Wn-Based Skin Cancer Lesion Segmentation of Melanoma Using Deep Learning Methods

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ABSTRACT

The incidence rate of skin cancer, particularly malignant melanoma, has risen to high levels during the last decades. The biopsy method used for cancer treatment was found to be a painful and time-consuming one. Also, laboratory sampling of skin cancer leads to the spread of lesions to other body parts. Due to the different colours and shapes of the skin, segmentation and classification of melanoma are more challenging to analyze. An automatic method of dermoscopic skin lesion detection will be introduced. Recognizing the skin lesions at an early stage is essential for effective treatment. Proposed an efficient skin cancer image segmentation method using Fixed-Grid Wavelet Network (FGWN) and developed a novel classification method using deep learning techniques. FGWNs constitute R, G and B values of three inputs, a hidden layer and an output. Input skin cancer image is segmented, and the exact boundary is determined accordingly. The features of the segmented images were extracted using the Orthogonal Least Squares (OLS) algorithm. The AlexNet model was first used to classify pictures of melanoma cancer. Next, ResNet-50 and Ordinary Convolutional Neural Networks (CNN) was deployed. Wavelet Network (WN)-Based segmentation achieved an accuracy of 99.78% in detecting skin cancer lesion boundaries. Ordinary CNN shows an accuracy of 93.37% for 100 epochs. ResNet-50 models show 88.37% accuracy for melanoma classification. The number of training epochs and the volume of training data both impact accuracy. Deep learning algorithms can significantly improve categorization efficiency.

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1. INTRODUCTION

The epidermis, the largest organ in the body, acts as a protective barrier against damage and disease. Furthermore, it regulates the body's core temperature and helps to avoid infections. Skin cancer can invade skin cells and alter their structure. The incidence of skin cancer has been increasing throughout the United States and much of the world. The leading cause of skin cancer is repeated exposure to ultraviolet (UV) rays. Skin cancer has two primary kinds. They exhibit both benign and malevolent characteristics. Melanocytes, or melanoma, are the cells that cause malignant skin cancer to develop. Another type of skin cancers, such as Kaposi Sarcoma, Cutaneous lymphomas, Merkel cell carcinomas, and Adnexal tumours, comes under the benign type. Melanoma is the most common type of cancer among Caucasian people around the world today.

A breakthrough regularizer algorithm precisely identifies skin lesions as benign or malignant, providing a revolutionary method of future prediction. The AUC-ROC, a novel regularizer [1], is used to analyze CNN performance in various situations. A fixed-grid wavelet network CAD system could detect melanoma in dermoscopy images. The D-Optimality Orthogonal Matching Pursuit (DOOMP) technique [2] improves the network model's approximate capacity, stability, and precision.

To maximize the CNN's performance, a redesigned iteration of the whale optimization technique was applied. The current optimization strategy seeks to reduce the discrepancy between the desired output and the Network's output [3] by selecting the best weights and biases for the Network [4]. A novel strategy for separating cutaneous lesions is developed by combining kernel graph cut segmentation with Neutrosophic C-Means (NCM) clustering. Many patterns that follow a Gaussian distribution can be used to extract particular properties and classify them into multiple categories efficiently. The GFAC model is capable of detecting early-stage melanoma skin cancer and analyzing dermoscopy images [5]. Deep Learning Studio (DLS) simplifies the development of intelligent models for data discovery. To create the appropriate model, use the drag-and-drop tool to choose and organize the relevant components [6]. A good segmentation mask helps to pull out specific features that describe the skin lesion, and a good registration technique let's to get a good idea of how the features are developing [7].

Shearlet transforms the breakdown of melanoma images. The shearlet coefficients are then selected from the deconstructed subbands—more specifically, 50, 75, or 100—a definite number of coefficients. The Naïve Bayes predictor [8] is immediately applied to the chosen sub band coefficients. Texture-based segmentation and classification using convolutional neural networks help detect skin cancer. A single convolutional neural network (CNN) in the context of deep learning was trained to extract properties from a photo using a grey-level co-occurrence matrix (GLCM). Two diagnoses using a gradient-boosting technique was combined to build a new classifier [9], [10]. The YOLOv8n model demonstrates potential for skin cancer prevention due to its initial development phase while offering better results than existing testing methods. This represents a beneficial outcome because YOLOv8n operates with amazing speed for image processing. Skin lesions detection uses dermoscopy images that link with deep learning models particularly convolutional neural networks known as CNNs [11] [12]. The research team conducted an organized evaluation of deep learning and self-service machine learning expression methods for diagnosing cancer. DenseNet-121 delivered a 90% accuracy level which surpassed other leading techniques by 10%. The research investigates and implements new machine learning together with deep learning computational approaches [12] [13]. Here is a proposed framework for the final sections of this work: This work can be described or organized as follows: Section 2 provides the related works. Section 3 provides a concise description of the dataset and strategies used. Section 4 examines and presents the experimental results. The report concludes with recommendations for future research.

2. RELATED WORKS

Numerous academics have devised diverse deep learning algorithms for the automated categorisation and detection of skin cancer in recent years. This book illustrates power with several examples. Melanoma screenings facilitated by computer assistance. The authors modified the CNN methodology using their proprietary automatic segmentation technique. The authors extracted characteristics using CNNs prior to their integration. Numerous observers deemed it implausible that the three-layer fully linked CNN network could operate independently as a classification model. The authors identified no secondary classifiers inside the SVM or KNN systems in their study. Transfer learning converted the skin cancer photos and their annotations into the Google Inception v3 format. Twenty-one qualified dermatologists evaluated biopsy-confirmed dermatological pictures.

Deep-learning convolutional neural networks demonstrated superiority over dermatologists in assessments of skin cancer utilising digital photos and dermoscopic examination data. This ensemble learning method, utilising a deep pretrained CNN, achieves diagnostic results comparable to those of professional dermatologists in the detection of dermatological lesions [15]. The artificial intelligence attained an accuracy of 84.8% in diagnosing seborrhoeic keratosis and 93.6% in identifying melanoma after analysing 2,000 picture samples from the 2000 ISIC 2017 dataset. An expert advocated for the utilisation of dermoscopy as a diagnostic instrument for melanoma, as referenced in [13] [16]. Table 1shows the challenges and features of Melanoma Detection Models

The investigation of thin effect attenuation utilised three distinct testing methodologies. Experts assess two distinct methodologies for the evaluation of skin lesions in their comparative analysis. Various melanoma forms may be swiftly categorised based on their distinct cellular characteristics. The strategy improves melanoma identification. The CNN model demonstrated superior accuracy and sensitivity compared to existing approaches, as indicated by ROC curve analyses [17] [18].

Table 1. Comparison of Melanoma Detection Models

Author	Challenges	Methods	Features
Dascalu and David [14]	Demands analysis of a sizable patient population.	NN	Accuracy is improved
Zanddizari et al. [15]	Smaller input size offers lower accuracy	MultiResUnet	Reduces inference
Balazs [16]	Both public & private image sets pose no problem	DCNN	Maximum accuracy
Mahbod et al. [17]	No attention was paid to the capacity for generalization	CNN	Constancy is better
Teck et al. [18]	Examination of alternative databases is necessary	PSO	Cost is lowest
Teck et al. [19]	Attention must be directed towards the optimal network parameters	PSO	Computational cost is low
Xie et al. [20]	No difficulties with semantic segmentation are present	CNN	Highly resilient Noise reduction
Alfed and Fouad [21]	Ambiguous regarding the orientation of the edges	SRM Algorithm	Accuracy is developed
Aima et al. [22]	A substantial dataset is necessary	CNN	Better accuracy
Zhang et al. [3]	Enhanced time utilization	CNN	Sensitivity is improved

3. PROPOSED METHODOLOGY

The block diagram for the proposed methodology is shown in Figure 1.

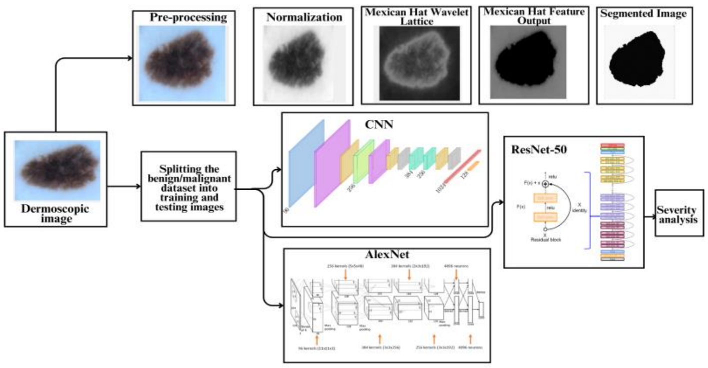

Figure 1. Overall Block Diagram of the Proposed Methodology

To evaluate skin lesion segmentation and classification algorithms, a Database from ISIC Archive, an international repository of dermoscopic images was considered. Then, skin lesions were segmented using the FGWN method. Features were extracted using classifiers such as CNN, ResNet-50, and AlexNet, respectively.

At the MICCAI 2019 conference in Spain, part of the International Skin Imaging Collaboration (ISIC) programme, participants contributed 12,500 photos, with 900 users enrolled. The precision of segmentation algorithms is inadequate since they inaccurately identify over 10% of images. Hence, researchers cannot depend on automated systems in healthcare environments [23]. A publicly accessible dataset including the information found at https://www.nature.com/articles/sdata2018161

A database of skin images from around the world can be created using the ISIC Archive. A dermoscopy is more accurate for diagnosing skin cancer than a naked-eye examination. On the other hand, doctors must acquire the necessary knowledge to realize such benefits. The International Skin Imaging Collaboration (ISIC) launched the ISIC Archive to make resources more accessible to a broader audience. The ISIC Challenges allow participants to investigate automated algorithmic analysis's technical and clinical aspects. The ISIC Archive has 25,331 photographs divided into eight unique categories, 2,286 of which are available for teaching purposes and include benign and malignant skin lesions from 6,000 images. Training on 5,000 images—70% of the entire collection—created the categorization system. The evaluation utilized a total of 2,400 pictures.

3.1. Segmentation using Wavelet Network

Wavelet networks integrate neural networks with wavelet functions to excel in the processing of temporal and frequency-based data. The wavelet functions serve as activation functions throughout the computing process for analysing data at different resolutions. Wavelet examines the various frequency components of incoming signals to identify patterns across several layers of resolution. The neural network design converts an input picture into output identifiers by using wavelet basis functions. Wavelet networks enhance lesion segmentation due to their robust pattern recognition capabilities within intricate data frameworks. The subsequent part presents a mathematical depiction of the wavelet network and its development process, along with equations elucidating the impacts of parameters. The basic wavelet is scaled as:

$$\psi_{m,n}(x) = \frac{1}{\sqrt{a}}\, \psi \frac{x-b}{a} \tag{1}$$

Where a is scale (dilation), and b is translation (shift).

The theory of wavelets and neural Networks combines wavelet neural Networks into one. A feed-forward neural network consists of an input layer (or layers), a hidden layer, and an output layer. The structure of FGWN can be shown in Figure 2.

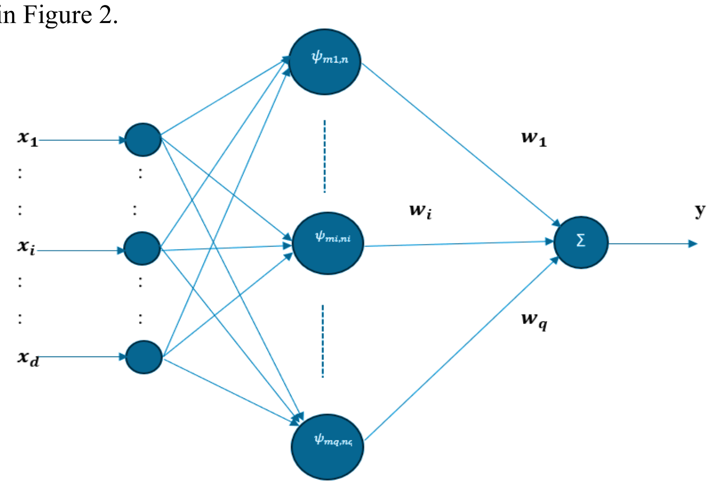

Figure 2. Basic Structure of Wavelet Network

Output value y can be expressed in terms of d inputs, q waves in the hidden layer and vector x = (x1, x2, …xd) T as shown in equation 2 [1].

$$y = \sum_i^d \psi_{m_{i,}n_j}(\mathrm{X}) = \sum_{i=1}^d w_i 2^{\frac{-m_i d}{2}} \psi(2^{m_i}\, X - n_j) \tag{2}$$

Where w_i the weight coefficients $\psi_{m_{i,}n_j}$ are dilated and translated versions of a mother wavelet function ψ. $\psi_{m_{i,}n_j}$ are scale and shift parameters. Implementation of WN could be possible with the help of the Mexican Hat Radial mother shown below in wavelet equation 3 [1].

$$y = \sum_i^d \psi_{m_{i,}n_j}(\mathrm{X}) = \sum_{i=1}^d w_i 2^{\frac{-m_i d}{2}} \psi(2^{m_i}\, X - n_j) \tag{3}$$

Where d indicates the value of the dimension, considering minimum and maximum values of scale and shift parameters, a spatial wavelet lattice can be formed. Two stages of screening follow the formation of a wavelet matrix. The orthogonal least squares algorithm helps to optimize the redundant members present in the wavelet matrix. Effective wavelets can be obtained by selecting the best subset from the matrix, and one wavelet is made orthogonal to another wavelet.

The FGWN has three origins: a buried layer and an outcome. Its network inputs are based on three colour matrix values. These grids connect the photos selected for the segmentation process. In this way, the FGWN is formed for effective segmentation, as shown in Figure 3.

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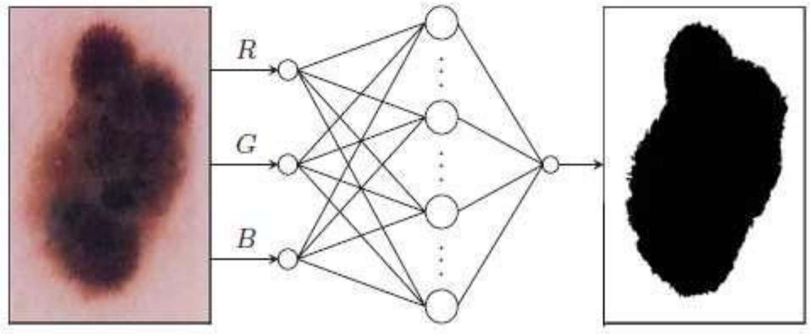


Figure 3. FGWN for segmentation of dermoscopic images

3.2. Classification using Deep Learning Models

One can create a complete model capable of converting raw medical image pixels into definitive categorization labels using continuous deep-learning approaches. Image processing is one of the many artificial intelligence applications, often known as artificial neural networks. A cutting-edge deep learning solution was aim to utilize three distinct deep network architectures for the automated analysis and classification of dermoscopic images. They are CNN, ResNet-50 and AlexNet, respectively.

3.3. Convolutional Neural Network

The architectural resemblance between conventional neural networks and convolutional neural networks (CNNs) is quite apparent. Their neurons can detect shifts in biases and weights. Every neuron absorbs data, analyzes it using the dot product, and exhibits linear or nonlinear activity. A deep convolutional neural network's first image follows an organizing pattern. To make the images smaller, keep the number of pooling layers minimum. Max pooling was used to retrieve the most significant element from the new feature map. The local Response Normalization layer is functional when dealing with Rectified Linear Units (ReLU) neurons. Also, it detects high-frequency features with a significant response. Fully connected layers are placed before the output of a CNN.

3.4. ResNet-50 Architecture

The Residual Network is 50 layers deep and can classify images into 1000 object categories. It has evolved to precisely display the minute details of several images. The Network is based on photos measuring 224 by 224 pixels. ResNets are somewhat adaptable; however, it's important to note that the training error of the initial stack layers grows with network depth. When pushed further, ResNets show significant improvements in performance and accuracy.

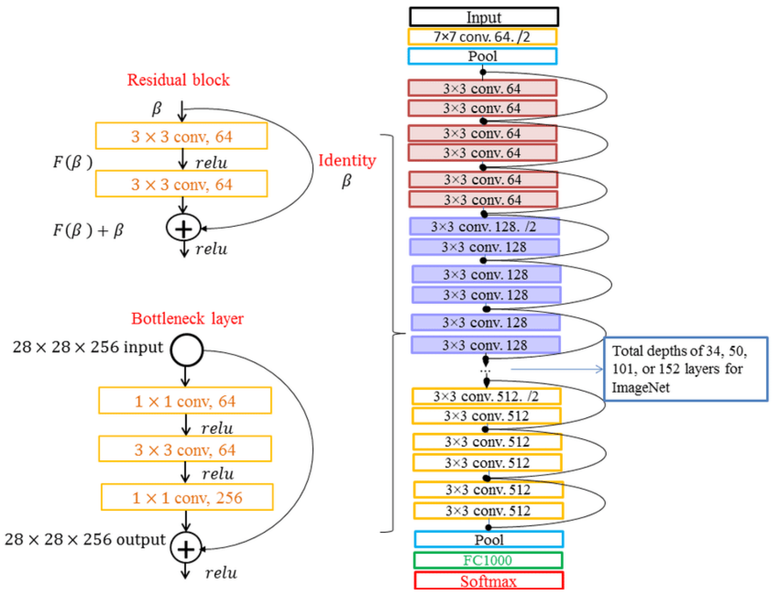


Figure 4. Overview of Resnet-50 Architecture

Figure 4 depicts the Resnet-50 model's architectural composition. Stacked residual blocks heavily influence ResNet's design. Each of the remaining blocks is marked with two 3x3 convolutional layers. The approach helps to reduce spatial information by employing 128 filters and two-fold step size. We precisely altered a residual mapping using network levels rather than simply attempting to replicate a desired underlying mapping. Additional convolutional layer was added followed by a global average pooling layer after the last convolutional layer. With a momentum and decay rate of 0.9, the optimizer will use the stochastic gradient descent (SGD) algorithm to normalize the groups after each convolutional layer.

3.5. AlexNet Architecture

The eight-layer Network can classify items into a thousand different groupings. In addition to convolution layers measuring 11x11, 5x5, and 3x3, the model contained dropout, ReLU activations, and max pooling layers. The final five layers comprise three ultimately linked layers and five convolutional layers. A 1000-way softmax layer evenly divides the output of the final entirely linked layer among all 1000 class names. The overview of AlexNet is shown in Figure 5.

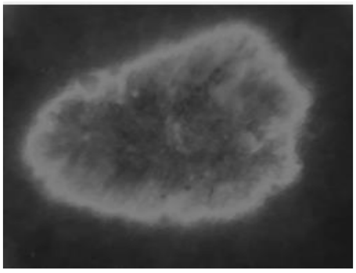
Figure 5. Overview of AlexNet Architecture

4. RESULTS AND DISCUSSION

The proposed algorithm is implemented using the MATLAB R2019a version, and dermoscopic image segmentation and classification results have been obtained. The input images were collected from the ISIC Archive Database. Initially, the image will be pre-processed for segmentation using Wavelet Network. Figure 6 shows the tabulated stepwise segmented output of the input skin lesion images.

Input dermoscopic image

Wavelet Lattice output



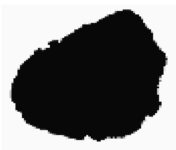
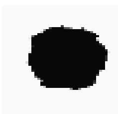
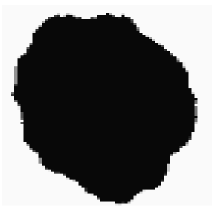
Mexican Hat Feature Output

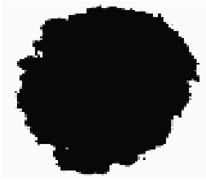
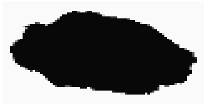
Segmented Image

Figure 6. Stepwise segmentation of dermoscopic Images using FGWN method

The FGWN method follows the formation of wavelet lattices, and the network weights are optimized using the OLS algorithm. It can be concluded that it is a less time-consuming analysis method for skin cancer detection with accurate lesion boundaries.

Table 2. Performance measure of segmented images

FGWN SEGMENTATION	**ACCURACY (in %)**			
SEGMENTED IMAGE	TRAINING	VALIDATION	TEST	AVERAGE
	99.874	99.884	99.886	99.877
	99.815	99.813	99.826	99.816
	99.967	99.968	99.969	99.968

	99.875	99.879	99.874	99.876
	99.924	99.923	99.928	99.925

It can be seen that an exact lesion boundary was obtained for input dermoscopic images with a maximum accuracy. The FGWN segmentation method provides better results than conventional methods in terms of accuracy. The time taken for the segmentation of each input image is 02, 03, and 04 seconds, respectively. It is a fast-segmenting method.

A range of classification algorithms was experimented, varying the number of epochs and the volume of training data to determine the technique with the highest degree of accuracy. Classification of 6,000 out of a total of 2,286 images as malignant (carcinogenic) and 5,800 as benign (innocuous) were performed. The analysis included a total of 2,486 pictures. The CNN training data consisted of fifty epochs, whereas the other part used one hundred epochs. The Base Learning Rate for training is around 1.000e-04.

Table 3. Performance of CNN Classification with 50 Epochs

Epochs	Iteration	Time Elapsed	Mini Batch Accuracy	Mini Batch Loss	Accuracy
1	1	00:00:04	38.72%	5.9447	83%
50	800	00:52:49	98%	0.502	

Table 4. Performance of CNN Classification with 100 Epochs

Epochs	Iteration	Time Elapsed	Mini Batch Accuracy	Mini Batch Loss	Accuracy
1	1	00:00:04	38.72%	7.5643	93.37%
100	800	01:37:53	98%	0.0106	

Table 3 and 4 infers that as the epochs used for training increase, accuracy also gradually increases from 83% to 93.37%. The number of epochs should be increased to get better classification results. Figure 8 shows CNN classification testing for different classes of input images, such as benign and malignant forms.

INPUT TEST IMAGE **OUTPUT**

Figure 7. CNN Classification Testing Output

Features can be learned from skin lesion images using the deep CNN Model. For better classification, skin shape, colour, and size were the learnable features. The performance of the CNN classifier is shown in Figure 8.

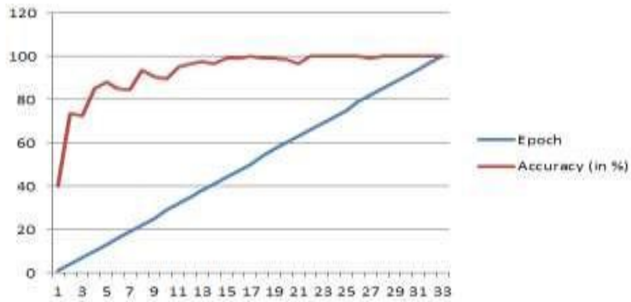


Figure 8. CNN Classification Accuracy vs. Epoch

Based on different parameters, ResNet-50 classifies the skin lesion images into benign and malignant, with 88.37% accuracy. Zero centre normalization was used, and the hyper parameter included a cross-entropy loss function. ResNet testing classification outputs are shown in Figure 9. From figure 9 it is observed that the results of the proposed method of malignant and benign are improved when compared with ref [8].

INPUT IMAGE	**RESULTS**	**ACCURACY Ref [8])**	**ACCURACY (Proposed)**
	Malignant	78.46%	87.21%
	Benign	77.65%	88.37%
	Malignant	76.85%	88.34%

Figure 9. ResNet classification outputs for different lesion images

ResNet provides less training classification accuracy than testing. The pre-trained AlexNet model shows better classification accuracy than other trained models. The column represents the target class, whereas the row represents the production class. The diagonal corresponds to consistent observations of cohesiveness. The erroneously assigned off-diagonal data is displayed. Each matrix column reflects the total number of observations and their corresponding shares.

The top two diagonal cells display the number of observations and the percentage of data correctly classified by the trained AlexNet. Label 1 represents the Benign class (consisting of 460 images), and Label 2 represents the Malignant class (consisting of 287 images). Figure 10 shows the Confusion Matrix. The model's predictions are illustrated in the following confusion matrix. TP results signify precise diagnosis of melanoma lesions, whereas TN, FP, and FN denote three categories of erroneous outcomes [1]. The three error types during evaluation consist of true negative outcomes, false positive results, and false negative results. The classification of a lesion as non-melanoma is deemed a genuine negative, whereas lesions misidentified as melanoma are classified as false positives, and the erroneous classification of non-melanoma as melanoma constitutes false negatives. The confusion matrix illustrates how accuracy quantifies the count of correctly detected true instances.

$$Precision = \frac{TP}{(TP+FP)} \tag{4}$$

Recall and sensitivity, denotes the model's capacity to recognize true positive instances.

$$Recall = \frac{TP}{(TP+FN)} \tag{5}$$

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} \tag{6}$$

The F1-score is a singular metric that evaluates both precision and recall.

$$F1\ Score = \frac{2*(Precision*Recall)}{(Precision+Recall)} \tag{7}$$

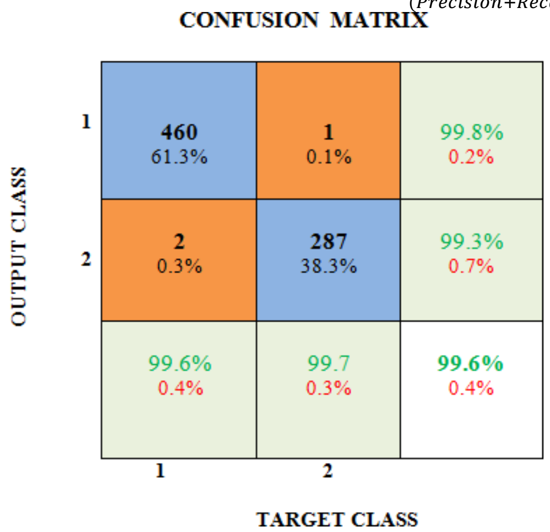


Figure 10. Confusion Matrix

Figure 11 shows a plot of deep learning models in terms of accuracy. Three deep learning models provide satisfactory results for classifying dermoscopic images as benign and malignant. The ISIC Archive contained 6,000 benign and 2,286 malignant images. The data can be split into training and testing data. Seventy per cent of the images were used for training, and the remaining were used for testing. AlexNet shows promising results compared to the other two methods

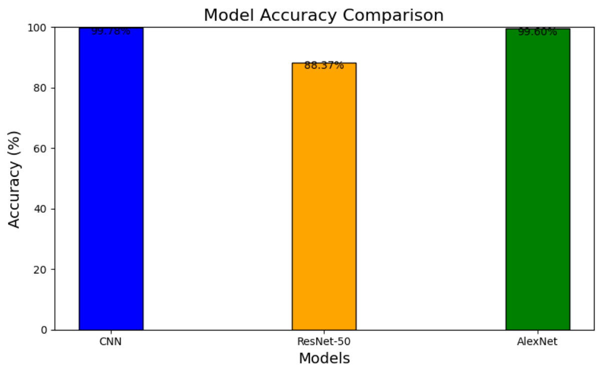


Figure 11. Classification Performance Analysis of Deep Learning Models

5. CONCLUSION

An efficient skin cancer image segmentation method was presented and developed a novel deep learning-based solution to solve the melanoma classification problem. The identification of skin cancer presents several challenges, since erroneous negative diagnosis can be very detrimental, while false positive screens incur significant expenses. The trained AlexNet correctly identifies the top two diagonal cells, revealing the number of observations and the percentage of data. Several deep-learning approaches were used after the first segmentation stage to determine whether skin lesions are benign or cancerous. Using an effective Wavelet Network, the segmentation algorithm correctly extracts the skin lesion boundary. The features of the segmented images were extracted using Orthogonal Least Squares Algorithm. Segmentation achieved an accuracy of 99.78% in detecting skin cancer lesion boundaries. CNN, ResNet-50, and AlexNet One all performed similarly in categorizing melanoma cancer pictures. The classification findings show that the length and frequency of training data affect melanoma categorization accuracy. Improvement of test results by using more data for training can be done. To acheive the highest level of precision, select a time period of 100 epochs. In this way, Ordinary CNN shows an accuracy of 93.37% for 100 epochs. The experimental results indicate that operating this approach incurs little expenditures.

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I want to acknowledge this manuscript has not been published elsewhere.

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