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Analysis of Melanoma Lesion Images using Feature Extraction & Classification Algorithms

Manjunath Rao, Calvin Joshua Fernandez, Sreekumar K.

Abstract: Among the most dangerous of cancers found in human beings, skin cancer is the prevalent one. These are of various forms. The most sporadic among them is melanoma. Early phase identification of melanoma will be helpful in curing it. Intensive skin exposure to UV radiation is the principal cause of melanoma. In this article, along with other techniques for extracting features (LDP [Local Directional Patterns], LBP [Local Binary Patterns], Convolutional Neural Networks [CNN]), we have used an SVM classifier for the study of melanoma skin photos. Such suggested algorithms are best graded when opposed to other recognition schemes. The LBP and LDP gives us means to extract features; these figures are subsequently used for identification of derived features from these methods or algorithms and classified or separated by the SVM (Support Vector Machine) classifier. For many of the classifications of melanoma skin images using these algorithms, we have accuracy nearly above 80 %, whereby the LBP system together with the SVM classifier was the most powerful attribute extraction tool of the three with their polynomial kernel type. Thus using this algorithm-classifier, the melanoma skin lesion images can be detected and diagnosed by the doctors in its early stage itself, resultantly, helping save lives.

Keyword: Lesions, melanoma, benign, algorithms, classification, SVM, LBP, LDP, CNN, feature extraction.

I. INTRODUCTION

Melanoma may be a lethal carcinoma and although it constitutes fewer than 4% of all carcinomas, it accounts for a larger percentage of all skin cancer deaths [1]. At diagnosis the size of melanoma could be a primary determinant of the outcome of the patient[2]. Melanoma will be healed when diagnosed and treated early, but when diagnosis is late, it can spread further over the skin and into other parts of the body.

Diagnosis is a challenging task; its distribution beyond skin in other sections is hazardous. The influence of melanocytes in any skin type tends to cause melanoma. Intensive skin exposure to actinic radiation is an attributable cause to melanoma[1]. Melanoma can generally be difficult to distinguish from other pigmented skin lesions [3].

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* Correspondence Author

Manjunath Rao*, MCA Scholar, Department of Computer Science and IT, Amrita School of Arts and Sciences, Kochi, Amrita Vishwa Vidyapeetham, India..

Calvin Joshua Fernandez, MCA Scholar, Department of Computer Science and IT, Amrita School of Arts and Sciences, Kochi, Amrita Vishwa Vidyapeetham, India.

Sreekumar K., Asst. Professor, Department of Computer Science and IT, Amrita School of Arts and Sciences, Kochi, Amrita Vishwa Vidyapeetham, India.

The diagnostic precision of dermoscopy often relies on the doctors ' skills, so the image processing methodology assisted by Computer-Aided diagnosis can assist with automated diagnosis, which is a key tool for beginners and less skilled physicians. Even while expert dermatologists use dermoscopy for diagnosis, the accuracy of the diagnosis of melanoma is estimated to be around 75-84% [6].

Given the pace, computer-aided diagnostics are useful in increasing the accuracy of the diagnosis even more. Despite its lack of human intelligence, a machine can collect details such as texture features, asymmetry – features that lie outside the normal scope of human vision. For computer-vision dependent melanoma, the key steps are image processing of skin lesion pattern, image recognition algorithms extraction function and SVM detection from non-melanoma vegetative cell pictures. The approaches of extraction of functionality is based on the correct data. Geometry and Appearance-based approaches are 2 types of methods used in function extractions. The abstraction of the facial features minimizes the resources needed for the process, without losing relevant information. This allows to reduce obsolete data back to restricted analysis [4].

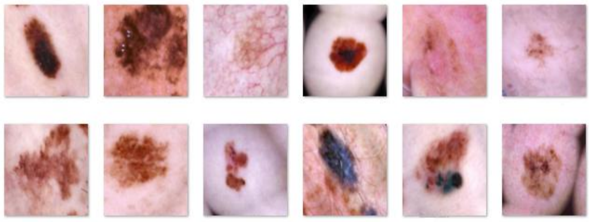

Fig. 1: Shows some of the melanoma skin lesion images.

Global face descriptor (GFD) and local face descriptor (LFD) are two of the most widely employed types of representation of faces. The LFD typically separates the entire image into multiple distinct images and then removes the attributes, but in the case of GFD, using the complete image to extend a representation[8] in the proposed scenario, we use the LFD approach such as LBP to resolve the contextual trends within the different visual recognition processes[5][6].The precision of the system relies on how the properties are derived from an image. For feature extraction purpose, we use the three-function extraction methods LBP [8][16], LDP [9] and CNN [7] and then employ the SVM classifier to achieve classification of the extracted features. Skin lesion images of non-melanoma and melanoma are the data set used for the purpose of assessment and teaching throughout this paper to measure the specificity or consistency of the picture distinguishing.

II. RELATED WORKS

The perception method for carcinoma diagnosis requires several researchers [1]. A significant portion of this latter progress was achieved, often encouraged to improve in-depth research techniques and more with CNN, which is one of all the deep learning solutions. Because of the info source accessible and numerical power extension, the neural system's machine learning approach was a renaissance in the field of identification,

and many of the above developments were due to the deep CNN within the field of face recognition.

Taskeed Jabid, *et al*. (2010) [14] implemented an LDP field descriptor feature for object detection. LDP code calculating sting answer values in several directions and encoding the local image property using this. The LDP descriptor's discriminative power comes from the incorporation of local edge response into one binary sequence, giving it robustness and freedom from being sensitive to changes in non-monotone lighting and noise. Experimental results showed that the LDP descriptor on database of the Brodatz textures had a higher classification accuracy which LDP descriptor uses the FERET database to give better accuracy of recognition in face recognition.

Suleiman Mustafa, *et al*. (2018) [15] suggested a way to detect melanoma carcinoma from a picture of the affected region of the skin. The paper included typical image processing, extraction feature, and SVM classification model, as well as the experiments showed that with few useful feature sets, prime accuracy will be achieved. Just 6 features (Circularity, High Luminance Level, FAST comers, Solidity, Form Skewness and Border Skewness) had the highest 86.67 % precision and offered reliable details for the identification of melanoma carcinomas.

Mohd Safirin Karis, *et al*. (2012)[8] researched item detection using local binary patterns and reported that similar object detection should benefit from separate LBP values as well as misleading the system to work out the item detected. Additionally, the first LBP can only reach limited local knowledge owing to its user serving a tiny area of small community.

Noel B. Linsangan, *et al*. (2018) [17]. The researcher may identify samples of potential carcinoma from malignant, benign and uncertain by the anatomical features of the skin lesion. Consisting of 10 images identified as skin cancer, 7 images as benign melanoma and three images as unclear, a total 20 photos were examined. The dataset consists of 90 samples for each section, including 30 samples. The system could conduct tests to determine 90 % accuracy. It was observed that photographs cannot be interpreted by the program; further, there would be errors in the extraction of image properties.

O. Abuzaghleh *et al*. (2015) [18] whose paper may be a non-invasive, early detection and prevention of melanoma skin lesions by automated analysis system. The first skin image is pre-processed during this paper by using 84 directional filters. Segmentation of lesions achieved utilizing Otsu thresholding. Form and color characteristics are extracted in feature extraction. SVM (Support Vector Machine) classifier is used for classification of melanoma images into normal skin images and those with cancer lesion.

S. S. Mane,*et al*. (2017) [19] whose paper can represent a Similar Carcinoma Detection Method Using Dermoscopy Pictures. The median filter is used for the pre-processing during this article. We use clustering of the K-means to achieve segmentation, then, we extract the feature using GLCM. Wikis Lambda is used for selection of the features. For classification the SVM classifier is used.

Moostafa. S,*et al*. (2017)[20] indicates that 6-9 useful features suffice for melanoma classification. To improve classification performance by adding sequential backward sorting function collection. It can also improve the algorithm of machine learning by reducing the size and reducing the issue of overfitting and reaching 91.30 %accuracy. The model will be tuned to training and test on more cancer recognition data from a limited number of features.

Rehman, *et al*. (2018) [21] proposed the use of CNN architecture to detect melanoma cancer Dataset obtained from ISBI2016 was comprised of two categories (images with melanoma and non-melanoma). CNN was used to extract the features of the picture and ANN was also used to classify certain features removed. Data from the proposed method produced 98.15 % of responsiveness, 98.41 % of precision, and 98.32 % of accuracy.

III. METHODOLOGY

In this research we used images of Non-Melanoma and Melanoma skin lesion as datasets. Entire dataset is split between learning and teaching sets (70 % is used in research and the remainder is used in testing). Next comes extractions of the functionality. The methods used in this paper include LBP, CNN, and LDP. LBP is a tool for extraction purposes of features only so we need an SVM classifier to identify extracted features. The CNN solution also incorporates an optimized Softmax classifier, which is used to label the pictures. CNN aimed to transform the set of inputs into precise and valid results.

A. LBP (Local Binary Pattern)

This method is used for feature extraction, which is the most important step in performing face recognition. In 1996, Ojala *et al*[10] made the LBP methods popular. It illustrates the shape and texture of an image very effectively. LBP is an optimal texture operator that marks image pixels by thresholding each pixel neighborhood, and determines binary results. The LBP works between each adjacent pixel by setting a centre-pixel threshold. If the adjacent pixel value is equal to or higher than the centre-pixel value, denote it with 1 otherwise 0.

As an example, let us consider the original LBP descriptor that operates on a settled 3 by 3 neighbourhood of pixels:

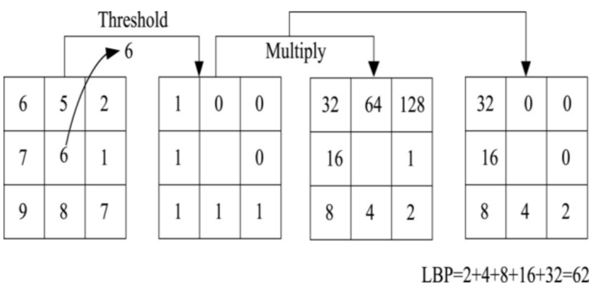

Fig.2:The construction of LBP by considering 8 neighbourhood pixels that surround the center pixel and applying a threshold to each pixel.

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B. Convolutional-Neural Networks

The CNN model is nearly identical to the synaptic processes in human brain activity. Initially Lecun [11] implemented CNN architecture that enables the transmission of human perception utilizing local receptive fields. The definition of the neural network, typically optimized for voice recognition and visual detection in deep learning. The CNN method is used to identify the image depending on different characteristics, and can be distinguished between them.

CNN preprocessing is far fewer than any other classification algorithm. The aim of CNN architecture is to scale the picture to a form that can be conveniently interpreted without losing vital characteristics to achieve a correct prediction. CNN method works by passing the input image into the set of different layers such as convolutional layer, rectified linear unit, fully connected layer and pooling layer to deliver the correct result. The following Fig. shows CNN construction consisting of only five layers:

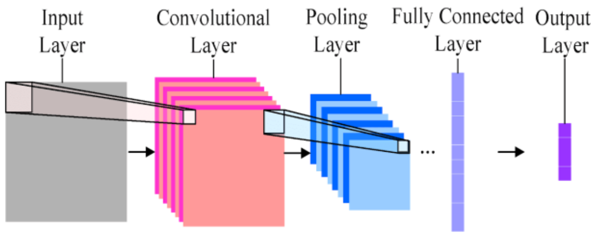


Fig.3: A simple CNN architecture, comprising just five layers.

a. The Convolutinal Layer

The aim of this layer was to collect valid features from input images and pass them to the layer to come. This layer establishes a spatial relationship between pixels through analyzing properties of the image. On the input image the selected filter is applied, and thus a converted feature is obtained. The multiplication of the matrix is performed by the filter and the result is returned on the converted map. This process is also called a "Map of Activation" The Fig. below shows the filter slides across the image input and provides the results to the converted map.

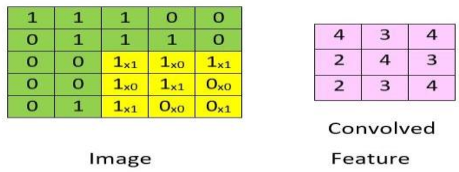


Fig.4:Shows the working of convolution layers on pixels.

With multiple convolutional inputs, we perform different filters and thus result in different transformed maps. Combining all these converted maps to form the final performance of the convolutional layers.

b. The Relu Layer

With the aid of activation functions, this layer transfers the feedback from the convolution layer to make our data nonlinear. The noise emerging from the convolved feature is eliminated and set to 0. Corrected linear units have proven to be the best alternative to the shortage of issues with gradients. The findings can be expressed as follows:

$$fr = ReLU(x_i) = \max(0, x_i) \quad (1)$$

c. The Pooling Layer

The intent of this layer is the separation of the characteristic maps by taking sum or average values all over the transformed function maps. Through reducing spatial dimensionality, the pooling layer focuses on creating flexible convolved functionality. This layer operates by sliding the filter over the migrated element in which the modified map's scale is larger than that of the pooling filter. The average and max pooling are two widely used pooling techniques. The Average pooling functions by measuring the average of each patch from the transformed feature. Max pooling operates by measuring the ceiling value from the convolved function for each layer.

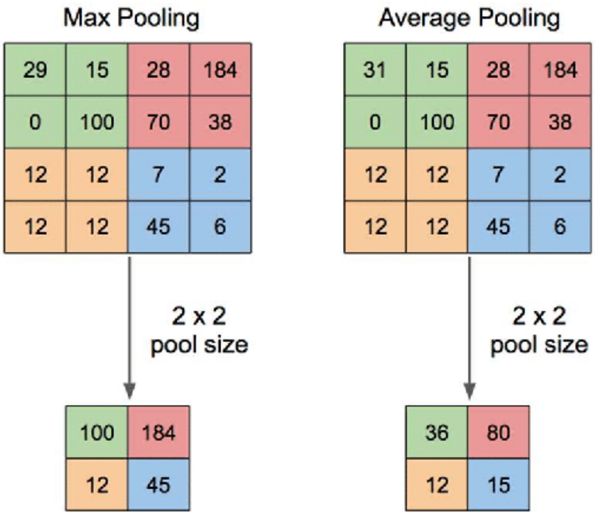


Fig.. 5: Shows the working of the pooling layer.

d. The Fully Connected Layer

This layer allows the combined function map to be reassigned between a 2D structure and a 1D vector. The layer's role depends on the convolution and pooling layer performance. This is the final layer in which all the signature maps are used and trained for the criterion of classification.

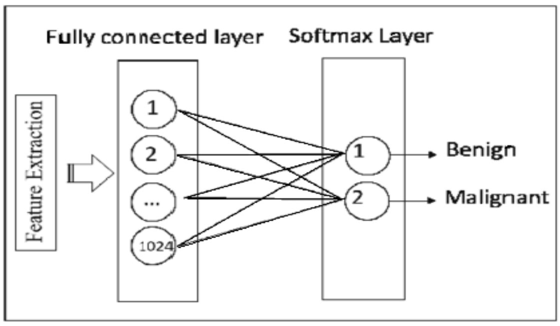


Fig. 6: Shows the working of the fully connected layer.

The grouping portion then follows after finishing all the above four levels. The CNN approach already contains an integrated classifier named "Softmax" which helps to classify the tested images We may interpret Softmax where ' a ' is any N-vector and ' y ' is numbered as follows to the output class,

$$S_j = P\,(y = j \mid \mathrm{a}) \quad (2)$$

C. LDP (Local Directional Patterns)

Recent researchers use a pixel-specific shift in gradient magnitude to represent local texture [12] and[13] during a given direction. Such strategies measure the gradient magnitude of adjacent pixels along the selected path rather than measuring and encoding the neighboring strength value as trivial LBP. It takes into account the magnitude of single-directional edges only.

In regard to this conclusion, we implemented the LDP (Local Directional Pattern) image feature, which calculates in several directions the string address values; it then uses these for encoding image textures.

$$\underset{\text{East } M_0}{\begin{bmatrix} -3 & -3 & 5 \\ -3 & 0 & 5 \\ -3 & -3 & 5 \end{bmatrix}} \quad \underset{\text{North East } M_1}{\begin{bmatrix} -3 & 5 & 5 \\ -3 & 0 & 5 \\ -3 & -3 & -3 \end{bmatrix}} \quad \underset{\text{North } M_2}{\begin{bmatrix} 5 & 5 & 5 \\ -3 & 0 & -3 \\ -3 & -3 & -3 \end{bmatrix}} \quad \underset{\text{North West } M_3}{\begin{bmatrix} 5 & 5 & -3 \\ 5 & 0 & -3 \\ -3 & -3 & -3 \end{bmatrix}}$$

$$\underset{\text{West } M_4}{\begin{bmatrix} 5 & -3 & -3 \\ 5 & 0 & -3 \\ 5 & -3 & -3 \end{bmatrix}} \quad \underset{\text{South West } M_5}{\begin{bmatrix} -3 & -3 & -3 \\ 5 & 0 & -3 \\ 5 & 5 & -3 \end{bmatrix}} \quad \underset{\text{South } M_6}{\begin{bmatrix} -3 & -3 & -3 \\ -3 & 0 & -3 \\ 5 & 5 & 5 \end{bmatrix}} \quad \underset{\text{South East } M_7}{\begin{bmatrix} -3 & -3 & -3 \\ -3 & 0 & 5 \\ -3 & 5 & 5 \end{bmatrix}}$$

Fig. 7: All 8 directions for the Kirsch edge response masks.

This is an 8-bit code. It is allocated to individual pixel that constitutes the image. This pattern is computed in several ways. One of the representative edge detectors, Kirsch masks Mi measures the eight directional edge response values, i=0, 1 ..., 7, based on their location in eight different orientations, provided a central pixel inside the image. Those masks are used in the fig. 7. In some specific directions a corner or edge intervention indicates higher values of reaction. So, we're interested in understanding the k's most influential paths for the LDP. Here bi is set to the maximum response of directional bit k.The remaining 8-bit LDP pattern (8-k) bits are set to 0. Eventually, the LDP code springs to (3). Fig. 8 Shows the response mask and the positions of the LDP bit, and Fig. 9 does have an exemplary LDP code of k=3[14].

$$LDP_k = \sum_{i=0}^{7} b_i(m_i - m_k) \times 2^i \,.$$

$$b_i(a) = \begin{cases} 1 & a \geq 0 \\ 0 & a < 0 \end{cases} \quad (3)$$

where, m_k is the k-th most relevant directional response.

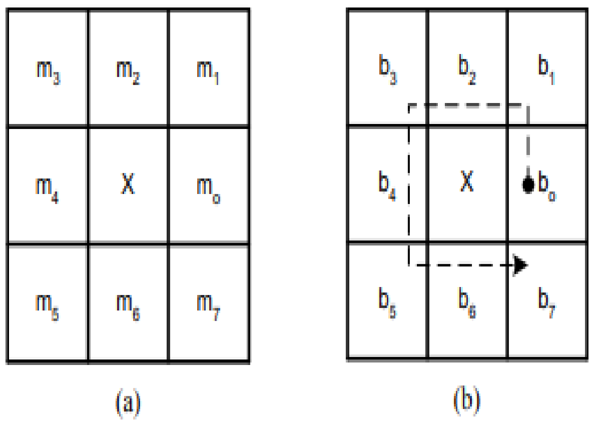


Fig. 8: (a) Eight directional edge response positions. (b) LDP binary bit positions.

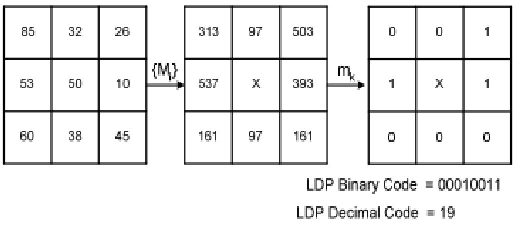


Fig. 9: LDP code with k = 3.

D. Classifier

Image recognition applies to a method in computer vision that can classify items according to their characteristics. This classification helps to categorize data sets or images as "benign" cancerous "malignant" or non-cancerous mole (melanoma or skin lesions that are not melanoma). The separate image sets are used both for training and for testing.

a. SVM

SVM was conceived, designed and built by Vapnik, *et al*. Multiclass SVM is selected as the classifier for the detection of skin melanoma lesions. Here, the classification is based on assigning the labels each during the training process for non-melanoma and melanoma skin lesions. The kernel feature helps convert the knowledge into another higher dimension which has a simple hyperplane. A large part of the kernel functions used are RBF, linear, and polynomial.

- **LINEAR KERNEL**

This kernel is used when the functions can be isolated linearly. It is mostly used when a given dataset contains a huge number of features. One of the main advantages of this kernel is that when the SVM preparation is completed it is faster than any other kernel.

$$k(x,y) = x^T y + c \quad (4)$$

- **POLYNOMIAL KERNEL**

The polynomial kernel is well adapted for problems when the entire trained data is normalized.

$$k(x,y) = \alpha x^D y + a \quad (5)$$

Where '*a*' is the constant term, *D* is the polynomial degree and adjustable parameters are the slope α.

- **RBF**

RBF is otherwise recognized as the Gaussian kernel, which is a radial basis function in form. The RBF kernel is defined as

$$K_{\mathrm{RBF}}(\mathrm{x}, \mathrm{x}') = \exp\left[-\mathrm{d}\,\|\,\mathrm{x}, \mathrm{x}'\|^2\right] \quad (6)$$

Where 'd' is a parameter that sets the "spread" of the kernel.

E. Evaluation Metrics

Every system's performance depends primarily on how precisely the features are extricated from the input file. For classification a misunderstanding matrix is used to summarize the performance.

Accuracy *A = (x / y) *100* (7)

Here, 'x' =s total no. of correct classifications; 'y' = no. of samples.

IV. EXPERIMENTAL ANALYSIS AND RESULTS

A. Dataset and Implementation

In this research we analyze and categorize melanoma from non-melanoma skin lesions. Datasets were obtained from the website ' www.kaggle.com,' which included 1,200 images of melanoma skin lesions and 1,200 images of non-melanoma skin lesions. All of the above data sets are critical to prepare, check and advance the method of detecting skin cancer(melanoma).

The computational algorithms have been designed and developed in the program MATLAB version 2015b and 2018b. The entire dataset was separated into the training and testing parts. Approximately 70 % is used for preparation, and the remainder is used in practice-to illustrate and begin evaluating the efficiency of the algorithms considered. To order to extract the attributes, the LBP, LDP and CNN methods are applied to the images and, as a result, three SVM kernels are added one after another to determine the predictive precision. LBP and LDP run with three of the SVM classifier kernel features, i.e. RBF, polynomial, and linear, respectively. The accuracy varies slightly, depending on the different functions used for the kernel. The CNN method is used to identify the image depending on different characteristics, and can be distinguished between them. The CNN method works by moving the input picture into the set of different layers including Convolutional, Relu, Pooling and Fully linked to produce the correct result. CNN also includes an adaptive classifier called "Softmax," which aims to identify the pictures evaluated. The corresponding accuracy of both methods is shown in the table in the segment that follows.

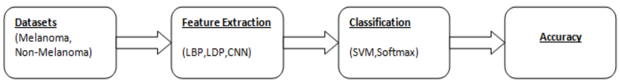


Fig.10:Work Flow Diagram

III. RESULT

The first table shows results achieved by applying the three functions of the SVM kernel using the datasets on the two LBP and LDP methods:

Table I: Illustrates the performance of each kernel function's highest values for different number of datasets using both LBP and LDP process SVM classifier.

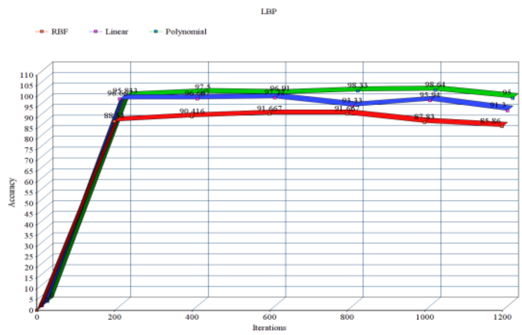
Dataset	Method	Accuracy by Kernel Functions (in %)		
		RBF	Polynomial	Linear
Melanoma and Non-Melanoma	LBP	91.667	98.64	97.22
	LDP	88.667	97.91	93.24

The results achieved by applying the three datasets using CNN are shown in Table II:

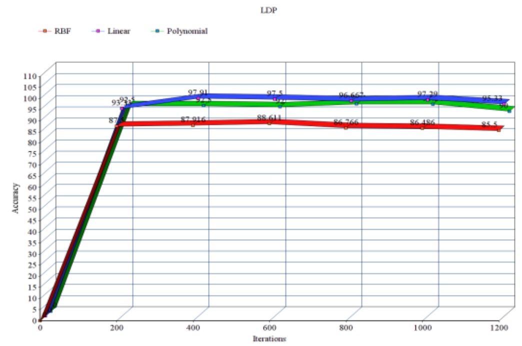
Table II: Illustrates the precision of CNN method for the dataset.

Dataset	Method	Accuracy (in %)
Melanoma and Non-Melanoma	CNN	71.08

The graphs of the three methods LBP, LDP and CNN plotted against numbers of increasing data sets for their detection or classification accuracies are:

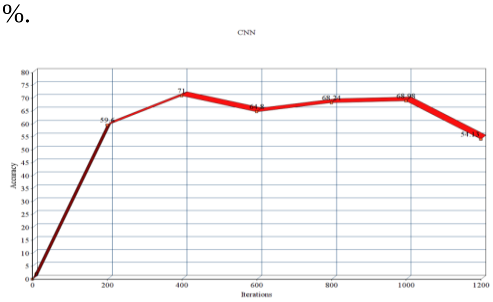


Graph I: Illustrates the LBP method and that the Polynomial SVM function shows better accuracy in classification or distinction of melanoma from non-melanoma skin lesion images.



Graph II: Illustrates the LDP process and demonstrates better accuracy of the Linear SVM feature when classifying or separating melanoma from images of non-melanoma skin lesion.

Both the LBP and LDP methods along with SVM commonly classify the dataset with accuracies in the range 88-98 %.



Graph III: Illustrates the CNN method where its maximum accuracy is 71%.

This indicates that together with SVM and its "Polynomial" kernel function, the LBP (Local Binary Pattern) method gives better accuracy along datasets to classify or distinguish melanoma from images of non-melanoma skin lesions. Together with SVM and its "Linear" kernel function, the LDP (Local Directional Pattern) method gives the next stronger precision numbers according to the charts. CNN (Convolutional Neural Networks) gives the three methods the least precision.

V. CONCLUSION AND FUTURE WORKS

The collection consisted of 1200 melanoma photographs, and 1200 non-melanoma skin lesion pictures. The LBP (Local Binary Pattern) approach along with SVM and its "Polynomial" kernel function gives better precision over datasets to identify or discern melanoma from non-melanoma skin lesion images when based on the three attribute extraction methods and when categorized using the SVM classifier. The accuracy of the above-mentioned method LBP-SVM(Polynomial) ranges from 95-98 % to most. According to the charts, the LDP (Local Directional Pattern) method along with SVM and its "Linear" kernel function gives the next better precision numbers in the 93-97 % range. The CNN (Convolutional Neural Networks) gives the least accuracy of 54-71 per cent of the three methods. Thus, in comparison with SVM, this research recommends the LBP-SVM(Polynomial) method for classifying or detecting melanoma or non-melanoma skin lesion images so that it can be detected and diagnosed by doctors at the early stages of the disease, or as soon as possible. In the possible future, there is even more advance LBP (Local Binary Pattern) which can be researched to fulfill the object or image detection task. Since the LBP method or algorithm is found better than two of the other well-known and well-used feature extraction algorithms, it can evolve (algorithm wise) and generalize more of object-detections, even in the medical field thus saving lives in the end result of their further medical processes.

REFERENCES

1. Computer aided Melanoma skin cancer detection using Image Processing. S.Jaina , Vandana J. , N. Pisea. ICCC-2015.
2. Balch CM, Gershenwald JE, Soong SJ, et al. Final version of 2009 AJCC melanoma staging and classification. J Clin Oncol. 2009;27(36):6199–6206. [PMC free article] [PubMed] [Google Scholar].
3. Murchie P, Campbell NC. Pigmented lesions, cutaneous melanoma, and future challenges for primary care. Eur J Gen Pract. 2007;13(3):151–154. [PubMed] [Google Scholar]
4. LeCun, Y. Generalization and network design strategies. Connectionism in perspective, 143-155, 1989.
5. Ramirez Rivera, A., Rojas Castillo, J., & Oksam Chae, O.(2013). Local Directional Number Pattern for Face Analysis: Face and Expression Recognition. IEEE Transactions on Image Processing, 22(5), 1740–1752. doi:10.1109/tip.2012.2235848.
6. Huang, D., Shan, C., Ardabilian, M., Wang, Y., & Chen, L. (2011). Local Binary Patterns and Its Application to Facial Image Analysis: A Survey. IEEE Transactions on Systems, Man, and Cybernetics, Part C (Applications and Reviews), 41(6), 765–781. doi:10.1109/tsmcc.2011.2118750.
7. Very deep multilingual convolutional neural networks for LVCSR Publisher: IEEE.Tom Sercu ; Christian Puhrsch ; Brian Kingsbury ; Yann LeCun. 2015.
8. Local Binary Pattern (LBP) with application to variant object detection: A survey and method.Publisher: IEEE.M. S. Karis ; Nur Rafiqah Abdul Razif ; N. M. Ali ; M. A. Rosli . 2016.
9. Facial expression recognition using Local Directional Pattern (LDP).Publisher: IEEE.Taskeed Jabid ; Md. Hasanul Kabir. 2010.
10. T. Ojala, M. Pietikäinen, and D. Harwood (1996), "A Comparative Study of Texture Measures with Classification Based on Feature Distributions", Pattern Recognition, vol. 29, pp. 51-59.
11. Lécun Y.; Bottou L.; Bengio Y.; Haffner, P. Gradient-based learning applied to document recognition. Proc. IEEE 1998, 86, 2278–2324. [Google Scholar] [CrossRef].
12. J. Guo, K. Shan, W. You, Di Lu.,R. Bie, “Automatic Facial Expression Recognition based on a Deep Convolutional-Neural-Network structure”, (2017) , IEEE SERA 2017, June7-9, London, UK.
13. Cha Zhang and Zhiding Yu. Image based static facial expression recognition with multiple deep network learning. In Proceedings of the 2015 ACM on International Conference on Multimodal Interaction. ACM, 2015.
14. Local Directional Pattern (LDP) – A Robust Image Descriptor for Object Recognition Taskeed J., Md. H. Kabir, Oksam Chae Department of Computer Engineering KyungHee University, Republic of Korea. 2010.
15. A SVM-Based Diagnosis of Melanoma Using Only Useful Image Features .Suleiman MUSTAFA, Akio KIMURA. 2018.
16. A. Hadid "The local binary pattern approach and its application to face analysis" in FirstWorkshop on Image Processing Theory, Tools and Applications, 2008, pp. 1-9.
17. Geometric Analysis of Skin Lesion for Skin Cancer Using Image Processing. N. B. Linsangan , J. J. Adtoon , J. L. Torres,School of Electrical, Electronics and Computer Engineering, Mapúa University Manila, Philippines. 2018.
18. O. Abuzaghleh, B. D. Barkana and M. Faezipour, “Non-invasive RealTime Automated Skin Lesion Analysis System for Melanoma Early Detection and Prevention”, IEEE Journal of Translational Engineering in Health and Medicine, vol. 3, 2015.
19. S. S. Mane, S. V. Shinde , “ Different Techniques For Skin Cancer Detection Using Dermoscopy Images”, International Journal of Computer Sciences and Engineering, Vol. 5, Issue. 12, pp. 165-170, 2017.
20. Mustafa, S. (2017). Feature selection using sequential backward method in melanoma recognition. 2017 13th International Conference on Electronics, Computer and Computation (ICECCO).
21. Rehman, M. , S. H., D. Rizvi, S. M., Abbas, Z., & Zafar, A. (2018). Classification of Skin Lesion by Interference of Segmentation and Convolotion Neural Network. 2018 2nd International Conference on Engineering Innovation (ICEI).

AUTHORS PROFILE

Manjunath Rao, is an MCA scholar in the Department of Computer Science and IT, Amrita School of Arts and Sciences, Kochi, Amrita Vishwa Vidyapeetham, India. He did his BCA from the same university.

Calvin Joshua Fernandez, is an Lateral Entry-MCA scholar in the Department of Computer Science and IT, Amrita School of Arts and Sciences, Kochi, Amrita Vishwa Vidyapeetham, India. He did his BCA from Siena College of Professional Studies (MG University), Edakochi, Kochi, Kerala.

Sreekumar K., is an Asst. Professor of Department of Computer Science and IT, Amrita School of Arts and Sciences, Kochi, Amrita Vishwa Vidyapeetham, India. He obtained M.Tech in Computer Science Engineering and M.Sc in Information Technology. He has more than 17 years of experience in teaching.