration and hair removal. In image enhancement portion they also used image scaling, color space transformation, contrast enhancement. Therefore, restoration from noise, restoration from blur, morphology methods, curvilinear structure detection methods used. This paper is useful for researchers working on skin cancer detection system [15].

In this paper, they showed challenges and opportunities of artificial intelligence-based image classification methods for diagnosis of skin cancer. They used publicly available dataset for skin cancer, artificial intelligence in thermoscopic images, artificial intelligence in clinical images. They discussed some challenges in artificial intelligence like performance of deep learning and unbalanced datasets, curious case of histopathology images, patients' medical history and clinical meta-data, inter-class similarities, inter-class dissimilarities etc. They also showed some opportunities like balanced dataset and selection of cases, computer aided diagnosis for digital pathology, color constancy for illumination and heterogenous dataset sources, data augmentation, diverse datasets, generation adversarial Networks identifying subcategories, rigorous clinical validation [16]. In this paper, they implemented a technique to classify skin lesion with the purpose of identifying melanoma. They used neural network and some methods. In neural organization they utilized fake neural organizations (ANN), profound neural organizations (DNN), Convolutional neural organizations (CNN), CNN Architecture layers learning move. In CNN Architecture layer portion applied four types of layer principles used to build CNN configuration such as convolutional layer (CONV), Rectified linear unit layer (RELU), pooling layer (POOL), and fully connected layer (FC). In method part they used image dataset, preprocessing, CNN network layer configuration. In preprocessing method some procedure applied to input image like mean subtraction, image normalization, image cropping and resizing, ISIC. They achieved accuracy score were 97.78% [17]. In this paper, they compared the challenges and opportunities for improvement skin cancer detection. They used some methods like Inception, CNN, DRNs, CNNs. A two phase structure made out of a fuply convolutional redidual network (FCRN) and profound lingering organization (DRN). ISIC had assumed a significant part by keeping up with the ISIC document [18].

In this paper, they implemented skin lesion segmentation using machine learning algorithm. They utilized ABCD rule, Artificial Neural Network (ANN), Support Vector Machine (SVM), K-Nearest Neighbor (KNN), Decision Tree (DT) calculation. They applied the commonly accepted performance evaluation measures such as TP, FP, TN, FN. Some mathematical portion applied like Sensitivity, Specificity, Balanced accuracy, Precision, F-measure, Roccure . They worked by some models like joint reserve classification (JRC), deep learning, SVM, Bow model with Harris Laplace features, Bow model with Shades of Gray transform [19].

In this paper, they compared different types of skin lesion using deep learning network and transfer learning. They used Augmentation process, Transfer learning. They applied ANN, MLR, JRC, DCNN, PH2 dataset, Alexnet. DNCC is applied to group the shading pictures of skin malignant growth into three kind like melanoma, abnormal nevus and normal nevus. AlexNet used in the visual recognition of imageNet. Some mathematical term applied like accuracy, sensitivity, specificity, precission [20].

In this paper, they implemented skin cancer detection using pattern recognition technique, preprocessing methods, feature extraction methods and public dataset. They used ISIC and HAM10000 dataset. In methodology they used four steps such as data preprocessing, feature extraction, melanoma classification and result analysis. In data preprocessing portion Gaussian blur, normalization performed. They proposed some features for different aspects of input image like Hue saturation value (HSV), Neighborhood Binary example (LBP), Histogram of Oriented Gradients (HOG), Scale Invariant element change (SIFT), In feature extraction they used HSV, LBP, HOP, SIFT method. In the classification portion they applied some Techniques such as Support vector Machine (SVM), logistic Regression (LR), Random forest (LR), Adaptive

Boosting (AdaBoost) , Balanced Bagging (BB), Balanced Random Forest (BRF). They applied accuracy, sensitivity, specificity and metrics [21].

In this paper, they implemented melanoma skin cancer detection using various machine learning approaches. Acquisition, preprocessing, segmentation, feature extraction and selection are used. In classification they applied k-Nearest Neighbour algorithm, Decision Tree, Logistic Regression, Artificial Neural Network, Support Vector Machines, Multiple Instance Learning techniques and Deep learning methods. ADWAT and LMT versions used in decision tree [22].

In this paper they have compared two method UNets and C-Means clustering to implement skin lesion segmentation. Standard skin cancer computer-aided diagnosis systems include five important steps: acquisition, preprocessing, segmentation, feature extraction, and finally, classification. They applied some methods. For UNet Approach they used Architecture and Training, Pre- and Post-Processing, UNet Algorithm. In the Clustering portion they also used Fuzzy C-means clustering, k-means clustering, Pre-Processing, Clustering Algorithm. They used ISIC dataset. They also showed, comparing the clustering and UNet algorithms, it was clear that UNets produce a much better segmentation result, especially using the histogram equalization based preprocessing step [23]. In this paper, they have implemented image segmentation using UNet . they have used some methods like: Motivations and High Level Considerations, Variation of Scale in Medical Images, Probable Semantic Gap between the Corresponding Levels of Encoder-Decoder, Proposed Architecture, Datasets, Fluorescence Microscopy Image, Electron Microscopy Image, Dermoscopy Image, Endoscopy Image, Magnetic Resonance Image, Baseline Model, Pre-processing , Post-processing, Training Methodology, Evaluation Metric, k-Fold Cross Validation, MultiResUNet Consistently Outperforms UNet, MultiResUNet can Obtain Better Results in Less Number of Epochs, MultiResUNet Delineates Faint Boundaries Better, MultiResUNet is More Immune to Perturbations, MultiResUNet is More Reliable Against Outlier, Note on Segmenting the Majority Class [24].

In this paper, they have implemented segmentation of skin lesions using the concept of the triple attention mechanism. They used some methods like: UNet, attention UNet, spatial attention module (SAM) , Squeeze-and-Excitation Networks (SENet) and Shape Attentive UNet (SAUNet), Triple Attention Decoder Block, Attention Gate, Spatial Attention Module, Channel Attention Module , Channel and Spatial Attention, Loss Function, Performance Evaluation Metrics, Ablation Experiment . they also used channel attention module (CAM), spatial attention module (SAM), convolution neural networks (CNN). In the Proposed ASCUNet Architecture portion they applied convolutional layer (ConvBlock), batch normalization (BN) layer, and rectified linear unit (ReLU). They used three data sets. They are ISIC-2016, ISIC-2017, and PH2 [25].

They have showed Image Segmentation using Convolutional Neural Network based on U-Net (R2UNet). They used some methods and algorithms. They utilized Recurrent Convolutional Neural Network (RCNN) in light of UNet just as a Recurrent Residual Convolutional Neural Network (RRCNN) in view of U-Net models, which are named RUNet and R2UNet individually. The models use the force of UNet, Residual Network, just as RCNN. For semantic image segmentation tasks they applied fully-connected convolutional neural network (FCN), SegNet. The field of computer vision, different variants were applied in different modalities of medical imaging including segmentation, classification, detection, registration, and medical information processing. Themedical imaging comes from different imaging strategies like Computer Tomography (CT), ultrasound, X-beam, and Magnetic Resonance Imaging (MRI). They showed Blood Vessel Segmentation, Skin Cancer Segmentation, Lung Segmentation also showed including accuracy (AC), sensitivity (SE), specificity (SP), F1-score, Dice coefficient (DC), and Jaccard similarity (JS) [26]. In this paper, they have shown image segmentation using different types of UNet. The UNets are Base U-net, 3D UNet, Attention UNet, Inception U-net, Residual UNet, Recurrent Convolutional Network, Dense UNet, UNet++, Adversarial UNet, Cascaded arrangement, Parallel arrangement. In Image modalities portion used Magnetic resonance imaging (MRI), Computed tomography (CT), Retinal fundus imaging, Dermoscopy, Ultrasound, X-ray. Challenges, UNet for COVID-19 also discussed. In Base UNet portion was used CNN, ReLU, max-pooling layer. 3D UNet has seen extensive use in volumetric CT and MR image segmentation applications, including diagnosis of the cardiac structures , bone structures , vertebral column, brain tumors, liver tumors, lung nodules, nasopharyngeal cancer, multi-organ segmentation, head and neck organ at risk assessment, and white matter tracts segmentation [27]. In this paper, they have implemented automatic skin lesion segmentation using Lightweight encoder-decoder. International Skin Imaging Collaboration (ISIC) 2017, 2018, and the PH2 database they were used to evaluate the proposed SLS method. They applied some methods such as Pre-processing and post-processing, Network structure, Stochastic weight averaging, Training and testing, Performance evaluation. In the Pre-processing and post-processing portion they used Image resizing, Image augmentation, Image normalization, Post-processing. In Network structure potion they applied decoder Standard U-Net, UNet-LSTM, BCDU, Separable-UNet. Five common evaluation metrics were used to evaluate the proposed segmentation method: accuracy (ACC), sensitivity (SEN), specificity (SPE), Dice coefficient (DIC), and Jaccard index (JAI). Unsupervised methods include thresholding, region-merging, energy functions, and clustering also used. In Results portion they also showed experimental results, Encoder network comparison, Decoder network comparison, Random augmentation and model performance, Learning schemes by different decoder networks, Post-processing, Performance comparison with other state-of-the-art methods [28]. In this paper, they have implemented Melanoma Skin Disease. They used deep learning based method. In deep learning based method portion they applied some methods such as Convolution Network-based Methods, Autoencoder-based Methods, Generative Adverserial-based Methods, Pre-Processing & Post-processing Techniques. They used International Symposium on Biomedical Imaging (ISBI) 2016, 2017,2017,2018,2019,2020 and PH2 dataset. In the results part they showed some value like Accuracy(AC), Sensitivity(SE), Dice coefficient(DI), Specificity(Sp), Jaccard Index(JA) [29]. In this paper, they have implemented segmentation of tympanic membranes from otoscopic images. EAR scheme is based on three main paradigms: Efficient Net for the encoder, Attention gate for the skip connection path, and Residual blocks for the decoder. They used a dataset from Cathay General Hospital (No.CGH-P103040), a database of 1012 OM otoscopic images from children aged 6 months to 12-year-old. They showed UNet architecture, Attention gate. They applied some methods such as the proposed approach for tympanic membrane segmentation, Loss function, Training protocol and testing. In the experiment portion they showed Performance metrics, Experimental results. In the Training protocol and testing portion they applied Accuracy, Sensitivity, specificity. In Performance metrics potion also showed e Dice similarity coefficient (DSC), and Jaccard coefficient (Jac) to evaluate the quantitative accuracy of segmentation results. Quantitative segmentation performance for the proposed EAR-UNet in comparison with the FCN, SegNet, UNet, AttentionUnet, and ResidualUnet. for TM segmentation of all test data. Metrics include DSC, Jac, Acc, Sen, Spe, HD, and MAD. Values in Mean (STD). The HD and MAD are in pixels [30].

# Chapter 3

# Overview of UNet Modified Model

## 3.1 Introduction

UNet was initially concocted and first utilized for biomedical picture division. Its engineering can be comprehensively considered as an encoder network followed by a decoder organization. Dissimilar to arrangement where the final product of the profound organization's what is main significant, semantic division requires segregation at pixel level as well as a component to project the discriminative highlights learnt at various phases of the encoder onto the pixel space. The encoder is the primary half in the design graph. It ordinarily is a pre-prepared grouping network like VGG/ResNet where we apply convolution blocks followed by a maxpool, downsampling to encode the information picture into include portrayals at numerous various levels. The decoder is the final part of the design. The objective is to semantically project the discriminative highlights (lower goal) learnt by the encoder onto the pixel space (higher goal) to get a thick characterization. The decoder comprises of upsampling and link followed by customary convolution tasks [23]. In elaboration we can say we use here Sigmoid capacity which is an actuation work that is utilized to give non-linearity to a model by concluding which esteems to pass as result and which not to pass. The capacities utilized in AI and profound learning.

## 3.2 Architecture of Unet

The UNet is convolutional network design for quick and exact division of Images. Up to now it has beated the earlier best strategy (a sliding-window convolutional network) on the ISBI challenge for division of neuronal constructions in electron tiny stacks. In this architecture we use Polling setup, MaxPolling, Upsampling, ReLu. The reason behind use this is Spatial Pooling (otherwise called downsampling or subsampling) diminishes the dimensionality of each component map while holding the most basic information. There are a few types of spatial pooling: Max, Average, Sum, etc. We set up a spatial area (for instance, a 22 window) and take the greatest component from the revised element map inside that window on account of Max Pooling. We may take the normal (Average Pooling) or all out of all things in that window rather than the best component. Max Pooling has been demonstrated to work better practically speaking. This architecture could be beneficial for implementing deep learning in CAD systems, specifically for real-time image semantic segmentation. In the decoder, standard UNet can rebuild features from stage to stage to obtain important information from the context and global information from MobileNetV3 [28].

### 3.3 Upsampling

Here, We also use Upsampling . To enhance the sampling rate, upsampling is the act of adding zero-esteemed examples between unique examples. (This is likewise known as"zero-stuffing.") This kind of upsampling brings undesirable otherworldly pictures into the first sign that are centered around products of the inspecting rate. Here are a few ways of upsampling such as Nearest Neighbor,Bilinear Interpolation, and Transposed Convolution from simplest to more complex.The main contribution of UNet in this sense is that while upsampling in the network we are also concatenating the higher resolution feature maps from the encoder network with the upsampled features in order to better learn representations with following convolutions. Since upsampling is a sparse operation we need a good prior from earlier stages to better represent the localization.

### 3.4 Rectified Linear Unit (ReLU)

Another non-direct enactment work that has acquired conspicuousness in the profound learning area is the ReLU . The ReLU is the most involved actuation work on the planet at this moment. Since, it is utilized in practically all the convolutional neural organizations or profound learning. Redressed Linear Unit (ReLU) is a shortened form for Rectified Linear Unit. The vital advantage of utilizing the ReLU work over other actuation capacities is that it doesn't all the while animate all of the neurons.we utilize this in light of the fact that practically speaking, networks with Relu will generally show preferred intermingling execution over sigmoid.

### 3.5 Unet Model Diagram

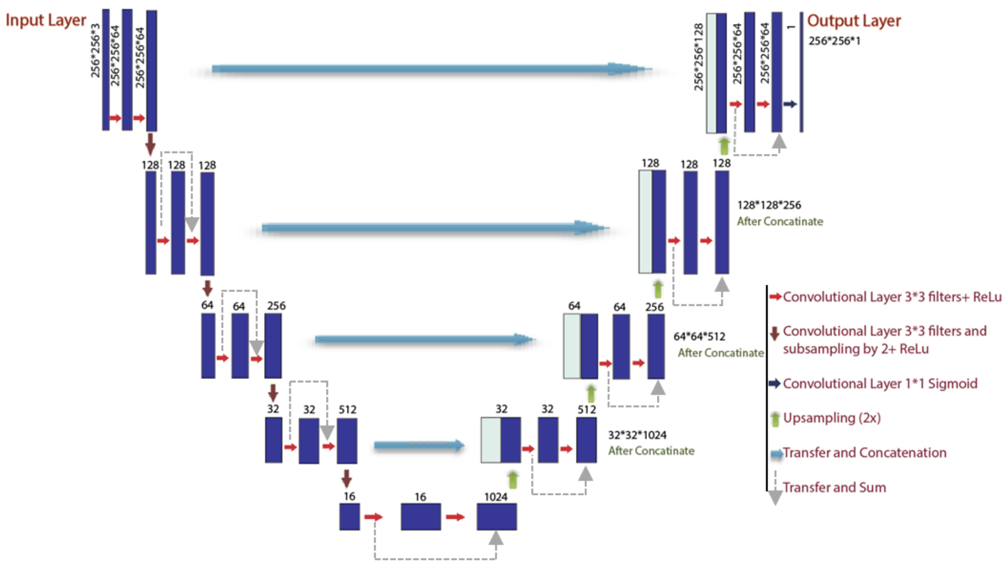



Figure 2: Architecture of UNet

In this UNet design we take 3* 3 convulation layer followed by 2*2 max polling. Here red bolts are demonstrated convulation layer After that the quantity of element maps later each square become pairs. Here dull browns bolts are demonstrated by convulation and subsampling. In the first to third layer everytime initial two component maps become half of the above which called max surveying and last element become two fold which called upsampling . In the last stage at input layer it become 16*16*1024. We utilized here adjusted UNet which isn't as base UNet model. In this engineering the another part is development segment, which isn't same as subsampling. In along these lines part it likewise has exactly a few squares, Every one of the squares passed the contribution to two 3*3 layer followed by 2*2 upsampling, Here green bolts are shown to upsampling. Later the main link's the element will became 32*32*1024. In silver bolts we showed all the tranfer and total in the end. From the info element to the result include the engineering shape is resembling 'U' Shape, which can legitimizes its own name. Later the all connect segment the quantity of element maps are same to the num of portioned want. Finaly, from this model we got a layer of 256*256*1 which is our outout layer. Here this 1 (one) is for Black and white Images.

The architecture looks like a ‘U’ which justifies its name. This architecture consists of three sections: The contraction, The bottleneck, and the expansion section. The contraction section is made of many contraction blocks. Each block takes an input applied two 3X3 convolution layers followed by a 2X2 max pooling. The number of kernels or feature maps after each block doubles so that architecture can learn the complex structures effectively. The bottommost layer mediates between the contraction layer and the expansion layer. It uses two 3X3 CNN layers followed by 2X2 up convolution layer. But the heart of this architecture lies in the expansion section. Similar to contraction layer, it also consists of several expansion blocks. Each block passes the input to two 3X3 CNN layers followed by a 2X2 upsampling layer. Also after each block number of feature maps used by convolutional layer get half to maintain symmetry. However, every time the input is also get appended by feature maps of the corresponding contraction layer. This action would ensure that the features that are learned while contracting the image will be used to reconstruct it. The number of expansion blocks is as same as the number of contraction block. After that, the resultant mapping passes through another 3X3 CNN layer with the number of feature maps equal to the number of segments desired.

# Chapter 4

# Result Analysis

## 4.1 Accuracy

we also used other metrics including accuracy, sensi- tivity, and specificity, to evaluate the performance of tympanic mem- brane segmentation algorithms. The accuracy (Acc) is the proportion of true results which measure the reliability degree of a diagnostic test. Accuracy is estimated as the capacity to separate the Melanoma and harmless cases accurately, characterized as:

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

## 4.2 Sensitivity

The sensitivity (Sen) shows how well the algorithm successfully predicts the eardrum regions. Particularly, it is used to indicate the true positive rate, Sensitivity is estimated as the capacity to decide the Melanoma cases effectively, characterized as:

**Sensitivity =** $\frac{TP}{TP+TN}$

## 4.3 Specificity

The specificity (Spe) indicates the true negative rate, showing how well the algorithm successfully predicts the non-eardrum regions, Specificity is estimated as the capacity to decide the harmless cases effectively, characterized as:

**Specificity =** $\frac{TN}{TN+FP}$

In these formulas, TP (True Positive) represents the number of Melanoma cases correctly identified, FP (False Positive) represents the number of Melanoma cases incorrectly identified, TN (True Negative) represents the number of cases correctly identified as benign, and FN (False Negative) represents the number of cases incorrectly identified as benign.

### 4.4 Area Under Curve

**AUC** (Area Under Curve) is a higher level statistic that combines the true positive rate (TPR, which is the same as sensitivity) and the false positive rate (FPR = F P/FP+TN , which indicates how effectively a classification system distinguishes between the positive and negative classes. It is difficult to tell if a classification system is overfit with positive data (high Sensitivity) or overfit with negative samples when specificity and sensitivity are used separately (high specificity). As a result, AUC is offered as the ultimate statistic to quantify the success of numerous categorization systems, both positive and negative. When the classification threshold fluctuates, AUC is determined as the area below a Receiver Operating Characteristic curve composed of different combinations of TPR and FPR. A higher AUC value indicates that the classification approach is getting closer to being a perfect prediction system.

### 4.5 ROC AUC Curve

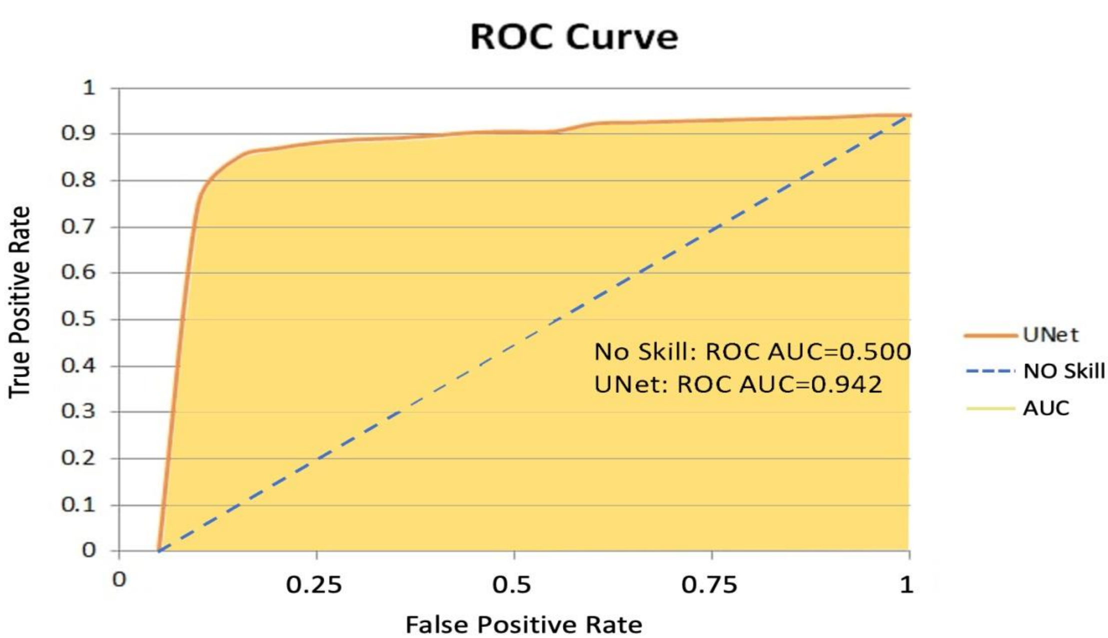



Figure 3: ROC AUC Curve

We use the UNet method which is most popular method in deep learning. This method is highly used in medical science. By using this method we get the proper output. The suggested method outperforms established classification approaches, such as the well-known support vector machine (SVM), in terms of both accuracy and sensitivity. By using the method we achieved good performance (Accuracy = 94.27% (percent), F1 Score= 84.87% (Percent) Recall= 85.32% (Percent), Jaccard= 77.14% (percent) and Precision = 89.91% (percent) using Kaggle skin cancer detection Dataset ISIC-2018. We use the training image for segmentation.

## 4.6 Comparison Table

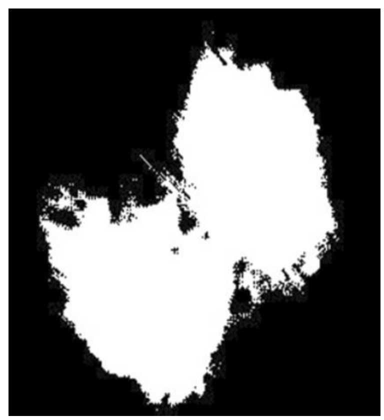
| NAME | DATASET | ACCURACY Score(%) | PRECISION Score(%) | RECALL Score(%) | JACCARD Score(%) |
|---|---|---|---|---|---|
| **Ref[2]** | ISIC-2018 | 93.74% | 92.52% | 90.33 | - |
| **Ref[4]** | ISIC-2018 | | 90.90% | 89.70% | 75.50% |
| **Ref[6]** | ISIC-2018 | 90.30% | - | - | 34.40% |
| **Ref[9]** | ISIC-2018 | 92.00% | - | - | 80.00% |
| **Proposed Model** | ISIC-2018 | 94.27% | 89.91% | 85.32% | 77.14% |

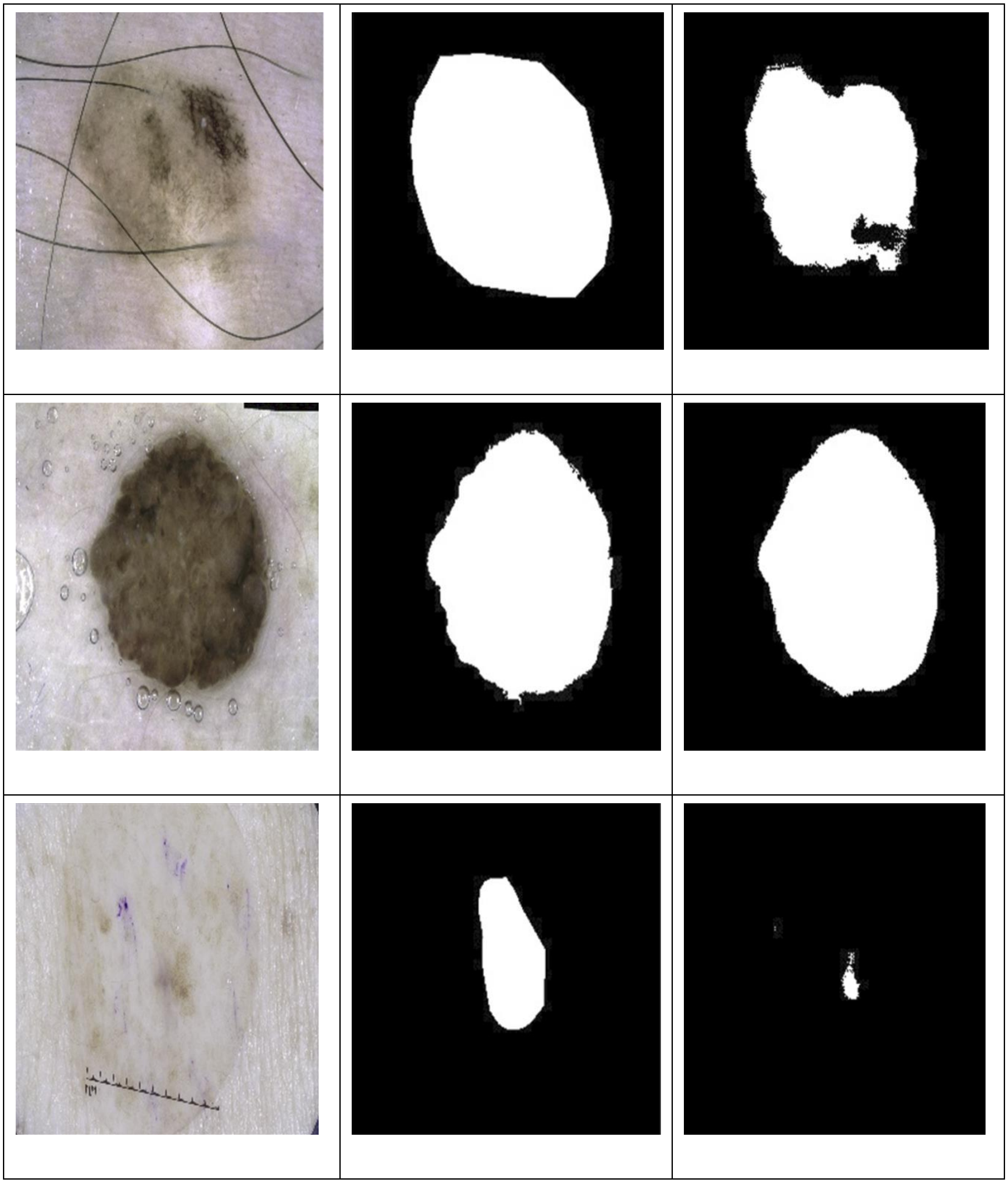
**4.7 Adam Optimizer**:

Optimizers are one kind of algorithms or methods which is used to change the attributes of the Neural Network such as weights and learning rate to reduce the losses of the system. It’s mainly used for solving optimization problems by minimizing the function. Most of the cases it’s said that Adam is the best optimizer. In the area of Neural Networks, the ADAM-Optimizer is one of the most popular adaptive step size methods.

It was invented  by Kingma and Ba Good with sparse data: the adaptive learning rate is perfect for this type of datasets. There is no need to focus on the learning rate value. Adam is a replacement optimization algorithm for stochastic gradient descent for training deep learning models. Adam combines the best properties of the AdaGrad and RMSProp algorithms to provide an optimization algorithm that can handle sparse gradients on noisy problems. Adam optimizer involves a combination of two gradient descent methodologies: Momentum This algorithm is used to accelerate the gradient descent algorithm by taking into consideration the 'exponentially weighted average' of the gradients. Using averages makes the algorithm converge towards the minima in a faster pace. Adam is an optimization solver for the Neural Network algorithm that is computationally efficient, requires little memory, and is well suited for problems that are large in terms of data or parameters or both.

### 5.2 Segmented Images

| **Original Image** | **Segmented Image** | **Ground Truth Image** |
|---|---|---|
|  |  |  |



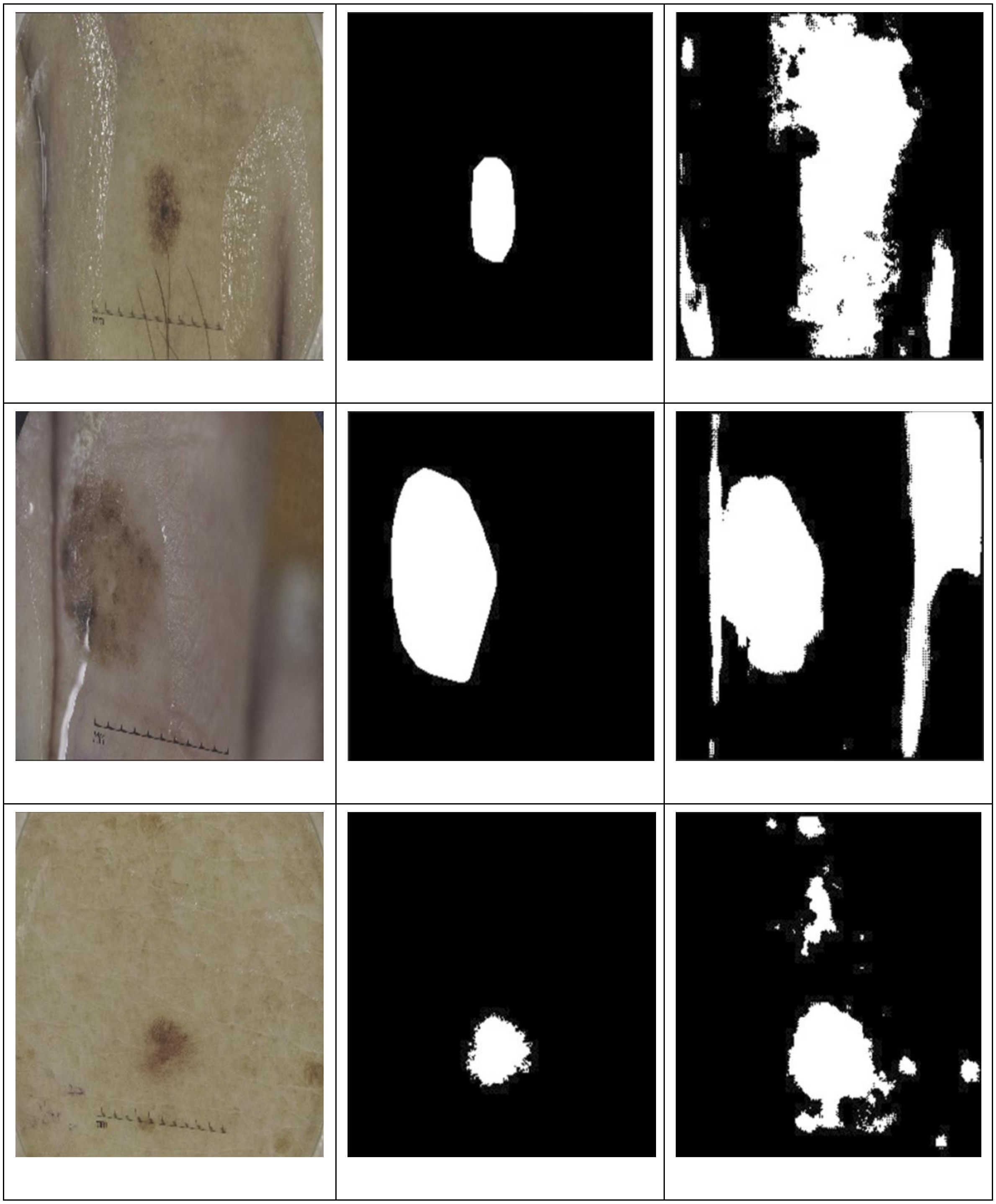


Figure 4: Segmented Images (Dataset ISIC-2018).

# Chapter 5

# Conclusion

## 5.1 Conclusion

This paper we present an useful approach automatically segmenting skin lesion. We use UNet architecture and Convolution Neural Network (CNN). Pre-processing techniques used for both approaches to improve the segmentation performance. ISIC-2018 dataset we used. The accuracy of our Model is 94.27%. These models were evaluated in different types of skin lesion. UNet based architecture is need quite ground-breaking and valuable in medical image analysis. This process help dermatologists in clinical decision making. It also help patients evaluate skin lesions outside the hospital. To perform an automated analysis of dermoscopic images, the separation of skin lesions from the normal region is usually the first step. In this paper, a method with a deep network architecture has been proposed to determine the lesion site from skin images. UNet architecture is used for lesion determination.

Skin cancer is a serious disease in this modern era. Day by day the research in this section is increase. We found the accuracy of this model is 94.27% on the validation dataset. In future, if anyone want to improve this model, he or she can improve it using this paper. This system is going to need in our daily life. For the better result we need to use a bigger dataset and apply image augmentation. We should change some parameters to get better accuracy. In future we will use multiple pre-trained model to get predictions on images.

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