A Comparative Analysis on Texture Pattern Feature Extraction Methods in Melanoma Prediction

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Abstract: The automation system in the medical image processing become a high impact for the real world applications. In that, most of the disease are can be identified by the basic instrument with medical assist such as normal camera, smartphones etc. that are externally exposed in the human body. Related to that, the melanoma skin cancer can predict with the images based on the color of the ROI and the texture of it. In this paper, the texture based melanoma image prediction techniques was discussed with the pattern classification methods. In this, the texture pattern of the image was extracted by the Octo-Directional image pattern method. Thus it focused on the different projection angle of the image mask to find the difference in neighboring pixels. This will estimate the depth of the image compare to traditional image pattern methods. The results were tested and compared with the other state-of-art methods that justifies the performance of the Octo-directionality prediction model.

***Index Terms*—Melanoma, ROI, Image texture pattern, Image classification,image pattern extraction method.**

I. INTRODUCTION

MElanoma is one of the harmful and lethal skin disease that causes the malignant tumor [1] in skin cells. According to the medical reports of WHO, it is analyzed that around 70% of people can die to the skin cancer disease [2]. Also, it is a kind of wide spread disease that has an increased mortality rate, and its survival rate is large if it could be identified at the earlier stages. Moreover, the malignant melanoma is not detected in prior, it can affect the other organs of lungs, bones, and liver, so it is very difficult to diagnose [3]. Typically, the dermoscopy is a kind of non-invasive imaging technique mainly used for detecting the cancer affected skin lesions. Since, it is one of the crucial and demanding task of detecting the melanoma skin disease from the given medical images. For this purpose, there are different types of Computer Aided Diagnosis (CAD) [4] systems developed in the existing works, which is a kind of automated detection framework mainly used for detecting the disease using the Artificial Intelligence (AI) methodologies. The typical skin cancer detection system includes the phases of image preprocessing, segmentation, feature extraction and

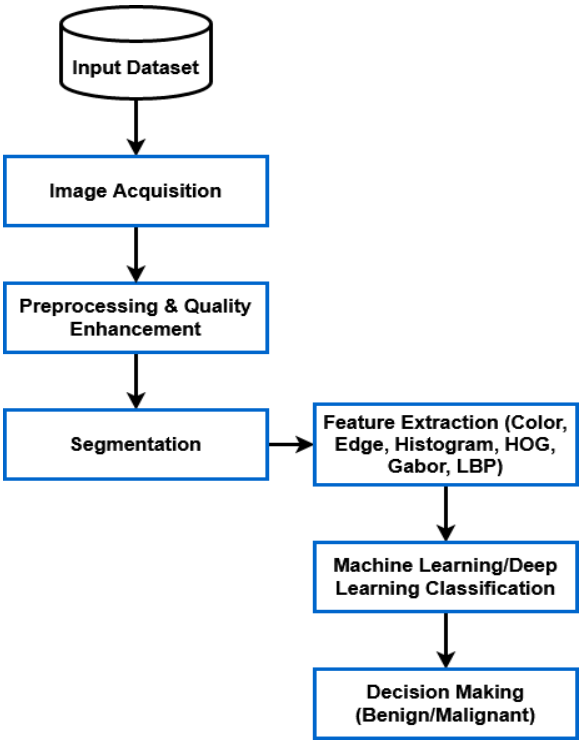

Figure l Typical skin cancer detection system

optimization, and is visually represented in Fig 1.The preprocessing is considered as the most initial and essential step of medical imaging systems. Because, it increases the contrast and quality of image by removing the noise artifacts [5], which is done by using various filtering techniques such as mean, median, Gaussian, and etc. Then, the image segmentation is performed to segment the ROI, which helps to increase the accuracy of classifier. There are different types of segmentation approaches like Otsu, contour, thresholding, Gabor, and etc have been utilized in the existing works [6] for segmenting the tumor affected region. Consequently, the features [7] like color, histogram, texture, shape, border, and etc are extracted from the segmented portions that helps to simplify the operations of classifier. Finally, the machine learning or deep learning [8] based classification techniques are employed to predict the accurate label as whether normal or abnormal (i.e. benign or malignant). This work mainly objects to survey the different types of methodologies used for developing an automated skin cancer detection system.

The major research objectives of this work are as follows:

- To investigate the different types of machine learning/deep learning methodologies used for detecting the melanoma disease based on pathological analysis.
- To study the working modules and operations involved in the detection system with its benefits and limitations..
- To validate and compare the results of existing medical image processing techniques based on the different performance measures.

The remaining portions of this paper are segregated into the followings: Section II examines the existing techniques and algorithms related to melanoma skin cancer detection and classification. Section III presents the description about the different types of methodologies used for developing an automated melanoma disease detection system. The comparative analysis among the existing approaches are validated by using various measures in Section IV. Finally, this review is summarized with its inference and future work in Section V.

II. Related Works

This section examines the existing preprocessing, feature extraction and classification algorithms used for developing an automated skin disease detection system. Also, it discusses the advantages and disadvantages of each technique according to its working functions and operations.

Sreetha, et al [9] implemented a Gradient and Feature Adaptive Contour (GFAC) model for segmenting the melanoma image to provide an earlier diagnosis to the patients. The main contribution of this work was to suppress the noise contents and to increase the speed of processing for improving the performance of segmentation. Moreover, the multiple Gaussian distribution patterns have been utilized to extract the set of features for reducing the error outputs. This framework comprises the working stages of preprocessing, thresholding and masking, lesion segmentation, feature extraction, and classification. Here, the performance of the segmentation technique could be assessed based on the measures of dice similarity, accuracy, and specificity. However, it limits with the problems of over segmentation, and inefficient region extraction. *Wang, et al* [10] implemented a 3D convolutional neural network technique for identifying the melanoma based on the histopathological analysis. The main purpose of this work was to avoid the false negatives and loss function during classification. Here, the encoder-decoder structure has been utilized to extract the fine-grained multiple features. The primary advantages of this work were increased accuracy, optimized performance, and efficiency.

Bi, et al [11] employed a deep class-specific learning methodology for segmenting the melanoma images by analyzing the characteristics of skin lesions. Typically, the Dermoscopy was a kind of imaging technique mainly used for validating the pigmented skin lesions. Moreover, the Probability based Step-wise Integration (PSI) methodology was also utilized in this system for accurately segmenting the disease affected regions. Yet, this work has the major limitations of increased complexity in classification, and requires more time for training and testing the classifier. The Social Group Optimization (SGO) methodology is for detecting the skin melanoma from the dermoscopy images. Here, the image preprocessing and post processing operations have been performed for increasing the performance of entire segmentation. Moreover, the Kapur's thresholding technique was deployed to integrate the level set with the segmentation process, which increased the performance values of classification. This system incorporates the working modules of preprocessing, multi-level thresholding, social group optimization, Otsu thresholding, Kapur thresholding, morphology, and active contour segmentation. However, this framework follows some complex computational operations for segmenting the melanoma images, which degrades the performance and efficiency of overall detection system. *Albert, et al* [12] implemented an advanced segmentation and ensemble classification methodologies for developing an automated melanoma disease detection system. This work mainly objects to develop a Synthesis and Convergence of Intermediate decaying Omni-gradients (SCIDOG) model for accurately detecting the contour lesions from the given image. Here, the morphological operators have been utilized to extract the attributes of color variance, border, and asymmetry features. Then, the classifier was trained by using these features, which helps to increase the accuracy and efficiency of classification.

Rokhana, et al [13] employed a Deep Convolutional Neural Network (DCNN) technique for classifying the melanoma images with increased accuracy. This work mainly objects to detect the skin lesions for categorizing the classes of images into benign and malignant. Moreover, this framework obtained an increased training and testing accuracy with respect to varying epochs and dropout functions. This formed as an automated melanoma skin disease detection system by using the deep learning methodology. Here, the multi-scale and multi-stage approaches have been utilized to improve the performance of classification. The lesion classification technique could produce the classified label as melanoma and non-melanoma modules. The different types of stages involved in this system were image preprocessing, feature extraction, pixel-wise classification, and lesion classification. *Sreedhar, et al* [14] presented a comparative analysis on various image processing techniques used for detecting the melanoma skin cancer. Here, three different types of

segmentation such as pixel based, edge based, and region based have been performed for separating the disease affected region. Then, the features such as shape, color, diameter, border, histogram, texture, and contour were extracted for enhancing the performance of classification. Moreover, the performance and efficiency of various classification methodologies were examined based on the evaluation metrics.

Mustafa, et al [15] suggested the Support Vector Machine (SVM) classification approach for extracting the features in order to detect the skin lesions. Here, various border, shape, and color features were extracted for increasing the performance of classifier. Yet, this technique has the major problems high false positives, inefficient classification results, and inability of handling large dimensional datasets. *Zghal and Derbel* [16] developed a new Computer Aided Diagnosis (CAD) tool for detecting and classifying the melanoma images. This framework includes the modules of preprocessing, segmentation, feature extraction, and classification. Here, the median filtering and morphological closing operations have been performed for enhancing the quality of image. A Deep Neural Network (DNN) classification technique for identifying and detecting the melanoma skin disease. Here, the OnDermNet architecture was constructed for classifying the sub-classes of disease. *Vocaturo, et al* [17] suggested a new preprocessing technique for improving the performance of skin cancer detection system. It includes the processes of image enhancement, restoration, and hair removal, where scaling, transformation, contrast optimization, and noise removal operations have been performed. This work indicated that the performance of classifier was belongs to the quality of image and its features. Moreover, the different types of filtering techniques have been investigated in this work, which includes the followings:

- Arithmetic mean filter
- Harmonic mean filter
- Geometric mean filter
- Contraharmonic mean filter
- Adaptive median
- Min-max filter
- Gaussian smoothing
- Mid-point filter

Chen, et al [18] suggested an AI framework for skin disease identification and classification, which includes the modules of data updating phase, training and testing phases. Moreover, the CNN technique was employed to predict the classified results with high detection accuracy, and reduced delay time. This utilize the texture form of the CNN technique for increasing the accuracy of detecting the melanoma disease identification and classification. Here, the performance and effectiveness of machine learning, deep learning, and AI methodologies have been validated and examined. Moreover, the different types of deep learning techniques were also separately investigated according to its architecture modeling and transfer learning.

From this review, it is analyzed that most of the conventional works are focused on the different types of feature extraction and AI methodologies for detecting the melanoma skin disease. However, it faced the challenges and problems of,

- Over segmentation of ROI
- Sensitive to noise factor
- Time consuming process due to looping of process.
- Large data feature set for training to classify.
- Less sensitivity and classification accuracy rate.

III. METHODOLOGIES

In this section, the detailed description about the texture based image feature extraction model and the overall work contribution with the work flow are explained. In this work, the melanoma image testing case was analyzed with the structure of algorithm explanation from the reference of Entropy based texture feature extraction model and the Deep Learning based classification model from [19] and [20] respectively.

The objective of this paper work are can be listed as,

1. Survey of different texture pattern extraction that are referred as by the block based structure that enhanced the image representation.
2. Identification of best feature extraction model for the melanoma image extraction
3. Representation of proposed flow architecture to overcome the limitations of existing model.

The figure 2 shows the overall block diagram of texture pattern based melanoma image prediction model. In that, the image was pre-processed by using the filtering method and some image enhancement process to improve the pixel quality and improve the edge information of that testing image. This can be achieved by referring the pixels that are present in the neighboring distance and form it as the group to separate the noisy pixel from image matrix. Then this can be removed by using the mean filtering or normalization method to suppress the pixels and equalize to the normal pixel range. Then from that, the image feature extraction can be implement by using the texture feature model to represent the image with standard pattern or structure of object that are easy to identify and classify from the classification model.

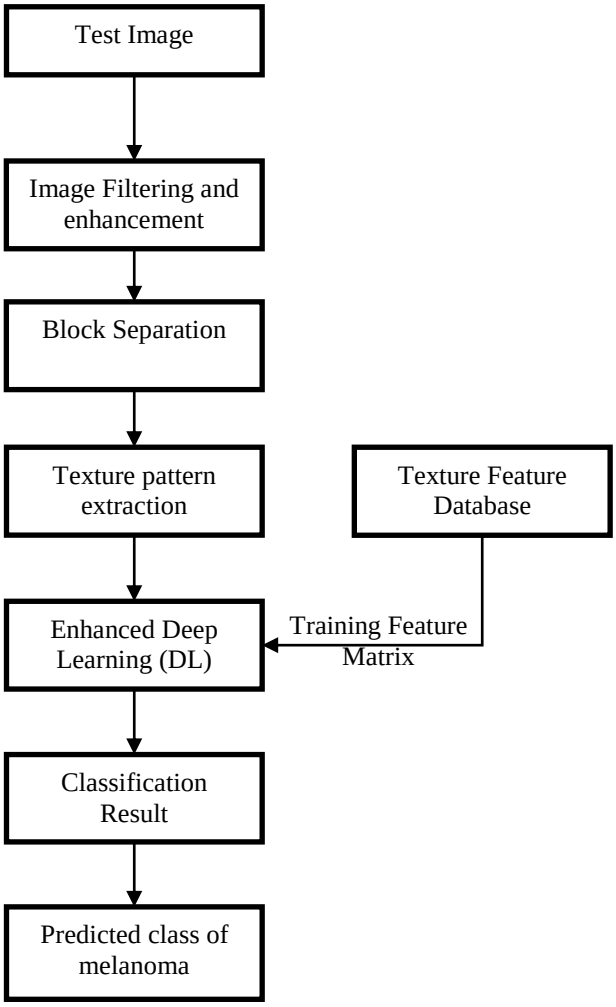

Figure 2 Overall block diagram of texture based melanoma image prediction model

The steps that are followed in the paper work can be sub-divided into two different layers that are can be listed as,

a) Texture Feature Extraction,
b) DL Classifier.

A. Texture Feature Extraction

In this section, the algorithm steps and its procedure were explained in detail. This extract the texture pattern in the basis of estimating the entropy value in the image matrix to find the relevancy between the neighboring pixels and represent the pattern of image.

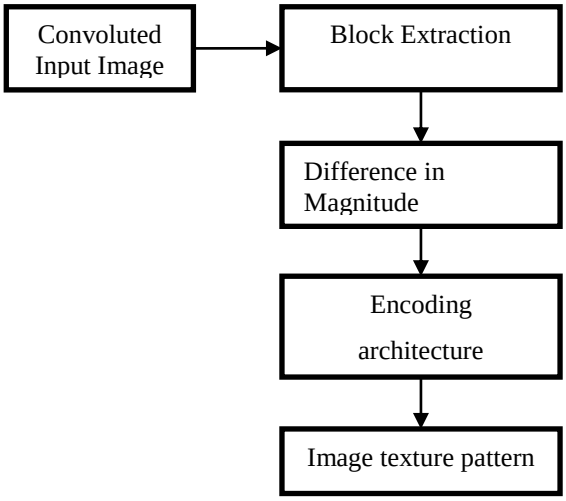

Figure 3 Block diagram of image texture pattern extraction model

The algorithm 1 explains the detailed steps of Eigen based texture pattern extraction model.

Algorithm 1: Eigen based texture pattern extraction

Input: Image, I
Output: Texture pattern of the image, I_p
Initialization the 2D-IMF indicator as by $X_0(a,b) = S(a,b)$ and j-1.
Calculate jth 2D-IMF by the below steps.

1. $Y_0(a,b) = X_{j-1}$, k=1.
2. Recognize minima and maxima of $Y_{k-1}(a,b)$.
3. Compute upper limit and lower limit of texture U_{k-1} and L_{k-1}.
4. Calculate the average value as, $mean_{k-1}(a,b) = \frac{1}{2} x [U_{k-1} + L_{k-1}]$
5. $Y_k(a,b) = Y_{k-1}(a,b) - mean_{k-1}(a,b)$
6. $Validate\ convergence\ point$
7. Residue $X_j(a,b) = X_{j-1}(a,b) - I_j(a,b)$

Repeat step 2 and 3 until it meets the convergence point.

The figure 3 shows the block diagram of image texture pattern that are referred from [19]. The figure 4 shows the texture pattern of input image for the image categories of benign and malignant case. In that, the first column shows the pre-processed image and the second column represents the entropy based texture pattern of the image using Bi-dimensional Empirical Mode Decomposition (BEMD).

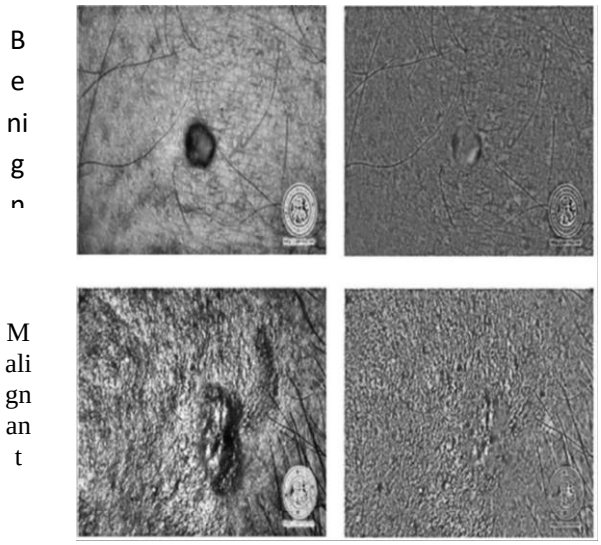

Figure 4 Texture pattern of image for benign and Malignant case

B. Texture Classification

In this texture classification model, the Deep Vector Network was used for the prediction of texture features by using the

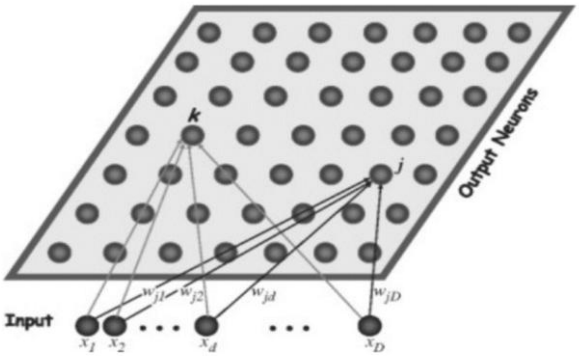

Figure 5 Representation of features in SOM

combination of SOM (Self Organization Map) and the CNN (Convolutional Neural Network) that is referred in [20].

The figure 5 shows the representation of image features in the SOM based feature arrangement before passing to the classification model. The algorithm 2 explains the steps of DVN model.

Algorithm 2: Deep Vector Network [20]

Input: Texture Pattern, I_p

Output: Classification Label, L

Training Model:

Step 1: Input texture pattern extracted from Dermoscopic image set.

Step 2: Arrange feature attributes.

Step 3: Apply active contour for segmenting ROI from texture pattern image.

Step 4: Find the relevant image features that are extracted by the PCA method.

Step 5: Arrange selected Feature vectors

Testing Model:

Step 1: Texture pattern I_p.

Step 2: Feature arrangemnet.

Step 3: Apply active contour segmentation for identification of ROI.

Step 4: Estimate relevant feature attributed by applying PCA.

Step 5: Pass the training feature database to the classifier with SOM before classification.

Step 6: Classification and identification melanoma categories using SOM and CNN.

Figure 6 shows the architecture diagram of Convolutional neural network for the input of image. In that instead of the direct image passing to the input of CNN, the extracted texture pattern was made it as the input that are organized from SOM model to represent the structure of image in detailed key points and feature data.

IV. Result Analysis

The result of various feature extraction and the classification model are discussed in this section with the comparison parameters and the other metrics. The algorithms are tested in the melanoma dataset that are from ISBI 2016 dataset [21], PH2 Dataset [22], and from Test Hair and Ruler dataset [23]. The overall simulation process is taken from the analysis report of existing classification model with the texture pattern based image feature extraction for melanoma image. The comparison methods are mainly focused on the texture based feature extraction models and the Deep learning classifiers to analyze the classification rate among several traditional model of image prediction methods.

The validation of classification model is can be present by referring the statistical parameters such as Accuracy, Sensitivity,

Precision, Recall, Harmonic Mean, Positive Predictive rate and Specificity of the classification result that are compared with the ground-truth of dataset to form the confusion matrix (CM) of predicted result. From that CM, the correctly classified result and misclassification count are can be analyzed.

$$Sensitivity, TPR = \frac{True\ Positive\ (TP)}{Total\ No.of\ Positive\ samples} \quad (18)$$

$$Specificity, TNR = \frac{True\ Negative\ (TN)}{Total\ No.of\ Negative\ samples} \quad (19)$$

$$Precision, P = (1 - FDR) = \frac{TP}{TP+FP} \quad (22)$$

$$Recall, R = (1 - FNR) \quad (23)$$

$$F1\ Score, F\_S = \frac{2TP}{2TP+FP+FN} \quad (24)$$

$$MCC = \frac{TP \times TN - FP \times FN}{\sqrt{(TP+FP)(TP+FN)(TN+FP)(TN+FN)}} \quad (25)$$

$$Accuracy, Acc = \frac{Total\ correct\ labels}{Total\ No.of\ Samples} \quad (26)$$

$$Error\ (\%) = (100 - Accuracy\%) \quad (27)$$

$$Harmonic\ Mean, HM = \frac{2 \times TPR \times TNR}{TPR+TNR} \quad (28)$$

$$Positive\ Predictive\ rate, PP = \frac{TP}{TN\_FP} \quad (29)$$

Where,
TP – True Positive,
TN – True Negative,
FP – False Positive,
FN – False Negative.

With the reference of these parameters, the table 1 and 2 shows the comparison results of different feature extraction techniques that are based on the texture pattern of image and with different classifier models respectively. In that comparison analysis, it shows that the INSCMOP texture features gains better result than the INSCF and INMOP methods. This also represents that the Random Forest classifier was achieved the better classification accuracy than the KNN and SVM classifiers. These table results are referred and validated from [21]. According to Precision, Recall and F1-Score, the INSCMOP based pattern extraction and the RF algorithm achieved better result than other existing methods.

Table 1 Performance measures with Random Forest (RF) classifier

Methods	Accuracy	Precision	Recall	F1-Score
INSCF-RF	0.8173	0.8473	0.7357	0.7594
INMOP-RF	0.8942	0.8823	0.876	0.8789
INSCMOP-RF	0.9327	0.9546	0.8971	0.9187

Table 2 Performance of INSCMOP with different classifiers

Methods	Accuracy	Precision	Recall	F1-Score
INSCMOP-KNN	0.7596	0.727	0.7155	0.7203
INSCMOP-SVM	0.7981	0.8318	0.7063	0.727
INSCMOP-RF	0.9327	0.9546	0.8971	0.9187

The analytical results are estimated for the implementation of ISBI 2016 dataset to classify the abnormality of melanoma cancer categories. These parameters are also considered for other classification models that are plotted in the figure 6. In that graph, it shows the RF, SVM and KNN are initially analyzed by the tradition feature extraction model and validated with the relevant parameters. That peaks are displays like, the SVM achieved better classification performance than the other two methods. While including the texture feature extraction model, the INSCMOP with RF classifier achieved higher value in all the parameters compare to the other classification models. This was in the range of ~93% in accuracy from the ISBI 2016 image dataset.

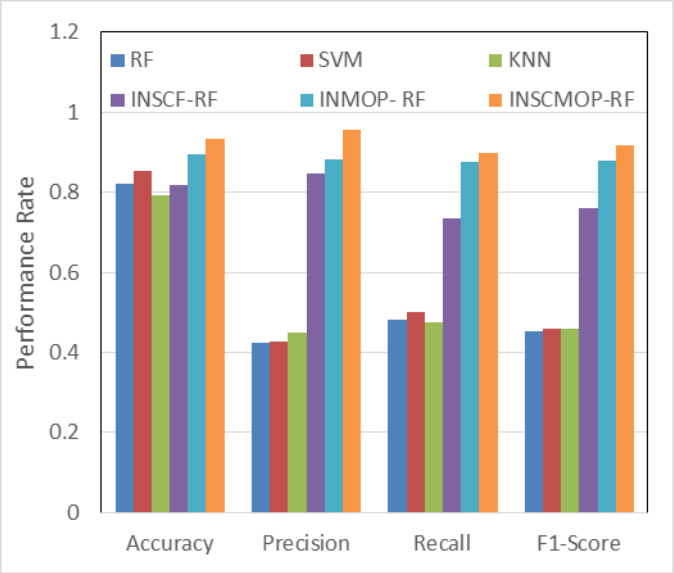

Figure 6 Comparison results for ISBI 2016 dataset

The table 3, 4, and 5 represents the comparison results of different classifiers from the reference of LBP texture feature method, GLCM and by [T1, T2, C1, S] feature vectors respectively in [22]. In this, the testing was processed in the PH2 type image dataset. The classifiers such as K-NN, Bayes model, LS-SVM, ELM, MLP and the stacked RBM methods are referred for the prediction of multiclass melanoma cancer prediction. In that compare to the several methods of classification, the stacked LS-SVM using RBF kernel achieved higher accuracy in the range of ~95%. Similarly, the results from the GLCM feature extraction type shows the stacked RBM model achieved better performance rate. Also by the reference of [T1, T2, C1 and S] combined feature set, the stacked RBM classifier achieved higher value in performance rate than the other classification model. These are all simulated in the PH2 image dataset referred in [22].

Table 3 Classification results for LBP feature extraction from PH2 dataset

Methods	Specificity	Sensitivity	PP	F-score	HM	Accuracy
K-NN	0.98	0.914	0.881	0.883	0.884	0.903
Bayes	0.9	0.872	0.89	0.87	0.88	0.87
LS-SVM(RBF)	0.947	0.929	0.903	0.945	0.941	0.948
ELM(RBF)	0.912	0.823	0.932	0.821	0.79	0.919
MLP	0.909	0.782	0.883	0.821	0.781	0.782
Stacked RBM	0.982	0.984	0.953	0.964	0.956	0.801

Table 4 Classification results for GLCM feature extraction from PH2 dataset

Methods	Specificity	Sensitivity	PP	F-score	HM	Accuracy
K-NN	0.952	0.914	0.922	0.933	0.921	0.9233
Bayes	0.823	0.802	0.821	0.812	0.814	0.825
LS-SVM(RBF)	0.942	0.909	0.883	0.905	0.9	0.928
ELM(RBF)	0.882	0.803	0.892	0.781	0.76	0.889
MLP	0.879	0.712	0.823	0.801	0.711	0.722
Stacked RBM	0.98	0.959	0.943	0.954	0.965	0.943

Table 5 Classification results for [T1, T2, C1, S] feature extraction from PH2 dataset

Methods	Specificity	Sensitivity	PP	F-score	HM	Accuracy
K-NN	0.982	0.964	0.981	0.983	0.984	0.9833

Bayes	0.901	0.872	0.893	0.873	0.883	0.871
LS-SVM(RBF)	0.947	0.929	0.903	0.945	0.941	0.948
ELM(RBF)	0.912	0.823	0.932	0.821	0.79	0.919
MLP	0.909	0.782	0.883	0.821	0.781	0.782
Stacked RBM	0.985	0.978	0.986	0.986	0.984	0.988

The comparative results of various texture feature extraction methods such as LBP, GLCM, and for [T1, T2, C1, S] which are being processed using the PH2 image dataset are shown in the following figures 7 to 9.

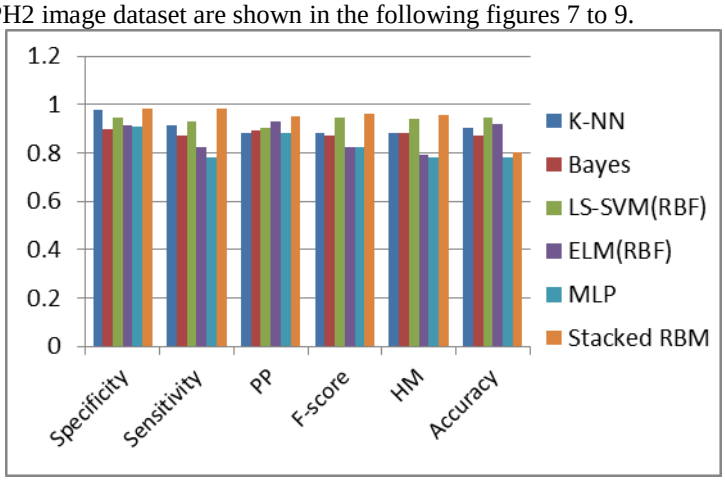

Figure 7. Comparison for LBP feature extraction from PH2 dataset

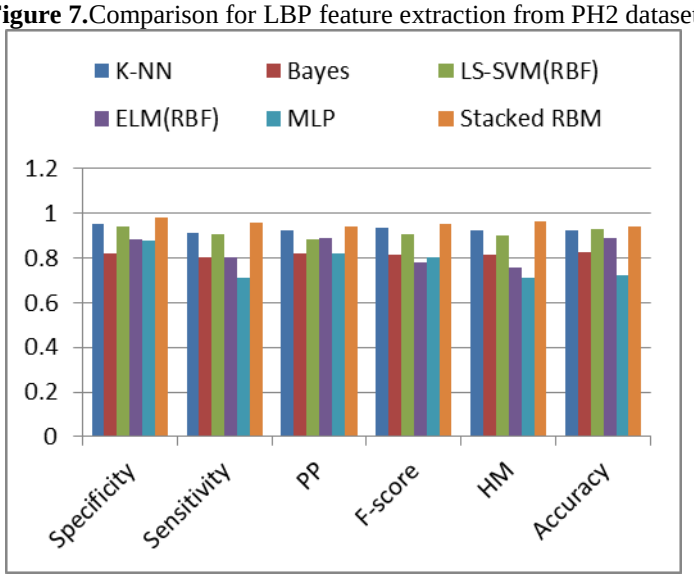

Figure 8. Comparison results for GLCM feature extraction from PH2 dataset

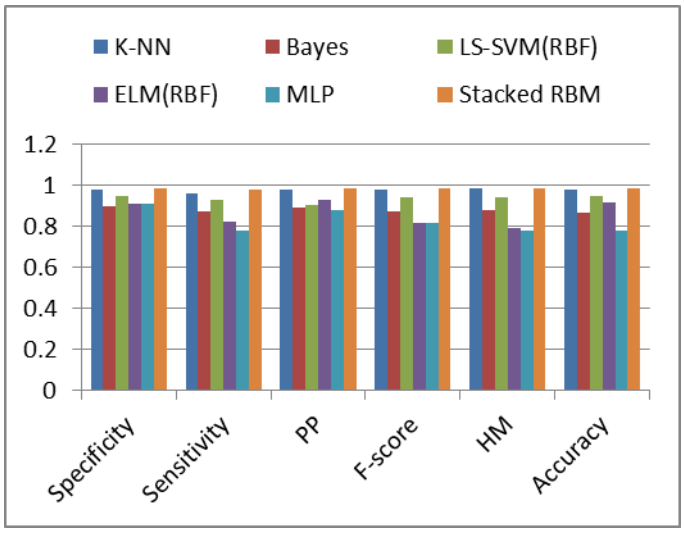

Figure 9. Comparison results for for [T1, T2, C1, S] feature extraction from PH2 dataset

From the overall result analysis, the combined texture pattern of image representation along with Stacked RBM classification achieved better performance than the other feature extraction methods. This can be enhanced by combining with the Deep Learning (DL) model for improving the prediction rate than the other types of neural network.

V. Conclusion

The overall paper work presents the survey of various feature extraction and prediction techniques for the classification of Melanoma skin cancer categories. This paper mainly focused on the image texture based feature extraction for the enhanced model of image representation. Based on that, the classifiers related to the melanoma cancer prediction are analysed and expressed in the parameters of different classification model. In that, there are different types of convolution techniques and the block based representation to extract the texture features of image. These are all can be effectively classified by using the Deep Learning (DL) model for better prediction rate compare to the other feature classification methods. Several types of DL methods in various analytical process are explained in this paper. The result analysis justifies the performance results of the texture based image classification along with the DL algorithms based on the statistical parameters. From that overall discussion, the block structured image texture extraction improves the accuracy with DL algorithm.

In the future work of melanoma cancer prediction, this was further enhanced by the implementation of a multi-angle projection based image texture analysis with the improved technique of Deep Learning model. This will improve the prediction rate with reducing the complexity of feature classification.

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