International Journal of Scientific Research in Engineering and Management (IJSREM)
Volume: 07 Issue: 03 | March - 2023 Impact Factor: 7.185 ISSN: 2582-3930

IMAGE PROCESSING OF SKIN CANCER DETECTION IN MATLAB USING GLCM AND SVM

Aakash.G , Adhithya.R , Barathwaj.T , Kandhaguru.M

Abstract – The incidence of skin cancer is high and rising worldwide, a trend that is likely to continue given the importance of solar ultra-violet as a cause and the modern propensity to indoor lifestyle with sun-seeking holidays. Malignant melanoma is the most deadly form due to its rapid development, invasion, and metastasis cycle. Early diagnosis is paramount as prognosis is greatly improved where the tumour is excised quickly. Many common benign pigmented skin lesions can resemble early melanomas. The primary objective of this work is cancer classification from melanoma images using deep learning model.

Keywords: Skin Cancer, K-Means, DRLBP, CNN.

1. INTRODUCTION

One of the primary causes of death in many nations is CANCER, which poses a serious concern on a global scale. By 2020, India is expected to have over 17.3 lakh new cases of cancer and over 8.8 lakh cancer-related fatalities, with breast, lung, and cervix cancers topping the list. This prediction was made by the Indian Council of Medical Research (ICMR) in 2016. The stage of the cancer at the time of diagnosis affects the survival rate. Therefore, an early diagnosis is very essential for properly treating the patients and also thereby reducing the mortality rate.

Skin cancer is the majority widespread form of cancer (American academy of Onto laryngology). The malignant cancerous cells appear in the surface of our skin leads to skin cancer. The percentage of all skin disease under basal cell carcinoma is 70 % and under squamous cell carcinoma it is 20%, which are arranged as non melanoma skin tumour. Melanoma (5%) is another kind of skin disease. Though it is in less percentage it is potentially much more serious than other types, which are highly hazardous and causes majority deaths. It takes up uneven borders and shapes with multi colors. In the current world, just about 3 million non-melanoma skin malignancies and 132,000 melanoma skin growths happen worldwide consistently (World Health organization). One in each three diseases broke down is a skin malignancy. In parallel, because of the exhaustion of ozone layer, coordinate sun based UV radiation enters the earth. According to a review, an expansion of 300,000 non-melanoma and 4,500 melanoma skin tumors will take place as a result of 10% decline in ozone levels.

The rest of the essay is organised as follows: Section presents the review of the literature. II. In
Section III, the system methodology is covered. Section IV of the report discusses the experiments' results. Section V contains the conclusion.

2. LITERATURE REVIEW

According to the classification of melanoma, Sáez et al. (2015) discussed pigment network features as well as colour, texture, and shape features. For the classification, learning methods like ordinal regression and logistic regression are

applied. (Xie et al. 2016) describes a NN ensemble model for the categorization of dermoscopic images. A selfgenerating NN is initially used to segment skin lesions. Then, feature descriptors are extracted, including colour, form, and texture. A A network ensemble approach that combines fuzzy-based networks with back-propagation is utilised for classification.

Yu et al. (2016) discussed an approach for skin lesion segmentation and classification using Convolutional Neural Network (CNN). A fully convolution residual network is used for segmentation, and for classification, a deep residual network is used. The degradation problem is avoided by sung residual learning. Symbolic regression algorithm-based skin lesion classification is described (Celebi & Zornberg 2014). It uses clinically significant colors to compute the malignancy scores. K-means clustering approach is used to reduce the number of colors in the given dermoscopic images.

Esteva et al. (2017) analyzed the most common human malignancy. Skin cancer is primarily diagnosed visually at the beginning of the skin disease with initial clinical screening followed by dermoscopy analysis, potentially using biopsy and histopathology investigation. Due to the fine-grained variety in how skin lesions develop, automatically classifying skin lesions using dermoscopy images is a difficult challenge.

The deadliest type of skin cancer, melanoma, develops from abnormal cell proliferation in pigmented skin lesions (Fidan et al. 2016). Melanoma accounts for 4% of all skin cancer deaths, or 75% of the overall mortality rate. Using AI techniques, a

skilled dermatologist employs the dermoscopy method to categorise skin lesions as melanoma, atypical skin, or normal skin. As the supporting system for decision-making that uses improvement of the diagnostic speed and accuracy, it assists in choosing the expert dermatologists in the diagnosis of melanoma skin cancer. The ANN system model for classifying skin lesions efficiently distinguishes between normal and pathological lesions using datasets from the PH2 database. The decision support system accurately classifies abnormal and melanoma skin cancer illness when used to diagnose skin lesions.

The pattern recognition classification technique presented by Sundar et al. is essentially used in the analysis of melanoma, the lethal skin cancer that may be detected early utilising skin lesion identification (2016). Multiclass SVM feature extraction and identification can be used to identify melanoma early by extracting features from the input signal and categorising them using a pattern matching model.

The back-propagation NN used to recognise texture and colour features based on the weighted least squares framework for skin cancer classification was investigated by Choudhury et al. in 2015. This approach's main benefit is the edge-preserving decomposition information that the normalised symmetrical GLCM algorithm adds to the original image's enhanced colour layer. The NN-based Extreme Learning Machine (ELM) model is also created using the histogram of directed gradients approach.

Duan et al. describe the automated basal cell carcinoma in mouse skin (2014). It uses an SVM classifier that is based on the polarisation sensitivity approach to demonstrate the accuracy of non-invasive skin cancer detection. The framework that selects the most pertinent feature subsets at each hierarchy node is used to decompose the classification task using the hierarchical structure.

3. SYSTEM METHODOLOGY

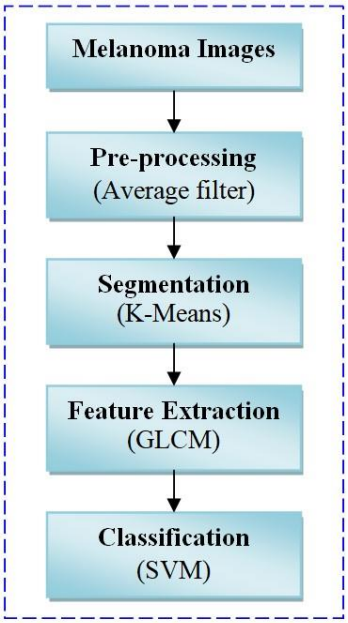

Figure 1 System Architecture

3.1 Segmentation

The segmentation process is used to partition the abnormal part from the normal part. On the RGB colour image, the precise skin cancer location is segmented using the k-means clustering method. Prior to segmentation, the hair and noise in the average filter with a preset window size of 21x21 removes pictures. Grayscale photos are segmented using the fundamental k-means clustering technique. It is updated to accept colour images because dermoscopic images are colour images and the colour information is highly helpful for extracting skin lesions. L*a*b* colour space makes the visual differences easier to quantify than RGB mode. Figure 5.3 shows the three channels of L*a*b* colour space of the input RGB image. The k-means clustering algorithm is widely applied in many medical image processing applications using grayscale images. More information about the k-means clustering algorithm can be obtained from. The steps to compute k-means clustering (k=3) for skin lesion segmentation are given below:

1. Randomly choose three initial clusters $(m_1^{(1)}, m_2^{(1)} and\, m_3^{(1)})$. The superscript identifies the initial cluster number.

2. The k-means clustering proceeds with two steps; assignment and update step.
   These steps are iterated until it converges in the update step when the assignment no longer changes.
   a. Assignment step: In this step, each observation (z_p) is assigned one of the clusters (C), which have the least squared Euclidean distance. Thus each observation (z_p) is assigned to exactly one cluster $(C^{(t)})$. It is defined by

$$C_i^{(t)} = \left\{ z_p : \left\| z_p - m_i^{(t)} \right\|^2 \le \left\| z_p - m_j^{(t)} \right\|^2 \ \forall j, 1 \le j \le 3 \right\}$$

   b. b. Update step: The means of the observations (z) in the new clusters are updated in this step. $(C_i^{(t)})$.

$$m_i^{(t+1)} = \frac{1}{\left| C_i^{(t)} \right|} \sum_{z_j \in C_i^{(t)}} z_j$$

3.2 Feature Extraction

Features from three categories are employed in the skin cancer diagnosis. This work used GLCM feature for skin cancer classification.

GLCM FEATURES

The first order statistics of an image, which are concerned with the characteristics of individual pixels, are obtained using the mean and the standard deviation of an image. The Gray Level Cooccurrence Matrix (GLCM), which is based on the spatial interdependence or co-occurrence of two pixels at specified relative locations in an image, is where the second order statistics are produced from. Angles of 0^0, 45^0, 90^0 and 135^0 are assessed for these co-occurrence matrices. Features of second-order statistics

These characteristics rely on the spatial cooccurrence or interdependence of two pixels at particular relative locations in a picture. A matrix that is constructed over an image and that displays the distribution of co-occurring values at a specific offset is known as a co-occurrence matrix. According to mathematics, a co-occurrence matrix of an image
(m,n) is defined as

$$C_{\Delta x,\Delta y}(i,j) = \sum_{p=1}^{n}\sum_{q=1}^{m}\begin{cases}1, & if\ I(p,q) = i\ and\ I(p+\Delta x, q+\Delta y) = j\\ 0, & otherwise\end{cases}$$

The information about the pixel places with comparable grey level values is included in GLCM. The rows and columns of this matrix indicate the variety of picture grey levels. The frequency of the grey levels I and j occurring at a particular distance and in a specific direction, such as 0^0, 45^0, 90^0 and 135^0 degrees, is represented by the value P(i,j) stored at the point (i,j).

3.3 Classification

The melanoma photos were classified into normal and abnormal categories using SVM. **Support Vector Machine (SVM)**

The most effective learning method for categorizing text texts is an SVM. It is founded on the computational learning theory's structural risk reduction concept. This principle's major objective is to identify the hypothesis values with the lowest error rate possible. In this study, the linear kernel threshold function is employed. Unlike the other classifiers, this one requires both positive and negative training sets. The decision surface is sought using these positive and negative training sets. It will distinguish the positive from the negative and the positive from the negative data in the high-dimensional feature space, also known as a hyper plane.

Algorithm: SVM Classification Algorithm

Input: Melanoma Images

Output: Classified Melanoma Images.

Procedure:

Step 1: Find the samples with minimum value of K

Step 2: Train SVM model on the k selected samples

Step 3: Classify the documents based on SVM probability

$$min\ \frac{1}{2}\ \| w \|^2$$

Subject to $y_i(w^T x_i + b) - 1 \geq 0\ \forall i = 1,2, \dots, N$

Step 4: Make the Decision using t

4. RESULTS AND DISCUSSION

4.1 Data set

Publicly accessible melanoma image databases, including PH2, are used to analyze the proposed approach. It is very beneficial for the development and assessment of any computerized system for categorizing skin cancer. In the first stage, the melanoma images are sorted using the method into normal and abnormal categories, and in the second stage, they

are classed as benign or malignant. Table 1 contains a collection of the various information about the databases.

Table 1 Details about the PH^2 database

Description	Parameters
Name of the Database	PH^2
#Normal images	80
#Benign images	80
#Malignant images	40
#Resolution	768x560
#type of images	RGB

Table 2 Performance of Proposed CNN

Performance Factors	Ratio
Precision	81.57
Recall	80.50
F-Score	82.24
Training Accuracy	82.10
Testing Accuracy	82.74

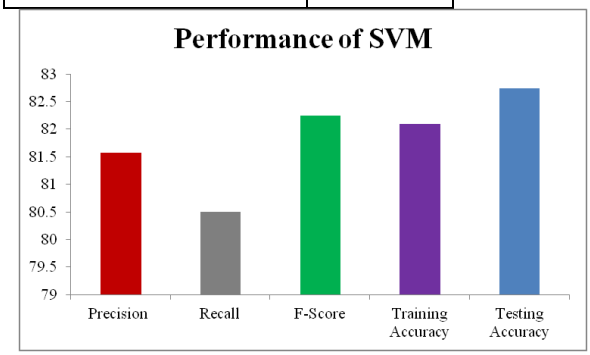

Figure 4 Performance of Proposed SVM

Table 2 and Figure 4 represented Performance of Proposed SVM using various performance factors.

Table 3 Comparative study of proposed SVM with existing systems

Author	Database	No. of Images used	A_c	S_n	S_p
Abuzaghleh *et al.* 2015	PH^2	200	-	97.5	96
Xie *et al.* 2016	PH^2	360	91.1	83.3	95
Nasir *et al.* 2018	PH^2	200	97.5	97.7	96.7
Hekler *et al.* 2019	PH^2	200	87.33	87.08	88.13
Maron *et al.* 2019	PH^2	200	90.50	90	91.25
Rodrigues *et al.* 2020	PH^2	200	95.3	95	96.25
SVM	**PH^2**	**200**	**97.75**	**97.59**	**97.86**

Table 3 shows Comparative study of proposed SVM with existing systems. For performance analysis, the same set of training and testing images are used for the analysis.

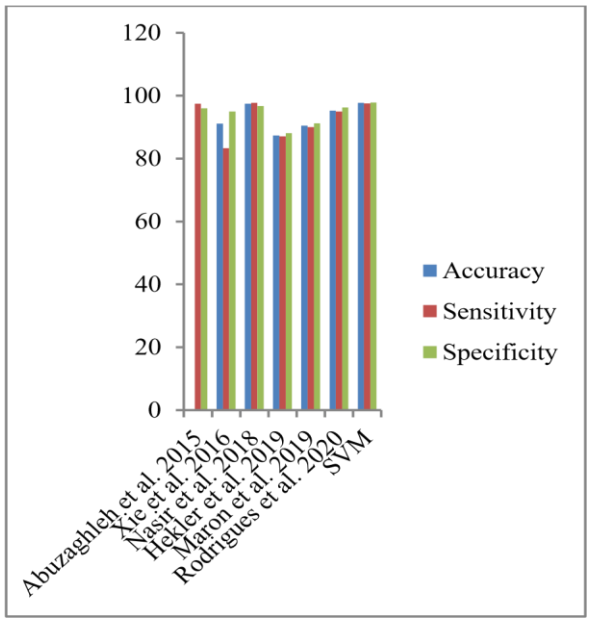

Figure 5 Performance analysis of existing and proposed work

5. CONCLUSION

The value of an automated pattern recognition system for skin cancer diagnosis is reflected in the considerable research interest in this area, particularly concerning melanoma image classification. Size, border irregularity, notching, and asymmetry are a few of the key diagnostic factors that have been found for the clinical assessment of melanoma malignancy. This work used cancer classification from melanoma images using deep learning model. From the performance analysis, it is observed that the proposed SVM algorithm gives better classification results than existing algorithms.

References

[1] Alberto Prieto, Beatriz Prieto, Eva Martinez Ortigosa, Eduardo Ros, Francisco Pelayo, Julio Ortega & Ignacio Rojas 2016, 'Neural Networks: An overview of early research, current frameworks and new challenges', International journal of Elsevier on Neuro computing, pp. 242-268.

[2] Amit Mehta, Arjun Singh Parihar & Neeraj Mehta 2015, 'Supervised Classification of Dermoscopic Images using Optimized Fuzzy Clustering based Multi-Layer FeedForward Neural Network', IEEE International Conference on Computer, Communication and Control, pp. 1-6.

[3] Fuyong Xing, Yuanpu Xie & Lin Yang 2016, 'An Automatic Learning-Based Framework for Robust Nucleus Segmentation', IEEE Transactions on Medical Imaging, vol. 35, no. 2, pp. 550 -566.

[4] Giap Hoang Nguyen, Jin-Ho Shin & Won-Ho Kim 2015, 'Auto tuning Controller for Motion Control System Based on Intelligent Neural Network and Relay Feedback Approach', IEEE/ASME Transactions on Mechatronics, vol. 20, no. 3, pp. 1138-1148.

[5] Hu, H, Guan, Q, Chen, S, Ji, Z & Yao, L 2015, 'Detection and Recognition for Life State of Cell Cancer Using Two-Stage Cascade CNNs', IEEE/ACM Transactions on Computational Biology and Bioinformatics, vol. 14, no. 8, pp. 1-12.

[6] Jiang, H, Ma, H, Qian, W, Gao, M & Li, Y 2017, 'An Automatic Detection System of Lung Nodule Based on Multi-Group Patch-Based Deep Learning Network', IEEE Journal of Biomedical and Health Informatics, vol. 22, no. 4, pp. 1227-1237.

[7] Li, C, Zhu, G, Wu, X & Wang, Y 2018, 'False-Positive Reduction on Lung Nodules Detection in Chest Radiographs by Ensemble of Convolutional Neural Networks', IEEE Access, vol. 6, pp. 16060-16067.

[8] Qiang Liu, Ming Gao & Qijun Zhang 2016, 'KnowledgeBased Neural Network Model for FPGA Logical Architecture Development', IEEE Transactions on Very Large Scale Integration (VLSI) Systems, vol. 24, no. 2, pp. 664-677.

[9] Saha, M & Chakraborty, C 2018, 'Her2Net: A Deep Framework for Semantic Segmentation and Classification of Cell Membranes and Nuclei in Breast Cancer Evaluation', IEEE Transactions on Image Processing, vol. 27, no. 5, pp. 2189-2200.

[10] Salvatore Caorsi & Claudio Lenzi 2015, 'Skin removal techniques for breast cancer radar detection based on Artificial Neural Networks', Proceeding of IEEE conference on Microwave Symposium, pp. 1-4.

[11] Sarikaya, D, Corso, JJ & Guru, KA 2017, "Detection and Localization of Robotic Tools in Robot-Assisted Surgery Videos Using Deep Neural Networks for Region Proposal and Detection," IEEE Transactions on Medical Imaging, vol. 36, no. 7, pp. 1542-1549.

[12] Shell, J & Gregory, W 2017, 'Efficient Cancer Detection Using Multiple Neural Networks', IEEE Journal of Translational Engineering in Health and Medicine, vol. 5, pp. 1-7.

[13] Wang, Z, Liu, C, Cheng, D, Wang, L, Yang, X & Cheng, K 2018, 'Automated Detection of Clinically Significant Prostate Cancer in mpMRI Images Based on an End-to-End Deep Neural Network', IEEE Transactions on Medical Imaging, vol. 37, no. 5, pp. 1127-1139.

[14] Yap, M, Pons, G, Marti, J, Ganau, S, Sentis, M, Zwiggelaar, R, Davison, A & Marti, R 2017, 'Automated Breast Ultrasound Lesions Detection using Convolutional Neural Networks', IEEE Journal of Biomedical and Health Informatics, pp. 1-9.

[15] Yu, L, Chen, H, Dou, Q, Qin, J & Heng, PA 2017, 'Integrating Online and Offline Three-Dimensional Deep Learning for Automated Polyp Detection in Colonoscopy Videos', IEEE Journal of Biomedical and Health Informatics, vol. 21, no. 1, pp. 65-75.

[16] Zhang, L, Lu, L, Nogues, I, Summers, RM, Liu, S & Yao, J 2017, 'DeepPap: Deep Convolutional Networks for Cervical Cell Classification', IEEE Journal of Biomedical and Health Informatics, vol. 21, no. 6, pp. 1633-1643.

[17] Zhang, R, Zheng, Y, Mak, TWC, Yu, R, Wong, SH, Lau, JYW & Poon, CCY 2017, 'Automatic Detection and Classification of Colorectal Polyps by Transferring Low-Level CNN Features From Nonmedical Domain', IEEE Journal of Biomedical and Health Informatics, vol. 21, no. 1, pp. 41-47.