

MIoT Based Skin Cancer Detection Using Bregman Recurrent Deep Learning

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Received: 01 March 2022; Accepted: 09 June 2022

Abstract: Mobile clouds are the most common medium for aggregating, storing, and analyzing data from the medical Internet of Things (MIoT). It is employed to monitor a patient's essential health signs for earlier disease diagnosis and prediction. Among the various disease, skin cancer was the wide variety of cancer, as well as enhances the endurance rate. In recent years, many skin cancer classification systems using machine and deep learning models have been developed for classifying skin tumors, including malignant melanoma (MM) and other skin cancers. However, accurate cancer detection was not performed with minimum time consumption. In order to address these existing problems, a novel Multidimensional Bregman Divergencive Feature Scaling Based Cophenetic Piecewise Regression Recurrent Deep Learning Classification (MBDFS-CPRRDLC) technique is introduced for detecting cancer at an earlier stage. The MBDFS-CPRRDLC performs skin cancer detection using different layers such as input, hidden, and output for feature selection and classification. The patient information is composed of IoT. The patient information was stored in mobile clouds server for performing predictive analytics. The collected data are sent to the recurrent deep learning classifier. In the first hidden layer, the feature selection process is carried out using the Multidimensional Bregman Divergencive Feature Scaling technique to find the significant features for disease identification resulting in decreases time consumption. Followed by, the disease classification is carried out in the second hidden layer using cophenetic correlative piecewise regression for analyzing the testing and training data. This process is repeatedly performed until the error gets minimized. In this way, disease classification is accurately performed with higher accuracy. Experimental evaluation is carried out for factors namely Accuracy, precision, recall, F-measure, as well as cancer detection time, by the amount of patient data. The observed result confirms that the proposed MBDFS-CPRRDLC technique increases accuracy as well as lesser cancer detection time compared to the conventional approaches.



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Keywords: MIoT; skin cancer detection; recurrent deep learning classification; multidimensional bregman divergencive scaling; cophenetic correlative piecewise regression

1 Introduction

Skin cancer is the most important type of risky form of cancer to affect the human death rate. Skin cancer is affected by the irregular development of skin cells. Melanoma and non-melanoma are the most common type of skin cancer. Skin cancer cases have enlarged significantly in modern years because of malignant melanoma. In the United States per year, 5.4 million patients are affected by skin cancer. The skin prevents the person's body from various undesirable impacts of surroundings. Therefore, skin fitness monitoring and early-stage detection are challenging task for effective treatment and it helps to cure it. Manually skin lesions detection is very complex. Besides, due to variants in skin textures and injuries, identification, as well as categorization of skin cancer, was a complex mission. Internet of things (IoT) and deep learning possess high accuracy with flexibility. This helps to detect skin cancer at an early stage for the enhancement of accuracy and time. In addition, the machine learning method is employed for discovering skin cancer to obtain good efficiency in detection.

An Automated Hyper-Parameter Optimized Convolution Neural Net (CNN) was introduced in [1] for detecting the class of skin cancer. The Grey Wolf Optimization algorithm was applied by choosing the applicable hyper-parameters and improving the accuracy. This helps to handle the skin cancer multi-class classification issue. Image preprocessing is performed by applying Bilinear Incorporation (BI) for protecting the training time. The designed method is introduced with higher accuracy and a lesser loss rate. But, the time complexity was not minimized by applying multiclass datasets. A Deep CNN-based structure of instantaneous identification, as well as recognition of skin lesions called Dermo-DOCTOR, was developed in [2]. But the accuracy of detection and recognition of the skin lesions was not improved.

The deep Convolutional Neural Network (DCNN) model was introduced in [3] to achieve the classification rate. But, the classification accuracy was not improved. In [4], machine learning techniques and their application in the diagnosis of skin cancer were studied. Integration of human and artificial intelligence techniques was introduced in [5] for skin cancer detection. But the different process of skin cancer detection was not analyzed with a large dataset.

The support vector machines and convolutional neural networks were developed in [6] for malignant melanoma skin cancer detection. But the designed classifiers models were not efficient to increase their accuracy. Malignant melanoma classification using deep learning classification was introduced in [7]. However, increasing the accuracy rate remains a major challenge. Several deep learning methods were developed in [8] for skin cancer diagnosis by applying the entropy as well as VIKOR approaches. But the designed method was not suitable for designing the diagnostic system.

Deep neural network was introduced in [9] for the skin lesions classification system. The designed model achieved a high accuracy rate but the precision and recall were not estimated. Deep learning-based model-driven construction was designed in [10] for Skin cancer detection. But the performance of time complexity analysis was not performed.

Most of the conventional CNN-based methods have been designed for the Internet of things (IoT). But it failed to consider the cancer detection time. In addition, the precision was not enhanced. Then, the existing CNN-based method failed to offer better accuracy and recall to identify cancer at an earlier stage. To overcome the existing issue, MBDFS-CPRRDLC technique is introduced to enhance

the accuracy with lesser cancer detection time. The novelty and contributions are illustrated as given below,

- An MBDFS-CPRRDLC was developed for improving skin cancer detection accuracy in lesser time.
- The Multidimensional Bregman Divergencive Feature Scaling technique is designed in the MBDFS-CPRRDLC technique with the novelty of the Bregman Divergence. It is utilized as a Recurrent Deep Neural learning classifier for determining the important features to find the disease with minimum time consumption.
- A new thought of the cophenetic correlative piecewise regression is applied in the MBDFS-CPRRDLC technique for analyzing the testing and training cancer data. The novel idea of the piecewise regression is useful for partitioning the data dissimilar classes, exhibit different relationships between the testing and training cancer data.
- Cophenetic correlation coefficient is employed to the relationships among the testing and training cancer data. This process is repetitively performed until the error gets minimized. In this way, cancer classification is accurately performed with higher accuracy.
- Extensive experimentation is conducted for calculating the MBDFS-CPRRDLC as well as related works. The obtained result shows that our proposed, MBDFS-CPRRDLC provides better performance in terms of accuracy, precision, recalls, F-measure, and detection time.

The main objective of the MBDFS-CPRRDLC technique is described as follows.

- To enhance the skin cancer detection accuracy, an MBDFS-CPRRDLC technique is introduced based on feature selection and classification.
- To reduce the cancer detection time the Multidimensional Bregman Divergencive Feature Scaling technique is employed in the MBDFS-CPRRDLC technique as a Recurrent Deep Neural learning classifier to find the significant features for disease identification
- To improve the precision and recall, a cophenetic correlative piecewise regression is utilized in the MBDFS-CPRRDLC technique to a hidden layer of Recurrent Deep Neural learning classifier to examine the testing and training cancer data.

The article is organized as follows. Section 2 discusses the related works. Section 3 describes the MBDFS-CPRRDLC by a neat figure. Section 4 explains the simulation settings. Section 5 provides the results and discussion. Section 6 gives the conclusion of the paper.

2 Related Works

In this section, we present contemporary pertinent related works to our work that led and motivated us to carry out this research work. The related works are related to deep learning methods along with the review of works conducted in the area Skin cancer detection. An architecture search framework was introduced in [11] for malignant melanoma detection. But it failed to yield accurate classification results. A new transfer learning-driven deep IoHT framework was developed in [12] for the recognition and categorization of skin cancer. However, it failed to improve the classification accuracy.

A deep learning feature fusion as well as extreme learning machine were introduced in [13] for multiclass skin lesion classification. But it failed to consider the recent deep learning models for accurate lesion classification. A novel method consisting of artificial intelligence and cloud-based IoT was introduced in [14] for skin disease classification. But it failed to provide efficient skin disease classification results.

A medical artificial intelligence structure was introduced in [15]. But the accuracy was not enhanced using self-learning scheme. A new hybrid machine learning approach was developed in [16] for various cases of melanoma skin cancer detection. But it failed to improve the model efficiency and performance of melanoma detection.

A Deep Convolutional Neural Networks architecture was designed in [17] for Skin Lesion Classification. But the time consumption of Skin Lesion Classification was not minimized. Transfer Learning with Deep Learning was introduced in [18] based on IoT for the diagnosis of skin lesions. But the designed approach failed to detect the different types of skin lesions with different datasets.

A deep convolutional neural network was developed in [19] for multi-class skin Cancer classification. However, deep learning computer-aided schemes were not applied. A fusion-based Deep learning methodology was developed in [20] for the Detection of different stages of melanoma skin cancer. But it considered every feature of classification as well as consumes greater time. Several machine learning techniques were developed in [21] for skin cancer detection. But the designed technique was not efficient for the large volume of data generated by the healthcare system. Lightweight CNN classification model based on transfer learning was developed in [22] to exactly find the COVID-19 diagnose patients. But the time was higher. Multi-label learning algorithms were introduced in [23] for improving accuracy. However, the relevant features are not selected.

We present contemporary pertinent related works to our work that led and motivated us to carry out this research work. The related works are related to machine learning and deep learning methods along with the review of works conducted in the area of remote monitoring systems. In recent few years, the healthcare industry has overlooked notable coercion owing to the ceaseless upsurge in patients concerning chronic diseases and their long-term treatment given to the patient. Different clinical applications have been proposed to provide solutions to the surge rate of chronic patients in the hospital.

3 Methodology of MBDFS-CPRRDLC for the Deep Learning MIOT

Skin cancer was a risky type of cancer as well as improves the cause of fatality for the need facts. Therefore, early identification of starting stage is essential to prevent the spreading of cancer. Skin diseases were the major widespread problem that needs survey. Diagnosis was reliant on the knowledge of physicians. Misdiagnosis, delayed diagnosis, or inability diagnosis cause life-threatening effects. Therefore, a novel work MBDFS-CPRRDLC improves the diagnostic procedure for skin cancer. MBDFS-CPRRDLC is used for the deep learning MIoT driven structure of skin cancer.

Fig. 1 given below demonstrates the architecture of the Mobile Cloud service provisioning based proposed MBDFS-CPRRDLC technique. The architectural model consists of three major entities namely the number of patients P_1, P, P_3, \dots, P_n and collects the image samples from the IoT. Then the data $d_1, d_2, d_3, \dots, d_m$ are extracted from the image. The extracted data are stored in the external data-storing center (i.e., mobile cloud server) and accessed from it. A mobile cloud server is an entity that provides a data-sharing service to many users. The collected training data as input and performs both feature selection and classification using various layers such as an input layer, a hidden layer, and an output layer. At first, the Bregman Divergence is applied for finding the dissimilarities features based on a distance measure. Then, Cophenetic correlative piecewise regression-based cancer detection is used to detect the different classes of cancer. In this way, the accurate prediction is carried out with minimum time. MBDFS-CPRRDLC technique employs two hidden layers for deeply learning skin features. Fig. 2 illustrates Recurrent Deep Neural learning.

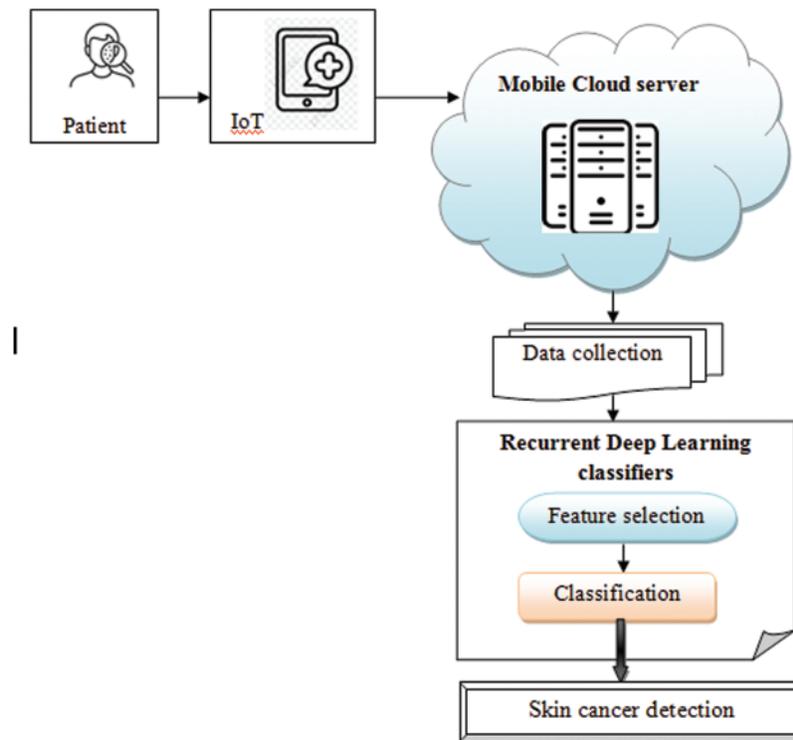


Figure 1: Architecture of proposed MBDFS-CPRDLC

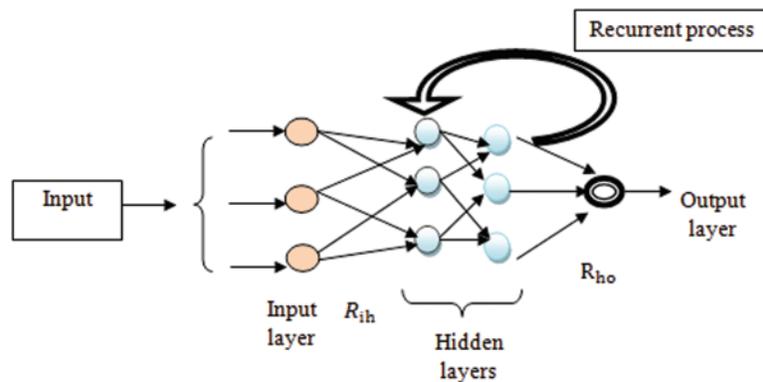


Figure 2: Structural diagram of Recurrent Deep Neural learning

Fig. 2 given above illustrates a structural diagram of adaptive deep Recurrent Deep Neural learning with multiple layers. The deep Recurrent Deep Neural network consists of the neuron-like nodes within various layers and connected within the subsequent successive layers. In one layer, the neuron is completely linked with the next successive layer as well as repeatedly performs deep feature learning it was termed a recurrent deep neural classifier. The input layer receives the number of features within a network by time ' t ' was indicated by ' $Q(t)$ '. Then the received input is transferred within the first hidden layers. Weights among input and hidden layers are denoted by R_{ih} . In Fig. 2, there are two hidden layers are used to perform feature selection and classification. The hidden layer is

indicated by ' $W(t)$ ', The last hidden layer is the response to the first hidden layer as well as frequently analyzing features as well as verifying with testing data. Hidden layers as well as productivity layers were interrelated via weights R_{ho} . The activity of neurons was formulated by,

$$Q(t) = \left[\sum_{i=1}^n R_{ih} * Q_i(t) \right] \quad (1)$$

From (1), $Q_i(t)$ symbolizes an input, R_{ih} denotes the weight among input as well as hidden layer, $Q_i(t)$ indicates input features $F_1, F_2, F_3, \dots, F_n$. The weight is used for identifying the strength of the connection between the layers. In the first, the hidden layer feature selection process is carried out using the Multidimensional Bregman Divergence scaling (MBDS) technique. In this work, MBDS aim is to remove irrelevant features with redundant information, select relevant features and minimize the time. The MBDS is a nonlinear dimensionality reduction method that helps to estimates the level of similarity between the features. The similarity between the features is identified by the nearest neighbor concept. By applying Multidimensional scaling, the relationship between the dissimilarities in the matrix is identified and the location of each item in the low-dimensional space. In order to reduce the complexity of cancer prediction, the Bregman Divergence is employed based on a distance measure for finding the dissimilarities features.

Initially, the features are arranged into the matrix in the form of row and column

$$M = \begin{bmatrix} F_{11} & F_{12} & \dots & F_{1n} \\ F_{21} & F_{22} & \dots & F_{2n} \\ \vdots & \vdots & \dots & \vdots \\ F_{n1} & F_{n2} & \dots & F_{nm} \end{bmatrix}$$

$$Div_B = \|F_i - F_j\|^2 \quad (2)$$

where, Div_B denotes a Bregman divergence between the two features ' F_i ', ' F_j '. The divergence among the features is determined based on higher differences between the two features. So, the divergence lower than given thresholds is selected because low variance features did not affect the target output.

$$Z = \begin{cases} Div_B < \delta, & \text{selected} \\ Div_B > \delta, & \text{notselected} \end{cases} \quad (3)$$

where δ denotes a threshold, Z indicates the output of MBDS, Therefore, the feature with minimum distance is selected for further processing to minimize the complexity of cancer prediction. After the feature selection, the proposed MBDFS-CPRRDLC performs the cancer detection based on a Cophenetic correlative piecewise regression. Regression is the statistical procedure to measure the interaction among dependent variable (i.e., outcomes) as well as one or more independent variables (i.e., testing 'features' and training 'features').

Fig. 3 shows the block diagram of Cophenetic correlative piecewise regression-based cancer detection. Piecewise regression function is applied to identify the training as well as testing data on Cophenetic correlation function. Main aim of regression analysis is used to predict types of skin cancer with a specific mathematical criterion. The mathematical criterion is performed using a Cophenetic correlation.

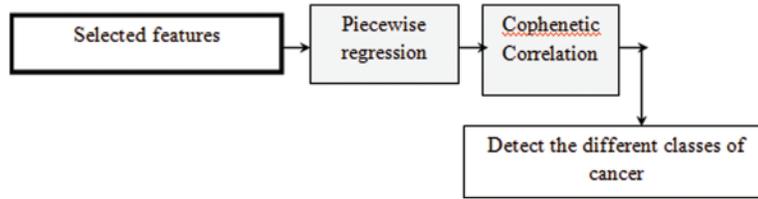


Figure 3: Block diagram of Cophenetic correlative piecewise regression-based cancer detection

The regression function considers the input training data $d_1, d_2, d_3, \dots, d_n$ collected from the dataset. Then the Cophenetic correlation is measured as given below,

$$C_f = \frac{\sum (d_t - \overline{d_t(c_i)}) (d_r - \overline{d_r(c_i)})}{\sqrt{\sum [d_t - \overline{d_t(c_i)}]^2 \sum [d_r - \overline{d_r(c_i)}]^2}} \tag{4}$$

From (5), ‘ C_f ’ indicates Cophenetic correlation coefficient, d_t and d_r indicates training and testing data. $\overline{d_t(c_i)}$ indicates the average of the testing data at a particular class, $\overline{d_r(c_i)}$ denotes an average of the training data at a particular class. The correlation coefficient results very close to + 1 indicating a better solution to provide accurate disease classification. Based on the correlation measure, the piecewise regression provides the different classes of the output.

The hidden layer output is given by,

$$M(t) = \sum_{i=1}^n x_i * R_{ih} + [R_h * m_{i-1}] \tag{5}$$

where, ‘ $M(t)$ ’ indicates the hidden layer result, ‘ R_{ih} ’ denotes the weight among input as well as hidden layer, m_{i-1} denotes the preceding hidden layer. Then error is calculated for each time step to obtain the final classification results.

$$E = |A_r - P_r|^2 \tag{6}$$

where ‘ E ’ denotes an error, A_r indicates actual results, P_r denotes predicted classification results. The output results of the hidden layer are fed into the input of the first hidden layer. This process is repeated until the error is minimized. If the error gets minimized, then the results are fed an output layer. The result of the output layer is expressed as given below,

$$Z(t) = \sum_{i=1}^n M(t) * R_{ho} \tag{7}$$

From Eq. (7), ‘ $Z(t)$ ’ symbolizes the output of classification result, ‘ R_{ho} ’ represents the weight between the hidden and output layer. In this way, accurate classification results are obtained at the output layer. The step-by-step process of MBDFS-CPRDL is explained by,

Algorithm 1: Multidimensional Bregman Divergencive Feature Scaling Based Cophenetic Piecewise Regression Recurrent Deep Learning Classification

Input: Dataset ‘ D ’, Features ‘ $F = F_1, F_2, \dots, F_n$ ’, data sample $d = d_1, d_2, \dots, d_n$

Output: Increase accuracy

(Continued)

Algorithm 1: Continued

```

Begin
Step 1.   Collect the number of features  $F_1, F_2, \dots, F_n$  in input layer
Step 2:   Features are arranged into the matrix in the form of row and column
Step 3:   For each feature—hidden layer 1
Step 4:   Measure divergence ‘ $Div_B$ ’
Step 5: If ( $Div_B < \delta$ ) then
Step 6:   Features are selected
Step 7:   else
Step 8:   Features are not selected
Step 9:   end if
Step 10:  Select relevant features
Step 11:  Remove the irrelevant features
Step 12: end for
Step 13:  For each training data sample—hidden layer 2
Step 14:  For each testing data sample
Step 15:  Apply regression function
Step 16:  Measure Cophenetic correlation
Step 17:  if ( $C = +1$ ) then
Step 18:  Data sample is classified into particular class
Step 19:  End if
Step 20:  For each timestep
Step 21:  Measure error rate ‘E’
Step 22: if ( $\arg \min E$ ) then
Step 23:  Obtain the classification results at the output layer
Step 24:  else
Step 25:  Repeat the process
Step 26:  end if
Step 27: End for
Step 28: End for
End

```

Algorithm 1 given above demonstrates the step-by-step process of skin cancer detection using MBDFS-CPRRDLC. First, the patent data samples are collected from the IoT. Then the Recurrent Deep Learning Classifier uses the different layers for cancer detection. First, the input layer receives the number of features. Then the Multidimensional Bregman Divergence Scaling is applied for finding the significant features in the first hidden layer of Recurrent Deep Learning Classifier. With the selected feature values, the classification is done at the second hidden layer by analyzing the testing and training data using cophenetic correlative piecewise regression. Based on regression analysis, accurate classification is performed and finds the different classes of skin cancer. For each timestep, the error rate is measured. If the error is minimal, then the process gets to stop. Otherwise, the process gets iterated until the minimum error is found. Finally, the classification outcomes were detected on the output layer. This in turn increases the accuracy of cancer prediction with minimum error.

4 Experimental Scenario

Experimental evaluation of the proposed MBDFS-CPRRDLC technique and existing Automated Hyper-parameter Optimized CNN [1], Dermo-DOCTOR [2], DCNN [3] are implemented in Java using Skin Cancer MNIST: HAM10000 taken from the Kaggle (<https://www.kaggle.com/kmader/skin-cancer-mnist-ham10000>). Based on the objective of the proposed MBDFS-CPRRDLC technique i.e., focused on improving the skin cancer detection accuracy and detecting cancer at an earlier stage with minimum time the existing methods such as Automated Hyper-parameter Optimized CNN [1], Dermo-DOCTOR [2], and DCNN model [3] are taken as base paper. These two base papers are explained to understand the proposed method. The proposed method concept is derived by considering the problems of these base papers. The drawbacks of these methods are effectively convinced by implementing the proposed method. The Skin Cancer MNIST: HAM10000 dataset is used to accurately identify cancer detection. This dataset consists of two CSV files. The dataset consists of 10015 images of skin lesions collected from IoT devices. From the images, different features are extracted for disease identification. There are different files are available corresponding to 28×28 colored images and which form a feature vector of $784 \times 3 = 2352$ and 8×8 colored images which form 192 features and lastly, 8×8 gray images or 64 features. The data samples are divided into 7 different classes of skin cancer and the description is shown in Tab. 1. Then, the dataset is selected to provide better performance for skin cancer detection.

Table 1: Class description

Classes	Description
0	akiec actinic keratosis/Bowen's disease (intraepithelial carcinoma)
1	bcc Basal cell carcinoma
2	bkl Benign keratosis (solar lentigo/seborrheic keratosis/lichen planus-like keratosis)
3	df Dermatofibroma
4	nv Melanocytic nevus
5	mel Melanoma
6	vasc Vascular lesion

5 Performance Results and Discussion

Simulation of MBDFS-CPRRDLC technique and existing Automated Hyper-parameter Optimized CNN [1], Dermo-DOCTOR [2], and DCNN [3] are discussed. Based on the objective of the proposed MBDFS-CPRRDLC technique, experimental parameters such as Accuracy, precision, recall, F-measure and cancer detection time are selected for analyzing the performance of the proposed and existing method. The performances of the proposed and existing methods were explained by the help of tables as well as graphical illustrations.

- **Accuracy:** It was referred by the number of samples were properly classified within various classes to the entire number of samples collected from the dataset. Therefore, it is expressed by,

$$Ac = \left[\frac{Tr_p + Tr_n}{Tr_p + Tr_n + Fs_p + Fs_n} \right] * 100 \quad (8)$$

From (8), ‘ Ac ’ indicates accuracy, Tr_p symbolizes the true positive i.e., number of samples correctly classified, Tr_n indicates a number of true negatives, Fs_p represents the false positive, Fs_n indicates a false negative. The accuracy is measured in percentage (%).

- **Precision:** It is referred to proportion of the number of samples that were properly classified from an entire number of samples collected from the dataset. The precision was formulated by,

$$Pr = \left[\frac{Tr_p}{Tr_p + Fs_p} \right] * 100 \quad (9)$$

where Tr_p denotes precision, Tr_p denotes the true positive, Fs_p symbolizes the false positive. The precision is measured in percentage (%).

- **Recall:** It is measured by the proportion of the amount of samples that were properly classified to the entire amount of samples. Formula for calculating the recall is expressed as follows,

$$Rc = \left[\frac{Tr_p}{Tr_p + Fs_n} \right] * 100 \quad (10)$$

where Rc denotes precision, Tr_p symbolizes the true positive i.e., number of samples correctly classified, Fs_n symbolizes the false negative. The recall is measured in percentage (%).

- **F-measure:** It is estimated based on the mean of precision as well as recall. The formula for calculating F-measure is expressed as given below,

$$F - measure = \left[2 * \frac{Pr * Rc}{Pr + Rc} \right] * 100 \quad (11)$$

where Pr denotes precision, ‘ Rc ’ indicates the recall. It is calculated by percentage (%).

- **Detection time:** It was measured by number of time taken with the algorithm for performing the cancer detection on classification. Detection time is measured as follows,

$$DT = n * time (dos) \quad (12)$$

where DT denotes a detection time, ‘ n ’ indicates a number of samples, dos denotes the detection of one sample. The Detection time was calculated by milliseconds (ms).

Tab. 2 portrays the accuracy by the number of samples taken in the ranges from 1000 to 10000. As shown in the table, the accuracy of four methods namely MBDFS-CPRRDLC and existing Automated Hyper-parameter Optimized CNN [1], Dermo-DOCTOR [2], DCNN [3] are reported. The results noted that the MBDFS-CPRRDLC provides superior results when compared to conventional methods. This is proved through the statistical measure. For example, with the number of 1000samples, the accuracy observed by applying the MBDFS-CPRRDLC technique is 93% and the accuracy was found to be 89%, 84%, 82% by applying existing Automated Hyper-parameter Optimized CNN [1], Dermo-DOCTOR [2], DCNN [3]. Subsequently, different performance results are observed for each method. MBDFS-CPRRDLC was compared with conventional methods. The comparison result demonstrates the proposed MBDFS-CPRRDLC technique enhances the accuracy by 6%, 9% and 11% when compared to [1,2] and [3] respectively. This is due to the application of Cophenetic Piecewise Regression Recurrent Deep Learning Classification. The cophenetic correlative piecewise regression is applied to the Recurrent Deep Learning technique for analyzing the testing and training disease data. Based on regression analysis, different levels of skin cancers such as akiec, bcc, bkl, df, nv, mel and vasc are identified with higher accuracy.

Table 2: Comparison of Accuracy

Number of samples	Accuracy (%)			
	MBDFS-CPRRDLC	Automated hyper-parameter optimized CNN	Dermo-DOCTOR	DCNN model
1000	93	89	84	82
2000	93.5	88.5	86	83.5
3000	93	88	86.66	85
4000	94.75	89.25	86.75	85.5
5000	95.2	89.8	87.8	86.6
6000	95.5	90.66	87.5	86.83333
7000	95.71	90	88.42	87.42857
8000	95.12	88.75	86.25	85.625
9000	95.11	89.66	85.55	85
10000	94.5	89.5	86	85.3

Fig. 4 illustrates the convergence diagram of precision vs. the number of samples taken from the dataset. The observed results indicate that the performance analysis of precision is increased by applying MBDFS-CPRRDLC when compared to conventional methods. This improvement of the proposed MBDFS-CPRRDLC is to apply the correlation-based regression is applied to recurrent deep learning classifier. The regression function analyzes the training and testing cancer data provides the higher true positive and minimizes the false positive. The overall results of precision are increased as 4%, 6% and 7% compared with [1,2] and [3] respectively.

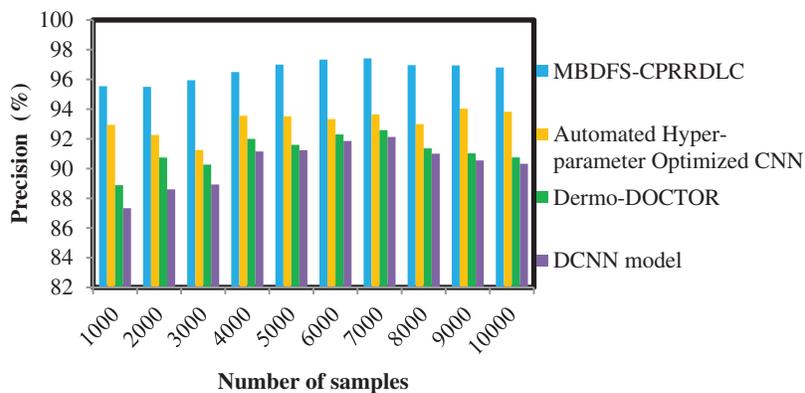


Figure 4: Performance analysis of precision

Tab. 3 demonstrates the performance of recall analysis using four methods and the number of samples collected from the dataset. For each method, ten runs are observed and the equivalent results are reported as a graph. As shown in Tab. 3, the performance of recall is observed using MBDFS-CPRRDLC is comparatively higher when compared to conventional methods. For example, with

1000samples are taken for experimentation, the recall rate using the proposed MBDFS-CPRRDLC was found to be 96.62%. By applying Automated Hyper-parameter Optimized CNN [1], Dermo-DOCTOR [2], DCNN [3], the performance of recall 94.04%, 91.13% and 89.61% was observed. Similarly, different outcomes are observed for each method with respect to a number of samples. Finally, the obtained ten results indicate that the overall performance of recall is considerably improved by 3%, 5% and 6% using MBDFS-CPRRDLC compared with [1,2] and [3] respectively.

Table 3: Comparison of Recall

Number of samples	MBDFS-CPRRDLC	Automated hyper-parameter optimized CNN	Dermo-DOCTOR	DCNN model
1000	96.62	94.04	91.13	89.61
2000	97.14	93.93	91.87	90.32
3000	96.3	94.86	93.92	92.97
4000	97.82	94.35	92.79	91.69
5000	97.84	95.01	94.39	93.17
6000	97.85	96.18	93.2	92.75
7000	98.02	95.15	94.26	93.35
8000	97.86	94.32	92.7	92.2
9000	97.86	94.38	92.2	91.86
10000	97.32	94.35	92.89	92.37

Fig. 5 given above illustrates the results of the F-measure against a number of samples taken from the dataset. The F-measure is calculated based on the performance of precision as well as recall. The observed results indicate that the MBDFS-CPRRDLC provides improved performance when compared to conventional methods. Finally, the MBDFS-CPRRDLC was compared with existing methods. F-measure is significantly improved as 3%, 5% and 6% compared with existing methods.

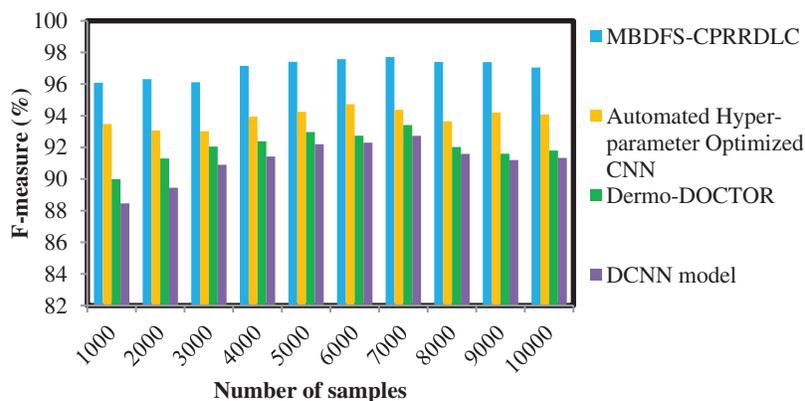


Figure 5: Performance analysis of F-measure

Tab. 4 illustrates the performance of cancer detection time versus the number of samples taken from the dataset. Here, the detection time is measured by number of time for detecting the different types of cancer. The cancer detection time is measured using three different techniques. Among three methods, the proposed MBDFS-CPRRDLC technique minimizes the cancer detection time when compared to conventional methods. Let us consider 1000samples for experimentation. The cancer detection time of the proposed MBDFS-CPRRDLC technique is 23 *ms*. The cancer detection time of Automated Hyper-parameter Optimized CNN [1], Dermo-DOCTOR [2], DCNN model [3] was found to be 27 *ms*, 30 *ms* and 32 *ms* respectively. For the different counts of input, various performance results are observed for all the methods. The overall results indicate that the cancer detection time of MBDFS-CPRRDLC is considerably minimized to 9%, 18%, and 22% compared with existing methods. In particular, enhancing a number of samples as well as improves into the detection procedure. Therefore, the detection time was reduced compared with existing methods. However, Multidimensional Bregman Divergencive Scaling technique is applied to the MBDFS-CPRRDLC to find the important features for cancer detection. With the selected features, classification is performed therefore minimizing the detection time using MBDFS-CPRRDLC when compared to Automated Hyper-parameter Optimized CNN [1], Dermo-DOCTOR [2] respectively.

Table 4: Comparison of detection time

Number of samples	Detection time (ms)			
	MBDFS-CPRRDLC	Automated hyper-parameter optimized CNN	Dermo-DOCTOR	DCNN model
1000	23	27	30	32
2000	26	30	36	39
3000	30	33	36	40
4000	36	40	44	46
5000	40	43	50	52
6000	42	45	48	51
7000	46	49	53	55
8000	48	52	56	58
9000	50	54	59	60
10000	54	60	65	66

6 Conclusion

An efficient detection model called MBDFS-CPRRDLC for skin cancer is developed by integrating feature selection and classification to improve accuracy. First, the patient skin data are collected from the mobile cloud server. Then applying the Multidimensional Bregman Divergencive Scaling technique is applied to the recurrent deep learning classifier for minimizing the cancer detection time by selecting the significant features from the dataset. In addition, the relevant feature selection process of MBDFS-CPRRDLC minimizes the complexity of cancer detection. Followed by, Cophenetic Piecewise Regression is applied to the Recurrent Deep Learning classifier to find the accurate class

of cancer detection by minimizing the error. This helps to improve the accuracy of cancer detection. A comprehensive experimental assessment is carried out with various parameters with respect to number of samples. The performance results in the discussion illustrate that the advantage of MBDFS-CPRRDLC technique achieves exactly identify the class of cancer detection, higher accuracy of cancer detection, precision, recall, F-measure, and perform relevant feature selection process with minimum time than the conventional methods. The results prove that the MBDFS-CPRRDLC technique attains better improvement of accuracy, and precision, recall, F-measure by 9%, 6%, 5%, and 5% and minimize the detection time by 16% as compared to another method. In future work, the proposed technique is further extended to obtain enhanced accuracy with higher precision and minimum detection time with aid of the data preprocessing stage by filling the missing value and removing the duplicate data for Skin Cancer Detection.

Acknowledgement: This research is supported by Princess Nourah Bint Abdulrahman University Researchers Supporting Project number (PNURSP2022R194), Princess Nourah Bint Abdulrahman University, Riyadh, Saudi Arabia for providing a research environment and platform to work.

Funding Statement: This research is funded by Princess Nourah Bint Abdulrahman University Researchers Supporting Project number (PNURSP2022R194), Princess Nourah Bint Abdulrahman University, Riyadh, Saudi Arabia.

Conflicts of Interest: The authors declare that they have no conflicts of interest to report regarding the present study.

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