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ENHANCED SKIN LESION CLASSIFICATION USING DEEP LEARNING MODEL IN INTERNET OF MEDICAL THINGS

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ABSTRACT

The recent development of the Internet of Medical Things (IoMT) has greatly benefited medical professionals, patients and physicians in accessing medical information. This information helps to detect and recognize the diseases in the patients through medical images. However, the automatic detection and classification of diseases in medical images like skin lesions, brain tumor, breast cancer, etc., are still challenging in IoMT due to image quality and irrelevant features. To solve this issue, a Logistic Chaotic Map based Red Panda Optimization algorithm (LCM-RPO) is proposed for the feature selection process to select the significant features. Additionally, a Long Short–Term Memory (LSTM) model is utilised to classify the medical images effectively by learning the sequential information. Initially, the medical images are acquired and then raw images are preprocessed to enhance the data quality for further processing. The DenseNet-169 based feature extraction model extracts the most important features from the diseased portion. The experimental results of the proposed LCM-RPO-LSTM model attained an accuracy of 95.40% and 0.973 for Ph2 and ISIC-2016 datasets, which is higher than existing classification approaches such as PLDG and SVM-IARO.

Keywords: *DenseNet-169, Internet Of Medical Things, Logistic Chaotic Mapping Based Red Panda Optimization Algorithm, Long-Short –Term Memory, Medical Image Classification*

1. INTRODUCTION

Nowadays, the growth of the Internet of Things (IoT) has increased the utilization of IoT devices in various fields, like smart cites, industrial, agriculture, and Internet of Medical Things (IoMT) [1]. These technologies are extensively available, specifically used to detect the diseases which have the highest mortality risk rate, namely melanoma, leukemia, and so on [2-3]. These IoMT technologies are widely used to obtain and analyze the data from patients to monitor them for proper diagnosis and reduce the mortality risk [4-6]. The Deep learning (DL) models are broadly used in medical image analysis like diagnosing breast cancer, brain tumor skin lesion, liver tumor diseases and so on from medical images of Computed Topography (CT), X-rays and Magnetic Resonance Imaging (MRI) [7-8]. Nonetheless, the existing traditional medical image classification approaches are computationally expensive, which involve specialized medical imaging equipment, and that are not accessible in various rural areas of developing countries. In recent years, the Deep Learning (DL) methods are widely used in various fields that attained better results in detection, prediction and classification-based tasks [9]. Thus, a DL based classification model is considered in this research to classify the medical image to diagnose the diseases correctly that helps to provide efficient and suitable treatment [10].

The DL based approaches are progressively utilize for both feature extraction and classification of medical images in IoMT, which is done automatically without human intervention [11,12]. Machine learning based medical image classification frameworks require manual feature extraction, whereas the DL based models, such as neural networks like Convolutional Neural Network (CNN), obtain the most relevant features from medical images automatically [13-14]. Since then, DL-based disease detection and classification approaches have been extensively used in computer-assisted medical image classification that represents higher classification accuracy. However, the previously utilized DL based models failed to classify various diseases using medical images efficiently due to inappropriate information from the irrelevant features. Thus, Logistic Chaotic Optimization based Red Panda Optimization is proposed for feature selection, and a Long Short-Term Memory (LCM-RPO-LSTM) model is proposed to detect and classify the medical images effectively in IoMT in this research. Also, a DenseNet-169 approach, which is a transfer learning model, is employed for feature extraction from medical images. The key contributions of this research are:

- In preprocessing, noise removal and CLAHE techniques are used to remove the noise present in the image and to enhance the image quality. This image quality enhancement helps to extract features from the disease portions efficiently.

- The DenseNet-169 approach is used for feature extraction to extract significant features from the lesion which are located sparsely that ensure it extracts the features even from the minor lesions.

- The proposed LCM- RPO based feature selection model with foraging and climbing tree strategies selects the useful set of features and eliminate irrelevant features efficiently.

- The LSTM based classification model learns the subtle difference for various skin lesions precisely from the selected features. This helps to differentiate between benign and malignant lesions that enhanced the classification performance for skin lesion classification in IoMT.

This research paper is organized as follows: Section 2 discusses the literature survey. Section 3 explains the proposed methodology implemented for this research. Section 4 illustrates the experimental results. The conclusion of this research paper is given in Section.

2. LITERATURE SURVEY

Jianqiao Xiong [16] developed an efficient classification model based on the Integrated Noise-adaptive Attention neural Network (INA-Net). The INA-Net model was developed to classify the medical images efficiently with a lightweight noise-range attention module that combines local and simulated noise features along with global data to improve the model's effectiveness. The main advantage of the developed INA-Net based classification model utilized a technique known as dynamic noise encoding module and Fourier wavelet analysis to enhance the medical image classification process. However, the developed INA-Net model was struggled to detect certain lesions due to their uneven distribution and which were located sparsely. This affects in feature extraction process which miss some significant information that lead to misclassification.

Siyuan Yan [17] designed a Prompt Driven Latent Domain Generalization (PLDG) model to classify the medical images. The designed PLDG model was employed to classify the medical images with the most appropriate features. An advantage of the designed PLDG model determined the pseudo domain labels and modified the collaborative domain prompts to guide the Vision Transformer model to learn information from diverse domains. However, the designed PLDG failed to detect the skin lesions effectively due to the presence of hair in the diseased portion and blurred images that degrades the performance of the model. This significantly impact skin lesion classification which hide important lesion features that make the developed PLDG model to misclassify diseased as normal.

Zhonghua Wang [18] explored an Automatic Super pixel based Masked Image Modeling (AutoSMIM) for skin lesion segmentation. AutoSMIM model was utilized to segment skin lesions from the acquired medical images that also represent the image features. The main advantage of the explored autoSMIM model was that it masks the super pixels of the diseased portion that allowed the model to obtain both low-level and high-level features from the unlabeled pre-training images. However, the explored autoSMIM model failed to focus on the detection and classification of skin lesions. In IoMT, the detection and classification plays an important role which helps to early diagnosis and provide right tratement.

Mohamed Abd Elaziz [19] presented an efficient Rabbit Optimization Algorithm (ROA) for skin cancer prediction. The represented ROA with MobileNet-V3 transfer learning model was utilized to improve detection and classify the medical images accurately. An advantage of the represented MobileNet-V3 model that extracts the significant features from the medical images helps to increase the accuracy of the classification model. However,

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the represented ROA model has limitations such as lacks of depth make less effective to capture the fine grained details of skin lesion that makes difficult to distinguish between Benign and Malignant lesions. This lead to increase high false negative and provide inaccurate classification results.

Arslan Akram [20] presented a skin lesion segmentation and classification model based on a hybrid DL model in IoMT. The presented hybrid DL model was employed for skin lesion detection, which was a combination of MASK Region Convolutional Neural Network (MR-CNN) and Residual Network-50 (ResnET-50). The main advantage of the presented hybrid DL model was the MRCNN approach precisely segmenting the diseased portion from the skin lesion images that helps to extract the features efficiently. However, the hybrid model failed to detect the skin lesion correctly. Since the hybrid model efficiently detect the lesions which were in regional part and that failed to detect the lesions that located sparsely as well as to capture fine grained details.

From the above relative studies of skin lesion classification in IoMT, it is observed various advanced segmentation, feature extraction and detection/classification methods are introduced. The existing approaches like INA-Net [16], PLDG [17], and AutoSMIM model enhanced the feature extraction where Mask RCNN-ResNet-50 [20] improved the segmentation accuracy, challenges such as sparse lesion location, distinguishing between benign and malignant lesions, image blur which lead to misclassification. These limitations are the motivation of this research which are essential to enhance skin lesion classification. To overcome these limitation, in this research preprocessing, feature extraction using pre-trained model, feature selection using optimization model are utilized to enhance the skin lesion classification.

3. METHODOLOGY

The main objective of this research is medical image classification in IoMT using the proposed LCM-RPO-LSTM model. This proposed classification process involves four phases: Dataset, preprocessing, feature extraction, and feature selection and classification with a proposed hyperparameter tuning model. Figure 1 represents the overall process diagram of the proposed medical image classification. Initially, the medical images are acquired from the PH2 dataset and ISIC-2016 dataset and preprocessed by the CLAHE technique. The preprocessed images are further passed to DenseNet-169 based feature extraction model to extract the significant features with relevant information about the diseases. To remove irrelevant information and utilizing the most important features, a feature selection method is proposed based on optimization algorithm. Based on these selected features, the LSTM model classifies medical images efficiently.

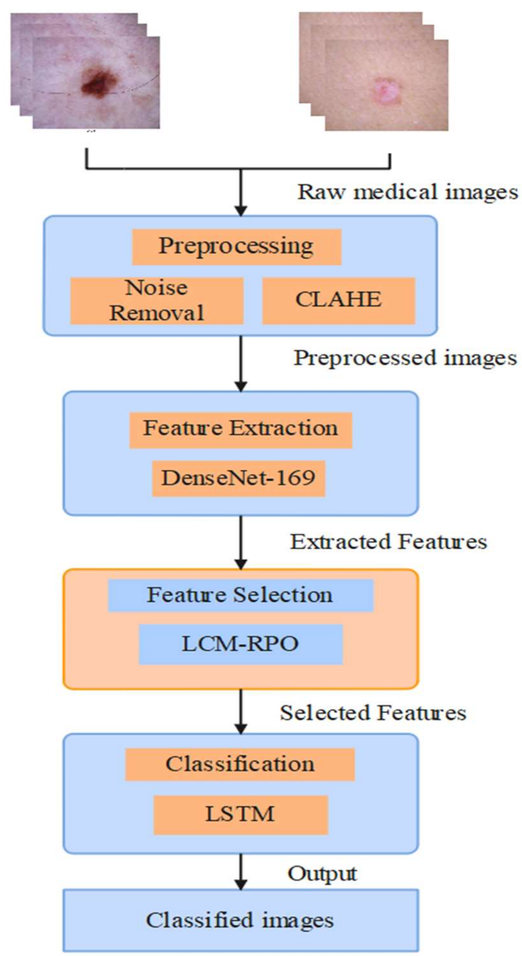

Figure 1: Overall process of proposed LCM-RPO-LSTM based medical image classification in IoMT

3.1 Dataset

For accurate classification of medical images in IoMT, the skin lesion images are considered and acquired from the benchmark datasets such as Ph2 and ISIC-2016 dataset.

3.1.1 Ph2 dataset

The Ph2 dataset is a publicly available dataset which is utilized in this research for medical image classification [21]. This dataset comprises of 200 skin lesion images of healthy people which are carefully segmented by cytogeneticists. The Ph2 dataset is used for skin lesion segmentation and detection of skin lesion images.

3.1.2 ISIC dataset

This ISIC 2016 dataset comprises 1179 images acquired from a hospital [21]. There are both benign and malignant images in this collected ISIC-2016 dataset. The ISIC-2016 dataset is widely used for the detection of skin lesions and skin cancer in people. The acquired images are further fed into the preprocessing phase.

3.2 Preprocessing

The raw images are converted into a useful format by utilizing two techniques such as Noise removal and CLAHE image enhancement technique. However, the existing medical image classification model faces difficulties in accurate classification due to the presence of noise, blurred images and various poor image qualities. Thus, preprocessing techniques are used to address the issues to improve the performance of the proposed medical images classification model. Initially, the raw images are fed to a Gaussian filter to remove the noise present in medical images. Then, the denoised images are fed to CLAHE based image enhancement technique, which is utilized to improve the quality of the image by adjusting the contrast in the medical images. This denoised and enhanced quality of images helps to identify and extract features from diseased portions. These preprocessed medical images are fed as input to the transfer learning-based feature extraction process.

3.3 Feature Extraction

The preprocessed medical images are forwarded as input to the DenseNet-169 [22] based feature extraction model to extract the most relevant features that help medical image classification efficiently. The DenseNet-169 architecture comprises dense blocks that are interconnected in a dense manner that receives input from each layer, which are direct inputs from the prior layers in the same block. This interconnection between layers enhances the reutilization of features that helps to mitigate the vanishing gradient problem without affecting the training efficiency of the model. The advantages of using the DenseNet-169 model for feature extraction in medical image classification are described as follows:

- Dense connections in the DenseNet-169 utilize the features extracted from the previous layer efficiently, which are useful to classify the diseased images from the normal images by extracting the features like shape, texture, and size by the various spatial resolutions.
- Due to its dense connections, the features from early layers are reused in this model, which solves the vanishing gradient problem in deep networks; this helps to represent the rich features.
- The DenseNet-169 based feature extraction model utilizes a transition layer, which ensures computational efficiency and makes the model suitable for feature extraction with resource constraints.

By utilizing the DenseNet-169 model for feature extraction, the model extracts 1024 features from each image that fed to proposed feature selection model.

3.4 Proposed LCM-RPO Based Feature Selection

The proposed RPO is one of the population based optimization algorithms which depends on the small endemic red pandas in southern China or the eastern Himalayas. The natural behaviors of the red panda, like foraging, climbing and resting, are also adopted in this optimization algorithm to select the most relevant features in this research. Here, the foraging ability of the red panda depends on the sight, smell and hearing capabilities along with its long whiskers used to search for food.

This foraging strategy is used to select important features by searching the features with the most relevant information from the numerous features that are extracted from the medical images. Next, the efficient climbing ability of the red panda due to its curved semi-retractile claws and flexible joints makes it well adapted for climbing the tree easily. During the time, the red panda sleeps and takes rests in the highest places, specifically in tall trees, using its climbing ability. This climbing and resting behavior is adopted to refine and select the optimal solution (features) from the explored features. The mathematical model of these behaviors of red panda are categorized into three phases such as initialization, exploration and exploitation phases [23] which are explained below:

3.4.1 Initialization

Each red panda in this optimization algorithm is denoted as the candidate solution for the problem that assists specific values for variables according to its location in the search space. Each red panda is mathematically represented using a vector, whereas a group of red pandas are represented by a matrix, which is expressed in Equations (1) and (2):

$$X = \begin{bmatrix} X_1 \\ \vdots \\ X_i \\ \vdots \\ X_N \end{bmatrix}_{N\times m}$$

$$X = \begin{bmatrix} x_{1,1} & \cdots & x_{1,j} & \cdots & x_{1,m} \\ \vdots & \ddots & \vdots & \ddots & \vdots \\ x_{i,1} & \cdots & x_{i,j} & \cdots & x_{i,m} \\ \vdots & \ddots & \vdots & \ddots & \vdots \\ x_{N,1} & \cdots & x_{N,j} & \cdots & x_{N,m} \end{bmatrix}_{N\times m} \quad (1)$$

$$x_{i,j} = lb_j + r_{i,j}.(ub_j - lb_j) \quad (2)$$

Where, X denotes population matrix of the red panda's location, x_i and $x_{i,j}$ represents i^{th} panda and j^{th} dimension problem variable; N and m stands for number of red pandas and problem variables, $r_{i,j}$ indicates random number; ub and lb represents the upper bound and lower bound.

3.4.2 Estimation of fitness value

Here, the fitness value indicates the quality of the solutions, which is used to evaluate the obtained solution by the red pandas. The fitness values are estimated by the following mathematical Equation (3):

$$F = \begin{bmatrix} F_1 \\ \vdots \\ F_i \\ \vdots \\ F_N \end{bmatrix}_{N\times 1} = \begin{bmatrix} F(X_1) \\ \vdots \\ F(X_i) \\ \vdots \\ F(X_N) \end{bmatrix}_{N\times 1} \quad (3)$$

Where, F represents fitness value; F_i indicates objective function value.

3.4.3 Exploration (foraging phase)

The velocity and position of red pandas in the exploration phase are estimated based on the foraging movement of red pandas. Since the red panda can search for food sources efficiently through its vision, smell and hearing senses, that enhances the exploration process. Based on the fitness function values, the location of the red panda is updated to obtain the most relevant features effectively. From this, one location is arbitrarily considered as the location of food whichever is chosen by the respective red panda. The mathematical representation of position of every red panda (candidate solution) is given in Equation (4):

$$PFS_i = \left\{ X_k \middle| \begin{matrix} k \in \{1,2,\dots,N\} \\ and\ F_k < F_i \end{matrix} \right\} \cup \{X_{best}\} \quad (4)$$

Where, PFS_i denotes a set of food sources; X_{best} represents the position of the red panda. When the red panda moves towards the food source, that makes huge changes in the red panda's location during global search and exploration of a useful set of features. Initially, a new position is evaluated to model the foraging behavior of the red panda according to the position of best food source. After attaining the new position, if the current fitness value is better, than the previous value, then the red panda is updated based on the location estimated in exploration stage by the Equations (5) and (6):

$$X_i^{P1}: x_{i,j}^{P1} = x_{i,j} + r.(SFS_{i,j} - I\,.x_{i,j}) \quad (5)$$

$$x_i = \begin{cases} X_i^{P1}, F_i^{P1} < F_i; \\ X_i, \quad else, \end{cases} \quad (6)$$

Where, X_i^{P1} indicates new position of red panda; SFS denotes selected food source; r and I represents random number.

3.4.4 Exploitation phase (climbing and resting phase)

In this phase, the explored solutions (features) are refined, and an optimal set of features are obtained by changing the positions based on the climbing and resting behavior of red pandas. The red pandas mostly spend their time sleeping and resting on the trees. After exploring the foods, the pandas search the tallest tree in their surroundings and climb to the top of the tree and take a rest. The movement of the red panda to the tree and climbing the tree leads to updating the panda's position, which increases the ability of the red panda to search more relevant features in locally promising areas. The mathematical representation of the climbing and resting behavior of the red panda is expressed in Equations (7) and (8):

$$x_i^{P2} = x_{i,j} + \frac{lb_j + r.(ub_j - lb_j)}{t} \quad (7)$$

$$x_i = \begin{cases} x_i^{P2}, \ F_i^{P2} < F_i \\ x_i, \quad else, \end{cases} \quad (8)$$

3.4.5 Logistic chaotic mapping

However, the RPO algorithm has a drawback in the exploration phase, where the red panda searches for food randomly. This leads the model to become stuck in local optima. Thus, a chaotic map based strategy is proposed to address the issue of local optimum points and to minimize the probability of getting stuck in local optima in the RPO algorithm. This chaotic mapped based RPO algorithm increased the feature selection

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performance that enhanced the medical image classification. In this research, a Logistic chaotic map is used to enhance the RPO algorithm, which is mathematically represented in Equation (9):

$$X_{n+1} = ax_n(1 + x_n) \quad (9)$$

Where, a represents chaotic factor; x_n and X_{n+1} denotes current iteration and the next iteration.

3.5 Classification

The LSTM is a type of recurrent neural network that is most widely used for sequential data that has strong long data processing capability. In LSTM, three important gates that control the processing of data from the input to the output stage are the input, forget, and output gates and a memory unit. The representation of the gates in LSTM and memory unit are mathematically expressed in Equations (10) to (13):

$$i_t = \sigma(W_i.[h_{t-1}, x_t] + b_i) \quad (10)$$

$$o_t = \sigma(W_o.[h_{t-1}, x_t] + b_o) \quad (11)$$

$$f_t = \sigma\left(W_f.[h_{t-1}, x_t] + b_f\right) \quad (12)$$

$$C_t = tanh(W_c.[h_{t-1}, x_t] + b_c) \quad (13)$$

Where, i_t, f_t, o_t, and C_t represent input, forget, output gates and memory cell unit. W and b denotes weights and bias of the layers. The attention mechanism is a data-processing approach extensively used in several machine learning and deep learning tasks, and it also includes natural language processing and image and speech recognition. An attention mechanism operates similarly to the way humans detect external objects; when humans detect something, they tend to focus first on important local details before integrating information from different regions to form a comprehensive understanding of text.

4. RESULTS AND DISCUSSION

The performance analysis of LCM-RPO-LSTM based classifier used for skin lesion classification which considers Ph2 and ISIC datasets. The simulation parameters of proposed model for skin lesion classification is illustrated in Table 1. The performance of the proposed classifier and feature selection methods are analyzed with approaches used in medical image classification illustrated in Table 2 & Table 3 and Fig. 2 & 3.

Table 1. Parameter settings of proposed LCM-RPO-LSTM model used for skin lesion classification

Parameter	Values
LSTM and RPO algorithms	
Activation function	ReLU
Batch size	32
Learning rate	0.0001
Loss function	Categorical loss entropy function
Dropout	0.5
optimizer	LCM-RPO
Population size	30
No. of iterations	100
Fitness	Classification accuracy

Evaluation measures such as accuracy, precision, recall, and F1-score utilized to estimate the performance of the methods utilized in this proposed medical image classification framework. The mathematical representation of these performance measures is expressed in Equations (14) to (17):

$$Accuracy = \frac{(TP+\quad)}{(TP+TN+FP+F\quad)} * 100 \quad (14)$$

$$Precision = \frac{(TP)}{(TP+FP)} * 100 \quad (15)$$

$$Recall = \frac{(TP)}{(TP+FN)} * 100 \quad (16)$$

$$F1 - score = 2 \times \frac{(Precision \times Recall)}{(Precision+Recal\quad)} * 100 \quad (17)$$

Where, TP- True Positive, TN- True Negative, FP- False Positive and FN- False Negative.

4.1 Performance Analysis

The quantitative and qualitative analysis of the proposed LCM-RPO-LSTM model for medical image classification utilizing the Ph2 and ISIC datasets are depicted in this section. The existing DL based classification approaches include CNN, Recurrent Neural Network (RNN), Deep Neural Network (DNN) and LSTM. The existing optimization algorithms such as Particle Swarm Optimization (PSO), Red Fox optimization (RFO), Grey Wolf optimization (GWO), and White Shark Optimization (WSO) are utilized for performance evaluation in feature selection with the proposed RPO algorithm. Tables 2 and 3 and Figure 2 and 3

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illustrate the performance analysis of feature extraction and classification models.

Table 2: Represents The Performance Evaluation Of The Proposed Method For Ph2 Dataset

Methods	Accuracy (%)	Precision (%)	Recall (%)	F1-score (%)
CNN	88.09	87.48	88.04	87.75
DNN	89.13	89.69	89.80	89.74
RNN	91.33	90.29	89.36	89.82
LSTM	93.81	92.17	91.77	91.96
Proposed LCM-RPO-LSTM	95.40	95.42	94.88	95.14

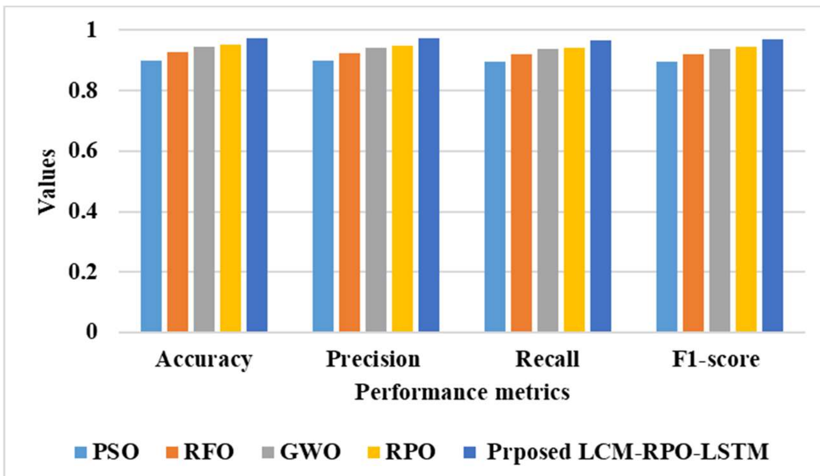

Figure 2: Illustrates Performance Analysis Of Proposed Method For ISIC-2016 Dataset

Table 3: Represents Performance Evaluation Of Proposed Feature Selection Method For Ph2 Dataset

Methods	Accuracy (%)	Precision (%)	Recall (%)	F1-score (%)
PSO	89.82	89.38	88.50	88.93
RFO	90.69	89.41	88.91	89.15
GWO	91.11	90.78	90.20	90.48
WSO	93.57	92.29	91.94	92.11
Proposed LCM-RPO	95.40	95.42	94.88	95.14

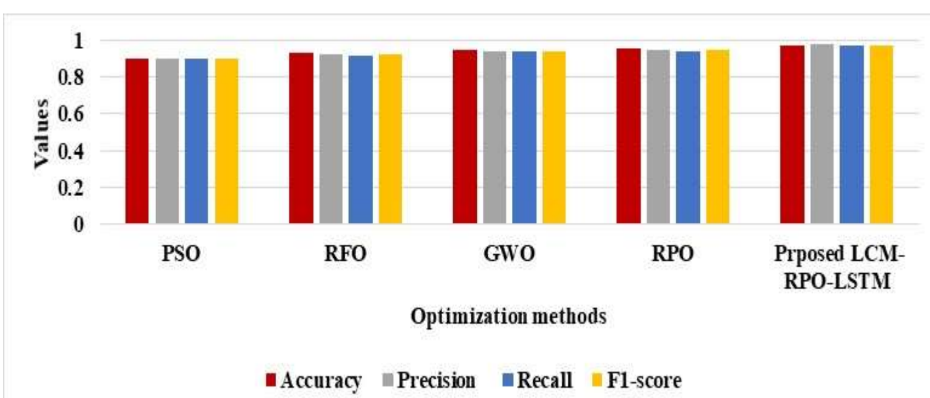

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Figure 3: Represents performance analysis of the feature selection method for ISIC-2016 dataset

4.2 Comparative Analysis

The comparative analysis of the proposed LCM-RPO-LSTM method employed for medical image classification utilizing two different datasets is represented in this section. The existing approaches for medical image classification like are utilized to evaluate the proposed approach for comparison. Evaluation metrics like accuracy, precision, recall and F1-score are utilized for comparative analysis of the proposed method. Tables 3 and 4 illustrate a comparative analysis of LCM-RPO-LSTM for the Ph2 dataset and ISIC-2016 dataset, respectively.

Table 3: Represents A Comparative Analysis Of The Proposed LCM-RPO-LSTM Method For The Ph2 Dataset

Methods	Accuracy (%)	Precision (%)	Recall (%)	F1-score (%)
PLDG [17]	89.09	N/A	N/A	N/A
Proposed LCM-RPO-LSTM	95.40	95.42	94.88	95.14

Table 4: Illustrates Comparative Analysis Of Proposed LCM-RPO-LSTM Method For ISIC-2016 Dataset

Methods	Accuracy	Precision	Recall	F1-score
Auto SMIM [18]	0.96	N/A	N/A	N/A
SVM-IARO [19]	0.865	0.857	0.865	0.858
Proposed LCM-RPO-LSTM	0.973	0.975	0.968	0.971

4.3 Discussion

The proposed LCM-RPO-LSTM achieved better results in medical image classification in IoMT by enhancing the image quality and selecting significant features. Existing DL based classification approaches used for medical image classification have limitations such as: PLDG [17] model failed to detect the skin lesions due to the presence of hair in the diseased portion and blurred images. AutoSMIM [18] model focused on segmentation and failed to detect and classify the skin lesion images. ROA [19] model has limitations that make the classification model provide inaccurate results. Thus, the existing approaches attained a detection accuracy of 89.09% in the PH2 dataset and 0.865 in the ISIC datasets, respectively. The DenseNet-169 based feature extraction model extracts various most relevant features with significant information that helps to enhance the medical image classification. The proposed RPO-based feature selection model with foraging and climbing tree strategies efficiently selects the useful set of features that enhanced the classification performance of LSTM for medical image classification in IoMT.

In this research, for feature extraction DenseNet-169 model is used to extract deep features about the skin lesion efficiently to improve classification performance. The DenseNet-169 model extracts fine grained lesion details that also handles small and sparse lesion by feature reuse across layers. This DenseNet-169 performed better than the existing feature extraction approaches like INA-Net [16], PLDG [17] and AutoSMIM [18] models that helps to achieve high accuracy in skin lesion classification. To differentiate between benign and malignant lesion precisely, a feature selection model based on LCM-RPO algorithm to eliminate irrelevant features and make significant feature subset for classification. These selected features are fed to the LSTM based classifier that learns the subtle differences and classify the skin lesions accurately. The proposed LCM-RPO-LSTM model achieved 95.40% and 0.973 of accuracy for benchmark datasets such as Ph2 and ISIC-2016 respectively. Hence, the proposed method achieved better results when compared the existing approaches in literature in skin lesion classification.

5. CONCLUSION

The proposed LCM-RPO-LSTM approach is used to enhance the skin lesion classification effectively. Since, the limitations of existing research on skin lesion classification such as poor image quality, inappropriate features, struggles to differentiate between benign and malignant lesions. The proposed model utilized a deep learning based classifier model and optimization based feature selection to eliminate redundant features and learn the subtle difference of lesion that enhanced the classification accuracy. Initially, the medical images (skin lesion images) are acquired from the Ph2 dataset and ISIC; then, raw images are preprocessed to remove noise by noise removal and CLAHE techniques that remove noise and enhanced the image quality. After that, features are extracted from the preprocessed images by the DenseNet-169 method, which extracts the significant features through its interconnected layers efficiently. Also, the feature reuse helps to mitigate vanishing gradient issues in deep networks. After that, the most useful set of features is selected by the proposed RPO algorithm. By utilising these selected features, the proposed LSTM model classifies the medical images precisely. The experimental results of the proposed LCM-RPO-LSTM model for medical image classification are evaluated by the performance metrics that attained an Accuracy of 95.40% and 0.973 for Ph2 and ISIC datasets, which is superior to existing models such as PLDG and SVM-IARO. However, the proposed LCM-RPO-LSTM model failed at certain conditions for skin lesion classification due to presence of hair, shadows and background of normal skin lead to misclassification. Therefore, in future, a segmentation technique will be used along with advanced DL models will be used to enhance the skin lesion classification in IoMT.

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