Addis Ababa University

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Electrical and Computer Engineering Department

Skin Lesion Segmentation Using Deep Learning Algorithm and Level Set Method

By: Selomie Kindu

June 28, 2019

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Declaration

I, the undersigned, certify that research work titled Skin Lesion Segmentation Using Deep Learning Algorithm and Level Set Method. The work has not been presented elsewhere for assessment and all sources of materials used for the thesis have been fully acknowledged.

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Abstract

Skin lesion can be benign or skin cancer. Skin cancer is one of the most dangerous cancers killing so many people all over the world. Skin cancer is the most curable cancer if skin lesions are diagnosed at early stage. Skin lesion segmentation is a crucial phase in automated skin lesion detection towards skin cancer. Segmentation of skin lesion is the most challenging task for dermatologists. The rest phases of computer analysis diagnosis of skin cancer mainly depend on the segmentation result. Due to this, many methods of skin lesion segmentation have been proposed to improve the segmentation technique performance in computer aided diagnosis.

In this work, skin lesion segmentation using convolution de-convolution neural network and contour level set method is used to segment dermoscopic skin lesion images. Convolution de-convolution neural network is trained pixel wise for semantic segmentation of pixels into lesion and background. Level set is used to find the exact edges of detected lesion boundary by convolution de-convolution neural network method. In addition to the two main proposed techniques, preprocessing of the input images is applied to remove unwanted artifacts such as hair over the skin lesion image using vector filters and data augmentation to overcome the over fitting problem of proposed deep learning network. 2017 International Skin Imaging Collaboration (ISIC) archive dataset hosted by International Society of Biomedical Imaging (ISBI) for skin lesion analysis towards melanoma detection is used.

The performance evaluations on the proposed skin lesion segmentation method is pixel wise average measurements validated against ground truth for test data set are 94.8% intersection over union, 98.80% specificity, 94.84% sensitivity, 97.84% positive predicted value and 95.58% negative predicted value. The proposed method out performs segmentation using convolution de-convolution neural network and level set method by more than 2% and 30% respectively. Therefore, using convolution de-convolution neural network with level set segmentation method of skin lesion results better than convolution de-convolution neural network segmentation and level set segmentation.

Key Words: **Dermoscope, Detection, Skin Lesion, Skin Cancer, Segmentation, CDNN, Level Set**

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List of Acronyms

AC	Accuracy
ANN	Artificial Neural Network
CAD	Computer Aided Diagnosis
CDNN	Convolution De-convolution Neural Network
CNN	Convolutional Neural Network
CSLM	Confocal Scanning Laser Microscopy
DCNN	Deep Convolutional Neural Network
DI	Dice Coefficient
FC	Fully Connected
FCN	Fully Convolutional Network
FN	False Negative
FP	False Positive
IOU	Intersection over Union
ISBI	International Society of biomedical imaging
ISIC	International Skin Imaging Collaboration
ISDIS	International Society for Digital Imaging of the Skin
JA	Jaccard Distance
LCR	Local Contour Refinement
MRI	Magnetic Resonance Imaging
NPV	Negative Predictive Value
OCT	Optical Coherence Tomography

PDEs	Partial Differential Equations
ReLU	Rectified Linear Unit
RCN	Recurrent Neural Network
ROI	Region of Interest
SP	Specificity
SE	Sensitivity
TN	True Negative
TP	True Positive
PPV	Positive Predictive Value
SVM	Support Vector Machine
DL CNN	Deep Level set CNN
UV	Ultra Violate

Chapter One

Introduction

1.1 Motivation

Skin lesion is a part of skin that appear differently from the normal appearance of skin due to infection in or outside of the body. Even if most skin lesions are benign, correct diagnosis should be followed under diagnosis towards detecting skin cancer. Skin cancer is a cancer that develops from abnormal reproduction of skin cells. There are two categories of skin cancer, that are melanoma skin cancer, which is an aggressive skin cancer and non-melanoma that develops in the outer part of epidermis [1].

There is lack of effective and accurate automatic diagnosis of skin lesion towards detection of skin lesion. Therefore, many people are dying in the world by Skin cancer because skin lesions are not diagnosed at early stage. The diagnosis result statistics of skin cancer indicates that 98% of patients survive when skin cancer is detected or diagnosed in the early stage, however 17% of them survive if the diagnosis is lately in its far away stage. Skin lesion treatment costs more than $3.3 million dollars in USA annually, so that early detection is worthy in minimizing economic cost and saving life [2][3].

Skin cancer is the most common cancer, so that many people are diagnosed with skin cancer in each year than the sum of all other cancers combined. The Skin Cancer Society Statistics shows that the diagnosis and treatment of skin cancer in U.S increased by 77% between 1994 and 2014. There is 7.7% increasing rate of new skin lesion cases per year. The statistical study on skin cancer society indicates that, an estimate of one person die from melanoma every hour in the world. Incidence of skin cancer has risen rapidly over the past 30 years. It kills an estimated 15,000 people per year, nevertheless it is the most curable kind of cancer if its detected at the early stage [2].

There are clinical skin lesion diagnosis methods such as ABCD rule, 7-Point checklist but manual skin lesion segmentation is very difficult due to variation of lesions. CAD is a clinical decision support system, which assists doctors in the interpretation of medical images. CAD is

used as a tool to provide additional information to clinicians for final decision of diagnosis. Its primary goal is to improve the diagnosis accuracy and consistency of clinicians by reducing the false negative rate due to observational subjectivity. Most of the time two types of general approaches are employed in CAD of skin lesions. The first one is to find the location of the lesions and the second is to quantify the image features of normal and/or abnormal pattern [4].

The standard procedure for automatic skin lesion detection towards skin cancer follows three steps: 1) skin lesion segmentation; 2) extract features from segmented image; 3) lesion classification [5]. Above all, accurate skin lesion segmentation or finding the location of skin lesions is the determining step for automatic detection of skin cancer.

Accurate detection of skin lesion segmentation improves the overall CAD accuracy. Therefore, skin lesion segmentation is still an open research area with aid of different international cancer society organizations for improvement of diagnosis using automatic segmentation method.

In this thesis, we propose skin lesion segmentation method that composes CDNN and level set segmentation method for dermoscopic skin lesion segmentation.

1.2 Problem Statement

There is no effective early detection of skin cancer. To overcome this problem skin lesion segmentation must be done using an effective segmentation method. There are many researches being done for automatic skin lesion segmentation to solve the problem of accuracy in CAD of skin lesion [5]. Skin lesion segmentation is an active research area because accuracy must be improved using a robust algorithm. Therefore, a lot must be done to improve accuracy performance of skin lesion segmentation because it is a fatal public health issue related to skin cancer.

Segmentation is a key stage in CAD. Recent studies of automatic skin lesion detection towards skin cancer show that, the accuracy of Skin lesion segmentation which is the first step in CAD affects detection of skin cancer [6][7][8][9][10][11][12]. The result of automatic analysis of skin lesion totally depends from the segmentation result because features for skin lesion classification are selected from segmented region of image. There are a lot of algorithms for skin lesion

segmentation [9][12][13][14][10][15], even if there is no accurate skin lesion segmentation algorithm because:

- Skin lesion segmentation is very difficult at early stage due to variation of lesions in color, texture, shape, similarity between cancerous and non- cancerous lesions, low contrast of lesion boundary in the early stage and the presence of artifacts
- The transition from normal skin to skin lesion is not easily identifiable

Based on the stated CAD and clinical diagnosis problems, this thesis proposes skin lesion segmentation method using CDNN and level set method from dermoscopic skin lesion images. CDNN is used for lesion area detection of skin lesion areas while level set is for finding the exact edges of the lesion detected by CDNN. Using CDNN and Level set algorithms integration for skin lesion segmentation solves the problem of skin lesion detection around the edges of skin lesion when there is a smooth transition between normal and lesion skin.

1.3 Research Questions

The scope of this research is improving skin lesion segmentation using integrated; composed of deep learning neural network and image level set method. The following are research questions answered by this thesis study:

1. Can automatic skin lesion segmentation performance be improved by using deep learning CDNN in comparison to Level Set method?
2. Can integrating deep learning CDNN with level set image processing improve the performance of skin lesion segmentation in comparison to CDNN?
3. Can preprocessing skin lesion image improve the performance of segmentation?

1.4 Objective

1.4.1 General Objective

The general objective of this thesis is to develop skin lesion segmentation method using CDNN and level set.

1.4.2 Specific Objective

The specific aims of this thesis are:

- Study different methods of skin lesion segmentation that used CDNN and level set methods.
- Integrate CDNN with level set method and evaluate the performance.
- Identify which step of the segmentation mainly affects the performance of skin lesion segmentation using CDNN and Level set method.

1.5 Methodology

The technical steps followed under this thesis, shown in Figure 1.5-1 are set in the sequence of accomplishment time. The parameters that are used for evaluation are AC (the correctness of detection), SP (the test's ability to correctly reject healthy patients without a condition), SE (the test's ability to correctly detect ill patients who do have the condition), IOU (intersection over union of prediction and ground truth), PPV (rate of positive prediction), and NPV (rate of negative prediction).

1.5.1 Design and Implementation Tools

Implementation of this study is using python backend tensorflow deep learning library on hardware of 4 GB GPU of GeForce 940MX on 8GB RAM core i5 hp laptop. The software's are python as main programming language and MATLAB 2017 is also used. The following are lists of steps with related implementation tools:

- Literature Review: read subject related articles, research papers, books and other materials that help to conduct the proposed thesis research successfully.
- Data set Selection: select publicly available dataset by reasoning out why selected and prepare to feed for CDNN.
- Preprocess Images: The second step is preprocessing the image for better resolution by using image processing mechanism such as enhancement which is suitable for this specified problem on selected dataset and prepare it for feeding to the network. MATLAB is used for preprocessing images.
- Train Network: train CDNN using preprocessed data. Python has been used as a main programming language and tensorflow deep learning framework for implementation.
- Integrate CDNN and level set: integration of the two algorithms to improve segmentation performance was has been done on python.

- Finally testing of each parameter on test data set and report the result.

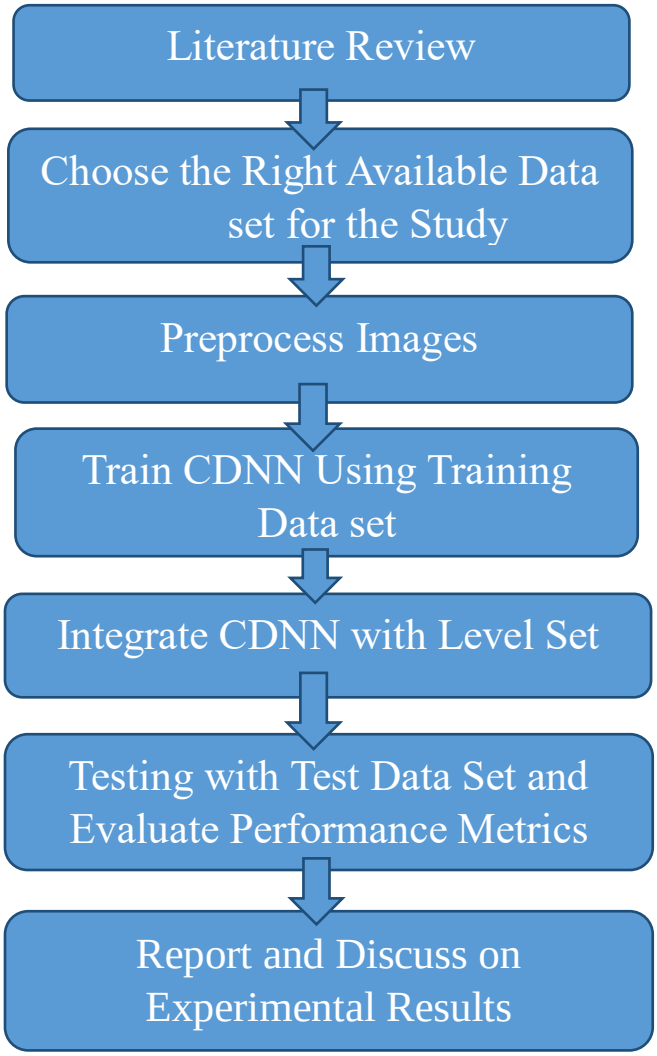


Figure 1.5-1 Conducted methodology to achieve the proposed study

1.6 Significance of Study

The incidence of skin cancer from skin lesion has been increasing through time and it became a reason for the death of many people globally. The usual clinical practice of skin lesion diagnosis is a visual inspection by the dermatologist and then taking a biopsy invasively. However, this diagnostic technique lacks visualization of morphological features, which are not discernible by examination with the naked eye. In addition, the high cost of examinations and the lack of specialists prevent many patients from receiving effective treatment. Because of these

challenges, developing an accurate image based automatic or computerized melanoma detection system becomes very important and a lot is being done.

Image segmentation is a critical issue in image engineering because missing the region of interest leads missing the subsequent analysis. There are different segmentation algorithms but their application is for a specific problem [16] because, there are different features for different problems of segmentation. Therefore, this study is a contribution for medical imaging challenge that uses CDNN and image boundary level set method for skin lesion segmentation.

In Ethiopian there is lack of dermatologists and no CAD is used for skin lesion diagnosis. They use illumination instruments like dermoscope for visualizing the lesion appearance. Therefore, this study provides CAD segmentation method for dermatologists in our country.

1.7 Thesis Organization

The rest of this thesis document is organized as follows: Chapter Two explains the background of study: skin lesion and how it is detected towards skin cancer, computer analysis diagnosis, skin segmentation, existing clinical diagnosis methods, CAD and dermoscope. Chapter Three discusses different automatic skin lesion mechanisms related works from image processing to machine learning based. Chapter Four presents the proposed skin lesion segmentation method using deep learning algorithm CDNN and image level set; this chapter explains the details of framework used in the design from preprocessing to result evaluation and validation. Chapter Five discusses the results on the evaluation metrics that are gained from the simulation result. Finally, Chapter Six concludes and gives recommendation.

Chapter Two

Skin Lesion and Computer Aided Diagnosis

2.1 Medical Background of Skin

Skin is the outer part of body for vertebrates, with a larger area of cover. It is like an interface for the body part with the environment, used for protection and sensations. The skin of our body makes up to one seventh of body weight and 20 feet or 1.5 to 2 square meter areas so that skin is the significant part of body that plays a great role for body organs and their metabolism [17]. This chapter explains about the skin structure, common types of skin lesion, skin cancer, clinical skin lesion diagnosis methods, and computer aided diagnosis, skin lesion segmentation in CAD, Dermoscope.

The skin anatomy has three division layers those are: epidermis, dermis and hypodermis or deeper sub cutaneous tissue. Figure 2.1-1 shows anatomy of skin layer with the contained tissue.

2.1.1 Epidermis

Epidermis is the outer layer of skin structure, which is the skin layer that acts the function of barrier with the environment. Epidermis layer does not have homogeneous thickness all over the body; its thickness is different for different body types. This layer of skin contains inner epidermis layers and tissues. The layers of epidermis from bottom to top are stratum basal, stratum spinosum and stratum granulosum, stratum corneum, stratum lucidum.

Stratum basal layer produce skin color melanin. The damage of this layer exposes to the deadliest form of skin cancer melanoma. Startum basal is the place of melanocyte cells that prevent the skin from being damaged by preventing from UV rays and tumors created by them. Stratum spinosum is the second inner layer and thickest layer containing keratinocyte cells that are responsible for producing a protein called keratin used for keeping the safety of skin, Langerhans cells that get access to attach external or foreign substance and also it regulates the immune system by synthesizing a protein called cytokines. The third inner layer of epidermis is stratum granulosum responsible for strength of skin by producing keratin protein. The fourth inner layer or top of the inner layers is stratum corneum contains dead keratinocytes; it prevents

the entrance of foreign things to the inner layers of skin. The fifth layer is stratum luciduma layer which is found on the palms of hand and feet of leg part of body skin. The most inner layer stratum spinosum is divided with the dermis layer by using a layer called basement membrane containing collagen and proteins [17][18].

Generally, Epidermis is a layer of skin which lesions are visible in different color those lesions can be infections allergies and other related damages. This layer is the origin of skin lesions that can be melanoma or non-melanoma skin cancers [1].

2.1.2 Dermis

Dermis is the second outer layer of skin layers, found in between epidermis and hypodermis and it is the thickest layer of skin layers as shown in Figure 2.1-1. Dermis contains highly connected tissues divided into two layers: pepillary region, which is the upper and contains loosely connected tissues; reticular layer the lower layer of dermis contains a strongly packed tissues. Dermis contains different structures such as hair follicle, sweet gland, lymph vessels and nerve endings [1].

The dermis layer has many responsibilities in the skin biology. Some of the roles epidermis layers' play are: producing sweat in controlling the body temperature, produce oil to protect bacteria growth over the skin, growing hair, distribute blood and protecting the inner body since it is composed of strongly connected tissues. Therefore, dermis is considered as a central or most important layer of skin anatomy. Most of the skin damages that come from this layer are [1][17][18].

2.1.3 Hypodermis

Hypodermis is the inner most layer or subcutaneous tissue of skin containing most of our body fat and connective tissues [17]. This inner most layer of skin is used for protection of insulation of the body from heat and cold, as a protective absorbent and used as for storage of energy [17][18].

From all cells of skin, melanocytes which are found in epidermis are responsible for skin color and protection. Melanocytes are the cause of skin cancer when they are not working properly. UV damages Melanocytes when there is a lack of DNA repair enzyme genes, genetic mutations

caused by heredity or environmental factor. If the melanocyte cells are not functioning as expected they may not produce melanin, there will be a different shape and color appearance on the normal skin which gradually grows so that incidence must be taken in to consideration towards detecting skin cancer [19].

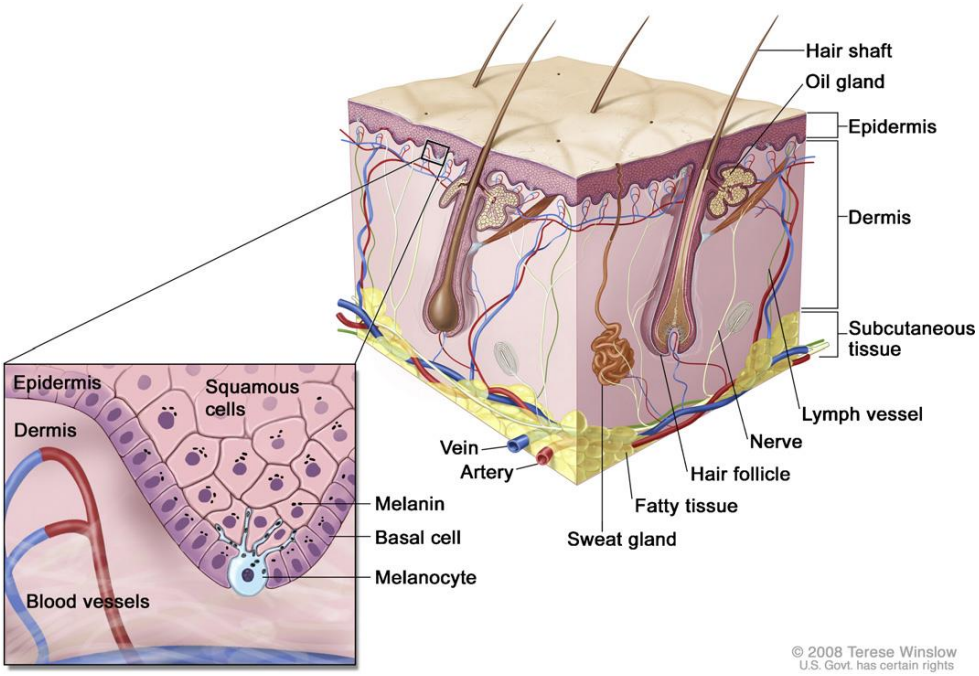


Figure 2.1-1Anatomy of skin showing the epidermis, dermis and hypodermis layers and their content [17]

2.2 Skin Lesion

Skin lesion is a rash suddenly happening on the skin called an eruption. Skin lesions have different structural appearance, which is a challenge for detection. Skin lesions are divided in two: primary lesions and secondary lesions. Primary lesions are the types of lesions that occur on normal skin while secondary lesions are lesions that are caused by eruption that happened before they exist [1].

The primary lesion contains no any pre-existed skin problem; these may be color change, papules, nodules and tumors. The possible color changes occur over the skin are black, deep brown, brown to black, violaceous to brown and bluish. Examples of primary skin lesion are

Erythema, purpura, pigmented macule, pustule, leukoderma and cyst. The secondary skin lesions may occur after primary lesions or other lesions. Atrophy is a secondary skin lesion characterized by skin thickness becoming thin; its cause is by aging when skin dries [1].

Other type of division for lesions is benign skin lesions and skin cancer. Benign skin lesions are non-cancerous lesions that may arise from melanocyte or non-melanocyte so that melanocytic lesions (malignant) can be cancerous or non-cancerous (benign). The most common benign non melanocytic skin lesions are: seborrhoeic keratosis caused by a benign pigmented tumor composed of epidermal keratinocyte and dermatofibroma caused by increase of melanin without melanocyte, increase of melanocytes in basement membrane of epidermis, melanin over production by UV radiation exposer and placement of a lot of melanocyte in dermis [1][15].

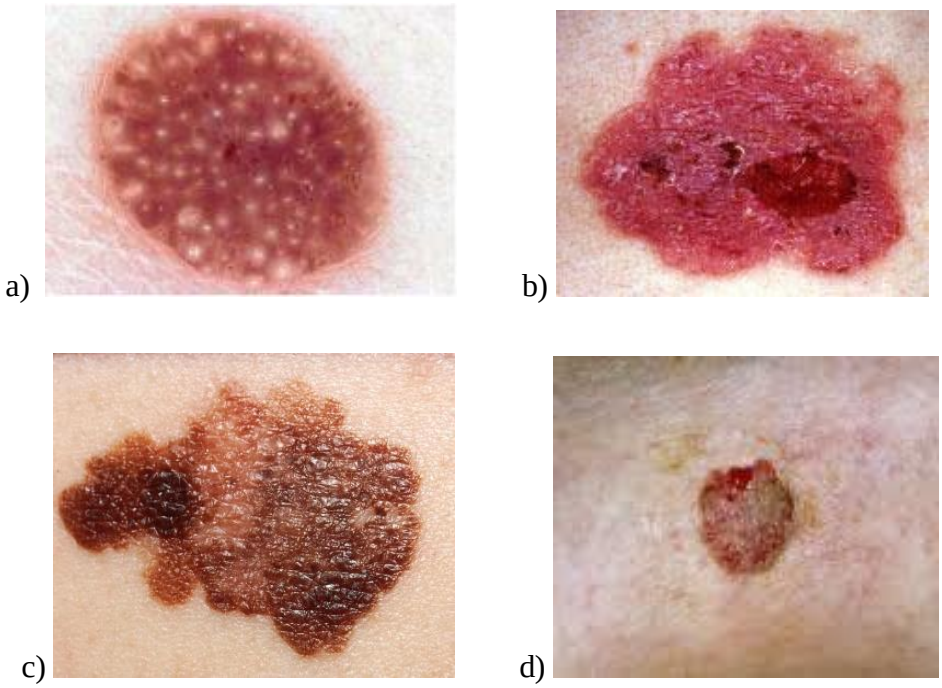


Figure 2.2-1 Samples of skin lesion images: a) Seborrhoeic Keratosis, b) BBC, c) Melanoma and d) SCC [15]

Skin Lesions can be cancerous; skin cancer is the most common cancer from all. It is caused by a continuous exposer to sun [2]. The same to the benign lesion skin cancer can originate from melanocyte or non-melanocyte. Squamous cell carcinoma (SCC); common skin cancer type that happened to black color skin, it is not too dangerous but spread to fast if not treated early and

Basal cell carcinoma (BCC); most common and least dangerous are the most non-melanocyte skin cancers named by the skin cell that develops the cancer. Malignant melanocytic skin cancer melanoma is the most dangerous and deadliest form of skin cancer, it is known by quickly growing to spread over the body part and it is the cause of many skin cancer deaths [2][15]. Figure 2.2-1 shown above shows sample images of lesions with different type.

If the general comparison of benign and malignant lesions characteristics is considered, the following are the notable differences between benign and malignant lesion. Benign; doesn't grow, no bleeding, no scab, most of them are similar lesion, have regular shape, uniform color and can present for many years. Malignant lesions; grow slowly or quickly, there is bleeding, scab, occur on a sun exposed area of body, there is no regular shape, variation of color over the lesion and it is a new happening lesion [15].

2.3 Clinical Diagnosis Methods of Skin Lesion

Dermatologists use specific but not explicit criteria for patient examination on skin lesion detection. Before dermoscopy, a non-invasive instrument used for visualization of pigmented skin lesions structure as a magnifying device is invested. Physicians used clinical images that are digital and the accuracy of such traditional method was about 60%. Use of clinical images was not different from naked eye visualization because the image represents what a dermatologist sees. The invention of dermoscope brings a great potential to improve the accuracy of diagnosis [20]. From the manual diagnosis methods, pattern analysis was the first and oldest clinical diagnosis method. ABCDE rule and 7 PCL are clinical diagnosis methods of skin lesion images [21].

ABCDE rule is a diagnosis method that helps dermatologists to examine the risk of skin lesion towards detecting if it is melanoma or not. There are certain criteria's used in ABCDE rule, and its name is by those criteria's. "A" stands for asymmetry, which is the overall shape of lesion. "B" stands for border irregularity: irregularity of border indicates getting into cancer. "C" stands for color of lesion: check the presence of six colors those are white, red, light brown, dark brown, dark blue and black. "D" stands for diameter: a lesion that is greater than 6mm diameter is likely to be melanoma, and "E" stands for evolution change of the lesion or mole of color, shape and size over time are the criteria's for ABCDE rule [15][21].

The second one is 7-PCL diagnosis method, used to detect melanoma using seven features those are: change in size of lesion, irregular pigmentation, irregular border, inflammation, diameter ≥ 7mm, crusting or bleeding, and sensory change. The dermatologist assess the lesion by giving each of the 7 criteria's equal weight of 1 and if the evaluation is greater than 3 the lesion is likely to be melanoma [15][21].

2.4 Computer Aided Diagnosis

CAD also called clinical diagnosis support (CDS) is a support tool to help medical doctors in analysis of different medical problems diagnosis and evaluation as a decision support. The main reason behind joining CAD for diagnosis is the clinical diagnosis methods are subjective and their accuracy is disappointing [22]. Therefore, the main goal of using CAD is accuracy improvement and it keeps the consistency of diagnosis. There are several automated systems that have been proposed to diagnosis skin lesion towards detection melanoma with inspiration of ABCDE rule and other clinical feature based diagnosis methods of melanoma [23].

The general framework of CAD systems for skin lesion diagnosis towards detecting skin cancer contains methods of finding the exact location of lesions and determining the prediction of the disease. The following are the main sequential steps followed in CAD for skin lesion diagnosis towards detecting skin cancer [22].

a) **Image Acquisition:** there are different imaging methods of skin, some of them include: total cutaneous photography, dermoscopy, CSLM, ultra sound, MRI, OCT and multi spectral imaging. Each of the acquisition methods have their advantage and dis advantage, even if dermoscopy is the fastest growing and highly performing instrument on skin imaging [20][23].
b) **Pre-Processing:** by any means the image is acquired there are artifacts to be removed and enhance the contrast for making the border detection easy to the system. This is an essential step for CAD because enhancing the quality of original image enhances the detection of lesion region [22].
c) **Image Segmentation:** segmentation is dividing an image into different parts, each part representing homogeneous regions that share the same features such as intensity, color, texture. Image segmentation is a very important task in imaging science, because the

segmentation result can affect all the subsequent steps of automatic image analysis. This step of CAD divides the lesion skin from normal skin [22][23].

d) **Feature Extraction and Selection:** feature extraction is reducing the dataset by taking certain parameters or features that mainly distinguish one input from the other on the segmented region. The feature extraction is performed by the measurements that are taken on the pixels of ROI [22]. Feature selection is selecting the features that are important, illuminate redundancy of extracted features and it is a crucial step of CAD analysis.

e) **Classification:** is the final phase of CAD responsible for making predictions or decisions about the extracted and selected feature information from the input. This phase is dependent on the previous phases performance [22][23].

In this thesis research, we do not intend in the technical aspects of CAD phases out of skin lesion segmentation. We are working on finding segmentation technique for skin lesion segmentation.

2.5 Skin Lesion Segmentation

Image segmentation is the main problem in medical imaging-based diagnosis, so that it is considered as a crucial step in CAD. In automated skin lesion diagnosis segmentation is also a very important determining step of in the analysis of lesions. In dermoscopy images skin lesion boundary detection is a difficult problem since the transition of normal skin to lesion is not easily distinguishable. Therefore, it has become an important research area and many algorithms and techniques are available [9][24][25]. Even if many researches are being done segmentation algorithms and techniques are not performing well equal for all problems [25].

2.6 Dermoscopy Images

The proposed segmentation of skin lesion uses images that are acquired by a special instrument Dermoscopy also known with different names; epiluminescense microscopy, dermatoscopy, and amplified surface microscopy. Dermoscopy is a non-invasive instrument used to diagnosis pigmentation of skin lesion. It is an imaging instrument that illuminates the surface reflection of skin with ability of visualizing deeper levels of skin. The equipment first come into consideration in 20^{th} century and now a day it is the most recommended device for different applications in

general dermatology. In addition, Dermoscope is in a high demand not only for dermatologists but also for plastic surgeons, general practitioners and other health professionals that are detecting melanoma at early stage. The device has a capability of capturing skin structures and patterns because it uses quality magnifying lens with a powerful lighting system [26].

Dermoscope can visualize distinctive features of skin lesion to analyze skin lesions pattern. Technically the optical instrument works using powerful lens, light source (LED) or halogen lamps, and observer as showed in the Figure 2.6-1. The lens or glass plate is made of silicon glass with a refractive index of 1.52 and it enhances trans-illumination of the lesion. LED are better to be used in the illumination system because they are designed with a capability of emitting lights of different colors which is helpful for clear visualization of skin lesion appearance and around ¾ of less power consumption than the halogen lamps. For effective penetration of skin layers up to deep dermis, the skin must be pigmented with Mineral(linkage oil) such as olive oil, water, glycerin, liquid paraffin [26][27].

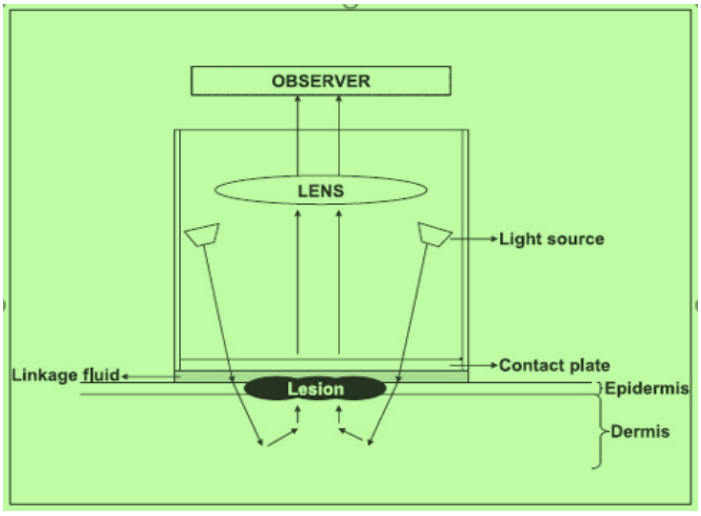


Figure 2.6-1 Optics of dermoscope the refracted light trans illuminates the lesion while passing through it and is perceived as a distinct pattern [27].

There are different types of dermatoscope [27], which can be categorized as polarized, non-polarized with contact and non-contact technique to skin during diagnosis and with image capturing and non-capturing capability. The polarized one is used for visualizing the deeper structure of skin lesions towards detection melanoma while the non-polarized is for visualizing the existing structure of lesions on skin that are not through. As it is shown in Figure 2.6-2,

dermoscopes can be used for manual detection of lesions or for CAD, camera phone or computer attached types are used for image acquisition.

Figure 2.6-2 Different types of dermoscope [27]

Epiluminscense microscopy improves the accuracy of skin lesion detection towards skin cancer by 5%-30% of the clinical visual inspection depending on the variety of skin lesion types. The sensitivity of skin lesion detection using dermoscope by expert dermatologists out-performs more than 20% of without using the non-invasive instrument [20]. Dermoscopy images are collected in different way. Tele dermoscopy is a way of collecting dermscope images from different clinical sites [28]. For the proposed method dermoscopy images that are available from ISIC (an international organization putting effort for improved melanoma diagnosis sponsored

by ISDIS) 2017 archive are used. ISIC archive [5] Contains the largest publicly available collection of quality controlled dermoscopic images of skin lesion that are collected from different leading clinical centers internationally and acquired from variety of devices with in each center. There are different dataset publicly available as it is indicated this archive contains images that are from dermoscope and collection is approved by expert skin cancer physicians, since the instrument provides improved diagnosis accuracy and we are working for accuracy improvement algorithm.

Chapter Three

Related Works

3.1 Introduction

Manual skin lesion detection for segmentation is quite challenging in medical image diagnosis because skin lesions are different in shape, color and texture. When lesion segmentation is done manually it is time consuming, no quantitative evaluation and the result is subjective. Therefore, automatic skin lesion segmentation overcomes the basic problem of manual medical image diagnosis. Advanced technology such as image processing and machine learning based detection mechanism bring not only early detection but also the reduction of ineffective clinical procedures and materials. Automatic system increases the accuracy and efficiency of dermatologists but there is still a limit of performance improvement, because lesions are variable in shape, size and texture. Also some lesions have irregular and blurred appearance and there is high degree of similarity between different types of skin lesion [29].

In additions, there are also difficulties on skin lesion detection while there is a smooth transition of normal skin to lesion, hair cover over skin and disturbance of specular reflection affects the segmentation result that in turn affects the subsequent stages of diagnosis of melanoma. So that the challenge is an active research area now a days [30].

In every medical diagnosis, use of advanced and sophisticated computer aided system is not under question because it definitely helps early diagnosis of clinicians. In addition, recent studies show that there is shortage of dermatologists for growing of automatic computer aided diagnosis [31][10][12]. A lot of computer aided skin lesion diagnosis methods are being done. The following section explains recent and most known skin lesion segmentation methods.

3.2 Level Set Methods

Level set is the classical method in computer vision. This method works based on differential operators which are basic tools in computer vision and graphics. The technique works by contour evolution which is done using PDEs. The image boundary or curve of image moves in different topology of the image pixel intensity distribution. Level set method is familiar in handling the

change in topology using the level set calculus. The image is considered as a continuous function sampled on a grid [32]. In PDEs level Set method handles topological change of surface pixel intensity using segmentation function ($\varphi(x)$) expressed in Equation 2.1 and 2.2.

$$\frac{\partial \varphi(X)}{\partial t} = -\alpha A(X) \cdot \nabla \varphi(X) - \beta P(X)|\nabla \varphi(X)| + \gamma k(X|\nabla \varphi(X)|) \quad 2.1$$

$$\partial \varphi(X, t = 0) = \emptyset o(X) \quad 2.2$$

where: A(X)=vector field image, P(X)=gradient magnitude image $\propto, \beta, \delta$ are advection, propagation and curvature term coefficients respectively and k(X) is mean curvature of level set at point X defined by:

$$k(X) = \text{div}\left(\frac{\nabla \varphi(X)}{|\nabla \varphi(X)|}\right) \quad 2.3$$

Hyper Parameters are $\alpha, \beta, \gamma \; and \; n$ (number of iterations to run level set). Boundary level set method works for cascading boundary curve between to the edges of interest region. If the PDEs value at a point is zero then the point will be set to the boundary and the negative, positive value is inside the region and outside the region respectively.

Level set is one of the best methods for medical image segmentation, since it has the ability to handle topological changes. It is gradient based segmentation [33], shows better performance of analysis of head and neck lesion than the other known image processing methods by using Equation 2.1.

Bladder segmentation detecting towards bladder cancer by using deep learning convolutional networks and level set image processing technique [34] after having the volume of interest. First images are segmented using DL-CNN classification result is set as initial segmentation and next using level set segmentation. The segmentation result of DL-CNN, Class with LCR method and DL-CNN with level set is compared for measuring the performance of their proposed method. The first doesn't segment low contrast parts as well the Class with LCR method. The proposed method out performs better by enclosing more of the lesion part than the rest. But for few test cases the method performs below the average performance.

Level set segmentation methods [5][32] work on level set mechanism by applying partial differential equation on the image content as described above. Most of the results said that the

level set method is best in handling the edge of image but they didn't show quantitative result evaluation.

Macroscopic pigmented skin lesion segmentation and its influence on lesion classification and diagnosis [35], proposes a segmentation algorithm that process multichannel MPSL(macroscopic pigmented skin lesion) images based on threshold and level set. In addition, the authors try to compare the effectiveness of different segmentation methods, for all methods shading attenuation preprocessing technique is used and the result shows that ICA (Independent Component Analysis) based active contour method that works with color information have smallest error segmentation than the threshold mechanism on monochromatic and multichannel images.

Studies show that level set method is resulting better performance in tracking changes in shape and appearance. The level set surface is defined based on mathematical morphology, by successive application of morphological operators to reduce the computation cost in PDEs contour algorithm evolution [12]. For the algorithm in [12], the standing point is expressing the morphological operators using PDEs i.e. curvature morphological operator. This work may have advantage in taking consideration the computation cost but qualitatively the results may not be efficient as numerical algorithm-based level set methods.

3.3 Artificial Neural Network Based Methods

ANN is a machine learning technique modeled by a number of connected neurons which are the basic processing unit of neural network. Neural network model consists of different layer neurons those are input neurons on input layer, hidden neurons on hidden layer and output neurons on output layer. ANN is used in supervised training machine learning technique. There are different types of ANN, some of the well-known are; multilayer perceptron and back propagation learning algorithm (MLP), Hopfield neural networks (HNN) and self-organizing maps (SOM) neural network are some of the algorithms.

Image segmentation using ANN is used to classify each pixel in the image according to some criteria (e.g. pixel intensity value), so that all pixels belonging to a region are given the same class [36]. One of the recent work [36] proposes a feed forward multilayer (3 layers: input, output and hidden layers) network which is used to segment and classify dermoscopic skin lesion images. Their result shows that 86.66% accuracy is achieved.

In [10], neural network is used for edge detection of skin lesion images and also iterative segmentation method is used and compared to ANN method. The iterative segmentation outperforms ANN edge detection; it is not capable of recognizing noisy lesion variation of edge. To improve the noisy variation detection of detected edge they have used Gaussian curve filter, whatever the final result of segmentation depends on the network detected edge.

Color and contrast enhancement for improved skin lesion segmentation [37], great emphasis is given to the preprocessing step for automatic border detection, since it is valuable for diagnosis and challenging step in segmentation. Automatic color equalization is used for pre-preprocessing, after detecting edges lesion segmentation is applied using two different techniques. The first one is iterative segmentation by thresholding and the second one cooperative neural network segmentation. Based on the results color enhancement with iterative segmentation performs better on the red, blue and green channels with an average error of 0.51, 0.22 and 0.15 respectively. The dataset used for training and evaluation is too small for training the network to detection of varieties.

ANN segmentation is suitable approach for segmentation when we don't have clear idea of segmentation criteria [38][36][10][39], even if it has its own limitation of no deep learning i.e. depending on the learning data size the network may face the problem of over fitting. One of ANN segmentation [10], is the best example to show how using neural networks for vision problems is not effective. Because of ANN limitations, deep learning CNN which is capable of understanding images like human eye comes to the research industry.

3.4 Fuzzy Logic-Based Methods

The concept of fuzzy system is introduced by Lotfi Zadeh in 1965 at university of California Berkeley and it is implemented in many application areas since its invention. The algorithm for Fuzzy system is based on the mathematical principle which states, if there is a fuzzy set which contains members the member of the set is considered as a set member based on degree of membership or degree of truth [40]. Fuzzy means works like a human brain similarly to neural network and expert systems, because it represents a general way of cognitive. In image segmentation fuzziness is considered by taking the degree of brightness or other feature relative to some set of the brightness level or feature level. Images used in pixel fuzzy logic techniques in

medical imaging for color analysis and segmentation applications. In fuzzy clustering image segmentation algorithms work based on statistical method. There are different statistic measures for classifying an item into its group or class [41]. Some of the notable pixel criteria (feature) measures in image segmentation are; distance, color and intensity. The following are some of the recent literatures on skin lesion using fuzzy logic method.

In [24], fuzzy logics are used for detecting blue areas of skin lesion for feature extractions of blue skin lesions. Representation of fuzzy set is using color parameter blue level of a pixel so that the decision of the blueness is taken under consideration for a member pixel to be lesion. The output of segmentation is used as an input for SVM based classification of lesions. The accuracy of diagnosis result is around 80%. Even if the result seems good the machine is trained only with the blue region features, the machine may face over fitting problem since the type of testing data is not clearly stated according to the training set.

Type-2 fuzzy logic technique [42], is a threshold value based fuzzy logic technique for dermoscopic skin lesion image segmentation. It is an improvement of conventional fuzzy logic technique, by determining the fuzziness by sliding fuzzy membership function along the histogram while determining the lower and upper values of membership at each position of the grey scale image. It is mentioned that the proposed technique is much better than adaptive threshold and Otsu threshold technique but there is no any quantitative evaluation.

Blotch detection in segmentation of pigmented skins using fuzzy co-clustering and texture segmentation [43], uses color and texture features as a clustering parameter. The color is set in the fuzzy set with the intensity values of all RGB channels and the feature is set for a member set with exponential entropy function. In addition to those parameters they also included the regularization parameter that every machine learning algorithm should take in to consideration while there is limited dataset. Their result is 4.85% of segmentation error.

One of the recent study on fuzzy related technique is fuzzy c-means, [41] discusses a survey of different fuzzy clustering methods for image segmentation. The comparison is made on MRI image data from those, [44] is the most recent one of the recent from fuzzy clustering method for medical image segmentation with robust result so that they conclude that using spatial information overcomes the problem of noise sensitiveness in image segmentation.

Fuzzy clustering means algorithm for brain MRI image [42], also discusses enhanced segmentation by applying a local filtering for each voxel then divide the pixel intensity values in to three regions; background, white matter and grey matter and finally by applying the proposed objective function for final segmentation. The function is time costly since there are consecutive derivatives and other operations on the Lagrange multiplication of the objective function.

Generally fuzzy logic technique covers most of the machine learning algorithms before a decade, and it has its own limitation. Firstly there may be a gap in the real-world implementation when small datasets are considered because definitely the algorithm encounters a problem of categorizing items that are not levels, secondly there no deep learning of features.

3.5 Support Vector Machine-Based Methods

SVM is one of supervised machine learning algorithm which is used for classification and regression. Their purpose is to identify in which category a data item or group of data is. SVM works by the principle of finding a hyper plane that divides the elements in to their category, and train the classifier with the samples the hyper plane categorizes [45]. SVM is one of the suitable technique for image segmentation [46], especially in medical image segmentation [47][13][48].

T.Ziang et.al [47] discusses the recent SVM and modified SVM methods on image segmentation and its comparison with other machine learning algorithms like clustering and ANN. They showed that how much SVM is preferable for accuracy improvement when it is used with modification. To the best of my knowledge literatures on melanoma detection, SVMs are not implemented for segmentation stage by them self. In most of the literatures they are used for disease characterization of classification since SVM are used for general classification.

One of the recent study in CAD of micro malignant melanoma lesion [13], SVM is used for classification of lesions as benign or malignant. [13] implements all the stages of CAD for skin lesion detection towards melanoma, segmentation is using region growing and SVM is trained with 200 images. Their result report shows that SVM under this study achieved 90% of sensitivity and 96% specificity but there is a very clear reason not to accept this result as a performance of SVM because it is not clearly stated how the evaluation testing dataset is acquired. Another one is, before proceeding to the classification stage of CAD accuracy evaluation of segmentation result should be considered because, as this paper and other related

bio medical imaging studies show that segmentation is the crucial step which determines the classification performance. These [49][50][51] are also some of notable skin lesion classification techniques using SVM.

Some other of the related studies show that they are used as a support of decision making, support of clinical decision on melanoma detection using SVM [48][50]. It is used to classify skin lesion into two classes (malignant melanoma and dysplastic naevus). But the machine may lead to a wrong decision since it is trained with a limited data samples, that means only two melanoma classes while there are a millions of melanoma cases melanoma and non-melanoma cases [2].

SVM show good performance improvement while they are used with modification. From all machine learning approaches the performance of SVM and ANN is comparable to each other and better than the rest well known ones on classifying pigmented skin lesion classification [13].

There are general limitations of using machine learning algorithms, e.g. they may result inaccurate predictions and it is not able to determine if the prediction is accurate or not and it is one of the motivations for the rise of deep learning algorithms.

3.6 Deep Learning Methods

Deep learning technique comes under the study after the concept of ANN. Hinton [52] proposed the birth of deep learning in 2006. Their idea is having a layered architecture that can train layer by layer by reducing the input data size which enables to extract more data features of the input. From its invention up to now deep learning technique is leading the competition of problem solving in different applications [6][53][54]. Some of them are speech recognition, natural Language processing, DNA prediction in gene expression, computer vision.

There are different types of deep learning architectures from those RCN, deep belief machine, auto encoders and CNN are some [55]. Even if those are notable architectures of deep learning they are so many variations of architecture using those as a base line.

CNN is a deep learning architecture inspired by the animal visual cortex in response to light detection [6][55]. CNN is successful than the other ones in processing two-dimensional data such as image and video because: processing of input in the layer replaces the matrix multiplication

with convolution, inputs to the network are feed directly without extracting features for learning function, no need of more preprocessing the input data and reduction in computation cost. So that CNNs are being used in many image analysis applications such as hand writing recognition, face detection, image classification and biomedical imaging.

CNN is a deep learning network that has a great role in computer vision application. Its working principle is by applying a function "f" on an input data "I" to get output vector "o". between the input and output there are computational blocks called layers, basically there are three layers [56]. Convolutional layer: apply convolution operation using kernels mainly to understand specific patterns, pooling layer: map sub region into sub sampling and ReLU: to increase non-linearity of CNN (since the basic operation of CNN is convolving matrix operation through with convolution kernel which is nonlinear mathematical operation).

There are different types of CNN models [57]. The building block of each of them is by forming a different framework or approach of layers arrangement (convolutional, pooling, ReLU and FC layer which is used for classification of processed data into its predictable category).

There are recent and well known different architectures of CNN that are used as a base line. The first one is CifarNet [58][59] used for object detection into 10 class category. CifarNet network contains three types of layer: 3 convolutional layer, 3 pooling layer and FC layer trained using Cifar10 dataset. Secondly AlexNet [60] architecture which is firstly implemented on ImageNet Large Scale Visual Recognition Challenge (ILSVRC) and shows outperformance as compared to non-deep learning-based image recognition methods. The layers of AlexNet are 5 convolutional layers with 3 pooling layer and 3 consecutively connected FC layers which imply there is a classification over classification 3 times. The third one is GoogleNet [61] model which brings the concept of inception layer, using the combination of six convolution layers with different kernel size plus one pooling layer as a single layer. This model is very deep model containing 2 convolutional layers with two pooling layer and nine inception layers totally. GoogleNet is the state of art for ILSVRC with 5.5% classification error.

Deep CNNs are the state of art of medical imaging challenge [63][64][62][8][6][55], this shows that CNN is being used with high performance for medical image segmentation. When CNNs are used in image segmentation each pixel is labeled to a class based on the ground truth. The network calculates the error of the network from the ground truth and predicted result so that the

network will be trained towards minimizing the loss (error of prediction). Convolutional networks are used to predict the class of region of image, however in medical imaging segmentation they are used to classify the class of each pixel [65][62].

Semi-automated skin lesion segmentation proposed by L. Bi et al [63][66], uses fully connected convolutional networks with multi scale integration to overcome the problem of low contrast image segmentation that are done only using convolution neural networks. The results are evaluated using most common matrices dice similarity coefficient, jaccard index, SP, SE, and AC. The values are 90.24%, 83.36%, 91.82%, 95.23%, 95.16% respectively. Best of all the authors also calculate the receiver operator characteristic (ROC) curve and precision recall (PR) curve. This work doesn't use any regulation mechanism to overcome over fitting problem according the dataset size.

Skin lesion analysis using deep learning network [67], uses a deep learning mechanism that built from fully convolution residual network (Lesion Index Network) and simultaneously performs skin lesion segmentation and classification. The authors didn't clearly specify what technique they have used for segmentation, greater emphasis is given to the classification and feature extraction.

One of the recent work using deep learning method [68], deep learning ensembles for melanoma recognition in Dermoscopy images is done for both segmentation and feature extraction using U-Net architecture of convolutional networks. The algorithm contains dropout which is not considered in most literatures and other well-defined descriptions of the system made the results acceptable. The authors say their evaluation on accuracy and other metrics are competitive performance to the ISIC 2016 state of art.

Skin lesion segmentation in clinical images using deep learning [69] uses CNN deep learning, preprocessing and post processing mechanism for accurate extraction of lesion. The images are divided in to patches and each patch is defined by local texture and global structure. Patches feed to the network for training. To smooth the images a guided filter (edge preserving smoothing operator) is used as preprocessing and for post processing each point is labeled by the probability of membership. Dataset used for training is camera taken image and it is too small for the network to learn the feature. The evaluation metrics are sensitivity, specificity and accuracy with values of 95.0, 98.9 and 98.5 respectively. There is no guarantee if this works well with any

problems because the network is trained with insufficient data set and there is no consideration of over fitting problem.

A novel multi task deep learning model for skin lesion segmentation and classification [70], the algorithm contains simple preprocessing mechanisms with DCNN. The main difference of this literature from others is detected features are shared among other components, e.g. disease classification. The evaluation metrics result is jaccard index of 0.724.

L.Yu.et.al. proposes a very deep fully convolutional residual network for skin lesion segmentation [65]. The framework for this network is convolution layers with down sampling, activation layers de-convolution layers with sampling and fully connected layer for classifying the pixel class. FCRN is different from residual network because it predicts pixel wise. Each pixel is predicted as lesion and non-lesion part of the skin. Their result shows that having a very deep network (increasing the number of layers) increases the number of features or parameters to be learned. The performance evaluation metrics on AC, DI, JA, SE and SP is by increasing the network depth, and the evaluation measurement is 0.949, 0.897, 0.829, 0.911 and 0.957 respectively at 50 layers' depth. There is improvement until the network depth goes up to 50 layers but if the depth goes as deep as 101 layers the result is the worst-case performance since the number of parameters to be learned is twice of 50 layers.

In [62], one of the deep convolutional network framework U-NET architecture is used for segmentation of neural structures. The architecture contains layers that consist of convolution, de-convolution and max pooling followed by fully connected layer. It is the combination of de-convolutional layer and FCN. The network is trained with too small images; to overcome this they have used excessive data augmentation to train the network with false features. This architecture achieved average IOU of 77.5%.

Mirsha and Daescu in deep learning for skin lesion segmentation [64], contribute a general CNN architecture designed with baseline of U-NET architecture with cross validation and parameter fine-tuning. Dice coefficient is used as a loss function for training the network. To train the network iterations of 250 and 100 batch size hyper parameters are used. The training iteration is small according to the device performance which they implement on so that it's not stated the network saturated at 250 epochs. The metrics evaluation shows that CNN method outperforms Otsu segmentation and other submissions of 2017 ISBI for skin lesion segmentation. However,

this paper states that training the network with dice coefficient as a loss function is better than others without any justification or reference.

3.7 Deep Learning Integrated Methods

Hybrid deep learning technique [12], Proposes composition of recurrent and convolutional neural networks. To overcome the problem of coarse segmentation mask recurrent neural networks are used to model contextual relationship between features that are extracted by convolution neural networks. To support joint training of recurrent and convolution neural networks the authors used predictions in a strided convolution by using the product of flattened input and sparse matrix [3]. The results of evaluation outperform the result gained on convolutional neural networks, but the authors didn't consider over fitting problem.

FCNs with level set approach [13], addresses combining best performing segmentation algorithm since the problem of traditional level set method is good contour initialization. The network is pre-trained. The initial segmentation is generated using the trained FCNs and the result which is initialization of region division is refined using level set module. The authors said the FCN level set method results better dice score than FCN and level set method.

3.8 Other Skin Lesion Segmentation Methods

K nearest neighbor is a type of machine learning algorithm but is not as comparable as SVM and ANN [13]. There are other skin lesion segmentation methods with notable result. One of the recent publications robust salient based skin lesion segmentation [71], is a framework designed based on identifying the saliency features of lesion image. K nearest neighbor is unsupervised and it doesn't require training. It works by detecting the background of lesion using clustering (k means to group segments belonging to a cluster); next the probability of a segment to a class is measured using the sparse representation model. From the error contextual based error propagation is used to smooth the errors. The evaluation is on PH2 and ISIC dataset using evaluation metrics of dice coefficient. The result measurement shows that dice coefficient of 93.12% on general case and 82.75% on extreme cases. Even if the results are good enough the algorithm is deals with many computations in the process, which means many mathematical computations are applied on a single pixel.

Image segmentation for cancer feature extraction [72], uses one of unsupervised segmentation technique k means clustering for color based segmentation. The authors say that their method is better than threshold and gradient vector field segmentation but there is no any quantitative measure for evaluating results. Comparison between other techniques is not based on parameterized measure.

A new architecture for optimization of IOU in segmentation loss function [73] also proposed. Softmax function is used to determine the probability of pixel's being in one class (background or lesion) and overall accuracy measure. Instead of softmax loss IOU loss expressed in Equation 3.3 is used to training the network.

$$IoU = \frac{TP}{FP + TP + FN} \qquad 3.3$$

But the output of the proposed network is probability of each pixels being the part of one class so that that they can't calculate IOU. They proposed to compute IOU using Equation 3.4.

$$IOU = \frac{\mathrm{I(X)}}{\mathrm{U(X)}} \qquad 3.4$$

where I(X) =$\sum Xv * Yv$ and U(x) = $\sum(Xv + Yv - Xv * Yv)$

V set of all pixels X is the output of the network (pixel probabilities) and Y the ground truth assignment for the set V.

$$IOU\ loss = 1 - IOU \qquad 3.5$$

From Equation 3.5, Argmin (W) IOU loss = 1-IOU where W is the set of parameters of deep learning. This work result that IOU loss leads better performance compared to the softmax loss, but it is computationally costly.

3.9 Summary

Generally, this chapter explained some of the very recent research on medical image segmentation. The reviewed literature is from different medical segmentation studies but most of them are on skin lesion segmentation towards melanoma detection. Addressing all the related works is not as such easy but the notable literatures are presented in this chapter.

As it is the main aim of this work most of presented literatures are from support of automatic skin lesion diagnosis.

Chapter Four

The Proposed Methods

This Chapter explains, the proposed skin lesion segmentation technique using deep learning algorithm and level set method. The proposed framework for segmentation follows sequential steps as shown in Figure 4.1-1. The Chapter is organized to explain flow chart of the proposed method, image preprocessing, selection of ROI using CDNN deep leaning method, image topology level set with its mathematical standing point for application and evaluation metrics of the performance of result.

4.1 Proposed Method: Skin Lesion Segmentation Using Deep Learning Algorithm and Level Set Method

4.1.1 CDNN Level Set Segmentation Method

CDNN level set is a proposed technique for skin lesion segmentation. Deep learning segmentation uses deep learned feature in the context of global region segmentation method i.e. it studies what is in image at the pixel level relative to the surrounding region. The segmentation performance is becoming based on finding deep learned features. Especially in medical imaging segmentation deep learning is becoming the most popular one due to its ability to predict each pixels of the input which have a great impact on the performance improvement of CAD systems. As it is sated in the problem statement of Chapter One, there is color variability due to different illumination condition. Human brain can detect such color variability but not computer systems. CAD must be supported with better image visualization algorithm [28][74][75].

Integrating CDNN with level set method improves the detection of lesion regions or detection of the ROI for dermatoscope skin lesion images. In addition, deep neural networks have the ability to extract deep feature patterns. Therefore, using CDNN for initial contour segmentation is done using intelligent way rather than setting manually which is subjective. CDNN and level set achieved the state of art of semantic segmentation and edge detection respectively [76][77].

Level set is used in many medical and non-medical problems for segmentation [25]. But the limitation of using level set for segmentation is not effective for variation of real world detection.

The performance of level set is dependent on the initial segmentation or initial contour and the number of iterations to cascade the initial contour towards the exact edge. Generally, the reason behind these two methods is exact detection of ROI results better segmentation of lesion borders.

To the best of our knowledge “CDNN Level set segmentation” is the first study on the proposed problem which is skin lesion segmentation detection towards melanoma that uses CDNN and level set in combination. Figure 4.1-1 shows the flow chart for the proposed method.

Overview of the proposed method flow of actions is: initially reading the image, apply image preprocessing; resize (if it is necessary) and median filter. Next the skin lesion detection using two class (back ground and forground) trained CDNN, after detection the initial contour is set to be the ROI boundary. If there is a detected feature as lesion the algorithm keeps moving for level set segmentation for a specified parameters over “n” iterarions and display the final segmented image, if no region is detected as a skin lesion the flow ends.

While performing level set at a time “t” after getting the initial contour, the level set function follows curve evolution equation given by Equation 4.10. The evolution at a time “t” is dependent on contour at time “t-1” until the level set function value is zero.

In the following sub sections, explanations of each steps of the proposed segmentation technique are organized sequentially and implementation configurations are discussed. The integration of the two methods shows by implementation it is possible to improve the performance of level set method and CDNN method.

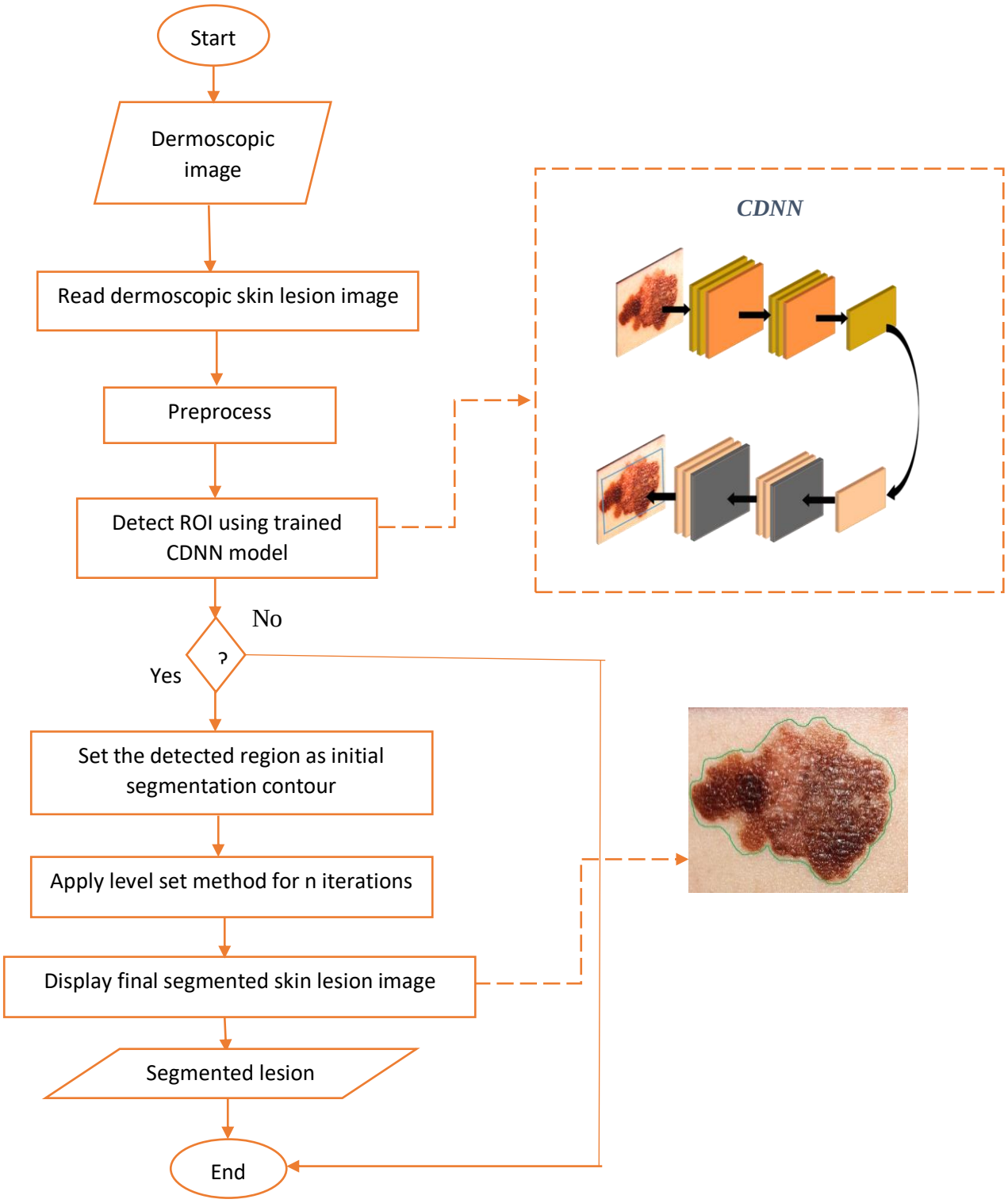


Figure 4.1-1 Flow chart for the proposed method

4.2 Preprocessing

In CAD systems preprocessing images is a valuable step since it improves the quality of the original images by removing unrelated parts of the image. Preprocessing facilitates the visibility of regions to be detected such as border detection. There are different preprocessing mechanisms such as color space transformation, contrast enhancement, approximate lesion localization and artifact removal. While automatic object detection and localization color image preprocessing is done, it provides a good quality by working on the original image visualization type [76].

Working with skin lesion images faces the problem of smooth intensity variation over the original homogeneous region that means intensity inhomogeneity due to appearance of different hair colors on the skin, noise while capturing image and other unwanted artifacts. Intensity inhomogeneity is one factor for automatic image processing applications (one of its application is image segmentation). Intensity inhomogeneity affects the accuracy of border detection and consumes computational cost. Therefore, intensity inhomogeneity correction to the skin lesion image must be applied as preprocess for region detection after resizing the images into the same size. There are different intensity correction methods for different problems [78].

For this thesis color image preprocessing is selected for preserving the original image appearance. Currently color images are widely used in many image processing applications such as: computer vision, object detection, remote sensing and medical imaging. In comparison to the grey scale images color images provide detailed information than one band images since there are more edges and other fine details of the image content that are greatly helpful for pattern recognition. In addition, the capacity of computers to process color images is increasing rapidly [74].

The problem of skin lesion images intensity is around the edge (boundary of lesions) which is on the transition between healthy skin and lesion skin as shown in Figure 4.2-1. For this thesis vector median filter [76] is used to facilitate the segmentation border detection. As it is shown in Figure 4.2-2 the steps of preprocessing for the proposed method are the following:

1. **Resizing Images in to 127x127 Pixels**: ISIC archive contains dermoscopic images of different size width in ranging between 540and 4499 pixels and length 772 to 6748 pixels. The basic reason for resizing images is, the data set images must be similar size

that is preferable for the proposed deep learning and the pixel's size is too large which consumes too much computational cost. Therefore, the images are resized to 127x127 pixels.

2. **Vector Median Filter Resized Image:**

Filtering gives the estimate of missing pixels by noise. Filtering methods are the most widely used image inhomogeneity correction (smoothing) mechanisms. Filtering methods consider low frequency artifacts as inhomogeneity. There are different types of filtering mechanisms that can be linear or nonlinear. Linear filters are the one that are applicable for single band (one channel) images, whereas nonlinear filters are used to preprocess more than one channel images. Nonlinear filters are preferable than linear filters since the human visual system is nonlinear by nature [79].

For the proposed method vector filtering specifically vector median filter which is a nonlinear filter used for processing RGB Dermosopic images. Vector median filter is used for preprocessing the input dataset one of edge preserving nonlinear filter which out performs other edge preserving nonlinear filter methods [80]. Vector filtering technique inputs a set of pixels of the channels while preserving the relation between each channels point to make sure the applied transformation is not bringing deformation. Mathematically vector median filter works as follows [79]:

a. For a given set of vectors $X_1, X_2 \dots X_N$ each of them are vectors in the form of X_i=**{**X_{i1}, X_{i2}, X_{i3}} for RGB images inside a filtering window W containing N pixels.

   For each vector element calculate the sum of distances to all vectors inside W: S_i using Equation 4.1

$$S_i = \sum_{j=1}^{N} ||xi - xj||\gamma \qquad 4.1$$

   where, γ is 1 or 2 according to the choice of type of distance to be evaluated for each pixel: 1 for city block distance and 2 for Euclidean distance.

b. Find X_{min} parameter thatgives S_{min} from S_i.

c. Represent X_{vmf}= S_{min}, X_{min}

The output of filter is pixel values inside the window replaced by X_{vmf} for the case of proposed system 3x3 window is used.

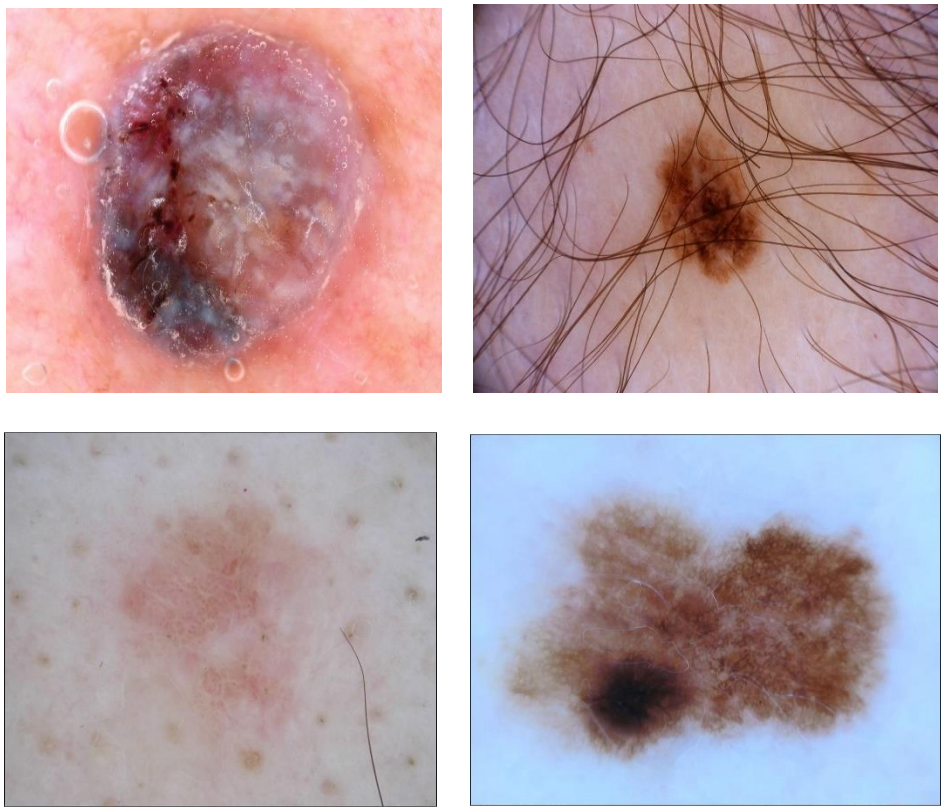


Figure 4.2-1 Intensity inhomogeneous dermoscopic images from ISIC 2017 archive

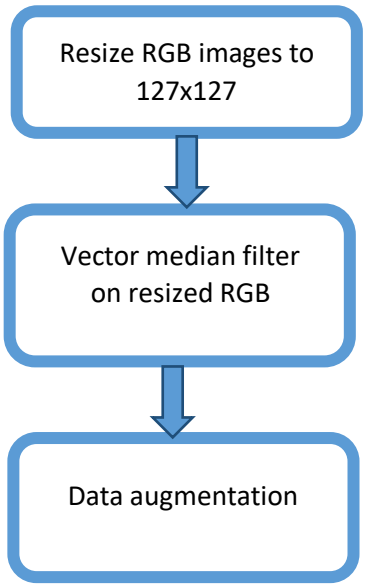


Figure 4.2-2 Steps of preprocessing for the proposed method

3. **Data augmentation:** data augmentation is one of regularization method to prevent machine learning models from over fitting. Regularization is the best way to enable machine learning model more general in Recognizing [81]. In this thesis data augmentation is applied after applying Vector median filter to each images of the dataset. 4000 images (2000 input and 2000 mask) are augmented by rotating 90 degrees left so that the dataset for machine learning model is better than training with only 2000 images. A total of 4000 images are used for training.

4.3 Detection of ROI Using Deep Learning Algorithm: CDNN

ROI detection is identifying the selected regions of the input image that may contain the interest features inside the ROI boundary. The concept of ROI selection is used in many applications, one of them is medical imaging. Image segmentation is process of getting the information that is needed under study by identifying from non-ROI area. Studies show that working segmentation on ROI improves identification accuracy and processing speed of CAD systems [74].

Edge detection is finding exactly the area of interest. For finding the exact edges getting the right ROI is greatly helpful. For the proposed skin lesion detection and segmentation technique to select the ROI of skin lesion images deep leaning model, CDNN model is used. The following sub section explains the deep learning method and how it is used to generate the initial segmentation of skin lesions.

4.3.1 Deep Learning Method: CDNN

CDNN is one of the special architectures of CNN. Before explaining how CDNN is used in the proposed method this section explains how CNN works.

Even if there are different architectures the general overview of CNN contains convolution layer, pooling layer, and finally fully connected layer for classification of sub contents. The details of mathematical operation are as follows [57]. CNN is a network that uses a convolution mathematical operation instead of general matrix multiplication.

The first layer of CNN is convolution layer. Convolution is an operation on two functions of real valued argument. For a given input image, “I” and convolving kernel “K” size of “mxn”, the convolution operation is written as Equation 4.2. The aim of CNN is to learn very deep features

of the image via convolution operation, so that the model is capable of identifying the invariant features from raw image data.

$$S(i,j) = (I * K)(i,j) \sum_{m} \sum_{n} I(i-m, j-n) K(m,n) \qquad 4.2$$

The input of CNN is a tensor, for the proposed problem the model takes an input of 3 order tensor (an image with 3 channels R, G, B) and size of width and length of each tensor "W" and "H", then the model runs layer by layer until the output layer is reached. CNN is a sequence of layers suppose the l^{th} layer receives input image I ε $R^{HXWXDXN}$ where D is the number of channel or depth of image and N is the size of mini batch used for accelerating the training by dividing spatial input. For each element of "I" there is an index set {i,j,d,n} where 0≤i≤H, 0≤j≤W,0≤d≤D and 0<n≤N the output of l^{th} layer Y which is an input for $(l+1)^{th}$ layer is computed using Equation 4.3 [57].

$$Y_{i+1,j+1,d} = \sum_{i=0}^{W} \sum_{j=0}^{H} \sum_{d}^{D} f_{i,j,d,n} * X_{i(l)} + i,j(l) + j,d(l) \qquad 4.3$$

where "f" is the kernel function used for generating weights to be adjusted on the training and i, j, d of "l" are values of index in the "l^{th}" layer or input layer. When applying convolution in actual training there are other hyper parameters selected manually additional to kernel. The hyper parameters are: output depth (depth of feature maps), stride (how far a filtering curve "f" is moving) and padding (for controlling the spatial size of the input volume) [57].

The result of convolution operation "Y" Equation 4.3 is called a feature map which is convolution of kernel and input. Convolution is needed to amplify different edges of the input image depending on the type of bias used. If V feature maps are gained by convolving a single channel of input X detection or object recognition is by combining all the feature maps from different channel.

The second layer is pooling layer that comes after convolution layer for reducing the spatial size. The data representation is progressively reduced over the network and it helps to control over fitting. There is no parameter learning in this layer, it results a new size spatial input for the next convolution layer without changing the depth or feature maps and preserving the location of

edges. Max pooling and average pooling are the most common down sampling methods [82]. The output of pooling layer for a new filter size of HXD is in Equation 4.4, the output returns the maximum in the selected neighborhood for max pooling. In average pooling the distance from the central pixel is returned as Equation 4.5.

$$Y_{i,j,d} = \text{Max}\{X_{i,j,d}\} where\ 0 \leq i \leq H, 0 \leq j \leq W, d \quad 4.4$$

$$Y_{i,j,d} = \text{Average}\{X_{i,j,d}\}, 0 \leq i \leq H, 0 \leq j \leq W, d \quad 4.5$$

Adding pooling layers to the CNN architecture helps to minimize cost of computation by reducing the number of parameters to be learned for the next convolution layer. Pooling is also helpful for handling inputs of varying size.

The third layer is ReLU activation layer applied after the convolution layer. This layer is used to increase the non-linearity of CNN. Image contains semantic information which is nonlinear pixel inputs the output also must be highly nonlinear to map the input and output of CNN [57]. Mathematically it is expressed in Equation 4.6.

$$\emptyset(Y) = \text{Max}(0, Y(l) \quad 4.6$$

where Y(l) is output from layer "l"

The forth layer of CNN general architecture is fully connected layer used to compute the class of prediction. This layer is applied at the end of deep CNN model. The feature output matrix is converted into a vector form and elements fully connected to each other. For each elements of the input to the fully connected layer the category of its class is computed using *softmax* activation function of Equation 4.7. Image pixel values in the form of vector are input for the function whereas output is the probability distribution of an item over P probabilities. The *softmax* doesn't do prediction it tells how sure our prediction is in quantity.

$$\sigma(Y_i) = \frac{e^{Y_i}}{\sum_{j=1}^{p} e^{Y_j}} \quad 4.7$$

where p is the number of prediction class for Y input with index of "*I"*

The above explanation is the forward run of CNN architecture the backward run computes the prediction loss, which helps to adjust the weights for the right prediction e.g. cross entropy loss used for multi class classification problems [82]. Cross entropy Equation 4.8 compares the actual distribution and predicted distribution i.e. ground truth comparison to the predicted value.

$$H(Y, Y') = \sum_{i} Y_i \log\left(\frac{1}{Y'_i}\right) \qquad 4.8$$

Once after the architecture is created what comes in question is getting the best parameter values of weight and biases for training. The process of adjusting those parameters while training is called back propagation. Back propagation keeps changing the parameters until we get the least loss or cost while increasing the accuracy of prediction.

For the proposed method deep learning is trained pixel by pixel since the final goal is classifying a pixel as a foreground or background which is semantic segmentation (segmenting parts of a single image for different class while Most of deep learning CNN predicts an image into its class). Semantic segmentation is classifying the pixel's class; this type of segmentation uses pixel with their label as a training data. An advanced CNN such as FCNN [83], CDNN [77] architectures are used to implement semantic segmentation. CDNN is used for pixel classification of this thesis.

CDNN is the most popular method for semantic segmentation After Zeiler et.al; bring the idea into the research industry of imaging. In CDNN architectures training is pixel by pixel and also prediction is pixel wise. Pixel wise training is helpful to strongly generalize the model since each pixel is considered as a training data the network gets greater information for what to decide. Specifically, for the proposed work the problem is intensity inhomogeneity of pixels so that training the detection network using pixel wise method is additional advantage of handling the edge pixels [84].

CDNN model contains a series of layers those are: convolution, pooling (down sampling), de-convolution, un-pooling (up sampling) and ReLU for activation of both convolution and de-convolution layer. The sequence of layers is, in the first part of the architecture after convolution

pooling comes for further map feature extraction. Next part is de-convolution and un-pooling for producing an enlarged dense activation map have identical size as input through learning by up sampling. A single activation results multiple outputs using K filters of the same size as convolution for expanding feature maps. In addition to CNN layers de-convolutional layer and un-pooling is used in CDNN network.

De-convolution is not really the reverse operation of convolutional rather it is the transpose of convolution used for restoration of full resolution of the feature maps to match with the ground truth resolution. Transpose convolution is convolving the input back to larger size. From the point of view of convolution, de-convolution operation is backward stride or fraction stride convolution.

The mathematical interpretation behind de-convolution is applying convolution on the output of convolution layer to produce a feature map with size of convolution layer input. The name trans-convolution is given because the output of convolution is an input for de-convolution and output of de-convolution is input for convolution. The other layer that follows de-convolution layer is un-pooling layer. Up sampling is done by un-pooling layer using interpolation e.g. bilinear interpolation filling the pixel's value based on their distance from the selected position which is returning back the pooled pixels [84].

In this thesis CDNN is chosen over FCNN because image pixel restoration of convolved feature is basic for semantic skin lesion segmentation since the labels of each pixel is the corresponding ground truth image and FCNN results low resolution pixel images.

As it is stated in the problem statement, CDNN model is used to detect the regions of lesion or to set the initial segmentation curve for the level set algorithm. Pixel wise classification is better than local region classification in identifying the edges of regions. When the network is well trained to generalize the pixel features to be lesion or back ground, most probably there will not be a pixel that is outside of the detected region. The proposed architecture contains 4 convolution layers with 1 pooling layer in the forward move, 4 de-convolution layers with 1 un-pooling layer in the backward move on an input of 127x127 inputs of 3 channels (RGB image). After each convolution and de-convolution layers' ReLU activation layers are used to keep non-linearity of feature extraction.

4.3.2 Visualization of CDNN

CDNN network visualizes the features of input image by a sequence of different layers' operation. CDNN is supervised deep learning algorithm, with a combination of convolution and de-convolution layers. Convolution of an image is finding pattern which is the beginning of the network, it is identifying lines and curves with colors. As the network convolution layer increases the network grows to understand the deep complex features to identify. Visualizing features is done by applying filters (kernels) on local region of the spatial region. During training of the model if the returned weight value is high, the network thinks it is detecting something to be seen as a pattern in the filtered area. On pooling layers, reduce the spatial dimension and feature extraction continues. The forward move or convolution plus pooling layers do understanding or visualization of direction and color of pixels encoded. Therefore, the combination of direction and color give a pattern for a region which is called feature map helpful to identify different types of skin lesions. Generally, convolution network is finding a pattern to identify the image [53].

De-convolution or transpose convolution and un-pooling (convert images from low resolution to high resolution) layers are used for restoring the size original input for the feature map. In this layer's map feature maps to required higher dimensions of feature maps is done while keeping the connectivity pattern extracted from convolution to classify each pixel. When up sampling is used parameters involved are trainable since naive up sampling loses details of image. The purpose of trans convolution is to map the size of predicted image to the ground truth size since each pixel have corresponding label [84].

Generally, de-convolution is implemented by fractionally strided convolution (one to many relationships between pixels and stride is using up scaling factor) and un-pooling is using bilinear interpolation.

There are hyper parameters to be decided during the selection of network architecture and those hyper parameters are: kernel size, max pooling size, number of features, de-convolution kernel size and window stride. Selected values for CDNN network convolution and de-convolution layer with layers of input size of 127X127 pixel image are: kernel size of 3X3, max pooling size of 2X2, 0 or 1 stride, 0 or 1 Zero padding. For all 3 channels the same kernel is used for

convolving the image and for transpose convolution the same hyper parameters are used in one to many relationships. Activation layers don't have any hyper parameters. Another hyper parameter receptive field (connectivity of neurons on a local region over a kernel size) is the measure of how much depth the neurons are connected towards depth. Receptive field is equal to the size of filter with extent of connectivity along depth which is 3. By using the above hyper parameters, the output from each layer is visualized as follows:

- Convolution layer 1: hyper parameters are input size = WXH, 127X127 pixels of depth 3, zero padding = 1 and stride = 1. the output feature by using krizhevsky et al. [59], architecture output features finding formula of Equation 4.9 the output will be: Output from convolution layer one is W1=H1=63, depth = 3. After convolving the inputs activation layer is applied for all of the coming layers except pooling layer

$$W_n x H_n = \frac{W-F+2P}{S+1} \qquad 4.9$$

where F size of filter, P= zero padding and S = stride

- Convolution layer 2: hyper parameters are kernel of 3x3, P = no, and S = 1. The output from convolution layer 2 is: W2=H2=30, depth = 3. After convolution layer 2 max pooling is applied with matrix size of 2x2. Therefore, the output from the pooling layer is 15x15 pixels with the same depth as input.
- Convolution layer 3: hyper parameters are with P = 1, S = 1 and kernel size of 3. The result from this layer is 7x7 feature map.
- Convolution layer 4: is the last convolution layer of the proposed method with input vales of P = 0 and S = 1 and the output size will be 2x2 maps. After this there will not be any convolution-based layer, since the size is the smallest 2-dimensional map (less than the kernel size) it is the end of the first section of model.

The second section of CDNN architecture is restoring the size of feature maps using de-convolution and un-pooling: The kernel is up scaling factor in this case and un-pooling is interpolation size. We have used 4 convolution layers and 1 pooling layer in between 2 sequences of convolution layers. Hyper parameters of the layers are similar to the corresponding forward move layer as shown in Table 4.3-1.

Standing from the hyper parameters of CDNN, the first layer trained by using 11,907 neurons with 3x3x3 weights and 1 bias result 11,907*28=333,396 parameter sharing. In the second layer 2700 neurons and 75,600 shared parameters. There are 6300 and 1372 parameters, for the third layer and fourth layer respectively. Parameters shared from all the layers that extract features are approximately 1M while ReLU, pooling and up sampling layers don't have parameters.

Layers of Forward Move	Layers for Resorting	Hyper parameters
Convolution-1+ReLU	De-convolution 4+ReLU	K=3x3,P=1,S=1, 1 filter for all move
Convolution-2+ReLU	De-convolution 3+ReLU	K=3x3,P=0,S=1, 1 filter for all move
Pooling-1	Un-pooling 1	2x2 bilinear interpolation (un pooling)
Convolution-3+ReLU	De-convolution 2+ReLU	K=3x3,P=1 S=1, 1 filter for all move
Convolution-4+ReLU	De-convolution 1+ReLU	K=3x3,P=0,S=1, 1 filter for all move

Table 4.3-1 List of layers with corresponding hyper parameters

4.4 Image Level Set Method

Level set is a concept that relies on the theory of curve and surface evolution and it is partial differential equation-based algorithm for image processing. It uses an implicit representation of contour and surfaces using zero level set of higher degree function i.e. a point on the curve with motion must always be zero [32]. Mathematically level set is defined in Equation 4.10. The initial segmentation is defined using lower part of Equation 4.10 ($\emptyset o(I)$).

$$\begin{cases} \dfrac{\partial \varphi(I)}{\partial t} = -\alpha A(I) \cdot \nabla \varphi(I) - \beta P(I)|\nabla \varphi(I)| + \gamma k(I|\nabla \varphi(I)|) \\ \varphi(I, n=0) = \emptyset o(I) \end{cases} \quad 4.10$$

where: I is input image or plane containing points defined by (x, y), A(I)=vector field image, P(I)=gradient magnitude image $\propto, \beta, \delta$ are advection, propagation and curvature term coefficients respectively and k(I) is mean curvature of level set at a point of I defined by Equation 4.11.

$$k(I) = \text{div}\left(\frac{\nabla\varphi(I)}{|\nabla\varphi(I)|}\right) \qquad 4.11$$

where ∇ is the gradient operator

The vector field image of Equation 4.10 drives the initial contour towards region of edges (high gradient) and the scalar term to expand the contour at a rate of Equation 4.11. Hyper Parameters $\alpha, \beta, \gamma \; and \; n$are coefficients for advection, propagation and curvature terms and number of iterations to perform level set respectively. The curve at the end of cascading level sets after n iteration is defined by Equation 4.12.

$$C = \{I(x,y)|\varphi(I(x,y) = 0\} \qquad 4.12$$

Equation 4.12 implies pixels where the function $\varphi(I(x,y)= 0$ implicitly defines the final contour of detected region or ROI by CDNN.

In this thesis level set method is used for segmenting the detected regions, as a post process for CDNN. It is used to locate the detection contour sharp on the edge of skin lesion. As it is discussed in the literature review level sets method is proposed because it is the best edge detection algorithm from other image processing methods in application of different imaging. In medical imaging problems level set method is the state of art of segmentation method [25]. Level set methods or geometric deformable models are ingenious solution to address the problem of other edge detection methods (parametric deformable models) because in the case of level set models there is no need of new parameterization. When the topology of detected region changes, the only thing needed is to set the initial segmentation contour. Therefor it is proposed as a post segmentation method for skin lesion segmentation ROI detection.

4.5 Performance Evaluation Metrics

Performance measure is a critical point for every system. Accuracy is the most general well-known performance measure metric for a system. There are specific quality measures that are

used in segmentation algorithms comparison. Performance evaluation metrics that are used in medical image segmentation [85][29][77][31] and ISIC evaluation [5] metric of skin lesion segmentation are evaluated for this study.

For evaluating the performance metrics, the result of comparing the prediction with the ground truth results the following listed outcomes, there are terms used to divide the predicted pixels status:

- True Positive: a positive label or result is detected as positive i.e. lesion region is detected as lesion.
- False Negative: a positive label is detected as negative i.e. lesion is detected as back ground.
- False Positive: a negative label is detected as positive i.e. back ground is detected as lesion.
- True Negative: a negative label is detected as negative i.e. back ground is detected as back ground.

The following are the performance evaluation metrics used to evaluate the performance of skin lesion segmentation based on the above out comes.

1. Accuracy: is the total number of correctly classified segments divided by the total number of outcomes. It is defined in Equation 4.13:

$$Accuracy = \frac{TP + TN}{TP + FN + TN + FP} \qquad 4.13$$

2. Sensitivity: is the measure of how much the detection of true positive is i.e. true positive rate, stated in equation 4.14:

$$Sensitivity = \frac{TP}{TP + FN} \qquad 4.14$$

3. Specificity: is the measure of how much is false negative rate of detection i.e. false negative rate as stated in Equation 4.15:

$$Specificity = \frac{TN}{TN + FP} \qquad 4.15$$

4. Positive Predicted Value (PPV): is the measure of the probability of real positives predicted as positive, defined in Equation 4.16:

$$PPV = \frac{TP}{TP + FP} \qquad 4.16$$

5. Negative Predictive Value (NPV): is the measure of probability of real negatives predicted as negative as stated in Equation 4.17:

$$NPV = \frac{TN}{FN + TN} \quad 4.17$$

6. Intersection over Union (IOU): also referred as jaccard index metric. It is the measure of percent of overlap between the ground truth and predicted output [73]. This metric is different from others because as it is stated in some of the recent studies the metric is used as a loss function for training learning model for optimization of the model performance. The mathematical interpretation is Equation 4.18:

$$IoU = \frac{T \cap P}{T \cup P} \quad 4.18$$

where T and P, are ground truth and prediction of segmentation respectively

The above six metrics are used for validation of the result on skin lesion segmentation using deep learning algorithm and level set method. The conclusion of the proposed method is based on the results achieved on the metrics value.

Chapter Five

Results and Discussion

This chapter explains skin lesion segmentation using CDNN and level set method implementation based on the framework design briefly explained in Chapter Four. In the next sub sections, the data set used for implementation, preprocessing and the results gained from implementing will be explained.

5.1 Dataset

The dataset for this thesis is from ISBI skin cancer challenge ISIC archive. The challenge contains three parts. Part one of the challenge is skin lesion segmentation. The data set organization is divided into three, those are training data set for training CDNN, validation data for validating training result and testing data set to evaluate testing results of different segmentation method implementations. Skin lesion segmentation data includes original image in pair with the ground truth image with a form of binary mask traced by expert manual tracing. All of the three divisions of data set contain input and ground truth[5].

1 **Dermoscopic Image Data:** The data set for training contains 2000 RGB color space images with 24bit depth of JPEG format taken by dermoscope. The set contains images that are from three different classes of cancer disease those are: Benign Nevi, Melanoma and Sebrrhoeic Keratoses. The three classes are used because they are very challenging to identify due to high similarity of appearance with different lesions[2].

2 **Ground Truth Segmentation Images:** For every image of dermoscope there is a ground truth of binary mask images in the form of PNG format with an identification name that matches the corresponding dermoscopic image. All the masks have exact dimension as the lesion image. The mask images are encoded as grey 8-bit images which means each pixel represents 0 or 255 where 0 (black) is representing background of lesion and 255 foreground of the image (lesion).

Generally, the data set contains 2000 training images and 150 validation images and 600 test images varying size in between 540x772 and 4499x6748. The data set ratio is 70% for training, 20% for testing and 10% for validation.

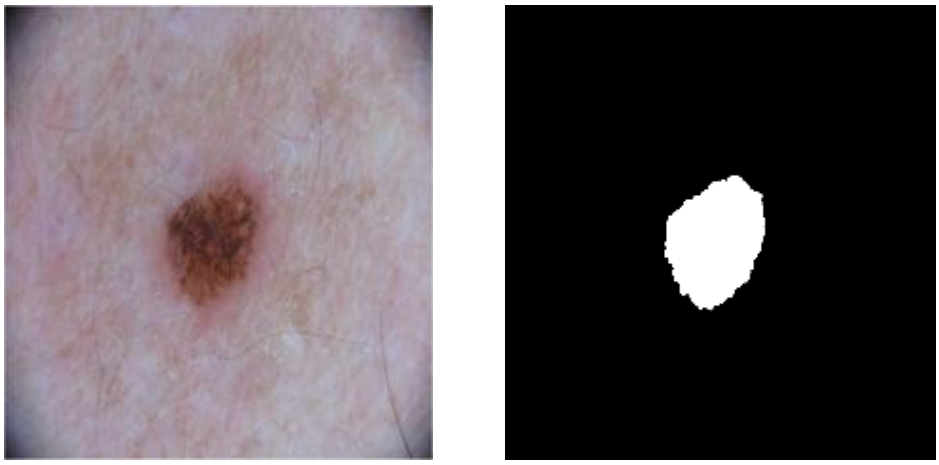


Figure 5.1-1 Sample images from the data set with id of ISIC_0000012 from ISIC archive

5.2 Experimental Results and Discussion

The implementation is done using python back end tensorflow framework for deep learning. There is a step wise phase to follow on implementation. The first phase is preparing the training data for training CDNN model and training; the second one is using the trained model to generate the initial segmentation for the level set, the third one is level set the initial segmentation and evaluations of different performance evaluation metrics.

Dataset is prepared to be used for training the model by using the preprocessing methods explained in Section 4.2. The images are resized for a size of 127x127. CDNN contains four convolution layers that extracts the feature the size must fit the model to extract features to the deepest as it is explained briefly in the visualization of the model Section 4.3.2. In addition, for enhancement vector median filter and for regularization data augmentation by rotation is applied. Preprocessing of the proposed segmentation is made on MATLAB 2017, since it is so fast by resizing all the images in an hour and the same for filtering than python 3.6 was too late by taking more than minutes to resize a single image. Data augmentation is used only for training purpose to increase the number of training data set so that, a total of 4000 preprocessed dermoscopic images are used for training the model.

5.2.1 Training CDNN

The proposed CDNN architecture explained in Section 4.3 is trained for classifying the pixels as lesion and background. Such type of classification is used for semantic segmentation. In this work after classifying the pixels to the corresponding class label it generates a detection area for skin lesion image to be further detected for sharply getting the edges of lesion. For each pixel in the input of CDNN there is a corresponding label of pixel with a class of lesion or background.

5.2.1.1 Hyper Parameters

While training the model, there are some hyper parameters i.e. variables that determine the network structure for optimized result of training. The first groups of hyper parameters are determined for the network based on number of training data set by choosing the batch size. Those are:

1. Number of Epoch: How many times the model reads all the data set
2. Batch Size: Parts from all dataset to be visited at a time
3. Number of iterations: The number of batches to compete the dataset in one epoch.

The second group of hyper parameters are discussed in visualization Section 4.3.2, which may different for different convolution layer and trans convolution layer of tensor flow based on the network architecture. Those are [82]:

1. Kernel Size: Filter size to generate feature maps.
2. Zero Padding: For keeping the size of output equal to the input of the next layer.
3. Stride: The distance of moving the kernel over convolving the image.
4. Pooling Size: Down sampling size of convolved result.
5. Learning Rate: a positive fraction determining the step of learning of the network neurons.
6. Dropout: a mechanism of regularization of the training to overcome over fitting.

The values of each hyper parameter in CDNN are shown in Table 5.2-1. The network is trained with Adam optimization by using cross entropy loss function. The number of layers is: 4 convolution layers, two consecutive convolutions followed by ReLU activation layer and the second convolution layer by pooling so that a total of two pooling layers for down feature

extraction and for restoring the convolution layers replaced by trans convolution layer and pooling with un pooling layers. For details of the architecture construction see Table 4.3-1.

Hyper Parameter	Value
Epoch	500
Batch	4
Iteration	500
Kernel size	3x3 for all layers
Padding	1 or 0
Stride	1 or 0
Pooling	2
Learning rate	0.001
Dropout	0.5

Table 5.2-1 Hyper parameters of CDNN network

The network is trained on 4 GB GPU of GeForce 940MX on 8GB RAM core i5 hp laptop. The time taken for training is 3 days and 1hour. The training result of accuracy for training and validation data sets is shown in the Figure 5.2-1 by taking the average of each of them accuracy over 50 epochs.

Figure 5.2-1 Accuracy of validation and training

As it is shown in the Figure 5.2-1, the network started saturating after epoch 400 and after 450 epochs the average loss for the training is 6.97% that means accuracy of 93.03% whereas the validation average loss is 4.87% i.e. accuracy of 95.13%. The network starts recognizing after 400 epochs of learning the validation loss is no more decreasing or saturated. The accuracy measure on the chart is the loss gained from network training, which means based on the cross-entropy loss. The network accuracy is measured from on Figure 5.2-1 is the loss gained while training. Another training evaluation is IOU evaluated on the training set and validation set shown in Figure5.2-2.

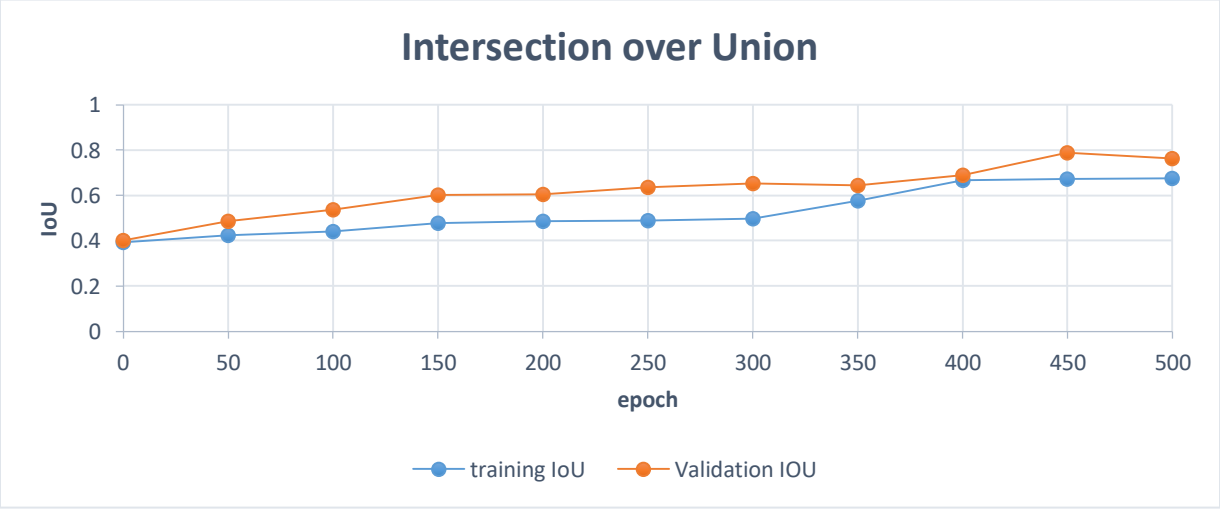


Figure 5.2-2 IOU of the training and Validation data on training over 500 epochs

After training the network it is used for evaluation the accuracy on test data set. The average accuracy of test data set is 94.83%.

IOU is evaluated over 500 epochs while the network trains, since it is the main performance evaluation metrics. For both the training and validation set, it wasn't changing as accuracy improvement of the network. For this case we were thinking about to train the network towards minimizing IOU loss [73]. Training a network towards minimizing IOU loss is computationally costly. Therefore, rather than training using IOU loss we decide to evaluate the IOU of prediction trained by cross entropy loss.

5.2.2 Generate ROI Using CDNN

Detection of ROI is made by using pixel wise trained network, CDNN. There are two labels of pixels either 0 or 255 to detect a pixel as in side a lesion boundary or out of the lesion. The performance of ROI detection generation has a great impact on performance of the overall framework. The detection is made by using semantic segmentation approach i.e. prediction the class of each pixel as lesion or non-lesion. Good detection result good segmentation since edge detection is moving inside the detected region. Accurate detection of ROI is vital for skin lesion type classification based on the features extracted over the extracted lesions in the subsequent steps of CAD. The result of this stage is a display of tested image detection areas inside a boundary box. The testing images are all from the test data set for knowing the real performance of the network. After predicting the class of each pixel, the pixels that are predicted as lesion displayed inside the box. For implementation of detection of ROI tensor flow API object for object detection is used.

ROI using semantic segmentation is set by including the lesion pixels inside a rectangle. As it is observed from Figure 5.2-3, the result of detection area includes the pixels that must be included as lesion as it is compared with the ground truth by using IOU of the ground truth and binary image of the ROI image which is the overlap performance evaluation criteria. IOU of predicted lesion and ground truth on the validation set is 76%, this implies that the detection is not missing most of the lesion pixel. The rest around 25% pixels included in the predicted region of interest are non-lesion (background) around the edges of the lesion since the prediction is detecting interest area it is obvious. From this we understand there will not be high probability of level set missing the lesion pixels outside of the edge is minimized because every lesion pixel lies inside the ROI.

The following samples in Figure 5.2-3 are from test images used to generate ROI using trained network. As it is shown from the last dermoscopic image sample using ROI detection is helpful for detecting lesions over the same background but with different location i.e. there is a non-lesion region between the two. Generally, we observe the lesion detection is acceptable at this stage even if we will make sure its acceptance based on the final segmentation evaluation metrics.

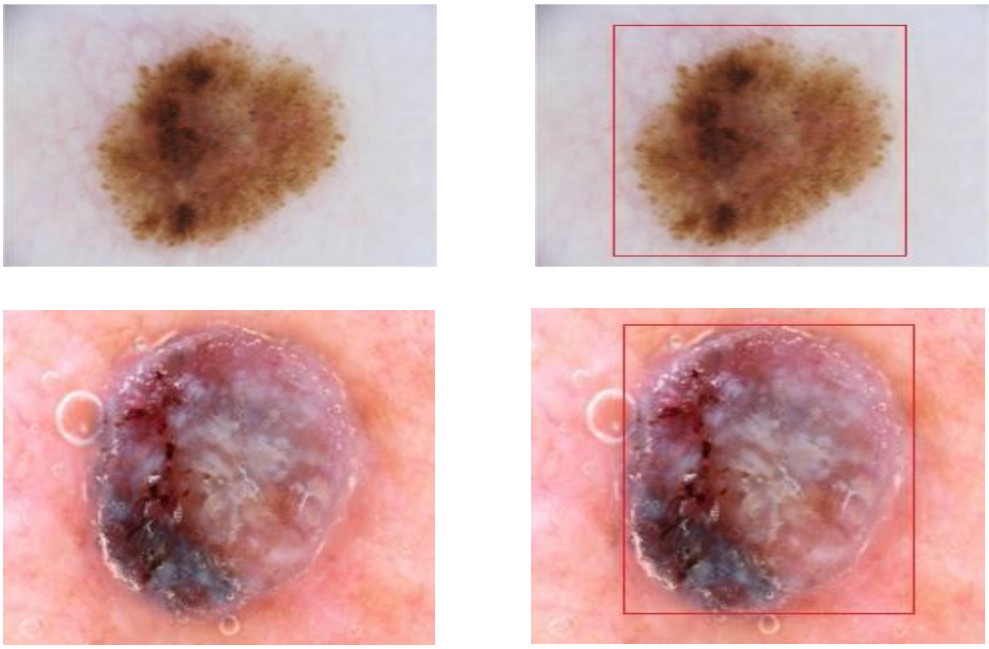


Figure 5.2-3 Samples of skin lesions (left) ROI predicted by CDNN (right)

5.2.3 Segmentation Using CDNN

CDNN is also evaluated for its performance on semantic segmentation of lesions and background i.e. pixel classification. The main aim of segmentation performance of the network is to compare the performance of level set supported deep learning segmentation method with only deep learning method, so during the implementation before integrating the two-methods segmentation test is made on skin lesion images using CDNN.

In this case of implementation final segmentation is made by using the trained CDNN: for each input pixel there is a label pixel which is labeled to background or lesion. The training is the

same for ROI generation which is explained in Section 5.2.1. The difference is in section 5.2.2 bounding box of ROI is predicted result while in this section, segmentation skin lesion is applied. The result of segmentation samples is shown in Figure 5.2-4.

The evaluation metrics which is considered in this case is IOU, over the test data set is the average IOU is92.854%. The results shown in Figure 5.2-4 are samples from test data set where the light blue region is predicted pixels as lesion. The first column of the Figure 5.2-4(a) is the input image from the test data set, the second column, Figure 5.2-4 (b) is the predicted image lesions labeled in white blue color and the third column and Figure 5.2-4 (c) is the ground truth from test data set.

As the result of average IOU indicates, the proposed architecture is good enough to perform semantic segmentation without losing the pixel information while performing convolution through down sampling and de-convolution through up sampling.

The main aim of evaluating the performance of CDNN for semantic segmentation is for comparison of the effect of level set integration to it. The evaluated IOU overlap difference between the two regions using CDNN 92,854% is promising result as it is comparable to recent methods of skin lesion segmentation methods [64][66][86].

Therefore, for this thesis we can say that CDNN results good in semantic segmentation for classifying the pixels to their predictable class. But there are instances the prediction of segmentation includes non-lesion area predicted as lesion. The other performance evaluation taken here is the response time or computation time to segment 127x127 pixel images was 2 minutes.

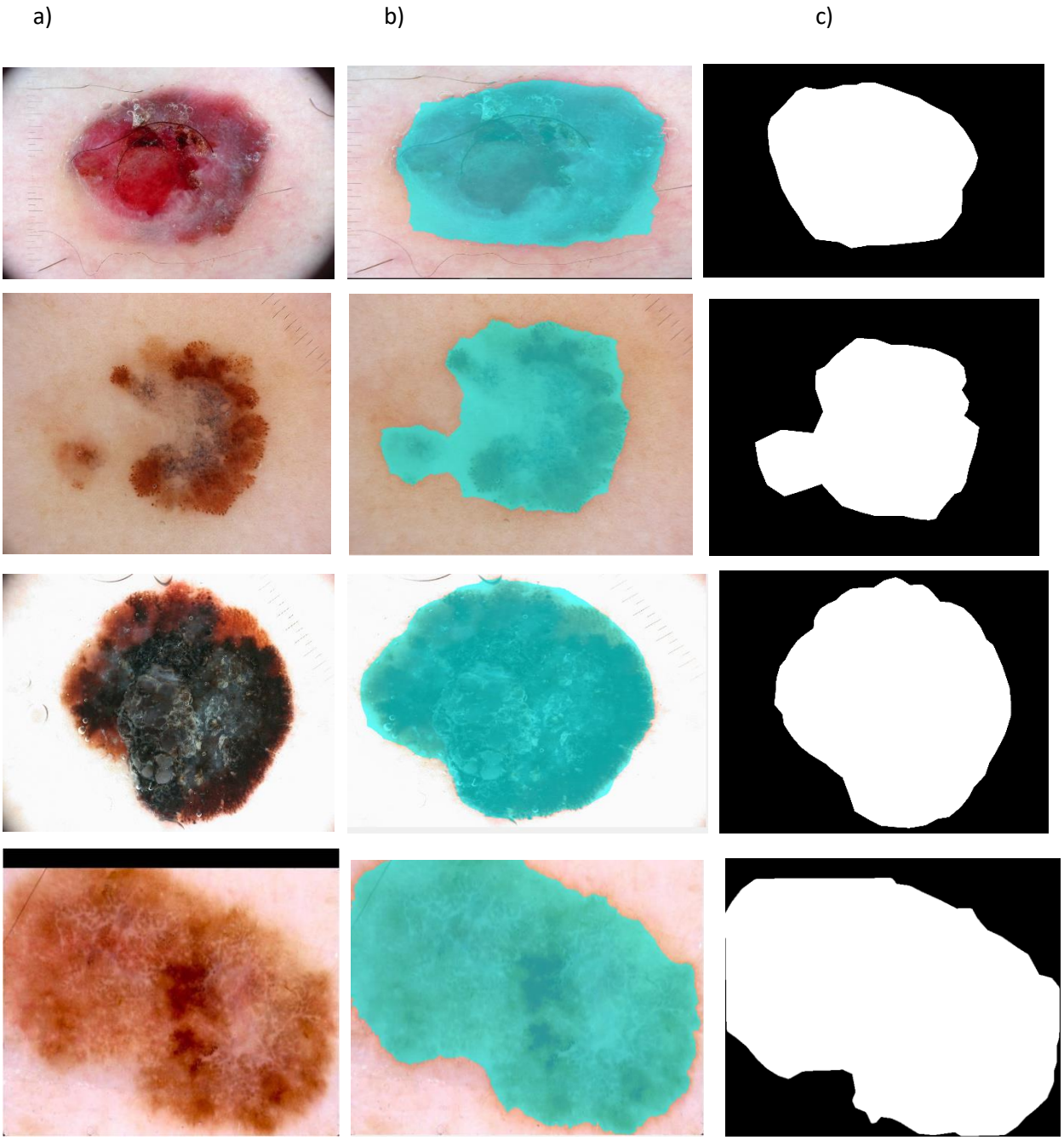


Figure 5.2-4: (a) Input image, (b) predicted image using CDNN, the regions shown in white blue are predicted lesion areas, (c) ground truth mask

5.3 CDNN Level Set Skin Lesion Segmentation

The proposed skin lesion segmentation using deep learning and level set method is implemented using CDNN and gradient based level set algorithm. After training the network for region detection, the bounding box of ROI is set as the initial contour of the level set method as

described in Section 4.1. ROI generation is a very important stage of the proposed segmentation method.

For level set the input is an image with initial contour, starting with the right initial segmentation results better finding of the exact edges of the lesion as explained in Section 4.4. In addition to the initial segmentation contour set by taking the ROI as initial contour and vector field of input image, there are hyper parameters to be set for moving the contour towards finding the edge. Those are advection, propagation and curvature terms and number of iteration of the curvature propagation. Table 5.3-1 is list of hyper parameters for applying level set.

Hyper parameter	Value
Number of iterations in level set	100
Advection	1
Propagation	2
Curvature Term	1

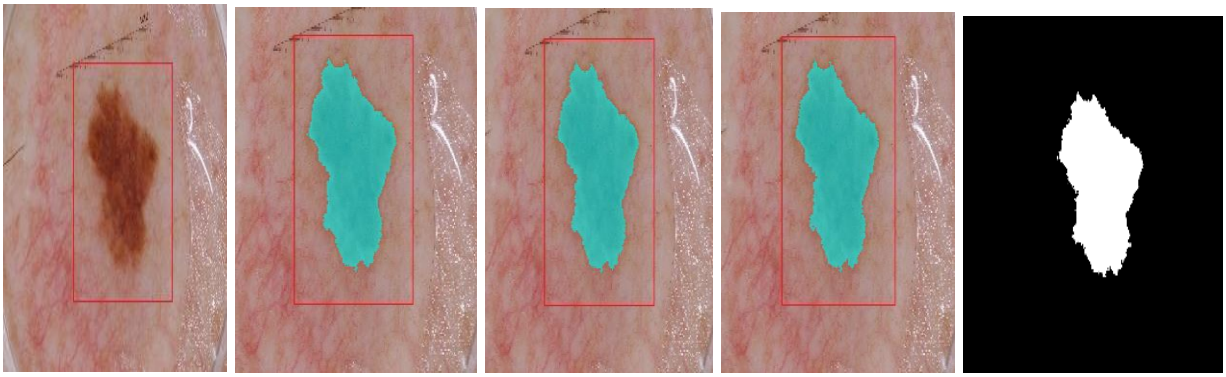
Table 5.3-1 Hyper parameters for level set method

As the number of iterations goes above 100 the level set starts losing the initial contour direction so that iteration 100 is used for testing the level set post processing on CDNN initial segmentation result. Table 5.3-2 and Figure 5.3-1 shows how the average IOU drops linearly as we evaluate by increasing the number of iterations by 25 standing from 100 to 200 iterations on few selected test images. From this we understand that ROI detection is not including a lot of non-lesion regions.

Sample Image id from test data set	IOU using n=100	IOU using n = 125	IOU using n = 150	IOU using n = 200
ISIC_0012199	0.9578	0.9336	0.9279	0.8721
ISIC_0012395	0.9356	0.9231	0.9260	0.9063
ISIC_0012708	0.9024	0.9073	0.9271	0.8569
ISIC_0013374	0.9089	0.9027	0.9040	0.8990
ISIC_0013399	0.8906	0. 8708	0.8501	0.8402
ISIC_0014720	0.9301	0. 9382	0.9283	0.9157

Table 5.3-2 Comparison of IOU when the number of level set iteration increases

Figure 5.3-1 shows the effect of increasing the number of level set iteration visually for ISIC_0012395 and the corresponding ground truth from left to right.



a) n =0 b) n = 100 c) n = 125 d) n = 200 e) Ground Truth

Figure 5.3-1 Effect of increasing the number of iterations on level set: even if the shape of segmented regions seems similar there is a difference when the IOU is evaluated pixel wisely.

Figure 5.3-2 shows input image and the corresponding CDNN plus Level set method segmentation visual results. The first column is input image and second column is ROI generation using CDNN, which means set initial contour of segmentation for level set result

discussed in Section 5.2.2. Figure 5.3-3 shows samples of test data images segmented using CDNN level set method. The first column segmentation result of our method and the second is ground truth. Based on the method stated in Section 4.1, the pixel wise quantitative evaluation is taken on the proposed segmentation method for detection of skin lesion towards melanoma detection. The result of the experimentation of proposed work is average IOU of 94.796%. The segmentation performance of applying only level set method by manual initial segmentation is 69.572%.

Another evaluation done on CDNN level set method is evaluating the IOU on input images that are not preprocessed, 93.67% IOU is gained without preprocessing and the response time is higher than segmenting preprocessed skin lesion images with a value of 2.3 minutes.

Skin lesion segmentation using deep learning and level set algorithms results outperformed result CDNN method according to the visual result and quantitative evaluation metric overlap between the ground truth and predicted lesion for different algorithms is shown in Table 5.3-3.

Algorithm	Average IOU
ROI Detection	76%
Level set	69.572%
CDNN	92.58%
CDNN Level Set	94.796 %

Table 5.3-3 Comparison of IOU of proposed CDNN level set with other tests

The other performance evaluations measured on the results of proposed method are SE, SP, PPV and NPV measures average of the test data set are discussed in the following Section 5.3.1.

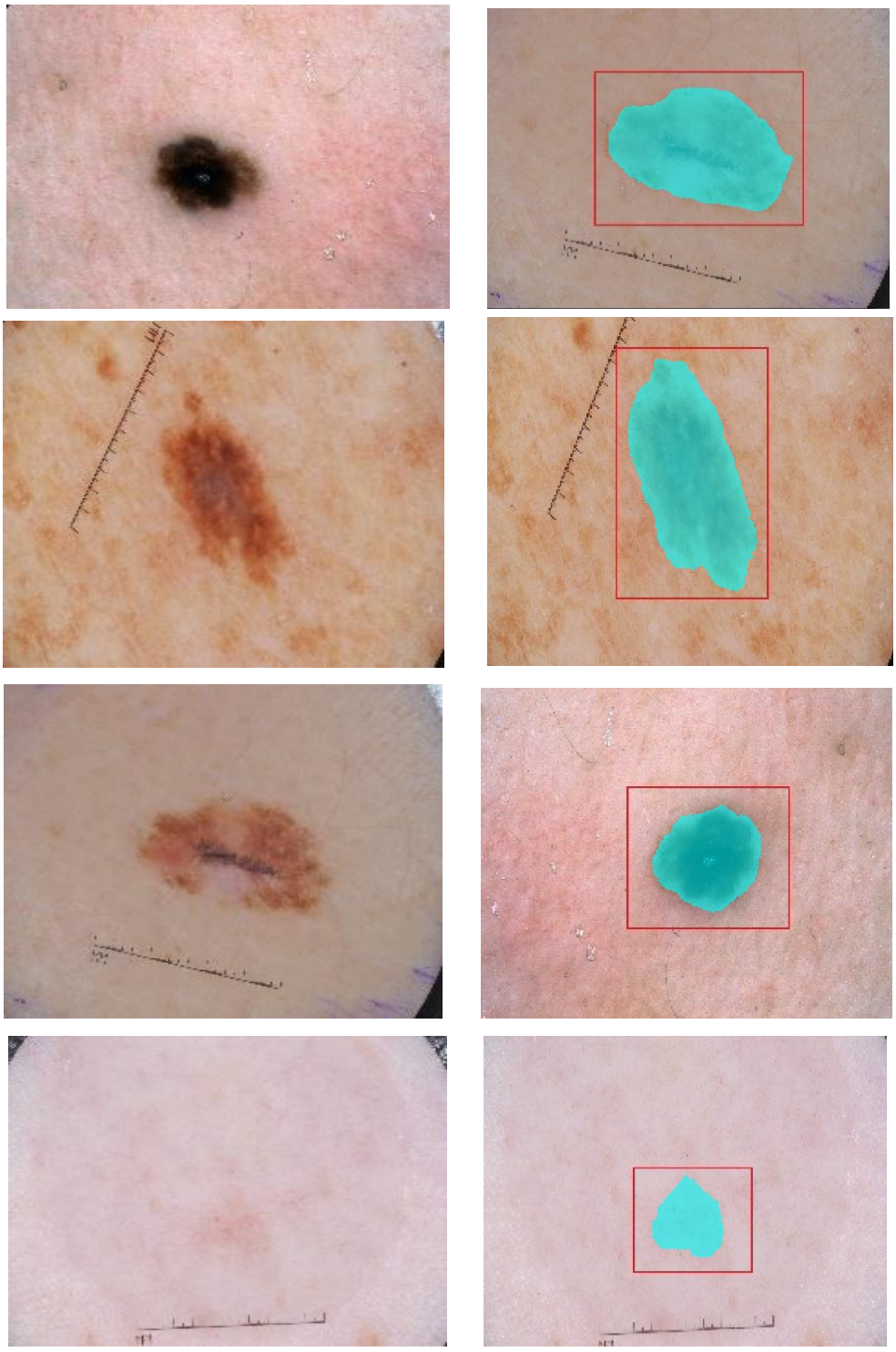


Figure 5.3-2 Samples of input dermoscopic images (left column) and corresponding segmentation by CDNN + Level set method (right column), in the segmented image white blue shoes the final segmented region while red box is region of detection (ROI).

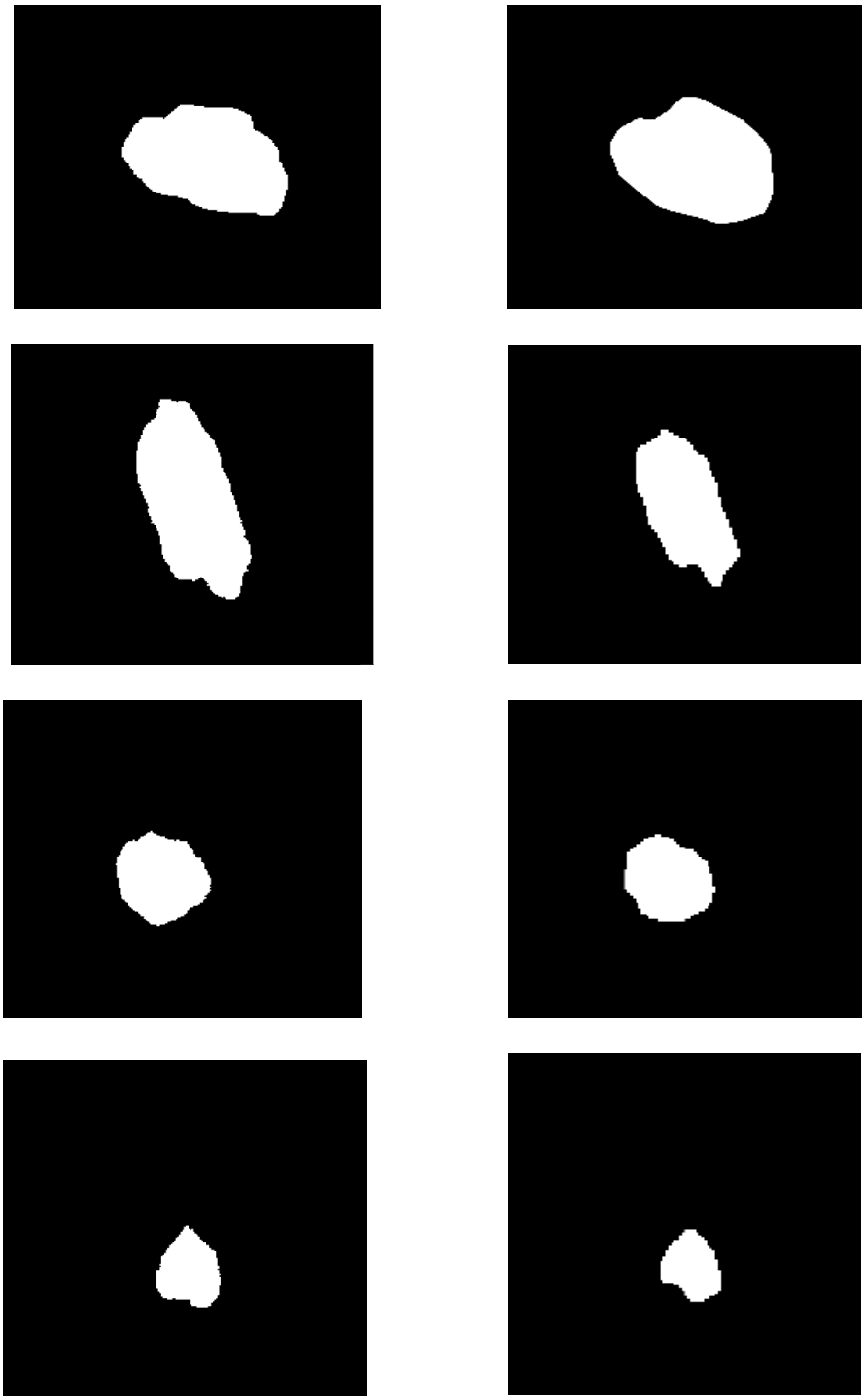


Figure 5.3-3 Binary mask of predicted skin lesion segmentation (left column) and ground truth (right column) of input image in Figure 5.3-2.

5.3.1 Performance Evaluation of CDNN Level Set Segmentation

In the previous sections and sub sections of this chapter we have seen different sequential implementation and evaluations of the proposed skin lesion segmentation method i.e. skin lesion segmentation using deep learning algorithm and level set: CDNN Level Set Segmentation.

The performance evaluation metrics used to validate CDNN level set skin lesion segmentation method are presented in Section 4.3, those are: IOU, SE, SP, PPV and NPV. These metrics are evaluated on the validation dataset of the total data set available that means 150 dermoscopic images with their corresponding ground truth mask images. The evaluation is pixel wise by considering:

a) The total number of pixels on the image, each image size of 127x127 (16,129) pixels
b) Number of pixels predicted as lesion by CDNN level set method
c) Number of pixels that are set as lesion by the ground truth

Based on the three classifications TP, TN, FP and FN values are calculated as explained in Section 4.5. The final reported evaluation of each metric is the average of the test data set.

The performance evaluations are shown in Table 5.3-4, sensitivity and specificity (measures of rate of correctly detecting lesion pixels and correctly classifying non-lesion pixels respectively) of CDNN level set on test data set is 94.988% and 98.804%. High sensitivity implies that the network is well trained to recognize lesions.

Evaluation metrics	CDNN + level set	CDNN
IOU	94.796%	92.583%
SP	98.804%	94.206%
SE	94.988%	91.569%
PPV	97.845%	94.754%
NPV	95.579%	93.892%

Table 5.3-4 Performance evaluation for CDNN + Level set and CDNN segmentation technique

All evaluated parameters are improved by applying level set method. Therefore, applying level set method over CDNN outperformed segmentation using only CDNN. Generally, the result shown in Table 5.3-4 shows that the effectiveness of initial segmentation contour (ROI) in the proposed segmentation method. Level set method contributed positive on improving edge detection. The computation time to detect and segment an image with a size of 127x127 pixels was 2 minutes on hp laptop with core i5 RAM 8GB. The response time is not fast as expected because the classification is pixel wise.

5.4 Answers to Research Questions

There are three research questioned answered after completing this study. The research questions of this thesis are fully answered.

The first research question of this thesis research is "Can automatic skin lesion segmentation performance improve by using deep learning CNN?" the answer for this research is yes because IOU since CDNN (92.58%) outperformed segmentation using level set method (69.572%). Segmentation using CDNN pixel classification is better in performance as compared with most of the recent literatures [9][29][31][35][65][76].

The second research question of this thesis is "Can integrating deep learning CNN with level set image processing improves the performance for skin lesion segmentation?" for this question also the answer is definitely yes. Based on the result shown in Table 5.3-4, performance evaluations on IOU is improved from 92.58% to 94.796%, SP from 94.206% to 98.804%, SE from 91.569% to 94.988%, PPV from 94.754% to 97.845% and NPV from 93.892% to 95.579%. So that we said the segmentation performance can be improved by applying level set method over CDNN deep leap learning based segmentation algorithm. As it is explained in Section 4.1 the reason behind is, the initial contour setting determines the performance of level set segmentation. Using Deep learning algorithm for initial contour setting is the right decision for performance improvement of segmentation.

The third research question is; "Does preprocessing dermoscopic skin lesion images affect the performance of CDNN level set method?" The answer for this research question is, preprocessing helps to refine the edges and remove artifacts so that the effect is improving the

detection time by 0.3 minute and IOU of 93.67% is gained. The IOU is less than the preprocessed images which is 94.796%. Therefore, preprocessing is helpful for segmentation using CDNN and level set method.

All the three research questions of this thesis are fully answered by quantitative measurement and visual results using test dataset results gained from the implementation.

Chapter Six

Conclusion and Recommendation

6.1 Conclusion

In this research, skin lesion segmentation method using deep learning algorithm and level set method is proposed and implemented. A great work has been on literature review to propose a better method for the problem of skin lesion segmentation, so that deep learning and level set approach integration method is taken in to action of the thesis research as a more holistic technique to succeed overcoming the limitation of skin lesion segmentation in CAD systems towards detecting the deadliest form of skin cancer melanoma. To implement the proposed method, we have selected and implemented CDNN deep learning architecture with level set image processing so that our framework is the integration of two robust methods of image segmentation. Four main steps are main concerns of the proposed method. Those steps are preprocessing dermoscopic images with robust method of image enhancement for RGB images, prepare image data set for the proposed architecture including data augmentation regularization to overcome over fitting, test the performance of semantic segmentation of the trained network before integrating to the level set method and finally apply CDNN plus level set method for segmentation.

This thesis research has advantages on automatic detection of skin lesion towards melanoma detection because it is based on deep learning algorithm which is known in today's research industry by achieving high accuracies on different application and also it shows edge detection level set algorithm results good performance when the initial segmentation is set automatically in intelligent way rather that manual initial segmentation contour setting.

Based on the qualitative (visually) and quantitative evaluation of the validation test a better result is achieved on each composed technique of CDNN level set method than the previous state of arts; training accuracy over the training set and validation set, performance of CDNN on segmentation, ROI detection performance, and finally composed implementation or overall performance of the propose technique. The quantitative evaluations are by using the medical

segmentation evaluation metrics including ISBI challenge evaluation metrics [5], those are jaccard distance (IOU), SE, SP, PPV and NPV. All the evaluations are pixel wise evaluation since the prediction is pixel wise classification with a value of 94.796% IOU, 98.804% SP, 94.845% SE, 97.845% PPV and 95.579% NPV. Above all evaluations the proposed method out performs deep learning method so that we conclude applying level set to segmentation result of deep learning improves the edge detection performance. Generally, our proposed frame work performed better result as compared to the most recent literatures [9][29][31][35][65][76], since the quantitative results are comparable to their evaluation results.

6.2 Recommendations

There may be still a gap to be improved, on skin lesion segmentation using deep learning and level set method, since the problem is a fatal issue i.e. public health issue as stated on the problem statement. The main goal of public health issue problem solving is to work for performance improvement of to be done continuously until the highest accuracy level is reached out. Therefore, the following are some notable future work recommendations observed while implementing this research work:

- The proposed level set integration is better to be automatic in adjusting itself for how many iterations initial curve is going through level set; because the proposed method level set iteration number is set by evaluating for different iterations and by selected the iteration that results better for most test images. Rather it is better if the level set iteration decision is made by some other method such as decide using learning algorithm.
- The effect of image acquisition by illumination must be studied on the performance of proposed method and also considering different preprocessing methods that result better performance.
- An app that is based on the proposed method should be developed for prevention and diagnosis of melanoma.
- Communicate with the dermatologists on the results achieved in this thesis research if the achieved result is promising. In addition, involve them under the study since they are able to guide engineers on the biological aspect of the study, because this is a study where engineering meets biology.

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