International Journal for Innovative Engineering and Management Research
PEER REVIEWED OPEN ACCESS INTERNATIONAL JOURNAL
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IJIEMR Transactions, online available on 26th Oct 2021. Link :http://www.ijiemr.org/downloads.php?vol=Volume-10&issue=Issue 10

10.48047/IJIEMR/V10/ISSUE 10/43

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Volume 10, ISSUE 10, Pages: 277-286

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SEGMENTATION AND CLASSIFICATION OF MELANOMA SKIN CANCER

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Abstract-Melanoma is the most destructive form of skin cancer. Early diagnosis of melanoma can be curable. At the same time accurate diagnosis is very essential because of the similarities of melanoma and benign lesions. Hence computerized recognition approaches are highly demanded for Dermoscopic images. The main purpose of this research is to develop an automatic system to improve the classification performance of melanoma. The effectiveness of this framework is evaluated on ISBI 2016 Skin Lesion Analysis towards Melanoma Detection Challenge dataset. Initially, Deep Learning based U-Net algorithm is used to segment the lesion region from the nearby healthy skin and then extract discriminate features with the help of Convolutional Neural Network. VGG16 Net algorithm is used to classify every lesion in a Dermoscopic image as a Benign or Melanoma. Results are found from classification with and without segmented images.Classification with segmented images produces accuracy of 83.18%, Sensitivity of 95.53%, and specificity of 96.22%. Based on these values the Deep Learning based classification with segmented images produces better result and it helps to improve the diagnosis performance. The proposed method would constitute a valuable support for physicians in every day clinical practice.

Key Words: Segmentation, Melanoma, U -Net, Deep Learning, Lesion, Dermo-Scope, Image Processing

1. INTRODUCTION

Skin cancer is an invasive disease caused by the abnormal growth of melanocyte cells in the body, which tend to replicate and spread through lymph nodes to destroy surrounding tissues [1]. The damaged cells develop a mole on the external skin layer, categorized as malignant or benign, whereas melanoma is considered cancer because it is more dangerous and life-threatening. Skin cancer is a widespread and dangerous disease globally, with 300,000 newly diagnosed cases and over 1 million deaths each month worldwide in 2018 [2]. Melanoma is more prevalent globally, becoming the 19th most common disease with the highest mortality rate [2]. As per the statistics of the International Agency for Research for Cancer (IARC) [3], 19.3 million new cases were diagnosed with cancer, with a mortality rate of about 10 million people in 2020. Moreover, the number of new cases found in the United States were 100,350, and the number of people who died in 2020 were approximately 6850. According to the American Cancer Society [4], 106,110 new melanoma cases were predicted to be diagnosed (nearly 62,260 in men and 43,850 in women) and about 7180 melanoma patients were estimated to die in 2021. Some environmental and genetic factors such as fair complexion, pollution, family history, and sunburn may lead to the formation of skin cancer. The control over mortality rate due to cancer is challenging;

However, the latest development in image processing and artificial intelligence approaches may help diagnose melanoma early as early detection and prognosis can increase the survival rate. Moreover, computer-aided diagnostic (CAD) tools save time and effort compared with existing clinical approaches. During diagnosis, an expert dermatologist performs a series of steps, starting with a visual inspection of a skin lesion by the naked eye; then Dermoscopic, which is a magnifying lens to view lesion patterns in detail; and finally, a biopsy [5]. These conventional methods are time-consuming, expensive, and laborious. Achieving an accurate diagnosis is entirely subjective depending upon the expert's skillset, resulting in variations in their predictions. Many experts analyse lesions based on the ABCDE [6] metrics, which define the asymmetry, border, colour, diameter above 6 mm, and evolution over time. However, it requires intensive knowledge and proficiency that might not be available in clinical settings. It is found that the accuracy of correctly identifying skin lesions by a dermatologist is less than 80% [7]. Additionally, there is a limited number of expert dermatologists available globally in the health sector. To diagnose a skin lesion at the earliest stage and to solve the complexities mentioned above, comprehensive research solutions have been proposed in the literature using computer vision algorithms [8]. The classification methods vary, including decision trees (DT) [9], support vector machines (SVM) [10], and artificial neural networks (ANN) [11]. A detailed review of these methods is explained in the paper in Reference [12]. Many machine learning methods have constraints in processing data, such as requiring high contrast, noise-free, and cleaned images that do not apply in the case of skin cancer data. Moreover, skin classification depends on features such as colour, texture, and structural features. The classification may lead to erroneous results with poor feature sets as skin lesions consist of a high degree of inter-class homogeneity and intra-class heterogeneity [13]. The traditional approaches are parametric and require training data to be normally distributed, whereas skin cancer data is uncontrolled. Each lesion consists of a different pattern; thus, these methods are inadequate. For these reasons, deep learning techniques in skin classification are very effective in assisting dermatologists in diagnosing lesions with high accuracy. Several detailed surveys elaborate on the application of deep learning in medical applications [14]. There are mainly three types of skin cancer: basal, squamous, and melanocyte [15]. The most commonly occurring type of cancer, basal cell carcinoma, grows very slowly and does not spread to other parts of the body. It tends to recur, so eradicating it from the body is important. Squamous cell carcinoma is another type of skin cancer that is more likely to spread to other body parts than basal cell carcinoma and penetrates deeper into the skin. Melanocytes, the cells involved in the last type, produce melanin when exposed to sunlight, giving the skin its brown or tan colour. The melanin in these cells protects the skin from sunlight, but if it accumulates in the body, it forms cancerous moles, also known as melanoma cancer. Based on their tendency to cause minimal damage to surrounding tissues, basal and squamous cancers are considered benign, whereas melanocyte-based cancers are considered malignant and can be life-threatening. The most popular datasets employed in this work is from the International Skin Imaging Collaboration (ISIC) [16], which contains different skin lesions. There are mainly four types of lesions (see Figure 1) in the ISIC 2016, 2017, and 2020 data: (a) Nevus (NV), (b) Seborrheic keratosis (SK), (c) Benign (BEN) (d) Melanoma (MEL). NV cancer has distinct edges that primarily appear on the arms, legs, and trunk in pink, brown, and tan colours. Next is the SK, of which its non-cancerous appearance is waxy brown, black, or tan colours. Another non-cancerous lesion type is BEN, which does not invade surrounding tissues or spread into the body. Both NV and SK lesion types are considered BEN. Lastly, MEL is a large brown mole with dark speckles; it sometimes bleeds or changes colour over time. It is a dangerous type of cancer that quickly spreads to other organs of the body. MEL is further divided into many types: acral, nodular, superficial, and lentigo. This research aims to identify and distinguish between MEL and BEN cancers.

2. EXISTING METHOD

Melanoma is one of the most harmful Type of skin cancer that begins in the pigment cells (melanocytes) of the skin. Due to the excess revelation of ultraviolet radiation from the sun, the skin cells are damaged and can affect the resistance capacity. Quick diagnosis and treatment can result in a very high possibility of melanoma Survival. At the same time, due to the similarities of skin lesion types, a correct diagnosis is essential. The visual difference between melanoma and benign skin lesions can be very elusive even for trained medical professionals under naked eye observation.

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A minor surgery can increase the chances of recovery if the melanoma is diagnosed in the early stages [8]. Dermoscopic is one of the dermatologists' most popular imaging techniques. It magnifies the skin lesion surface and its structure became more visible to the dermatologist for an examination. However, this technique can only be used effectively by trained physicians, because it is totally based on the practitioner's visual acuity and experience

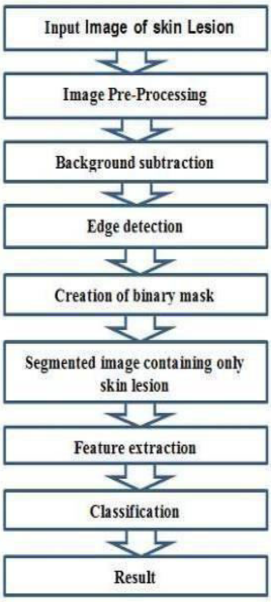

Fig.1 Flow chart of existing method

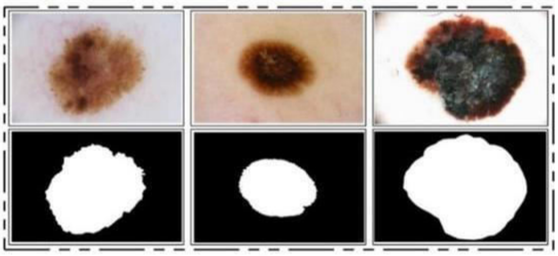

Fig.2 Sample Representation of Background Subtraction

3. PROPOSED METHOD

These challenges motivate the research community to develop new techniques for visualization and diagnosing of melanoma. Computer-aided diagnosis (CAD) system assists in the diagnosing of melanoma cancer. The CAD tool provides a user-friendly environment for non-experienced dermatologists aims that to develop an automatic diagnosis system of melanoma

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using Deep learning methods. For this purpose, initially the skin lesions were segmented using deep learning based U-Net algorithm. From the segmented images, deep features were extracted using Convolutional Neural Networks (CNN's). Then the extracted deep features were fed into the VGG16 Net classifiers for classification.

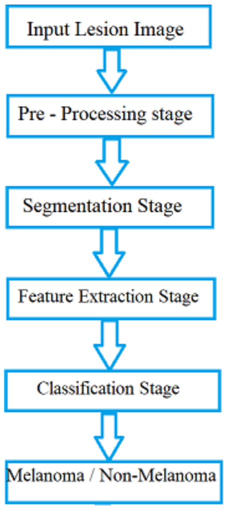

Fig. 5 Flow Chart of Proposed method

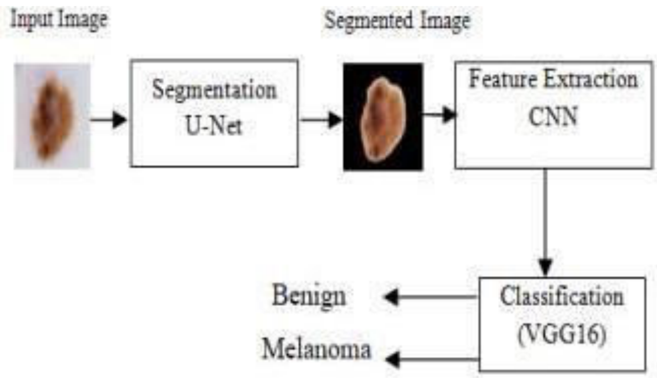

Fig. 6 Block Diagram of Proposed method

4. METHODOLOGY

Lesion Segmentation: Lesion Segmentation is the process of splitting an image into multiple segments, set of pixels. Segmentation is needed to improve the image contrast and reduce the noise levels. There are various forms of network architectures that can have performed segmentation. Here U-net algorithm has been adopted. The U-Net has CNN architecture for fast and accurate segmentation of images. This network combines Convolutional network architecture with a de-convolutional architecture to produce the segmentation. It is a grouping of De-convolutional network and Fully Connected Network (FCN)

Contracting: Figure.3 reveals the U-Net Architecture which consists of contracting path and an expansive path. The contraction section contains many convolutional blocks. Each block Receive an input and applies two convolutional layers of size 3x3 and followed by a Rectified Linear Unit (RELU) and a max-pooling layer of size 2x2. The number of channels or feature maps are doubles after each block so U-Net design can learn the complex images effectively. The bottom layer intermediates contraction and Expansion layers.

Expanding: Expanding layer also consists of many blocks. Each block passes the input to convolutional layer of size 3x3 and followed by a up sampling layer of size 2x2. After each block, the number of channels used by convolutional layer becomes half of a size. However, all the time the input is also appended by the channels of corresponding contraction layer. This integrated image is then led to a convolutional and RELU layer. Hence the cropping is required due to the loss of border pixels in every convolution. At the last layer, a 1x1 convolution is applied to map each 64 components feature vector to the required number of classes

Feature Extraction: Feature extraction is a method to extract the unique feature of the skin lesion from segmented image. In some articles small set of features or hand-crafted features were extracted but there is a chance to missing some accurate features. Convolutional neural networks automatically extract high level features effectively without the need of manual feature extraction task.CNN Architecture Convolutional Neural Network (CNN) is a best standard and dominant algorithm for deep learning in areas such as image recognition, segmentation and classification [16]. It consists of an input layer, an output layer and several hidden layers in the hidden layers in which the features are extracted. It performs three operations: Convolution, Pooling and Rectified Linear Unit (RELU). In Convolutional layer several convolutional filters are applied the input images; each filter activates certain features from the image. Pooling layer reduces the number of parameters by simplifying the output performance of nonlinear down sampling. Rectified Linear unit (RELU) helps for faster and effective training by changing negative values to zero and retaining positive values. Because of that the above three operations are repeated over hundreds of layers, with each layer learning to identify different features.VGG16-Net Architecture: The VGG16 network is a convolutional neural network model comprises 16 convolutional layers with 3x3 filter size, five max-pooling layers with 2x2 window size. A heap of convolutional layers is followed by three fully connected layers. Figure 4 shows architecture of VGG 16 network architecture. It consists of five convolutional blocks; first two blocks have two convolutional layers and one max-pooling

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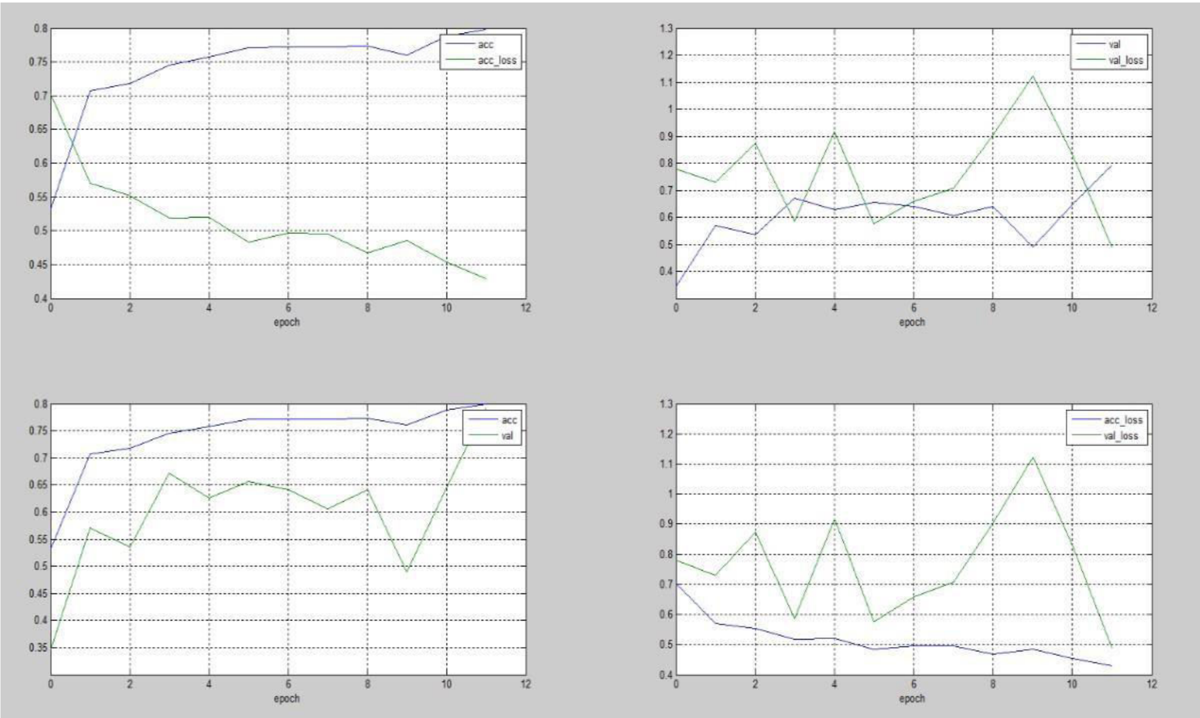
layer. Remaining three blocks have three convolutional layers and one max-pooling layer. The Input of first convolutional block is 240x240x3, because of RGB image the channel size is 3. Output of first block is 120x120 x 64 that is 64 channels. This feature map is fed into the input of second block and so on. For the coming blocks output is reduced half the size and the channel size is doubled. The final feature map produced by fifth block of size 7x7x512.

5. RESULT



6. APPLICATIONS

Some of the practical applications of image segmentation are:

- Medical imaging
  - ✓ Locate Tumors and other pathologies
  - ✓ Measure tissue volumes
  - ✓ Computer-guided surgery
  - ✓ Diagnosis
  - ✓ Treatment planning
  - ✓ Study of anatomical structure
- Locate objects in satellite images (roads, forests, etc.)
- Face recognition
- Iris recognition
- Fingerprint recognition

- Traffic control systems
- Brake light detection
- Machine vision
- Agricultural imaging – crop disease detection

7. CONCLUSION

The method is used to classify the pre-processed skin lesion images into normal and abnormal images. And it also defines what type of cancer it is. This method is proposed to reduce the manual segmentation time and increases the accuracy than that segmented by a physician.

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