Stochastic Modelling and Computational Sciences

AN ENHANCED DISTRIBUTED DEEP PREDICTION MODEL WITH OPTIMIZATION FOR PRECISE MELANOMA DETECTION

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ABSTRACT
One of the most deadly forms of the disease is skin cancer. Unrepaired breaks in the DNA of skin cells, which result in genetic disorders or deformities on the skin, are the primary cause of skin cancer. It is best to detect skin cancer early since it is more treatable then and tends to spread gradually to other parts of the body. The high death rate, increasing prevalence of cases, and high cost of medical treatments associated with skin cancer make early detection of symptoms essential. Because of how serious these issues can get, researchers have developed a number of early screening techniques for skin cancer. The novel deep learning classifier for pattern extraction-based melanoma detection and classification is proposed in this research. Features predictive of malignant regions will be retrieved from the images using Multi-Directional Patterns (MDP) with geometric details. To choose these parameters and improve the segmentation process' accuracy, Batched Quantum Intensity Spot Optimisation (BQISO) will be employed. Then, in order to expedite and improve the accuracy of the segmentation process, the model would be trained via Distributed Deep Prediction (DDP), which makes it possible to identify cancerous regions in skin scans with remarkable precision. The suggested MDP-DDL method's outcomes are evaluated and validated through the use of multiple performance metrics and publicly available statistics.

Index Terms— Skin Cancer, Feature Extraction, Automatic Diagnosis, Multi-Directional Pattern (MDP), Distributed Deep Prediction (DDP), and Segmentation.

VI. INTRODUCTION
Skin cancer is the leading cause of death for people in today's world [1]. Skin cancer is defined as the abnormal proliferation of skin cells. It can occur anywhere on the body, however it typically occurs on areas exposed to sunlight. Early treatment is possible for the majority of skin malignancies. So, a patient's life may be saved by early and prompt discovery of skin cancer. Early identification of skin cancer at its first stage is now achievable owing to new technology. Skin cancer is the most deadly form of skin disease that affects people among all other skin conditions [2, 3]. Fair skinned people are most likely to have this. Malignant melanoma and non-melanoma are the two kinds of skin cancer. One of the deadliest and most dangerous forms of cancer is malignant melanoma; although just 4% of the population is estimated to be affected, it accounts for 75% of skin cancer-related deaths [4]. If melanoma is discovered or diagnosed in its early stages and treated promptly, it can be cured; but, if it is discovered in its later stages, treatment may not be possible [5]. The biopsy method is the official way of diagnosing and detecting skin cancer. Skin cells are removed, and the sample is then used for a variety of laboratory tests. It is an arduous and drawn-out procedure. There are three fundamental layers of skin. The outermost layer, which is composed of basal cells in the second layer, squamous cells in the first layer, and melanocytes in the middle or third layer, is where skin cancer first appears [6, 7]. Non-melanoma cancers are another term for squamous cell and basal cell tumors. Skin melanocytes that have achieved malignant transformation are the source of melanoma. Dark pigments on the skin, hair, eyes, and other body parts are produced by melanocytes. As a result, the majority of melanoma tumors are brown or black. However, melanomas can occasionally resemble pink, red, or purple because they lack pigment. Skin cancer that is not melanoma always reacts well to treatment and hardly ever spreads to other tissues of the skin [8]. The majority of other forms of skin cancer are less hazardous than melanoma. It will swiftly infiltrate the tissues surrounding it

and spread to other areas of the body if it is not discovered in the early stages. The biopsy method is a formal diagnosis procedure for skin cancer detection [9, 10].

Even if there is a good probability that this cancer will heal, because of its high incidence, people are nevertheless very concerned about it. Melanoma can occasionally reach the remotest regions of the body by spreading through the circulatory or lymphatic systems. Among the different types of skin cancer, this one has the highest chance [11]. Research has indicated that melanoma cancer death rates can be considerably decreased by detecting the disease at an early stage. The fact that early melanoma diagnosis is a rigorous procedure, even for experts, is a serious issue [12]. For this reason, the professionals may find it useful to employ a technique that streamlines the diagnosis. The use of machine learning and image processing for various medical imaging applications has grown rapidly in the last ten years. By using these methods, human error is reduced and the diagnosing process moves more quickly [13, 14]. Additionally, it can enhance the accuracy and practicality of the radiologists' and physicians' melanoma diagnosis.

Deep convolutional neural networks, or CNNs, are a novel class of artificial neural networks that perform well on a wide range of tasks in various image processing applications. Deep neural networks have seen several uses in medical imaging in recent years [15]. CNNs have several uses in various areas of medical imaging, including fusion of MR images, tumor diagnosis and analysis, because of their great precision. In order to apply the stated CNN-based approaches, the image was first split up into several tiny super pixels, and each of these super pixels was then given the operator [16, 17]. The usage of CNN models raises the diagnosis system's efficiency, according to the literature described above. Combining them with optimization algorithms is another way to increase the system's efficiency. The proposed work's objectives are given below:

- To improve the accuracy of the segmentation process, this application would employ images of moles or other skin lesions as its input data.
- Next, using Multi-Directional Patterns (MDP) with geometrical details, characteristics from the images that are predictive of cancerous regions will be extracted.
- Using Batched Quantum Intensity Spot optimization, these features would be selected in order to improve the segmentation process' accuracy.
- The model would next be trained using Distributed Deep Prediction (DDP), which would enable very accurate detection of cancerous areas in skin scans, in order to improve the speed and accuracy of the segmentation process.
- This flow may have a huge impact on the early diagnosis and treatment of skin cancer, a key global public health concern.

The remaining portions of this article are divided into the following sections: Section 2 offers a thorough review of the literature in order to analyze the conventional models for the diagnosis and categorization of skin cancer. Section 3 outlines the specific objectives of the proposed method as well as its flow and algorithms. Section 4 validates the results and compares them with other models using certain publicly available skin cancer datasets. The results and next steps are outlined in Section 5, along with the manuscript as a whole.

VII. RELATED WORKS

Recent breakthroughs in science and technology have led to the replacement of digital dermatoscopes with traditional dermoscopes that are capable of taking and saving dermatology images [18, 19]. Therefore, funding programs might be made available to help with the detection of certain skin lesions, data building, and the compilation of therapy summaries for each patient. Research indicates that the best course of action for analysing dermatoscopic images of melanocytic lesions is to determine the boundaries of the lesion. Indeed, it is believed that critical elements in the diagnosis of malignancies are the size, shape of the lesion in the area between the lesion and the backdrop. Recently, Uzma Jamil et al. [20] presented an interesting method that involves using a

gradient magnitude filter to separate the lesion, which is in the front, from the background [21]. The researcher employed watershed and active contour methodologies for segmentation in the publication. Shape, color, and texture-related components were removed. After being trained on fifty DermIS datasets, the proposed architecture obtained eighty percent performance accuracy. An entirely new CAD technique for melanoma early detection has been proposed for usage in Android mobile and web applications [22]. Dermoscopy images are used in most of the current approaches, and they have been proven to be especially useful for melanoma inspection. These systems are capable of processing images using both conventional machine learning techniques and deep learning, an extremely powerful and sophisticated methodology [23]. After the image has been taken, a lesion segmentation procedure is utilized to isolate the troublesome skin lesions from the surrounding healthy skin. This stage is regarded as the most crucial of the entire melanoma detection procedure. The researcher employed watershed and active contour methodologies for segmentation in the report. Shape, color, and texture-related components were removed. After being trained on fifty DermIS datasets, the proposed architecture obtained eighty percent performance accuracy. An entirely new CAD technique for melanoma early detection has been proposed for usage in Android mobile and web applications. The authors employed K-Mean clustering and textural color derived attribute to extract ROI from non-demographic skin cancer pictures [24]. Additionally, other graphic components were found after the doctor was inspected. Feature extraction was used to automatically classify skin cancer cases.

The researcher used a Support Vector Machine and differential evolution setup to build their feature selection technique. Researchers extracted features using machine learning techniques in order to detect skin cancer. In recent years, skin cancer has been diagnosed using deep learning and CNN; nonetheless, computational cost remains a problem. They used CNN to collect features from the DermIS dataset, however the SVM classifier was able to classify them with 95% accuracy [25]. The approaches listed all yield good results, but there is not enough data to support their validity. It has been observed that the majority of the research being done on this topic now concentrates on using human expert knowledge to extract and choose discriminative traits. It takes effort and a deep comprehension of the subject to choose these handcrafted nuances. Since these hand-picked features necessitate human contact, they are not entirely automated [26]. Deep learning-based algorithms often extract information from complete images, therefore the region of interest is not very large. Consequently, the original large pictures may have an impact on the overall feature learning process of deep learning models [27, 28]. Furthermore, a large amount of labelled data is usually required for deep learning in order to achieve higher performance and avoid overtraining.

VIII. PROPOSED METHODOLOGY

The sections that follow in this section go into more detail about the model we've suggested. Fig. 1 depicts the proposed work's flow. This system would be upgraded to use pictures of moles or skin lesions as its input data in order to increase the accuracy of the segmentation process. The features that are suggestive of malignant regions will next be extracted from the photos using Multi-Directional Patterns (MDP) with geometrical intricacy. Dermoscopy subjectivity and need for intensive training are two of its main drawbacks. The scientific community has worked very hard to create computer-aided diagnostic (CAD) technologies that dermatologists can utilize to get around the problems stated above. After that, the model would be developed with Distributed Deep Prediction (DDP) that might accelerate and improve the segmentation process while enabling very accurate identification of malignant regions in skin scans. A crucial global public health concern is the early identification and treatment of skin cancer, which might be significantly impacted by this movement. The steps in this pipeline are as follows:

- Pre-processing of the images;
- Segmentation of lesions;
- Extraction of features;
- Optimal feature selection;

- Classification;

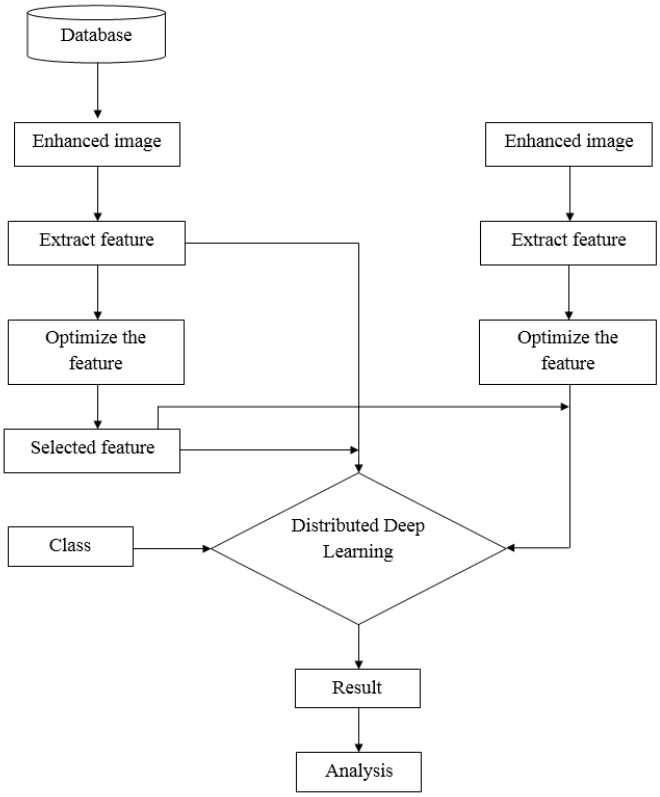

Fig 1. Flow of proposed system

Pre-processing images is a necessary step when dealing with images that are too low quality for analysis. The existence of abnormalities (such hair) may be the cause of this poor quality, which could have an adverse effect on how well the following procedures work. Color standardization is another significant issue. Unreliable color information might result from the use of disparate devices and lighting conditions when acquiring dermoscopy images. As such, it can be crucial to incorporate a color adjusting step during the preprocessing stage. Following preprocessing, lesion segmentation is carried out to precisely identify the area of the image that is impacted by malignancy. As a result, in order to extract the required features from the segmented area, operations including feature extraction and optimal feature selection are also carried out, greatly enhancing the efficiency of the skin cancer detection system. Lastly, using the provided photos, the DDP approach is used to forecast the type of cancer.

A. Feature Extraction

To obtain a biased representation of the skin lesions, feature extraction is an essential step. It can be challenging to find the right traits, but a lot of study has been done in this area, allowing for the identification of a wide range of features that describe skin lesions. In certain CAD systems, feature selection is used to decrease the dimension of the feature space through the elimination of features that are noisy, unnecessary, or repetitive. The MDP technique is used to extract the characteristics from the preprocessed image after the image has been enhanced. Feature extraction is the process of taking the required information out of the raw image that is already available. A machine learning algorithm needs the gathered features to be non-redundant and yield high-quality results. All of the photographs in the dataset are reduced to a small feature vector using the feature extraction technique. The color, edge, and texture data are combined into a feature vector using the least amount of computations possible in the proposed feature extraction approach. Quantitative information about the picture of skin covered in lesions is

provided by the MDP technique. This technique can be applied as a preventative measure against skin cancer. In a skin cancer image, the boundaries of objects are represented by edges. The image's edges, or pixels, are experiencing sudden changes in brightness. The vector variable is the product of the gradient's size and the edge's direction. The edges of an image are computed using the link between a pixel and its surroundings. If a pixel's value is the same as the values of the pixels surrounding it, it is not regarded as an edge. If the pixel values of a pixel and its neighbors diverge, then the pixel may represent an edge. It is possible to achieve good color discriminating accuracy using the RGB distributions. The MDP operator can be used to extract the color texture in RGB space. Each color channel in an RGB image receives a distinct application of the MDP operator. In this instance, every pair of color channels is used to gather the enemy's color patterns. The center pixel and the surrounding pixels are chosen using a range of color channels. One distribution is created by combining the six resulting feature distributions.

Algorithm 1 - Multi-directional patterns with Optimize the data based on the relative patterns

Input: I,ws ,Class

Output: Optimize Mdp

Angle = random(10,90);

For i is ws-1 to length(I)-ws

For j is ws-1 to length(I)-ws

PA = I(i-1to i+1,j-1 to j+1):

For k=1 to length(Angle)

If (i=j)

OP(k) = 1

Else

OP(k)=0

Mdp(i-1,j-1) = $\sum_{o}^{k}(2)^{k-1}.*OP)$

CLV = Mdp,class

CR = length(CLV==class)/length(CLV) Pre_Angle=Angle

Pre_CR = CR

If Pre_CR<CR

Best_CR = CR

Best_Angle = Angle

Else

Best_CR = Pre_CR

Best_Angle = Pre_Angle

If (Pre_Angle ==Best_Angle)

n= n+1

Angle = update(Pre_Angle)

Optimize Mdp = Best_Angle;

B. Distributed Deep Prediction (DDP) Algorithm

The last stage in the CAD system is lesion categorization. In this case, a diagnosis prediction is trained into a classification system. Since melanoma has a higher degree of malignancy than benign or irregular neoplasm most CAD systems concentrate on making this distinction. However, there are additional CAD systems available that seek to differentiate multiple types of skin cancer as well as melanocytic and non-melanocytic lesions. It is difficult to make a clinical diagnosis of melanoma since other pigmented skin lesions can have morphological characteristics that are similar to cancer. Dermoscopy magnifies the skin, enabling clinicians to analyze morphological features that are difficult to see with the unaided eye more accurately. The use of dermoscopy is expected to improve diagnostic sensitivity. The DDL technique is used to predict and classify skin cancer from the provided dataset after the features have been selected. In this case, the training and testing procedures are effectively used to forecast the outcomes. In this model, the defined label is returned as the output after processing the ODP features as the input. The following are the steps that are involved in training and testing the classifier:

Algorithm 2- Distributed Deep Prediction (DDP)

Input: MDP features obtained from the given image;

Output: Predicted 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 BQISO method.

Step 5: Arrange selected Feature vectors

Testing Model:

Step 1: Mdp.

Step 2: Feature arrangement.

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

Step 4: Estimate relevant feature attributed by applying BQISO.

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.

IX. RESULTS AND DISCUSSION

Various datasets and metrics are employed to assess the efficacy and results of the proposed skin detection method. Several characteristics are employed in this study to assess the performance of the proposed and current classification systems for the prediction of skin cancer. Its accuracy, sensitivity, specificity, Area under Curve (AUC), and other metrics are computed using the following models:

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \quad (1)$$

$$Sensitivity = \frac{TP}{TP + FN} \quad (2)$$

$$Specificity = \frac{TN}{TN + FP} \quad (3)$$

$$\Pr ecision = \frac{TP}{TP + FP} \quad (4)$$

$$\mathrm{Re}\, call = \frac{TP}{TP + FN} \quad (5)$$

$$Error\_Rate = 1 - Accuracy \quad (6)$$

$$Kappa\_Coeff = \frac{P_o - P_e}{1 - P_e} \quad (7)$$

$$F1\_Score = \frac{2 \times \Pr ecision \times \mathrm{Re}\, call}{\Pr ecision + \mathrm{Re}\, call} \quad (8)$$

$$MCC = \frac{TP \times TN - FP \times FN}{\sqrt{(TP + FP)(TP + FN)(TN + FP)(TN + FN)}} \quad (9)$$

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

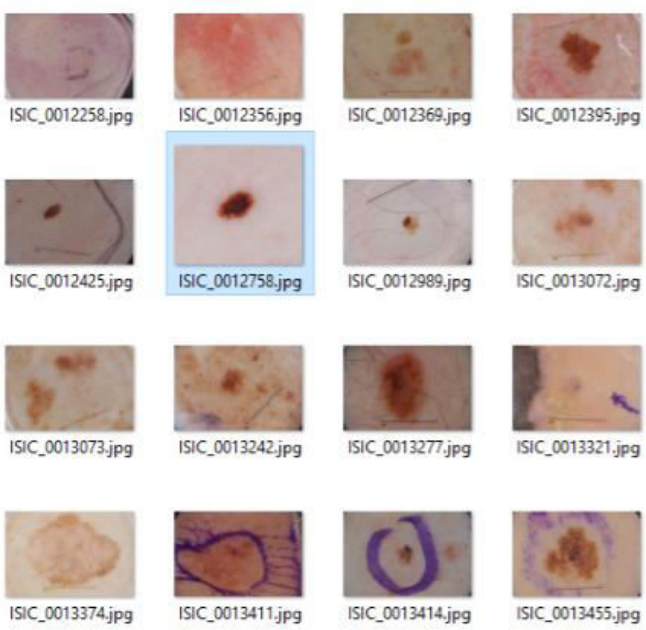

Fig 2. Sample input images

Fig. 2 displays the sample input skin images that were taken from the dataset. Additionally, Fig 3 display the input image together with its matching grayscale image, enhanced image, segmented region, and tumor identified region outputs.

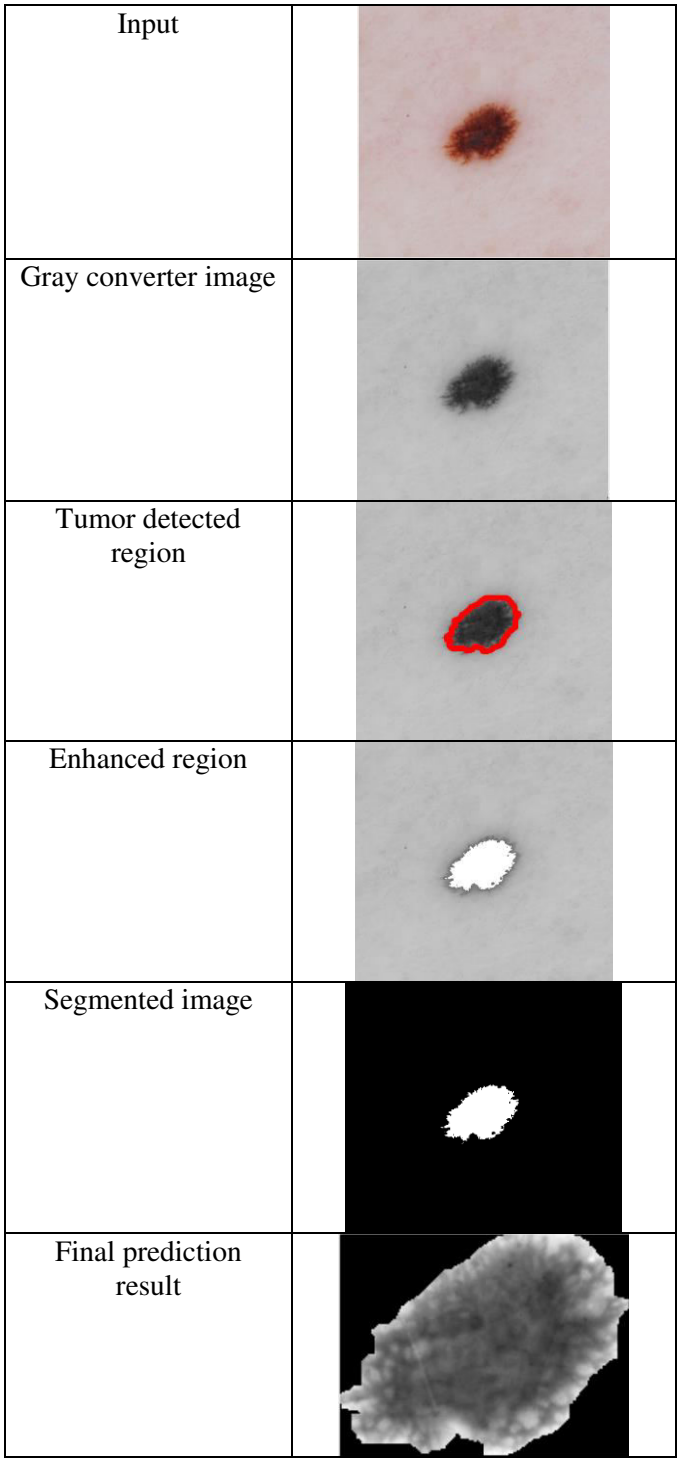

Fig 3(a). Input image (b). Gray image (c). Enhanced image (d). Segmented image and (e). Detected region

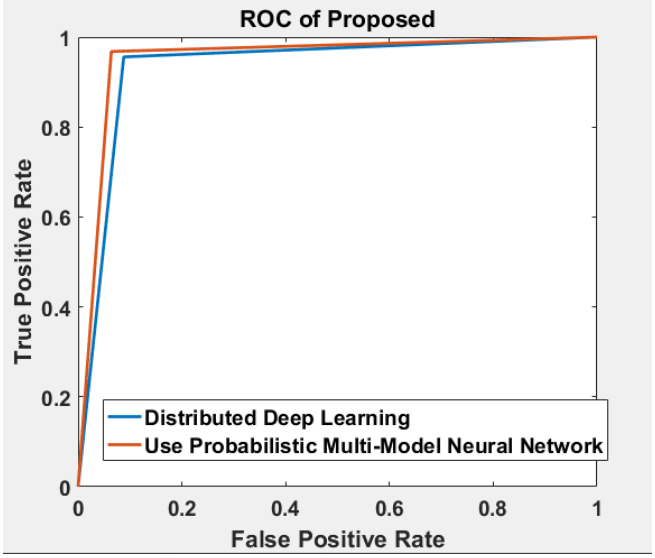

Fig 4. ROC analysis

The proposed CAD model's ROC analysis, which is estimated to assess classifier accuracy, is displayed in Fig 4. Table 1 to Table 4 compare and validate the performance of the proposed and standard feature extraction models used in the skin cancer detection system. Several criteria are used in this evaluation to examine the efficacy of feature extraction techniques combined with conventional classifiers. It has the LBP, GLCM, T1, T2, C1, S, and OCTAL characteristics. The results of the forecasts demonstrate that the recommended MDP method performs better than alternative models with high performance values. Next, Fig 5 to Fig 8 display the related graphical depictions of these evaluations.

Table 1. Classification results for LBP Feature extraction from PH2 dataset

Methods	Specificity	Sensitivity	PP	F-score	HM	Accuracy
Bayes	0.90	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
Proposed	0.989	0.975	0.982	0.975	0.985	0.90

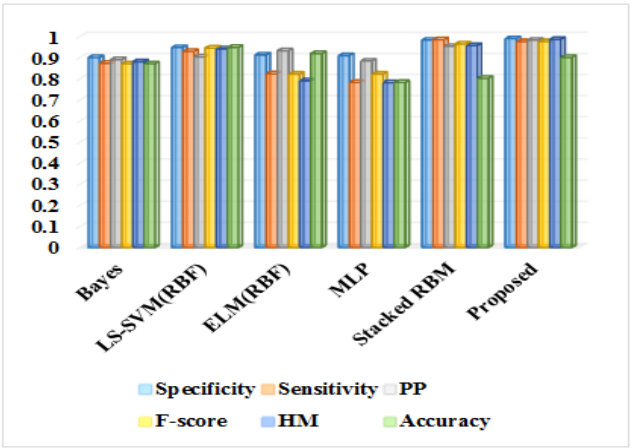

Fig 5. Performance comparative study using LBP features

Table 2. Classification results for GLCM feature extraction from PH2 Dataset

Methods	Specificity	Sensitivity	PP	F-score	HM	Accuracy
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
Proposed	0.982	0.979	0.963	0.96	0.972	0.98

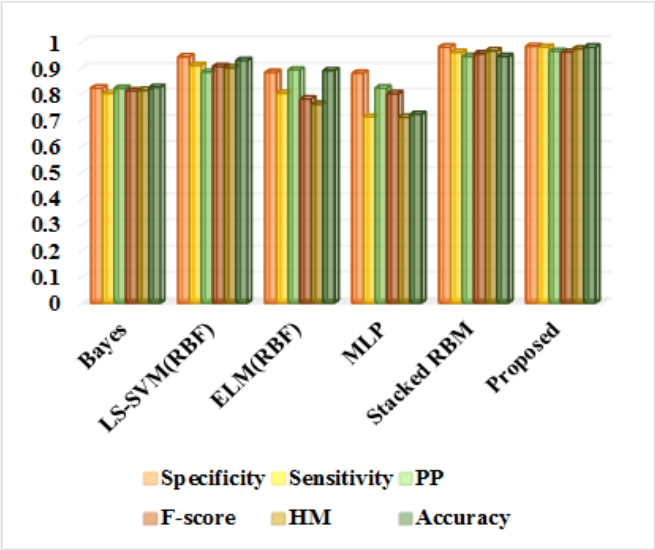

Fig 6. Performance comparative study using GLCM features

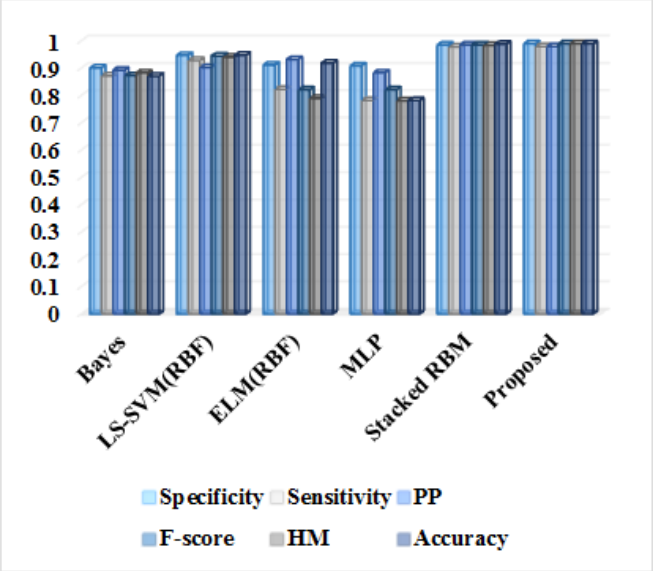

Fig 7. Performance comparative study using T1, T2, C1, S features

Table 3. Classification results for [T1,T2,C1,S] feature extraction from PH2 dataset

Methods	Specificity	Sensitivity	PP	F-score	HM	Accuracy
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
Proposed	0.99	0.98	0.98	0.99	0.99	0.99

Table 4. Classification results for OCTAL feature extraction from PH2 Dataset

Methods	Specificity	Sensitivity	PP	F-score	HM	Accuracy
Bayes	0.91	0.881	0.903	0.881	0.891	0.882
LS-SVM(RBF)	0.95	0.93	0.912	0.956	0.956	0.953
ELM(RBF)	0.92	0.833	0.42	0.831	0.780	0.923
MLP	0.91	0.79	0.893	0.831	0.791	0.792
Stacked RBM	0.965	0.981	0.992	0.991	0.992	0.989
Proposed	0.983	0.989	0.99	0.99	0.99	0.99

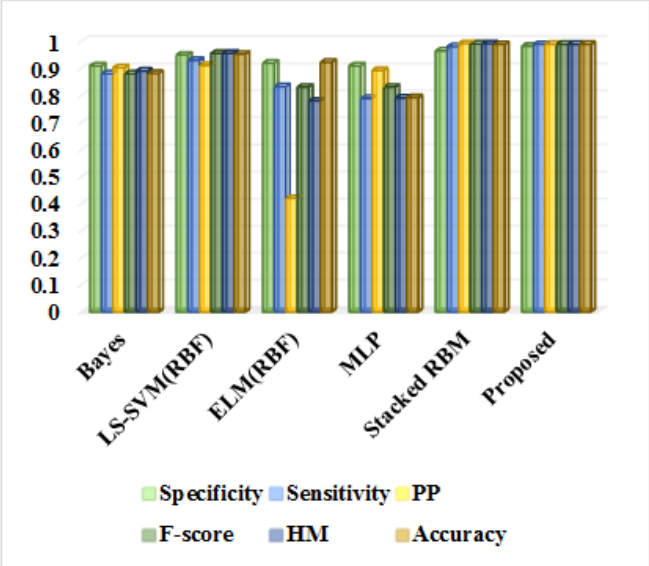

Fig 8. Performance comparative study using OCTAL features

Tables 5 to Table 7 validate and compare the testing performance outcomes of the developed and current deep learning classifiers for the diagnosis of skin cancer. Then, Fig 9 to Fig 11 demonstrate its suitable graphical representations. These results also demonstrate that the proposed MDP-DDP approach works better than other existing models.

Table 5. Performance metrics of the models for Melanoma dataset

Methods	Accuracy	Sensitivity	Specificity	Precision
Proposed	0.95	0.952	0.948	0.951
Dense Net 121	0.89	0.92	0.858	0.861
ResNet50	0.865	0.91	0.82	0.839
AlexNet	0.85	0.862	0.83	0.839
VGG16	0.87	0.815	0.915	0.91

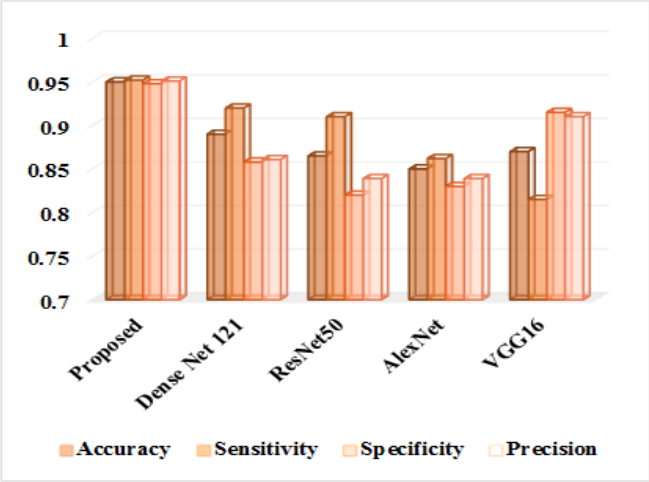

Fig 9. Comparative study using Melanoma dataset

Table 6. Performance metrics of the models for nevus dataset

Methods	Accuracy	Sensitivity	Specificity	Precision
Proposed	0.96	0.95	0.95	0.96
Dense Net 121	0.885	0.89	0.87	0.90
ResNet50	0.88	0.863	0.871	0.90
AlexNet	0.842	0.863	0.92	0.862
VGG16	0.861	0.819	0.915	0.91

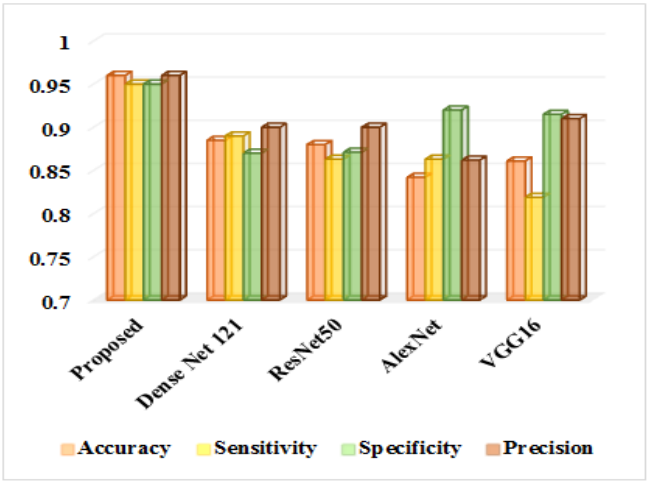

Fig 10. Comparative study using nevus dataset

Table 7. Performance metrics of the models for seborheic keratosis dataset

Methods	Accuracy	Sensitivity	Specificity	Precision
Proposed	0.95	0.94	0.93	0.94
Dense Net 121	0.852	0.89	0.82	0.81
ResNet50	0.85	0.86	0.82	0.805
AlexNet	0.82	0.848	0.755	0.755
VGG16	0.825	0.94	0.72	0.73

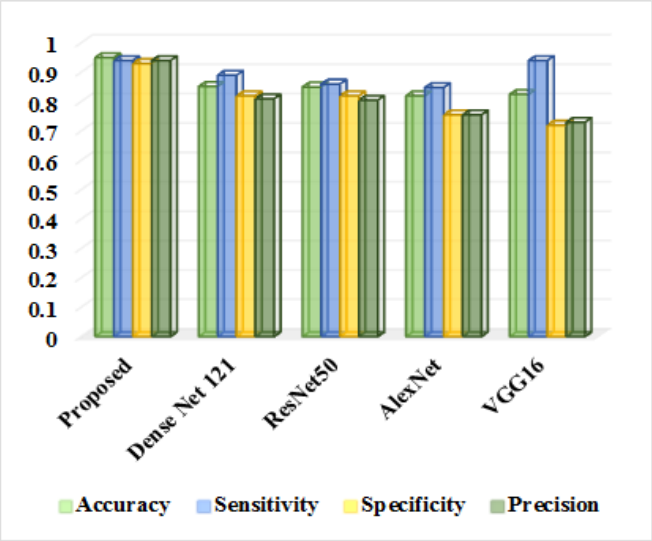

Fig 11. Comparative study using seborheic keratosis dataset

X. CONCLUSION

In order to detect and diagnose skin cancer, a unique MDP-DDP approach is proposed in this research. MDP with complex geometric patterns will next be used to extract from the images the characteristics predictive of cancerous regions. These criteria would be selected using BQISO in order to improve the segmentation process' accuracy. After that, the model would be trained using DDP, which would enable very precise identification of cancerous areas in skin scans in addition to speeding and enhancing the accuracy and speed of the segmentation process. This trend may have a major impact on early detection and treatment of skin cancer, a critical global public health concern. After that, the model would be trained using DDP, which allows for extremely accurate detection of malignant spots in skin scans, to speed up and enhance the accuracy of the segmentation process. The suggested MDP-DDP approach's results are validated and assessed using a number of performance metrics. This study evaluates a variety of characteristics to determine the efficacy of the proposed and existing classification systems for skin cancer prediction. The results show that the suggested MDP-DDP strategy outperforms other current models in terms of performance.

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