Multi-Scale Deep Learning-based Recurrent Neural Network for Improved Medical Image Restoration and Enhancement

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***Abstract*—Improving medical image quality is essential for accurate diagnosis, treatment planning, and ongoing condition monitoring. A crucial step in many medical applications, the restoration of damaged input images tries to retrieve lost high-quality data. Despite significant advancements in image restoration, two major problems still exist. First, it's important to preserve spatial features, although doing so frequently results in the loss related data. Second, while producing linguistically sound outputs is important, location accuracy can sometimes suffer. To overcome these issues and improve medical imaging, the Multi-Scale Deep Learning-based Recurrent Neural Network (MSDL-RNN) is offered in this paper. The model makes use of various scales during building, in contrast to standard RNN-based techniques, which generally use both full-resolution and gradually reduced-resolution approximations. This multi-scale approach uses deep learning to address problems including noise reduction, defect elimination, and increase of overall image quality. Artificial Bee Colony Optimization is employed for efficient segmentation. By combining local and global data, the MSDL-RNN technique effectively improves and recovers a variety of medical imaging modalities. It generalizes the optimization strategy for model capacity assurance by incorporating crucial pre-processing methods targeted to various medical image types. The suggested approach was implemented in Python software and has an amazing accuracy of 99.23%, which is 4.33% higher than other existing methods like DesNet, AGNet, and NetB0. This study sets the way for important developments in improving the quality of medical images and their uses in healthcare.**

Keywords*—Multi-Scale Deep Learning (MSDL); Recurrent Neural Network (RNN); deep learning; medical image; Artificial Bee Colony (ABC)

I. INTRODUCTION

A critical step in image processing is the restoration procedure, which seeks to extract high-quality data from a broken or corrupted input image [1]. It uses various techniques and algorithms that examine the data at hand and try to restore the image to its initial condition or enhance its quality. Image restoration is necessary in various contexts, such as imagey with digital cameras, images from satellite surveillance systems and healthcare imaging. The restoration method aims to improve image information, decrease noise and artifacts, and produce attractive and educational images. It utilizes cutting-edge algorithms for image processing and machine learning approaches. The need for high-quality visual content is driving more studies into creating cost-effective and successful restoration techniques. Moreover, image deterioration of different degrees happens frequently due to the acquisition process due to the camera's physical constraints because of challenging illumination circumstances [2]. For example, mobile phone cameras have a tiny detector, wide opening and little range in dynamic. As a result, they frequently generate low-contrast images that are noisy. Comparable to how images are taken in poor illumination can appear excessively dark or excessively bright. Recovery of the distinctive, clear image from its damaged dimensions is the goal of image restoration. Because of the many potential answers, the opposite issue is poorly presented.

Deep learning skills utilization in medical tomography has recently received a portion of interest in image enhancement. One of the challenges that numerous scholars are now interested in is how to identify and split grazes that appear on healthcare images mechanically. Medical image enhancement is essential for several clinical uses because it makes it possible to analyze structures of the body and diseased regions accurately and quickly [3]. According to research, U-Net has displayed exceptional achievement in healthcare image breakdown through various imaging techniques, including magnetic resonance imaging (MRI), computed tomography (CT), ultrasound, and others. The effectiveness of it can be due to the network's capacity to precisely differentiate among various kinds of tissues, tumours or organs by learning a hierarchical structure of healthcare images. Nevertheless, image restoration (IR), which has a significant practical value in numerous low-level vision software, has proven to be an ongoing problem [4]. Image restoration generally aims at restoring the hidden clear image x from its deteriorated measurement y = T (x) + n, where T is the noise-irrelevant degrading procedure and n is believed to be additive white Gaussian noise (AWGN) with standard deviation. Furthermore, one can obtain distinct IR assignments by defining various degrading procedures.

Consequently, the purpose of numerous image processing issues, such as super-resolution, deblurring, inpainting, colorization, and compression detecting, is to reconstruct an image from relatively noisy information provided by a known linear deterioration pattern [5]. These issues are examples of linear inverse issues. Employing sets of the initial and damaged images, end-to-end supervised training of neural networks can be utilized for image restoration for a particular degrading paradigm. Nevertheless, versatility is frequently needed in practical applications, such as medical imaging, to handle numerous, endless deterioration patterns. Because they can adjust to the particular issue without re-training, unsupervised techniques based on learned priors may be preferable where the deteriorating concept is initially unknown and employed throughout deduction. Considerably, the collection of all essential info from at minimum two images and the basic creation is alienated into fewer image pixels, characteristically into a solitary one, to create the image's standard and decrease repetition, refining all the basic features of the medical image that is second-hand for investigating all medical problems. It is known as a clinical indication combination cycle. These regions are cast-off to switch to the combined phase. The stuffing by the watersheds computation for these sub-images represents determining the regions at individual levels [6]. This watershed computation has become utilized for completing the image separation to maintain the basic enumeration.

Nevertheless, with the introduction of modern technology into the medical industry, medical image enhancement techniques have received a lot of interest. A surgeon needs improved medical images to help with diagnostic and analysis due to noise, other data-gathering equipment, lighting circumstances, etc. It commonly degrades the quality of medical images [7]. Additionally, the major goals of healthcare image improvement are to address issues with a medical image's low brightness and elevated degree of contamination. Moreover, several research efforts have focused chiefly on greyscale and frequency spectrum transformations in healthcare image improvement techniques [8]. Also, Histogram equalization is a widely used technique for image enhancement in the spatial field, while research on the frequency-domain transformation mainly focuses on the Fourier transformation. While most methods for image enhancement are normally used to offer better images for human observers, some are used as an initial processing stage to deliver better images to later techniques for computer-assisted studies. Therefore, the initial category consists of methods for reducing noise, boosting contrary, and sharpening features. Edge recognition and segmentation of objects for machine learning are the two more methods included in the subsequent type, which largely overlaps with the first [9]. It has been demonstrated that a medical image with a significant contrast can aid in an additional exact valuation of the various tissues in the examined body area.

Therefore, separating the most beneficial data from the processed images is the study's key goal. As a result, many strategies are used to separate the fundamental facts, such as image registration and image fusion [10]. Creating a network of connected images is the goal of image registration. Image registering is also recognized as image merging or pairing and combines more than one image based on how they seem from the outside. Moreover, the healthcare image registration process seeks the ideal spatial transformation assessment that organizes the fundamental physiological frames. Also, healthcare registration of images is used in several healthcare programs, including radiation buildup, tracking of motion, image rebuilding and image navigation. Every procedure performed on an image aims to improve its quality. Because of the issues with the image source of information, there are regular or ad hoc defects and disturbances in the image structure [11]. These flaws and disturbances damage every pixel in the image. For the images to be employed in practice and more intelligible, these flaws must be removed with the use of initial processing techniques.

The key contributions of this research are given below as follows:

- By effectively decreasing noise and maintaining significant image information, the application of a median filter during the pre-processing phase improves image quality and guarantees that the next analysis will benefit from cleaner input data.
- By optimizing the process of locating and isolating regions of interest, the ABC optimization Algorithm is used to image segmentation, enhancing the precision and effectiveness of medical image analysis.
- The GLCM's ability to extract texture features provides insightful information about the structural properties of medical images, enabling more accurate and thorough analysis for diagnostic reasons.
- By using RNN for image classification, the system is able to efficiently classify medical images, which helps with medical condition detection and treatment by using learnt patterns and features. This, in turn, enhances the overall efficiency of the medical image processing pipeline.

This article's remainder is organized as follows: In Section II, a summary of related research is provided. Section III presents the problem statement. The suggested approach's methodology and architecture are explained in Section IV of the article. The findings and subsequent discussion are covered in Sections V and VI, respectively. The conclusion is covered in Section VII.

II. Related Works

For historical years, machine learning, especially deep learning, has improved the analysis of medical images said by L. Chen et al. [12]. It takes a lot of labelled information to train an effective deep-learning algorithm. Nevertheless, getting enough annotated images for training is frequently a challenge. The dataset in consideration frequently contains more unlabelled images than tagged ones. Consequently, it is necessary but difficult to improve the efficacy of machine learning models by employing labeled and unlabelled data. Self-supervised learning is one approach to resolving this issue. Existing self-supervised learning techniques that are suitable for medical images are unable to achieve appreciable improvements in performance. They frequently produce very slight benefits as a result. To more effectively utilize unorganized images, researchers offer a new self-supervised learning technique built around background restoration in this research.

In demand to create novel medical image processing methods, deep learning has involved much study care, as said by X. Chen et al. [13]. Deep learning-based replicas have been confirmed to be tremendously active in a series of medical imaging activities that permit disease detection. Several investigations have remained completed in the last five years with the goal line of solving this tricky. Researchers analysed and synthesized this current research to present an in-depth review of the use of deep learning techniques in various medical imaging analysis challenges in the present research. Moreover, researchers concentrate in particular on the furthermost fresh growths and achievements of state-of-the-art unsupervised and semi-supervised deep learning in the analysis of medical images that are outlined according to many different application instances, spanning separation, identification, and registration of images. Furthermore, researchers discuss the main technological difficulties and offer potential fixes for future research projects.

In his paper, Ahuja [13] said that following the combination of machine learning and deep learning methods, medical imaging has undergone a substantial revolution that has resulted in the creation of smart imaging equipment. These devices use artificial intelligence to improve the precision, effectiveness, and comprehension of healthcare images. To help with evaluation and therapy organizing, machine learning techniques enable the computerized evaluation of healthcare images, encompassing the process of segmentation, categorization and registrations. Convolutional neural networks specifically have demonstrated outstanding results in applications like segmentation based on semantics, recognizing objects, and image classification. The developing subject of generative adversarial networks shows potential for exceptional case synthesizing and data augmentation. It is necessary to handle issues like data accessibility and interpretability. The primary problem of this is quality control and governance.

J. Liu et al. [14] discussed in his paper that by taking into account the particular needs of medical image security for the injury regions, a new zero-watermarking method for healthcare images that utilize DTCWT-DCT has been suggested to address safety concerns with healthcare images that are saved and sent in the cloud. Initially DTCWT is applied to healthcare images. A graphical feature vector consisting of healthcare images that resist geometrical attacks is also obtained from the low-frequency DTCWT parameters. The logistic map is then used with the idea of zero-watermarking to secure the watermark. Based on this, the encoding and retrieval of the watermark is implemented by fusing conventional watermarking techniques with random data encryption cryptography and third-party notion. In contrast to conventional watermarking methods, the suggested approach using DTCWT-DCT does not involve deliberately selecting the region of interest, therefore resolving the quick issue associated with integrating the watermark. Additionally, the incorporated watermark is a zero-watermarking, which leaves the genuine healthcare images unchanged. Logistic Map handles the chaotic encrypting processes, which might increase the watermark's safety.

The main medical imaging (MI) issue is the image denoising discussed by Elhoseny and Shankar [15]. The most difficult part of denoising an image is preserving the data-bearing surface and borders while improving Peak Signal to Noise Ratio (PSNR). In this research, the innovative Bilateral Filter (BF) optimization-based clarifying technique is engaged in deliberation for the MI noise reduction process. The conclusion to select the best variables, i.e., Gaussian and spatial weights, is inclined by how the denoising procedure is passed out. These variables are designated in this case using the DF and MFF algorithms. PSNR and VRMSE are used to determine this variable. The denoised image is additionally classified as normal or abnormal using a CNN classifier with a higher classification rate.

Protecting the authenticity and validity of healthcare images is crucial in telehealth said by X. Liu et al.[16]. Two methods, region of interest (ROI) lossless and reversible watermarking, concentrate on these. Nevertheless, the latter pose safety hazards by splitting the image geographically for watermark implantation and distorting diagnostic by altering the region of no interest (RONI). When ensuring image authenticity, the latter lacks a dependable restoration mechanism for the altered portions. In this research, an innovative and resilient reversible watermarking approach is developed to deal with these problems. To prevent distortions in assessment, this approach uses a reversible watermarking technique that employs recursive dither modulation (RDM).

Suri et al. [17] discussed in his paper that radiology is one area of healthcare where artificial intelligence (AI) has made inroads. Since its discovery, the very aggressive coronavirus disease 2019 (COVID-19) has spread to more than ten million individuals. As of July 1st, 2020, it caused more than 500,000 fatalities. Nearly 28,000 publications concerning COVID-19 have been released since the epidemic started, but few have examined the use of radiography and machine learning in COVID-19 patients, particularly those with multiple medical conditions. The four different routes that can result in brain and heart damage after a COVID-19 illness are first described in this research. According to probabilities calculated from COVID-19 symptomatic research, the survey also provides information about the part radiology can play in the management of comorbidity people. The main objective of this research is the implementation of image-based AI to describe the structures of a COVID-19 patient and categorize the degree of severity of their illness. As the global epidemic spreads and nation’s worldwide struggle with limited healthcare facilities for surveillance and treatment, image-based AI is more crucial than before.

Wang et al. [18] discussed in his paper that a coloured image rectification approach that utilizes non-linear functionality conversion by the brightness-reflection model and multi-scale concept is presented to enhance the flexibility of visualization in images with low illumination. The initial RGB image is altered to HSV color space before extracting the illuminating part of the illustration utilizing the multi-scale Gaussian function. The setting parameters of the image-enhancing mechanism are then adaptively adjusted depending on the spatial distribution characteristics of the lighting elements to produce two images. The correction mechanism is then built using the Weber-Fechner law. The features underlying the two images are then extracted using an image fusion approach. The suggested technique, when compared to the traditional method, can enhance an image's total contrast and brightness while lessening the effects of unequal brightness. The improved images are crisp, inevitable and precise. This paper's lack of brightness is its fundamental flaw.

Greater detail is available in high-quality MR images, enabling accurate diagnosis and statistical image analysis [19]. A deep CNN has demonstrated its potential capacity for super-resolution imaging given LR images. The underlying texturing of various sizes, the highly correlated edges, and the backdrop that is less instructive are a few visual traits that the LR MR images often have in common. Although the backdrop is smoother, multiple scales structural details are instructive for image restoration. The majority of earlier CNN-based SR techniques treat all spatially pixels identically and employ an individual field of reception. For superior MR image SR, it fails to detect the full space and extract a variety of attributes from the input. To solve these issues, a wide weighted attention multi-scale network (W2 AMSN) is suggested for precise MR image SR. On the opposite, the broad multi-scale branching may be used to extract the characteristics of various sizes. On the contrary, in order to continually calibrate feature reactions, a non-reduction attentiveness technique. This focus maintains ongoing cross-channel contact and concentrates on areas that are more relevant. The accessible weighting factors, however, dynamically combine recorded characteristics. A recurrent foundation and a global system for attention are used to incorporate the encapsulated W2AMSB numerous evaluations and a variety of research on ablation demonstrate the usefulness of the suggested W2 AMSN, that outperforms cutting-edge techniques on the majority of common MR image SR standards both numerically and subjectively. On actual MR images, this method still provides greater accuracy and flexibility.

SISR has been shown to greatly benefit from CNN [20]. Previous studies, nevertheless, have not fully used multi-scale characteristics and have disregarded the inter-scale relationship among various up sampling parameters, leading to poor results. It is devoted to mining image characteristics and discovering the inter-scale relationship among various expanding variables rather than only raising the level of the network irrationally. A MDCN is used to do this, which delivers outstanding efficiency with fewer settings and shorter processing time. DRB, HFDB, and MDCBs make up MDCN. They include DRB, which aims to reconstruct SR images with various up sampling variables within a single model, and MDCB, which concentrates on automatically recalibrating channel-wise feature reactions in order to accomplish feature the distillation process. It's important to note that each of these modules has autonomous operation. To enhance the accuracy of the model, these components may be selectively integrated into any CNN model. Numerous investigations demonstrate that MDCN performs competitively in SISR, particularly when it comes to reconstruction tasks involving numerous up sampling values. On GitHub, the code is available under the name MIVRC/MDCN-PyTorch.

The interpretation of medical images has greatly increased in recent years due to machine learning, especially deep learning, but labelled data is still hard to come by. Researchers have developed a unique self-supervised learning method based on backdrop restoration to overcome this problem. Additionally, researchers have studied state-of-the-art unsupervised and semi-supervised deep learning approaches. Deep learning has proven crucial in a variety of medical imaging applications, including illness diagnosis. Meanwhile, the combination of deep learning and machine learning has produced smart imaging devices that increase the precision and effectiveness of the interpretation of medical images. Medical image security is an issue, and to improve image safety, a zero-watermarking technique utilizing DTCWT-DCT has been developed. Moreover, image denoising is crucial for medical imaging, and noise reduction is achieved using an optimization-based technique based on bilateral filters. Furthermore, maintaining the integrity of images is essential in telehealth, and to avoid distortions, a robust solution to reversible watermarking has been created. Particularly in the context of COVID-19, AI has advanced significantly in radiology, with image-based AI being essential for controlling the severity of sickness. Deep CNNs have demonstrated potential for super-resolution imaging, and an inventive method of image correction improves image visibility. Finally, a multi-scale network method that offers faster processing times and more efficiency is suggested for image super-resolution. In a number of respects, these developments are spearheading the revolution in medical imaging and healthcare.

III. Problem Statement

The above discussed literatures states that, in healthcare, the effectiveness of medical imaging is crucial for precise diagnosis, treatment planning, and continuing condition monitoring. Despite significant advancements in image restoration methods, there are still two significant problems. First, it is necessary to protect important spatial elements without losing context-related data, which is frequently lost during restoration methods. Second, while maintaining exact location precision might be challenging, creating linguistically sound outputs is essential. This paper presents an MSDL-RNN to overcome these problems and enhance medical imaging.

The MSDL-RNN uses various scales during model development, in contrast to typical RNN-based techniques that frequently depend on both full-resolution and gradually reduced-resolution approximations. A comprehensive solution to increase medical image restoration and enhancement across many modalities is provided by this ground-breaking multi-scale technique, which efficiently uses deep learning capabilities to address issues including noise reduction, defect elimination, and overall image quality enhancement [21].

The selection of the suggested approach is supported by a number of elements that make it extremely suitable for handling the particular issue at hand. First off, the segmentation process is made more flexible and precise by using the ABC optimization method. This is especially important for medical image analysis, since precise identification of regions of interest is critical. Second, applying a median filter during the pre-processing phase guarantees that noise is efficiently minimized, maintaining crucial image features and enhancing the quality of the input data a feature that is especially helpful for medical images that are frequently tainted by noise. Moreover, the application of the GLCM for feature extraction yields a thorough comprehension of the textural and structural characteristics present in the images, which is an essential component of medical image analysis. However, the constraints of current approaches, such as basic pre-processing's limited noise reduction capabilities and classic segmentation techniques' lack of flexibility, make them ill-suited for the complexity and requirements of medical image analysis. These drawbacks highlight the need for the integrated approach of the suggested strategy, which combines these deficiencies and makes it a strong option for the given situation.

IV. Proposed ABC-RNN Methodology

The second dataset for training and testing is the Kaggle dataset. This is employed to show the efficacy of the analysis and to find the diseases in patients. Pre-processing is used to eliminate unwanted noise distortions and improve specific qualities that are essential for the process. Correspondingly, the standard MSDL-RNN technique is employed to restore and enhance the medical image. Furthermore, it is employed to attain a better accuracy value. Fig. 1 shows the architecture of the proposed MSDL-RNN.

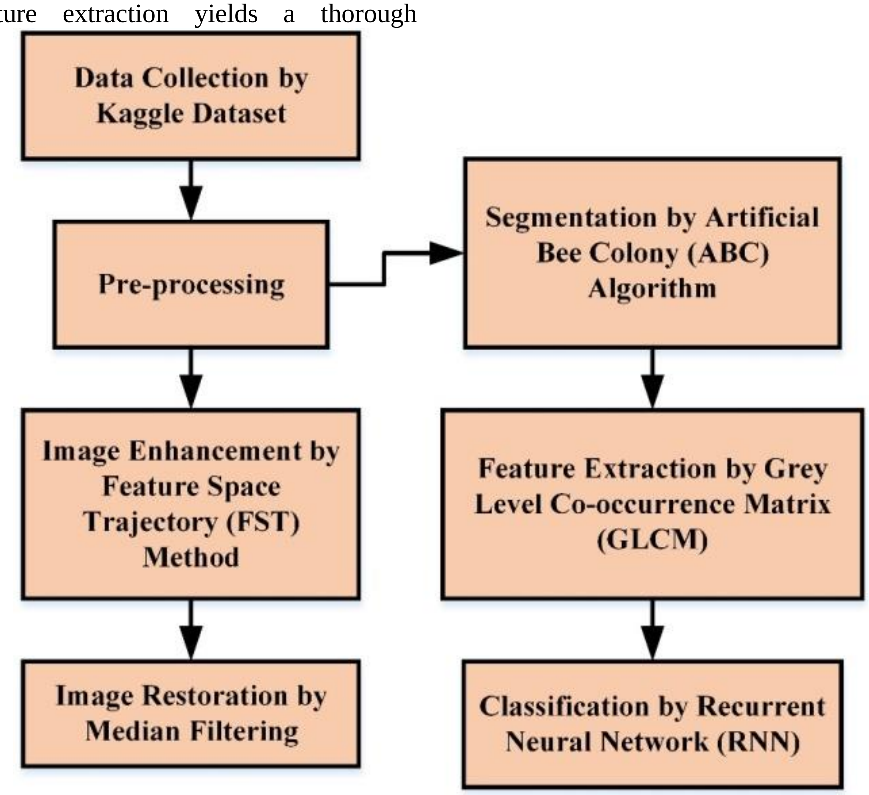

Fig. 1. Proposed ABC-RNN architecture.

A. Data Collection

The dataset used here is the Kaggle dataset [22]. Nearly, 10,000 datasets are used. From this, 50% of the datasets are second-hand for the training process and the other 50% for the testing process.

B. Median Filter for Pre-processing

Pre-processing is done to remove unwanted noise, eliminate defects, and ensure the comprehensive quality of images. Here, pre-processing is used to improve and improve the image quality. The image enhancement is done by Feature Space Trajectory (FST) method. The route or trajectory data points taken when traversing the space of features is referred to as the FST [23]. The space determined by the data's characteristics or qualities is referred to as feature space in the arenas of machine learning and data analysis. The exact location of every data point in the space of features is determined by the set of value features that represent it. And also, the image restoration is done by Median filtering [24]. The steps and equations of the median filtering are given below:

Step 1: Give an input image that is represented as J

Step 2: The image's channels is divided, and the highest and lowest P pixels in every channel are determined in (1) and (2)

$$minimum = minimum_{(i,j)} P(i,j) \quad (1)$$

$$maximum = maximum_{(i,j)} P(i,j) \quad (2)$$

Step 3: The channel of the image is non-linearly modified as seen below in (3)

$$P_1(i,j) = minimum - (maximum - minimum) \times \left(\frac{(P(i,j) - minimum)}{maximum - minimum}\right)^{\beta} \quad (3)$$

The change in wavelength is comparable to the beta transformation but is not the same. The result of the transformation, which is the input image, does not change the image when β=1 is applied. When $\beta \neq 1$, the transformation may extend or conceal the image's pixel values, boost contrast and recover high-frequency elements that disappeared because of border data and the distance, among other capabilities. When β<1, extending the low-pixel frequency band and decreasing the high-pixel frequency band is possible In this instance, it is possible to efficiently recover the minute details of the deeper portion of the image while also improving the local brightness of the darker region of the image and the effect of the stronger lighting on the image. When $\beta > 1$, low-pixel data can be muted by stretching the spectrum of high-pixel data. In this scenario, it is possible to efficiently recover the minute details of the brightest portion of the image by increasing the local brightness of the brightest section. So, grounded on the image's circumstances that need improvement, one can select the c value. Stronger lighting will result in poorer image pixel values.

Step 4: The image was transformed logarithmically, as displayed in the resulting manner given below in (4),

$$P_2 = log(P_1 + n) \quad (4)$$

The alteration can broaden the image's low-pixel frequency spectrum, boost the darker image's contrast, which helps to recover the darker image's features more effectively and is more suitable for outdoor locations with lower light levels. Nevertheless, logarithmic treatment significantly diminishes the image's luminosity and reduces the high-pixel frequency. To compensate for this, the image's luminosity can be somewhat improved by setting an even amount preceding the logarithmic adjustment.

Step 5: The image is normalized to have pixel values that range from 0 to 255. Eq. (5) provides the particular conversion.

$$P_3 = \frac{(P_2 - minimum) \times 255}{(maximum - minimum)} \quad (5)$$

C. Segmentation using Artificial Bee Colony Optimization Algorithm

Segmentation has become more important in various aspects of image processing, especially classification, image recovery and object recognition [25]. It is an essential step in numerous applications. The suggested approach employs Artificial Bee Colony Optimisation (ABC) to discover similar regions and appropriately inspect every section once images have been segregated following the pre-processing stage.

The ABC algorithm, which stands for Artificial Bee Colony, is an optimization method that mimics the honey bee's feeding behavior and has been effectively used to solve several real-world issues. The class of algorithms for swarm intelligence includes ABC. A group of honey bees known as a swarm can work together to complete activities effectively [26]. Additionally, the ABC method has three different kinds of bees: working bees, observers and scouting bees. The recruited bees searching for food nearby the food resource in their memories while informing the spectator bees about these food sources. Despite the food resources discovered by the worker bees, the onlooker bees frequently select the best ones. The likelihood that the onlooker bees will select the nourishment basis with better quality (fitness) is much greater than the likelihood that they would choose the one with a lower level of quality. Scout-type bees are derived from a trivial number of worker bees that leave their nourishment foundations and look for new ones. The employed bees make up the initial part of the swarm in the ABC algorithm, and the onlooker bees make up the second half. The total number of solutions in the swarm is equivalent to the number of engaged bees or observers.

This study aims to investigate the effects of ABC parameters in a Multi-Scale Deep Learning-Based Recurrent Neural Network on Medical Image Restoration and Enhancement. ABC is an optimization method that carefully adjusts the hyper parameters of the network. The model's overall performance is significantly impacted by the meticulous selection of ABC parameters, such as colony size, convergence criterion, and exploration rate. When these parameters are optimized with expertise, the network is able to perform very well in the complex field of medical image restoration and enhancement, leading to better denoising and sharpening of medical images. The careful choice of ABC parameters results in improved image quality as well as increased network accuracy when it comes to medical image restoration. This significantly increases the Multi-Scale Deep Learning-Based Recurrent Neural Network's overall efficacy in the field of medical image processing.

The ABC algorithm creates a starting population with a uniform distribution of randomness. Every solution y_j (j = 1, 2..., SN) in this group has a solution number (SN). The formula for ABC optimization is given in (6) below:

$$y_j^i = y_{minimum}^i + random\ (0.1)\left(y_{maximum}^i - y_{minimum}^i\right), \forall\ i = 1,2, \ldots V \quad (6)$$

Where, y_j stands for the j^{th} source of nourishment in the starting community; $y_{maximum}^i$ and $y_{minimum}^i$ are the boundaries of y_j in the i^{th} route.

According to the nectar's efficiency data, the hired bee stage improves the hired bee's present strategy. This also comprises modifying the location of the nourishment basis according to its output and its calculation is given in (7). If it is discovered to be smaller than the previous one, the food sources with significant quantities are upgraded; otherwise, they are eliminated.

$$u_{ji}= y_{ji}+\emptyset_{ji}\left(y_{ji} - y_{li}\right) \tag{7}$$

Where, $\emptyset_{ji}\left(y_{ji} - y_{li}\right)$ is denoted as the step size; $\in \{1,2, \dots SN\}$, $i \in \{1,2, \dots V\}$ are represented as the indices that are chosen randomly; $\emptyset_{ji}$ belongs to the range [-1,1].

The observer bee phase evaluates the collective nectar fitness and positional data provided by worker bees and according to the fitness chance and it selects the optimum course of action. The location of the worker bees is updated by the greater fitness chance and is given in (8) below:

$$q_j = \frac{g_j}{\sum_{i=1}^{SN} g_i} \tag{8}$$

Where, g_j denotes the j^{th} fitness solution.

The hunter-bee phase starts looking for additional food sources when the food supply is depleted. This condition occurs if a source of nourishment disappears and its location has not been verified for the required number of cycles. A scout bee begins creating novel food sources in the surroundings and has a connection with discarded food. Nevertheless, in its simplest form, the ABC approach struggles with efficiency when handling challenging issues with a large search area. It demands a lot of fitness assessments and gets caught in regional minima. ABC also excels in discovery but struggles with the harvest. Many researchers were motivated by these flaws to suggest ABC versions for resolving various actual, empirical restrictions.

D. Feature Extraction by GLCM

Feature extraction is selecting and highlighting raw data's most important information or characteristics [27]. It transforms the basic data into a more streamlined and practical form that might be used for tasks demanding simulation or further analysis. In machine learning and pattern recognition software, feature extraction is widely utilized to enhance computational effectiveness and presentation. This research uses a Gray-Level Co-Occurrence Matrix (GLCM) to extract features. In extracting features, the initial information is changed into mathematical topography that is devoid of any construction of alterations in the strange datasets, and its features are based on its pixels. It employs multiple parameters, such as energy, correlation, contrast, homogeneity, entropy, etc., which are second-order image characteristics to remove the statistically significant texture characteristics from the image.

1) Energy: The squares with regularly greater grayscale and erratic image concentration standards are summated to generate energy. In (9), the energy formula is shown.

$$\text{Energy} = \sum i \sum j \{N(i,j)\}^2 \tag{9}$$

Here, N is denoted as the images; (i, i) is represented as the squares of the image.

2) Contrast: The regional intensity of an image is calculated using characteristics and is expected to be lower when the value of attentiveness is even. The comprehensive grayscale data of the original image is then displayed and its calculation is given in as (10).

$$\text{Contrast}= \sum_{x=0}^{H_j} x^2 \left\{\sum_{i=1}^{H_j} \sum_{j=1}^{H_j} N(i,j)\right\} \tag{10}$$

Here, H stands for the grayscale images; N is represented as the images; (i, j) is represented as the square of the greyscale image.

3) Correlation: By using the correlational features, it is feasible to adjust the mathematical links among the parameters and the inverse relationship of the grey levels on pixels. Its calculation is indicated in (11).

$$\text{Correlation} = \frac{\sum_i \sum_j (i,j) N(i,j) - \mu_p \mu_q}{\sigma_p \sigma_q} \tag{11}$$

The images' μ_p, μ_q, σ_p, and σ_q values for the average and the standard deviation are denoted as row and column correspondingly.

4) Entropy: The anticipated substantial amount of the randomness of the distribution of grey levels is entropy and its calculation is shown in (12).

$$\text{Entropy} = - \sum_i \sum_j N(i,j) \log(N(i,j)) \tag{12}$$

Algorithm 1: *Pseudo code for ABC Optimization*

The problem should be defined initially.
Prioritize the ABC algorithms parameters.
Develop the colony of the worker bees.
Then the estimation of all the bee's fitness values should be done.
Repeat the process
M=0
Repeat the process
(l=a result in the locality of j)
($\emptyset$ = a random number in the range $[-1,1]$)
Develop novel results using Eqn. (7)
Then the process of greedy selection is applied.
The likelihood functional values are estimated using Eqn. (8)
Next the onlooker bees are assigned.
Do ∀ onlooker bees.
Again, the process of greedy selection is applied.
If the fitness worth of the onlooker bees is lesser than the fitness worth of the worker bees
Exchange it with the worker bees.
End
End
If the fitness of the best onlooker bees is lesser than the fitness of the best bee
Exchange all with the superior results.
End
M=M+1
Until (M=Number of the worker bee)
Define the rejected result with Eqn. (6)
If the scout bees result is superior to the worker bees result, replace it with the scout bees' result.
Until the maximum iteration

E. Classification using RNN

The results from positive nodes can impact upcoming inputs to exact similar nodes via a recurrent neural network (RNN), an intimate of artificial neural networks whose interconnections among vertices can create a loop [28]. It can show continuous fluctuation. RNNs originated from feedforward neural networks and can handle classifications of inputs of various lengths by using their internal state. They can be used for applications like linked, not segmented recognition of handwriting or speech. A recurrent neural network describes networks with an infinite impulse response. The behavior of RNNs is temporally unpredictable. The architecture of RNN is shown in Fig. 2, followed by the algorithm of ABC optimization is given below. Fig. 3 displays the illustration of the proposed MSDL-RNN technique.

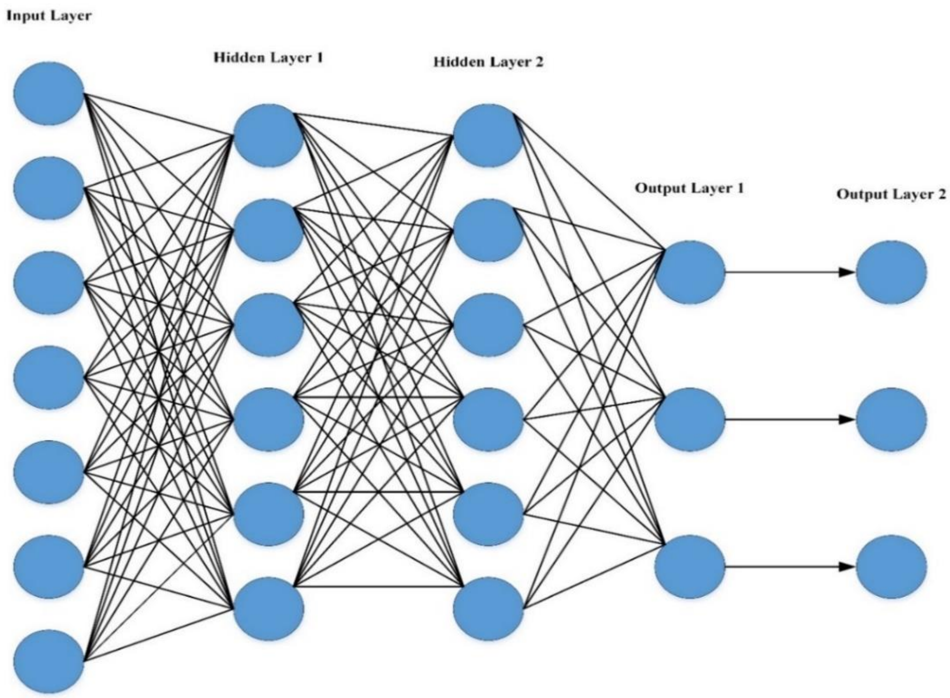

Fig. 2. Architectural diagram of RNN.

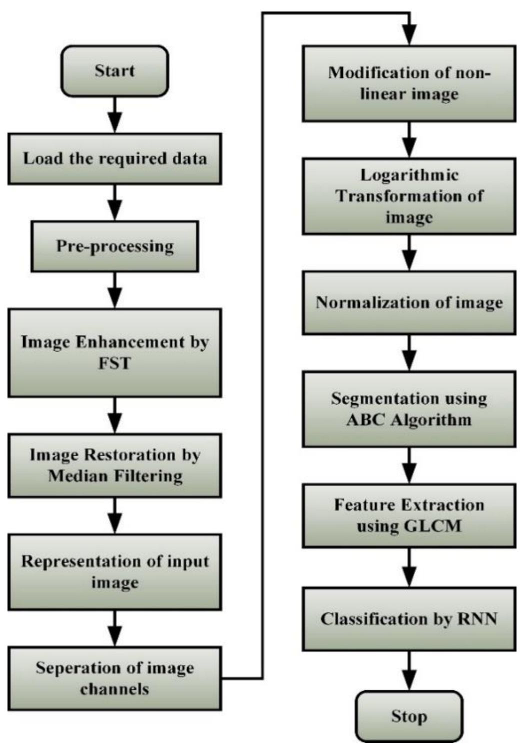

Fig. 3. Flowchart of proposed MSDL-RNN.

V. Results

The planned method has been investigated by using some datasets. Here, the Multi-Scale Deep Learning Based Recurrent Neural Network is used in this research for the procedure of image restoration and image enhancement. The description of the planned model is discussed by some parameters such as Accuracy, Recall, Precision, F1 Score, MSE, PSNR, and SSIM.

A. Performance Metrics Evaluation

1) Accuracy: The easiest metric to comprehend is accuracy, which measures how many examples in a dataset have been correctly categorized as a percentage of all instances. It offers a broad gauge of overall accuracy. The accuracy calculation is given in (13) below:

$$Accuracy = \frac{(TP+TN)}{(TP+TN+FP+FN)} \quad (13)$$

2) Precision: The percentage of cases that were correctly foretold as positive compared to every instance is what precision measures. It gauges the framework's capacity for avoiding erroneous positive results. For precision, use the formula which is shown in (14) below:

$$Precision = \frac{TP}{(TP+FP)} \quad (14)$$

3) Recall: Recall counts how many advantageous circumstances were properly predicted out of all the favorable instances. It measures how well the model can find every instance of positivity. The recall equation is given in (15) below:

$$Recall = \frac{TP}{TP+FN} \quad (15)$$

4) F1-Score: Precision and recall are harmonically summed to produce the F1 score. It yields a single value by combining the two metrics, giving a fair assessment of the efficacy of a model. The formula for F1-Score is given in (16) below:

$$F1 - Score = 2 \times \frac{(Precision \times Recall)}{(Precision + Recall)} \quad (16)$$

5) Mean Square Error (MSE): An average square variance among the values of the pixels of the underlying and altered images are calculated by MSE. Lower scores suggest higher levels of quality in the restoration or enhancement process, and it estimates the overall appearance reconstruction inaccuracy. The calculation for MSE is given in (17) below:

$$MSE = \frac{1}{MN}\sum_{n=0}^{M}\sum_{m=1}^{N}[\hat{g}(n,m) - g(n,m)]^2 \quad (17)$$

Where M and N are represented as the total number of pixels in the images; the $\sum$ is represented as the summation; $\hat{g}(n,m)$ is represented as the original pixel value image; $g(n,m)$ is represented as the pixel value of the processed image.

6) Peak Signal Noise Ratio (PSNR): The PSNR scale gauges the difference between the highest possible signal power and the strength of corrupted interference. Contrasting the initial and modified images is a common way to gauge how well the image restoration or enhancement techniques perform. Greater PSNR readings indicate greater image quality. The calculation of PSNR is given in (18) below.

$$PSNR = \frac{10\,log_{10}\,(peak\ value)^2}{MSE} \quad (18)$$

7) Structural Similarity Index Metric (SSIM): A statistic called SSIM evaluates how structurally two images are similar. It verifies perceived image quality by considering contrast, brightness, and structural data. The range of the SSIM is 0 to 1, with readings nearer to 1 and that suggests higher resemblance. The calculation of SSIM is given in (19) below.

$$SSIM = [l(x,y)]^{\alpha} \times [c(x,y)]^{\beta} \times [s(x,y)]^{\gamma} \quad (19)$$

Where l is represented as the luminance, c is represented as the contrast and s is represented as the structure.

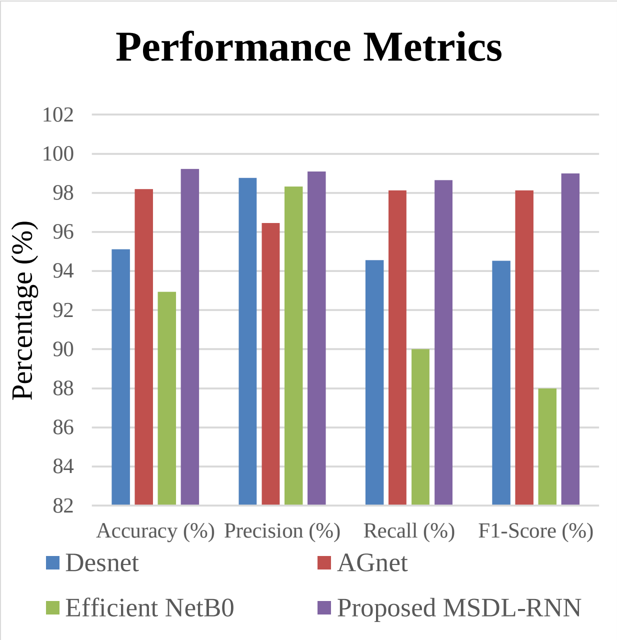

Fig. 4. Comparison graph of accuracy.

The Table I presents a comparative examination of the accuracy, precision, recall, and F1-score performance measures of several approaches and it is depicted in Fig. 4. It analyse four approaches: Desnet, AGnet, Efficient NetB0, and Proposed ABC-RNN. Desnet obtains an F1-score of 94.53%, an accuracy of 95.11%, a precision of 98.77%, and a recall of 94.56%. With precision and recall both above 96% and high accuracy of 98.20 per cent, AGnet has an F1-score of 98.13%. Efficiency NetB0 has a 92.93% accuracy, a 98.32% precision, a 90% recall, and an 88% F1-score. With extraordinary accuracy of 99.23%, precision of 99.10%, recall of 98.65%, and an F1-score of 99%, the proposed ABC-RNN approach beats others.

TABLE I. COMPARISON OF PERFORMANCE METRICS

Method	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
Desnet [29]	95.11	98.77	94.56	94.53
AGnet [30]	98.20	96.45	98.13	98.13
Efficient NetB0 [31]	92.93	98.32	90	88
Proposed MSDL-RNN	99.23	99.10	98.65	99

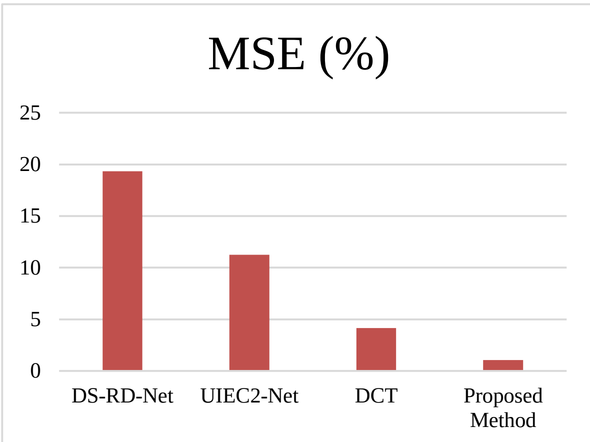

Fig. 5. Comparison graph of MSE.

Table II and Fig. 5 show the evaluation and performance estimation of MSE. When associating the MSE of the planned technique with the following three existing methods, i) DS-RD-Net [32] ii) UIEC2-Net [33] iii) DCT [34], the proposed MSDL-RNN algorithm produces a lower MSE of about 1.04.

TABLE II. COMPARISON TABLE OF MSE

Method	MSE (%)
DS-RD-Net [32]	19.34
UIEC2-Net [33]	11.26
DCT [34]	4.15
Proposed Method	1.04

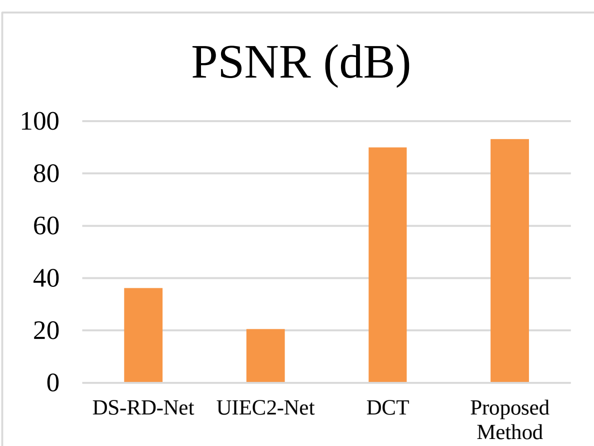

Fig. 6. Comparison graph of PSNR.

Table III and Fig. 6 show the evaluation and performance estimation of PSNR. When associating the PSNR of the planned technique with the following three existing methods, i) DS-RD-Net [32] ii) UIEC2-Net [33] iii) DCT [34], the proposed MSDL-RNN algorithm produces a greater PSNR of about 93.12 dB.

TABLE III. COMPARISON TABLE OF PSNR

Method	PSNR (dB)
DS-RD-Net [32]	36.21
UIEC2-Net [33]	20.54
DCT [34]	89.97
Proposed Method	93.12

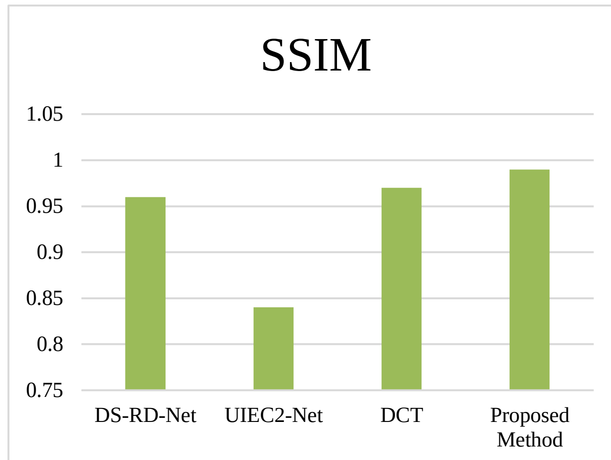

Fig. 7. Comparison graph of SSIM.

Table IV and Fig. 7 show the evaluation and performance estimation of SSIM. When associating the SSIM of the planned technique with the following three existing methods, i) DS-RD-Net [32] ii) UIEC2-Net [33] iii) DCT [34], the proposed MSDL-RNN algorithm produces a greater SSIM of about 0.99.

TABLE IV. COMPARISON TABLE OF SSIM

Method	SSIM
DS-RD-Net [32]	0.96
UIEC2-Net [33]	0.84
DCT [34]	0.97
Proposed Method	0.99

VI. DISCUSSIONS

The efficiency of the recommended MSDL-RNN strategy is higher when compared to earlier-used methods like Desnet, AGnet, and Efficient NetB0. The proposed methods' MSE value range is lesser than the other DS-RD-Net, UIEC2-Net and DCT methods values. The PSNR and SSIM values range higher than the other DS-RD-Net, UIEC2-Net and DCT methods. The anticipated technique's accuracy is greater than the efficacy determined by MSDL-RNN alone. The accuracy level achieved by utilizing this model is 99.23%. This suggests the multi-scale deep learning-based recurrent neural network will enhance and restore medical images. The Kaggle dataset was utilized in this instance. The pre-processing approach is employed to lessen noise, eliminate corrupted images and enhance the superiority of the images. The FST technique is used to improve the image, and median filtering is used to restore it. After that segmentation is completed. ABC optimization performs segmentation, splitting an image or a bigger dataset into unique, significant segments or areas. The GLCM approach is used for feature extraction, choosing and emphasizing the most crucial details or traits from raw data. The classifying procedure is finished at that point. A machine learning model must first be trained to classify or categorize data into pre-set categories or groups. RNN handles it. The ABC algorithm's fictitious code is then presented. It now gets to the section where results and discussions take place. The proposed method is shown to have superior outcome statistics than every other approach when accuracy, recall, precision, f1-score, MSE, PSNR and SSIM are evaluated. The research then presented its findings and plans for the future.

VII. Conclusion and Future Work

The findings of this study underline how crucial it is to improve medical image quality for precise diagnosis, treatment planning, and ongoing condition monitoring in healthcare applications. By restoring lost high-quality data, the restoration of damaged input images constitutes a crucial step in accomplishing these goals. Despite substantial advancements in the field of image restoration, this work addresses two enduring problems. An innovative response to these problems is provided with the launch of the MSDL-RNN. MSDL-RNN differs from traditional RNN-based algorithms that depend on both full-resolution and gradually reduced-resolution approximations by using a multi-scale approach during model development. Deep learning is used in this breakthrough to efficiently solve problems including noise reduction, defect eradication, and the improvement of overall image quality. The MSDL-RNN technique's combination of local and global data enables the enhancement and recovery of a variety of medical imaging modalities. Despite these encouraging results, a noteworthy drawback of this work is that it largely concentrates on the improvement of image quality, leaving opportunity for potential future research in real-time applications and computing efficiency. Future studies should focus on reducing the processing requirements of the model to enable a smooth incorporation into clinical operations. The results of this study set the way for substantial developments in the field of medical imaging by providing a solid answer to problems relating to image quality improvement. The results of this study offer significant potential for enhancing patient care, diagnostic precision, and the general usability of medical images in healthcare applications, since the healthcare sector continues to rely heavily on them.

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