J. Electrical Systems 20-7s (2024): 816-830

[1] Rakesh Patnaik

2 Premanshu Sekhara Rath

[3] Sasmita Padhy*

[4] Sachikanta Dash

A Novel Optimized Colonic adenocarcinoma Detection using Deep Transfer Learning Approach with XceptionTS Model

Abstract: - Colonic adenocarcinoma is a major contributor to global mortality, highlighting the crucial need for efficient detection and classification techniques. This research presents a new method called XceptionTS for classifying and detecting colon cancer using colonoscopy pictures. The XceptionTS method utilizes deep transfer learning techniques by leveraging the Xception model architecture. Nonlinear Mean Filtering (NMF) is used as a noise reduction method in image processing to improve the quality of colonoscopy pictures. We combine the MobileNetV2 and ResNet-50 models for healthcare image segmentation and feature extraction, respectively. The XceptionTS classifier efficiently gives accurate class labels to medical photos by combining Tabu Search Optimization with the strong Xception architecture. The assessment of the effectiveness of XceptionTS model is done using a dataset of 1560 colonoscopy images. An extensive comparison study is undertaken by analyzing the efficacy of our suggested approach with existing research. The XceptionTS system outperforms previous methodologies in colon cancer classification and detection tasks, showing higher accuracy and robustness according to experimental results. Our findings indicate that the XceptionTS technique shows potential as an advanced tool to increase the effectiveness of Colonic adenocarcinoma diagnosis, which could lead to better patient outcomes and healthcare management.

Keywords: Colonic adenocarcinoma, ResNet-50, Tabu Search, Deep Transfer learning, Xception.

I. Introduction

Colon cancer is extremely public, and it is frequently accompanied with metastasis [1]. Peritoneal Carcinometastasis (PC), in specific, can develop in the later part of progress, significantly shortening patient survival periods [2,3]. As a result, initial and dependable diagnosis of metastases is critical. Opinion Due to the high resolution needed, employing conventional computed tomography (CT) technique and magnetic resonance imaging (MRI) are difficult for PC. Preoperative CT, for example, has been demonstrated to be poor in identifying specific peritoneal deposits of tumors, with high inter-observer inconsistency among experts [7]. Furthermore, combined PET/CT did not give enough data for reliable findings. Although studies have demonstrated that MRI is superior to CT alone for assessment, its resolution remains a constraint. As a result, exploratory laparoscopy is commonly used to determine the existence of PC. One of the most common cancers diagnosed globally is Colonic adenocarcinoma (CRC). Following breast cancer (11.6%) and lung cancer (11.6%) in terms of prevalence, CRC accounted for 10.2% of all cancer cases in 2018 [9]. With 9.2% of all cancer-related deaths, it is the second most dangerous tumor in terms of mortality. Statistics show that both men and women are affected virtually equally. Despite the high rates of occurrence and fatality, CRC fatalities have been falling with an increasing drop rate for both men and women since 1980. This trend is primarily due to advancements in early detection and treatment [10,12]. Early detection is critical in the fight against CRC. It not only reduces mortality but also minimizes excessive treatment costs by detecting CRC before it spreads to distant organs. According to the stage of the disease at which it is diagnosed has a strong correlation with mortality, with a 90 percent in terms 5-year mortality rate for localized cancer, 70% for regional cancer, and 10% for distant malignant tumor [13].

In the realm of medical image analysis, deep learning (DL) technology has been held up as the benchmark. It has demonstrated good performance in a number of healthcare imaging sectors, including pathology, dermatology, radiology, and ophthalmology, which are among the most specific fields involves humanoid experts [14,15]. The current methods in DL that have been incorporated to the path of clinical change sometimes rely on a huge

[1,] Computer Science and Engineering , GIET University, Gunupur, Odisha, India, rakesh.patnaik@giet.edu

[2] Computer Science and Engineering, GIET University, Gunupur, Odisha, India, premansusekhararath@giet.edu

[3] School of Computing Science and Engineering , VIT Bhopal University, Bhopal-Indore Highway, Kothrikalan, Sehore, MP, India, pinky.sasmita@gmail.com

[4] Computer Science and Engineering, GIET University, Gunupur, Odisha, India, India, sachikanta@giet.edu

* Corresponding Author : Sasmita Padhy

volume of extremely reliable annotated pictures. Figure 1 shows a most general traditional supervision learning. In low-resource circumstances, other difficulties arise, such as acquiring extremely reliable data, which becomes a bottleneck for progressing deep learning applications.

Because image annotation is both cost-effective and time-consuming, learning from few labelled images is a significant difficulty in the domain of healthcare data analysis utilizing DL. DL, on the contrary, requires a vast amount of clinical images to function properly [18-20,]. Then, in this study, transfer learning (TL) is presented as a solution to this difficult problem.

Transfer learning (TL) is the essential component of success for many good DL models. These models are initially trained and evaluated using a given dataset. These are then fine-tuned with the help of the objective task. Whenever there is a scarcity of original dataset, it has been shown to be an effective strategy [22-25]. Due to the difficulties of obtaining medical image collections, this is a regular occurrence in medical imaging. An instance weighting strategy is used to develop instance-based transfer learning systems. Transfer learning approaches for medical image analysis are primarily parameter-based deep learning techniques that are either employed as feature extractors or customized for the analysis purpose [27].

This paper offers a novel Tabu Search Optimizing with Deep TL-based colon cancer classification and detection (XceptionTS) model based on colonoscopy images. The XceptionTS method uses colonoscopy images to perceive and characterize the occurrence of colon cancer. Nonlinear mean filtering (NMF) is primarily utilized as a noise reduction technique in image processing. For healthcare image segmentation MobileNetV2 model and feature extraction ResNet-50 model is used. Finally, the XceptionTS classifier assigns suitable class labels to medical images using Tabu Search Optimization and the Xception model. The performance of the   is evaluated using the 1560 collected dataset. A comparison study is also conducted utilizing the suggested model between both the benchmark dataset and the collected dataset. The experimental results revealed that the XceptionTS strategy outperformed earlier methodologies.

1.1. Objectives

The main goal of this study is to present an innovative method, termed XceptionTS, for classifying and detecting Colonic adenocarcinoma (CRC) using colonoscopy pictures. The research aims to address the significant global mortality associated with CRC by proposing an efficient detection and classification technique.

The key components and methodology of the proposed XceptionTS method:

1. The method leverages the Xception model architecture, a deep learning framework, through transfer learning techniques.
2. NMF is employed as an image processing technique to enhance the quality of colonoscopy pictures by reducing noise.
3. The MobileNetV2 and ResNet-50 models are combined for healthcare image segmentation and feature extraction, respectively.
4. The XceptionTS classifier incorporates Tabu Search Optimization to further optimize the performance of the Xception architecture in providing accurate class labels to medical photos.
5. The efficacy of the XceptionTS approach is judged by utilizing a dataset consisting of 1560 colonoscopy images.
6. The research conducts an extensive comparison study to analyze the efficacy of the proposed approach against other existing studies.

The findings of the research suggest that the XceptionTS technique outperforms previous methodologies in CRC classification and detection tasks, demonstrating higher accuracy and robustness according to experimental results. The study concludes by highlighting the potential of the XceptionTS method as an advanced tool to optimize patient outcomes and enhance healthcare management, thereby contributing to more effective treatment strategies and improved overall well-being for individuals affected by colorectal cancer through CRC diagnosis methodologies,

1.2. Contribution

This research developed a cutting-edge Colonic adenocarcinoma diagnosis tool using deep learning, image processing, and optimization. This research could improve Colonic adenocarcinoma healthcare management and patient outcomes by increasing Colonic adenocarcinoma detection and classification.

- The study introduces XceptionTS, a colonoscopy-based Colonic adenocarcinoma classification and detection tool. It uses deep transfer learning, noise reduction using Nonlinear Mean Filtering (NMF), and Tabu Search Optimization to increase Colonic adenocarcinoma diagnosis accuracy and efficiency.
- The research uses NMF to reduce noise in image processing to improve colonoscopy images. Patients and doctors benefit from better Colonic adenocarcinoma diagnosis due to image quality improvements.

- The research uses MobileNetV2 and ResNet-50 for healthcare image segmentation and feature extraction. Integrating various models enables for thorough colonoscopy image processing and interpretation, improving Colonic adenocarcinoma diagnosis decisions.
- The research uses the XceptionTS classifier, which blends Tabu Search Optimization with the Xception architecture, to improve Colonic adenocarcinoma classification and detection accuracy and robustness. This improvement may improve Colonic adenocarcinoma detection and results.
- Empirical Evaluation and Validation: 1560 colonoscopy pictures are used to evaluate the XceptionTS technique. The study extensively compares with the state-of-the art studies and shows greater performance versus earlier methods.

1.3. Paper Outline

The remainder of this research report is organized in the manner listed below. Section 2 provides the background details and most common notations used in the following sections. In this study, deep transfer learning's relationship to the classification of colonoscopy images is comprehensively investigated. This part will review earlier deep transfer learning investigations, and Section 3 describes the suggested deep transfer learning model technique. Part 4 describes the specifics of the experiment and the planned works, and Section 5 concludes with recommendations for potential future studies in this area.

II. LITERATURE STUDY

According to ICMR and NCBI statistics, Colonic adenocarcinoma cases have increased significantly over the last ten years, and by 2022, there is expected to be a roughly 71% increase in cases. Changes in food habits and lifestyles are blamed for this increase. The secret to dramatically raising patient survival rates is early diagnosis. The detection and classification procedures have benefited from the integration of computer systems, with learning techniques improving precision and detail. G.F. Jumnake et al. [4] investigate the impact of various parameters and model-related factors on the identification and classification of malignant cells in Colonic adenocarcinoma using stained tissue image samples. Their study delves into the experimentation and analysis of deep learning and transfer learning methods for this purpose.

In their research [5], M. Masud et al. propose a classification framework utilizing histopathological images to distinguish between five types of lung and colon tissues. Their approach integrates cutting-edge Deep Learning (DL) techniques and Digital Image Processing methods for accurate tissue type differentiation.. The findings show that detecting cancer tissues may be done with a high degree of accuracy—up to 96.33%. The suggested framework might lead to the creation of an automated and dependable system that would let doctors quickly and accurately distinguish between various kinds of colon and lung cancers, which would be extremely helpful for early detection and treatment planning.

A Khan et al. [6] in their study uses digitized hematoxylin and eosin-stained sections to evaluate Colonic adenocarcinoma lymph node metastases using a deep learning-based approach. After being trained on 100 whole-slide pictures, the segmentation model showed good congruence with the ground truth, obtaining a respectable Hausdorff distance and a Matthews's correlation value of 0.86. After adjustments, the F1 score and area under the receiver operating characteristic curve of two separate models—Xception and Vision Transformer—trained for metastatic detection showed notable gains. Excellent results were obtained via validation on four separate cohorts, with good sensitivity and specificity. This proposed approach serves as a practical computer-assisted diagnostic tool, facilitating efficient lymph node screening in individuals diagnosed with colorectal cancer, thus potentially enhancing the accuracy and speed of diagnosis for better patient care.

To improve accuracy and robustness, M Murugesan et al. [8] in their study find and categorize distinct stages of colon cancer using the single-stage YOLOv3 object detection model in our research, based on the TL value. Preprocessing issues such as low contrast and hazy pictures are handled by the model using jitter-value-0.3 data augmentation. To identify and annotate cancer stages, YOLOv3-MSF DL architecture with multiscale detection layers is used. The K-Medoids technique is used to choose anchor boxes while using transfer learning with YOLOv3. A fully connected layer is one of the integrated layers, and training and assessment are conducted on the CVC colonDB database. We evaluate our model's performance against the most advanced object identification models to demonstrate its efficacy.

To classify lung and colon cancer, H A. Mengashet al. [11] in their study presents the MPADL-LC3 approach, which combines deep learning with an algorithm designed for marine predators. The technique seeks to accurately distinguish between distinct forms of colon and lung cancer in histopathological pictures. MPADL-LC3 additionally uses MPA as a hyperparameter optimizer, preprocessing using CLAHE-based contrast enhancement and generating feature vectors using MobileNet. DBNs, or deep belief networks, are used to classify cancer. The simulation results on benchmark datasets highlight the improved performance of the MPADL-LC3 system over other methods, highlighting its efficacy across a range of metrics.

CNN-based MA_ColonNET, a new colon cancer detection technique, is presented by M Yildirim et al. [16]. The MA_ColonNET, which makes use of a 45-layer model, accomplishes an impressive accuracy rate of 99.75%, proving its usefulness in the early diagnosis of colon cancer. Because the suggested paradigm allows for early intervention in cases of colon cancer, its success raises the possibility of more effective treatment regimens.

A. S. Sakr et al. [17] in their study present an innovative lightweight deep learning method for effective colon cancer diagnosis that is based on convolutional neural networks (CNNs). To effectively identify cancer, the approach entails normalizing input histopathology pictures before feeding them into the CNN model. A publicly accessible library of histopathological images is used to assess the effectiveness of the proposed system. When compared to the most advanced techniques, the deep model achieves an astounding accuracy of 99.50%. Due to its high accuracy, the suggested method is deemed computationally efficient and performs better than many of the current deep-learning techniques for the identification of Colonic adenocarcinoma.

Instead of current detection techniques, S. Mehmood et al. [21] have presented a model that provides both high accuracy and computational efficiency, enabling rapid and precise identification of malignancies in lung and colon tissues. It offers a promising solution for timely and effective cancer diagnosis.. Four layers of a pre trained neural network (AlexNet) were adjusted using a huge dataset of 25,000 histopathological photos, uniformly dispersed across five classes of lung and colon tissues. All classes showed good first classification results, except for one that had an accuracy of 89%. By using a contrast enhancement approach exclusively to the underachieving class, accuracy was increased to 98.4% while retaining computing efficiency. The suggested approach shows increased computing efficiency and accuracy.

Devvi Sarwinda et al. [28] investigate the use of deep learning, particularly using the ResNet architecture, for Colonic adenocarcinoma picture categorization and diagnosis. The goal of the project is to train ResNet-18 and ResNet-50 to distinguish between benign and malignant Colonic adenocarcinoma using pictures of colon glands. Upon evaluating the models on three distinct testing data subsets, it is consistently seen that ResNet-50 exhibits superior accuracy, sensitivity, and specificity values compared to ResNet-18. The study highlights the promise of deep learning techniques, especially ResNet-50, in the field of Colonic adenocarcinoma diagnosis by showing that they produce highly dependable and repeatable results for biomedical image analysis.

A. C. d. M. Lima et al. [30] in their work present a two-step transformer-based polyp identification technique for colonoscopy pictures. To find possible polyp locations, the first step uses an extraction model for saliency maps that is backed by extracted depth maps. Using the green and blue channels in conjunction with the previous stage's photos, the second step entails looking for polyps. The approach demonstrates strong performance, achieving 91% Average Precision in the CVC-ClinicDB dataset, 92% in Kvasir-SEG, and 84% in CVC-ColonDB. Its effectiveness is evaluated across four public colonoscopy datasets, showcasing its robustness and potential for reliable application in diverse clinical scenarios. The work shows how to effectively employ transformers, salient object-extracted maps, and depth maps to locate polyps in colonoscopy pictures.

Manju Dabass et al.[34] introduced an innovative model that enhances the traditional U-Net architecture by incorporating novel structural components. These include Hybrid Convolutional Learning Units in both the encoder and decoder, Attention Learning Units within skip connections, and a Multi-Scalar Dilated Transitional Unit serving as the transitional layer. These additions aim to improve feature extraction, attention mechanisms, and transition between encoder and decoder pathways for more effective segmentation tasks. To improve the receptive field size, these components incorporate attention learning, several convolution approaches, and multi-level convolutional learning. Using several datasets, the model successfully classifies cancer with outstanding accuracy, precision, F1-score, and recall. The generalizability of the model is enhanced by pre-processing methods including stain-normalization, augmentation, and patch-sampling. This method seeks to lessen human error in cancer detection, aid pathologists in making correct diagnoses, and eventually increase patient survival rates.

By using an ensemble learning strategy, Gaurav Srivastava et al. [36] proposed research that seeks enhancing DL model classification performance. In contrast to earlier research, the Differential Evolution optimization technique is used in this study to optimize given weights. By removing the need for meta-learner training, the authors present a unique ensemble approach that is based on Condorcet's Jury Theorem and saves computing resources. The optimized ensemble model and Condorcet's Jury Theorem-based approach surpass contemporary methods, showcasing the effectiveness of the ensemble learning technique. Achieving 99.78% accuracy, the optimized model, along with the Jury Theorem-based ensemble model reaching 99.88% accuracy in 5-class classification, demonstrate superior performance. These results underscore the efficacy of the proposed methodology in enhancing classification accuracy and highlighting its superiority over existing approaches.

III. Material and Methodologies

3.1. *Description of Dataset*

The datasets utilized in this research are collected from "Jeevandeep Hospital & Research Centre" Mayurbhanj, Odisha, India. Utilizing the gathered colonoscopy dataset, the XceptionTS model's performance is validated. It includes 266 normal photos, 420 malignant images, and 874 benign images from 45 gathered videos. The dataset's sample frames are displayed in Figure 1. The collected dataset contains approximately 56% benign images, 27% malignant class images and 17% normal class images.

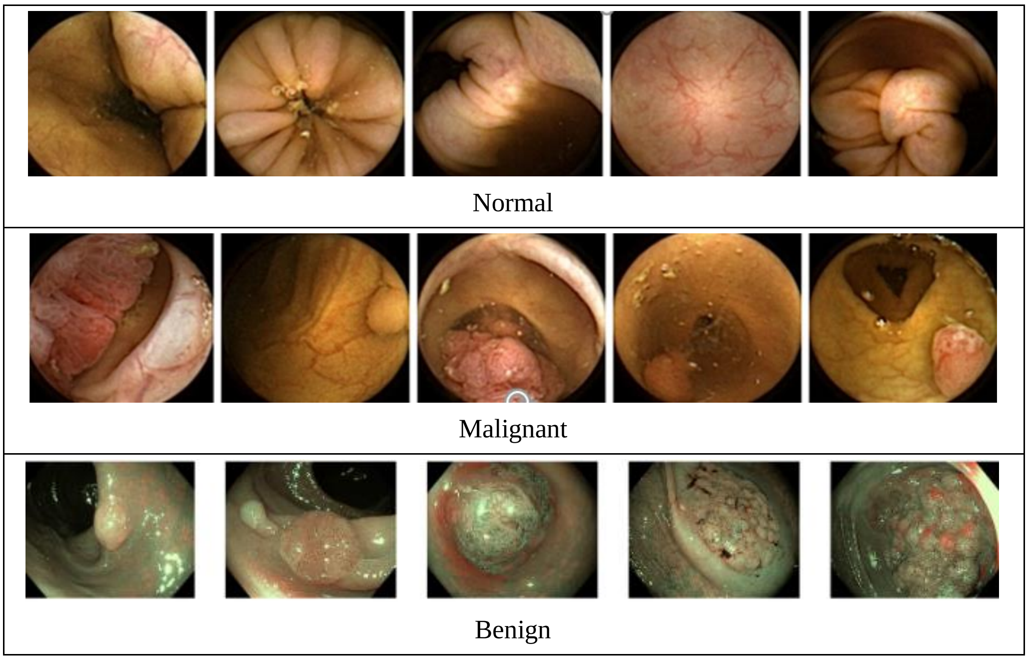

Fig 1: sample dataset of colonoscopy images

3.2. *Preprocessing*

The Nonlinear median filtering (NMF) approach is employed as an image preparation tool in this investigation [29]. This filter is most likely the simplest non-linear filter. Unlike convolution filters, it does not execute a linear combination of kernel weights and picture pixels. Rather, the filtration of image is obtained by calculating the median in each pixel's neighborhood in the actual picture, which necessitates a non-linear operation. The median is estimated by using a dynamic panel model (here simply termed "window") that represents the neighborhood around the examined pixel and from which the statistical information required in the calculation is gathered. The pixels in the window are first sorted numerically, after which the median is picked as the center pixel in the sorted array and used as the final pixel in the finished image.

In its most basic version, a median filter calculates each pixel $g_f(x,y)$ in the median filter as follows, given a window W of size $m * m$.

$$g_f(x,y) = median\left(W(x,y)\right)\left(W(x,y)\right) = mid\ (sort(W(x,y))$$

(1)

where sort () produces a vector v of numerically sorted values from the window $W(x,y)$, and $mid(v)$ delivers the mid element(s) of a vector, described as below

$$mid(v) = \begin{cases} V_{\frac{m^2+1}{2}}, & if\ m\ is\ odd \\ \frac{1}{2}\left(V_{\frac{m^2}{2}} + V_{\frac{m^2+1}{2}}\right), & if\ m\ is\ even \end{cases}$$

(2)

NMF plays a crucial role in image preprocessing by effectively reducing noise, preserving edges and details, enhancing textures and structures, and preparing images for further analysis or computer vision tasks. Its ability to maintain image quality while reducing noise makes it a valuable tool in various image processing applications.

3.3. Methods

3.3.1. Image Segmentation

Image segmentation is performed using MobileNetV2. The model gets 320 x 320 input images, which are then fed into the pre-trained encoder, which is built on reversed residual blocks (or structures) and contains a blend of spatial convolution layers with 3x3 kernels, ReLu activation, and Batch Normalization layers [31,32]. In this case, the encoder employs compact depth-to-depth convolution to filter and comprehend image characteristics. By utilizing reversed residual blocks, the model reduces parameter count, facilitating faster and simpler training. This approach enhances efficiency by effectively capturing image features while streamlining the training process through parameter reduction. Figure 2 represents an architecture of MobileNetV2 which applied for image segmentation.

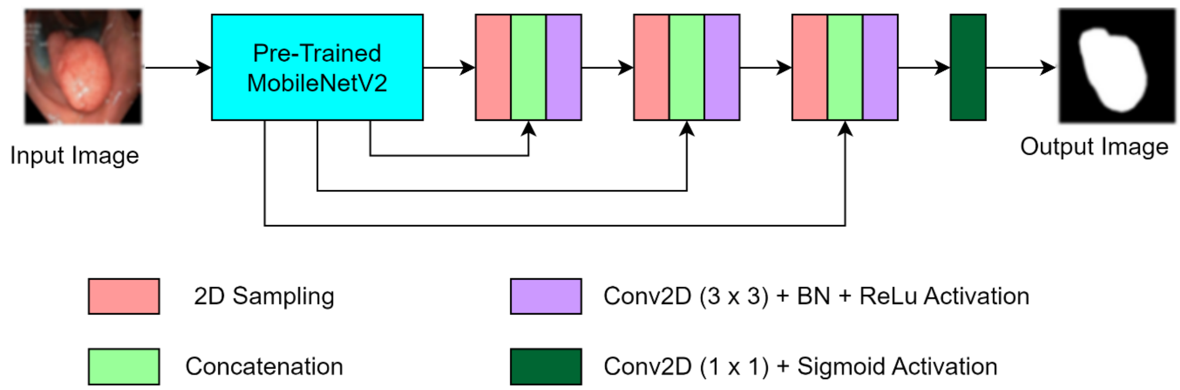

Fig 2. MobileNetV2 model for image segmentation Architecture

Leveraging a pre-trained network enhances system performance and expedites convergence compared to starting from scratch. In the decoding phase, up-sampling techniques are utilized to restore the feature map to its original dimensions. This approach not only ensures better functionality and quicker convergence but also preserves crucial details by accurately reconstructing the original size of the feature map. The characteristics are multiplexed between the encoder and decoder blocks during this journey, and they also pass through a 3x3 convolution, after by Batch Normalization and ReLu activation. Finally, the network's final block is a frame with a 1x1 convolution layers and Sigmoid activation, which allows the network to generate segmentation.

3.3.2. Feature Extraction

ResNet-50 Model is used for feature extraction. During the feature extraction phase, the segmented colonoscopy image is sent into the ResNet-50 algorithm, which is used to locate lesion locations in colonoscopy images [33]. A deep CNN that had been trained was required for identifying deep features from input photos. However, When the model becomes complex, the deteriorating problem is likely to appear and while the approach delves deeper, the performance of the model doesn't get better; it gets worse. The foundation of ResNet is based the residual block which is layered in different form in the models.

Unlike standard CNNs, which are made up of convolution and max pooling, Each and every RB consists of two CNN layers and a few connections. The outcome of RB before the second layer activation function is $F(x)$, and x is the input signal at this point. When the first and second layers of RB's weights, W1 and W2, respectively. $F(x)$ is calculated by $f(x) = W_2 * f(W_1 x)$. ReLU is used by activation function f in the RB. As a result, the final result of RB is $f(F(x) + x)$. Assume the goal output of RB is comparable to the easily seen input x in a DL framework.

In addition to that we need to improve x from the traditional method of CNN procedure without a shortcut linking to $F(x) = x$. It is possible to train a 50-layer CNN (ResNet-50) with eight RBs, 7 x 7 convolutional layer, one FC layer, and two pooling layers after scaling and padding. Furthermore, all RBs are made up of two 3 x 3 convolutional layers.

3.3.3. Classification of Images

Optimal Xception model is used for image classification. Finally, using colonoscopy images, the XceptionTS model can be used for the diagnosis and categorization of colon cancer. Two well-known deep learning frameworks, Keras and TensorFlow, are also used to implement an investigation based on the Xception model [35]. It is worth noting that the model used in the transfer learning method has already been trained on a different but substantial dataset.

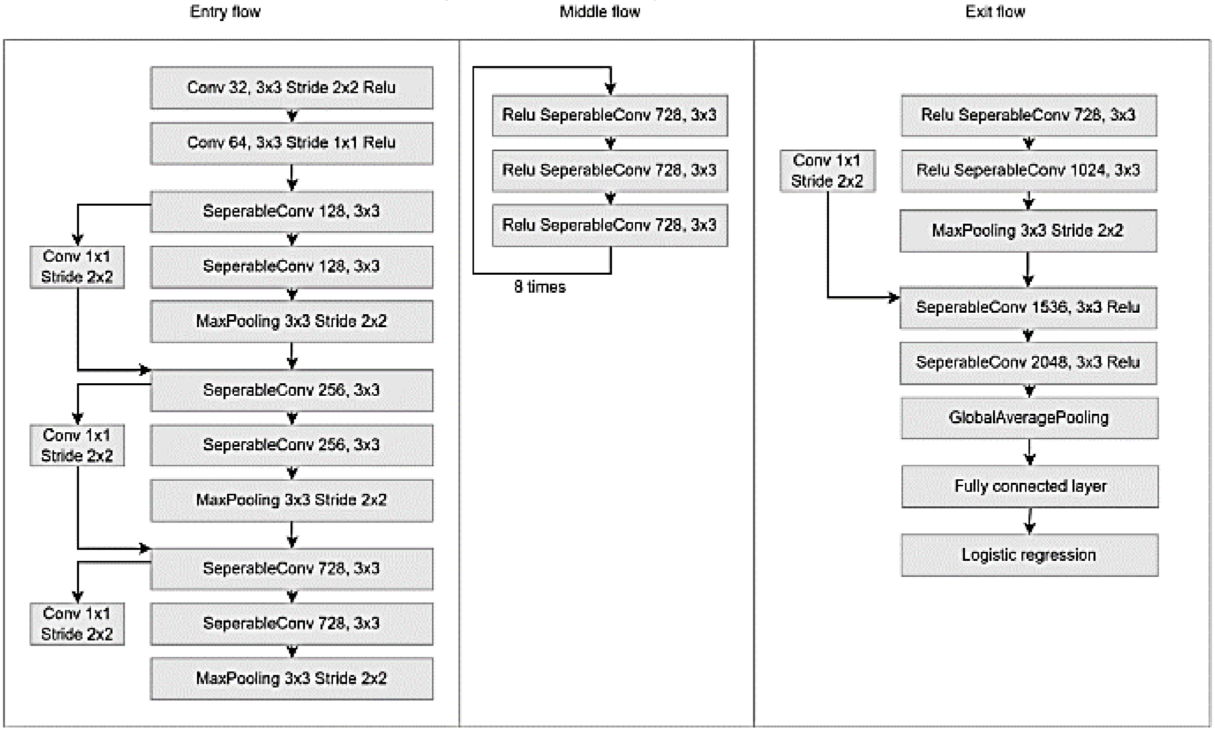

Fig 3: Xception Model Architecture

The Xception model is also trained on the largest natural picture dataset, ImageNet. The network's 36 Xception convolutional layers serve as the foundation for feature extraction. There are 14 modules in the design, each with 36 convolutional layers. Notably, all modules contain linear residual connections, with the exception of the first and last ones.

Figure 3 shows the Xception model's architecture, which is used for classification of images in this study. It is a depth wise separable stack of fully connected layers with feedback connections. Xception's architecture simplifies definition and modification, requiring only 30 to 40 lines of code with high-level libraries like Keras or TensorFlow-Slim. Unlike Inception V2 or V3, known for their complexity, Xception's structure resembles VGG-16 in simplicity. An open-source implementation of Xception, under the MIT license, is accessible via the Keras Applications module, enabling easier adoption and integration into various projects.

The Tabu Search Optimization approach can be used to optimally tune the hyperparameters in the Xception model. It is crucial to lower the amount of samples across the layers by cutting down on the steps. Xception model pre-trained weights on large-scale datasets are valuable for transfer learning. Researchers and practitioners can fine-tune the model on specific tasks with smaller datasets, leveraging the knowledge learned from the vast amount of data used for pre-training.

3.3.4. Tabu Search Optimization (TSO)

TSO is a metaheuristic approach that, in its fundamental form, involves a process for searching neighboring solutions. At each step, a thorough examination is conducted to evaluate all potential actions that can be taken from the current answer, and the optimal action is chosen. The approach enables transitions to solutions that do not enhance the existing solution. In addition, in order to avoid the algorithm from repeating the same actions, certain movements are designated as "null" and are initially excluded from consideration. We examined three categories of motion:

1. Inserting an element $u_j' \in \mathrm{U}-\mathrm{T}$;
2. Eliminating an element $u_j \in$ T; and
3. Swapping an element $u_j \in$ T with another element $u_j' \in \mathrm{U}-\mathrm{T}$.

The collection of adjacent solutions, T, accessible through defined movements, constitutes the neighboring solutions set, denoted as N(T). This set encompasses all potential solutions achievable through specified actions from the current solution space**.**

In order to eleminate cycles, the output from T and the input into T for elements recently entered or left are labeled "tabu." The current tabu state is determined by tracking the entry section or exit portion of an element $u_j \in$ U.

VectIn (j) - : Denotes the number of iteration at the element u_j entered T.

VectOut (j) -: Denotes the number of iteration at the element u_j left T.

Therefore, the presence of an element $u_j' \in \mathrm{U}-\mathrm{T}$ is $tabu$ if

$itr \le \mathrm{VectOut}$ (3)

Furthermore, the departure of an element $u_j \in$ T is $tabu$ if

$itr \le \mathrm{VectIn}$ (4)

Ultimately, the substitution of an element $u_j \in$ T with another $u_j' \in \mathrm{U}-\mathrm{T}$ occurs $tabu$ only if any of the two previously specified conditions is verified to be present.

The parameter no_{itr} signifies the number of repetitions for a $tabu$ input or output, while "itr" represents the count of these repetitions. Conversely, a movement's $tabu$ status can be overridden if it yields a solution with a higher objective function value than previously encountered solutions. ("aspiration criterion"). Algorithm below demonstrates the $TabuSearch$ algorithm.

As shown in Algorithm, each iteration takes into account all the arrangements those are not $tabu$ prohibited or that satisfy the ambition requirement. The variable T^b stores the optimal solution among neighboring solutions, providing a reference point for evaluating potential improvements. This change is implemented ($g^b = g(T')\ and\ T = T^b$), and the values of VectIn and/or VectOut are modified based on the type of movement conducted and the elements implicated. After each iteration T^* and g^*, the best solution obtained during the search and its corresponding objective function g value, denoted as and , are updated. The operation terminates once a predetermined number of iterations ($\max_{itr} TSO$) have occurred without any enhancement of g^*. The parameter no_{itr} is a crucial factor in this technique. Higher values of tenure lead to a larger number of movements being designated $tabu$, which in turn reduces the flexibility of the process. On the other hand, lower values of tenure may not effectively avoid cycles. Hence, the process of choosing appropriately is of utmost importance.

Algorithm: $TSO(no_{itr}, \max_{itr} TSO\ ,\ o/p,\ T^*)$

1. Compute $T^* = T, g^* = g(T), itr = 0, itr_{best} = 0$
2. Compute

$$VectIn(j) = -no_{itr}, VectOut(j) = -no_{itr}, for\ all\ j = 1,2, \ldots\ldots, n$$

3. Do

- Compute $itr = itr + 1$
- Compute $g^b = -\infty$
- ∀ ′ ∈ ( ) Execute:

Begin

- Find out the $tabu$ status of the associated process
- Find out if the "aspiraon criterion" is met or not, i.e., verify whether $g(T') > g^*$
- If the process is $not\ tabu$ or meets the aspiraon criterion, then if $g(T') > g^b$
- Compute: = $g^b = g(T')\ and\ T^b = T'$

End

4. Compute: $T = T^b$
5. Update VectIn and/or VectOut
6. If $g(T) > g^*\ then\ , T^* = T, g^* = g(T)\ and\ itr_{best} = itr$

7. Until $itr > itr_{best} + \max_{itr} TSO$

IV. Proposed XceptionTS Methodology

A unique XceptionTS technique for the identification of Colonic adenocarcinoma using colonoscopy image has been developed in this work. The proposed XceptionTS technique includes Nonlinear median filtering (NMF) model for pre-processing, MobileNetV2 model for segmentation procedure, ResNet-50 model for feature extraction process, Xception model classification, and Tabu Search Optimization -based hyper parameter regulation. The following describes the specific operation of each module included in the XceptionTS approach. The whole procedure of the XceptionTS approach is described in Figure 4.

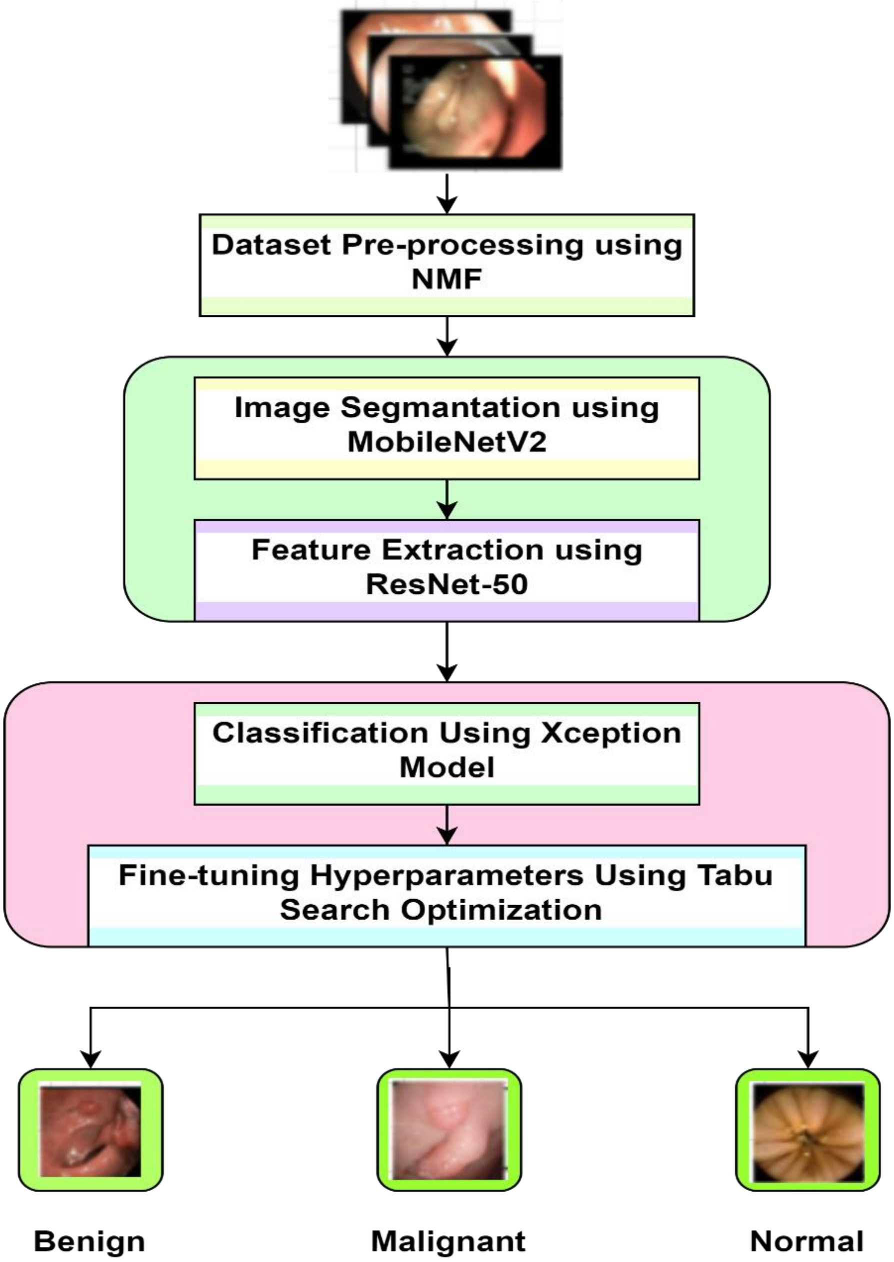

Fig 4: Flow architecture of XceptionTS Model for classification

Below is the algorithm describing the specific operations of each module included in the XceptionTS approach for Colonic adenocarcinoma identification using colonoscopy images:

Input:
Colonoscopy image dataset
Hyperparameters for Tabu Search Optimization

Output:
Predicted class label for Colonic adenocarcinoma presence

Algorithm:

Step-1: Preprocessing using Nonlinear Median Filtering (NMF):
Apply Nonlinear Median Filtering (NMF) to the input colonoscopy image to reduce noise and enhance image quality.

Step-2: Segmentation using MobileNetV2:
Utilize the MobileNetV2 model for segmenting the preprocessed colonoscopy image into relevant regions of interest, focusing on areas indicative of potential cancerous lesions.

Step-3: Feature Extraction using ResNet-50:
Apply the ResNet-50 model to extract discriminative features from the segmented regions, capturing important visual patterns and characteristics associated with Colonic adenocarcinoma.

Step-4: Classification using Xception Model:
Employ the Xception model for classifying the extracted features into categories representing the presence or absence of Colonic adenocarcinoma.

Step-5: Tabu Search Optimization for Hyperparameter Regulation:
Initialize hyperparameters for the Xception model and Tabu Search Optimization process.
Define the objective function to be optimized based on the performance metrics (e.g., accuracy, F-score).
Implement Tabu Search Optimization to iteratively adjust the hyperparameters of the Xception model, aiming to maximize classification performance.

Step-6: Training and Optimization Loop:
Iterate through multiple rounds of training and optimization using the Tabu Search algorithm.
Train the Xception model on the preprocessed and segmented colonoscopy images, incorporating the extracted features.
Update the hyperparameters of the Xception model using the Tabu Search Optimization approach based on the observed classification performance.

Step-7: Model Evaluation and Selection:
Evaluate the trained Xception model on a validation dataset to assess its performance in Colonic adenocarcinoma identification.
Select the model configuration that achieves the highest classification accuracy or desired performance metric.

Step-8: Final Prediction:
Use the selected Xception model to make predictions on new, unseen colonoscopy images for the identification of Colonic adenocarcinoma presence.

V. EXPERIMENTAL RESULTS

We separate the combined dataset into training, test and validation sets so that we may evaluate the performance of the suggested learning models. We choose randomly 70 percent, 15 percent, and 15 percent of the sequences for each class in a dataset to create the training, test sets and validation, respectively. While creating the training, testing and validation sample, we maintain the class percentage (i.e. 56:27:20).

5.1. Performance Measures

The study assesses performance using metrics like accuracy, recall, precision, and F1-Score, providing a comprehensive evaluation of the model's effectiveness. The followings are the detail description of these metrics.

$$Accuracy = (TP + TN)/(TP + TN + FP + FN) \quad (5)$$

$$Precision = TP/(TP + FP) \quad (6)$$

$$Recall = TP/(TP + FN) \quad (7)$$

$$F1 - Score = (2 \times Precision \times Recall)/(Precision + Recall) \quad (8)$$

In this context, TP represents true positives, TN denotes true negatives, FP signifies false positives, and FN indicates false negatives. These terms are fundamental in assessing classification performance.

A pair of confusion matrices produced by the XceptionTS method on the test dataset are shown in Figure 5. The outcomes demonstrated that the XceptionTS model performed effectively with training and testing data of various sizes. For instance, the XceptionTS model identified 263 instances in the benign class, 144 images in the malignant class, and 77 images in the normal class when the training/testing data was 70:30. The proposed model has been trained and tested using 10-fold cross validation.

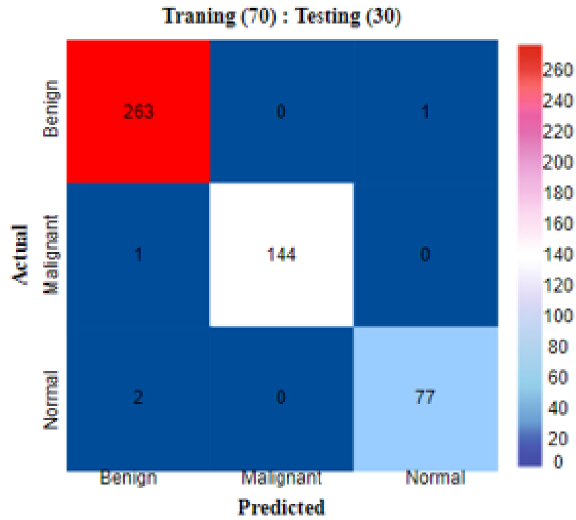

Figure 5: The detail confusion matrix for XceptionTS model.

5.2. Result Analysis

The categorical classification findings of the XceptionTS model on different train-test data shown in Table 1. The XceptionTS procedure is a highly effective method for identifying and classifying Colonic adenocarcinoma using colonoscopy images. It has high precision, recall, accuracy, and F-score across all classes, indicating its effectiveness in classifying Colonic adenocarcinoma types. The model's accuracy is 99.23%, with 99.24% of instances predicted as Benign and 99.80% of instances predicted as Malignant. The model achieves a balance between precision and recall for each class, ensuring reliable and accurate predictions. The F-scores for the Benign class are 0.9924, indicating a harmonic mean of recall and precision, while the Malignant class has a F-score of 0.9980, indicating a balance between precision and recall. The overall accuracy of 99.23% reflects the model's ability to correctly classify Colonic adenocarcinoma instances across different types. Overall, the XceptionTS procedure is highly effective in identifying and classifying Colonic adenocarcinoma using colonoscopy images, with strong performance metrics across all evaluated categories. Figure 6 and depicts the performance analysis of proposed XceptionTS model with 70:30 ratio of training and testing dataset, respectively.

Table 1: The Analysis of Result for XceptionTS procedure with 70:30 split ratio.

Types	Precn	Recal	Accuy	Fscore
Training/testing -70 : 30				
Benign	.9924	.9924	.9915	.9924
Malignant	.9980	.9980	.9998	.9980
Normal	.9750	.9750	.9915	.9750
Average	.9905	.9896	.9923	.9901

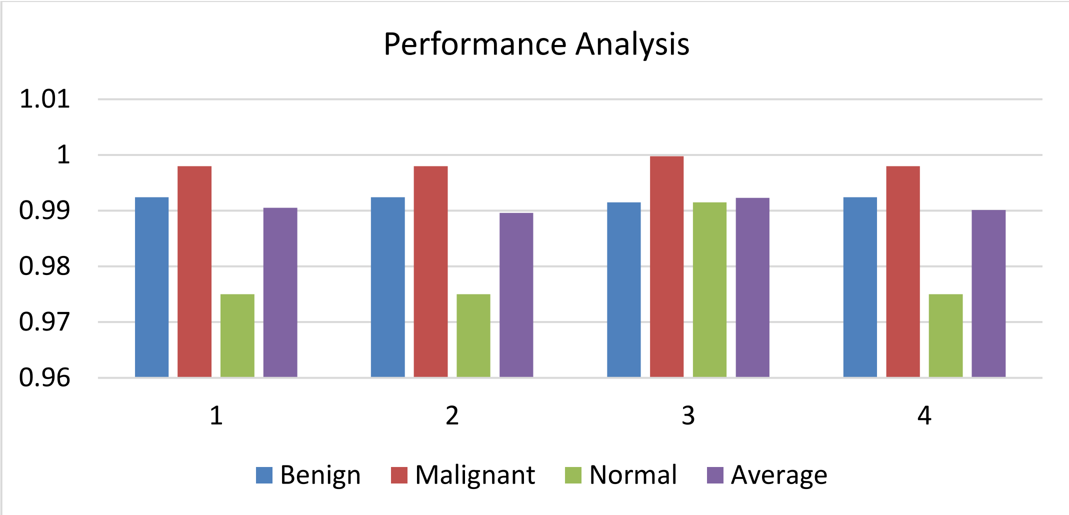

Fig. 6: Result Analysis of XceptionTS for Training/testing -70: 30

Table 2 and Figure 7 support a broad comparative evaluation of the XceptionTS model with the available traditional models using a 70:30, train and test data ratio. The experimental outcomes presented that the XceptionTS approach outpaced the other techniques, with higher precn, recal, accuy, and Fscore values of 99.05%, 98.96%, 99.23%, and 99.01%, respectively.

Table 2: Analysis of the XceptionTS technology in comparison to current methods for training and testing (70:30).

Performance/ Model	YOLOv3 [8]	Hybrid AlexNet [21]	ResNet-50 [28]	Hybrid U-Net [34]	AdBet-WOA [26]	TS-Xception
Precn	96.30	98.67	95.45	96.78	98.02	99.05
Recal	98.50	98.34	95.37	96.77	98.90	98.96
Accuy	96.80	98.40	94.85	95.00	98.17	99.23
Fscore	95.90	98.29	95.54	96.80	98.89	99.01

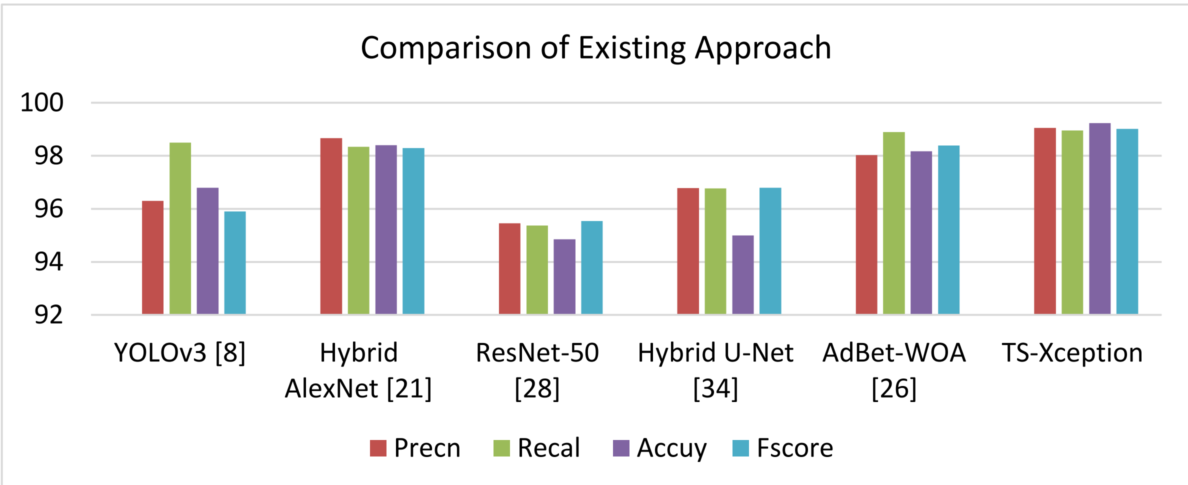

Fig. 7. Analysis of the XceptionTS technology in comparison to current methods for training and testing (70:30).

VI. Discussion

In "Colonic adenocarcinoma Classification and Detection Using Tabu Search Optimizing with Deep Transfer Learning", the XceptionTS model is introduced to identify and classify CRC using colonoscopy images. Combining clinical imaging information with cutting-edge machine learning technologies improves CRC detection. The paper's introduction emphasizes CRC's high mortality rate and the importance for early identification. It underlines the challenges of small-scale data scarcity and large-scale dataset costs. The authors present the XceptionTS model, which uses deep transfer learning and classifiers. The authors test the XceptionTS model with 1560 colonoscopy images. They show the model's superiority over competitors with excellent results. Table 1 shows that the proposed technique had 99.23% accuracy for all image datasets. Table 2 addresses improving the suggested work using all measuring criteria. With a 70:30 split, accuracy increases by 0.06% compared to other models in the study. The model recognizes CRCs well with high precision, recall, accuracy, and F1-score values. The model's clinical efficacy and accessibility and comprehensibility may be considered in AI-assisted medical diagnosis.

VII. Conclusion

The study uses colonoscopy images to identify and classify Colonic adenocarcinoma using a unique XceptionTS technique. The methodology includes NMF for data preprocessing, MobileNetV2 for segmentation, ResNet-50 for feature extraction, Xception-based classification, and Tabu Search optimization-based hyper-parameter tuning. The 1560-collected dataset was used to validate the XceptionTS method, which outperformed earlier approaches. The model achieved higher precn, recal, accuy, and F score values of 99.05%, 98.96%, 99.23%, and 99.01% for a 70:30 ratio of training and testing samples. The authors plan to expand the dataset and explore optimization techniques to enhance accuracy further. In the future, sophisticated DL models may be used to improve Colonic adenocarcinoma classification performance.

Acknowledgement

The authors are immensely thankful to Dr. Pinaki Mohanty and Dr. Ranjulata Mohanty for all kind of support during the collection of polyp dataset for this study.

Funding:

There is no fund acknowledged from any agency.

Conflicts of interest / Competing interests:

The authors affirm that they do not have any competing interests.

References

[1] Ishak Pacal, Dervis Karaboga, Alper Basturk, Bahriye Akay, Ufuk Nalbantoglu, A comprehensive review of deep learning in colon cancer, Computers in Biology and Medicine, Volume 126, 2020, 104003, ISSN 0010-4825, https://doi.org/10.1016/j.compbiomed.2020.104003.

[2] Ruihao Luo, Thomas Bocklitz, A systematic study of transfer learning for colorectal cancer detection, Informatics in Medicine Unlocked, Volume 40, 2023, 101292, ISSN 2352-9148, https://doi.org/10.1016/j.imu.2023.101292.

[3] AbdElNabi, M. L. R., Wajeeh Jasim, M., El-Bakry, H. M., Hamed N. Taha, M., & Khalifa, N. E. M. (2020). Breast and colon cancer classification from gene expression profiles using data mining techniques. Symmetry, 12(3), 408.

[4] Jumnake, G. F., Mahalle, P. N., Shinde, G. R., & Thakre, P. A. (2023). Deep and Transfer Learning in Malignant Cell Classification for Colorectal Cancer. In Information Systems for Intelligent Systems: Proceedings of ISBM 2022 (pp. 319-329). Singapore: Springer Nature Singapore.

[5] Masud, M., Sikder, N., Nahid, A. A., Bairagi, A. K., & AlZain, M. A. (2021). A machine learning approach to diagnosing lung and colon cancer using a deep learning-based classification framework. Sensors, 21(3), 748.

[6] Khan, A., Brouwer, N., Blank, A., Müller, F., Soldini, D., Noske, A., ... & Zlobec, I. (2023). Computer-Assisted Diagnosis of Lymph Node Metastases in Colorectal Cancers Using Transfer Learning with an Ensemble Model. Modern pathology, 36(5), 100118.

[7] Al-Rajab, M., Lu, J., & Xu, Q. (2021). A framework model using multifilter feature selection to enhance colon cancer classification. Plos one, 16(4), e0249094.

[8] Murugesan, M., Arieth, R. M., Balraj, S., & Nirmala, R. (2023). Colon cancer stage detection in colonoscopy images using YOLOv3 MSF deep learning architecture. Biomedical Signal Processing and Control, 80, 104283.

[9] Hage Chehade, A., Abdallah, N., Marion, J. M., Oueidat, M., & Chauvet, P. (2022). Lung and colon cancer classification using medical imaging: A feature engineering approach. Physical and Engineering Sciences in Medicine, 45(3), 729-746.

[10] Petäinen, L., Väyrynen, J. P., Ruusuvuori, P., Pölönen, I., Äyrämö, S., & Kuopio, T. (2022). Domain-specific transfer learning in the automated scoring of tumor-stroma ratio from histopathological images of colorectal cancer. arXiv preprint arXiv:2212.14652.

[11] Mengash, H. A., Alamgeer, M., Maashi, M., Othman, M., Hamza, M. A., Ibrahim, S. S.. & Yaseen, I. (2023). Leveraging Marine Predators Algorithm with Deep Learning for Lung and Colon Cancer Diagnosis. Cancers, 15(5), 1591.

[12] Kumar, N., Sharma, M., Singh, V. P., Madan, C., & Mehandia, S. (2022). An empirical study of handcrafted and dense feature extraction techniques for lung and colon cancer classification from histopathological images. Biomedical Signal Processing and Control, 75, 103596.

[13] Tasnim, Z., Chakraborty, S., Shamrat, F. M. J. M., Chowdhury, A. N., Nuha, H. A., Karim, A., ... & Billah, M. M. (2021). Deep learning predictive model for colon cancer patient using CNN-based classification. Int. J. Adv. Comput. Sci. Appl, 12, 687-696.

[14] Irawati, I. D., Larasaty, I. A., & Hadiyoso, S. (2022). Comparison of Convolution Neural Network Architecture for Colon Cancer Classification. International Journal of Online & Biomedical Engineering, 18(3).

[15] Gupta, S., Kalaivani, S., Rajasundaram, A., Ameta, G. K., Oleiwi, A. K., & Dugbakie, B. N. (2022). Prediction performance of deep learning for colon cancer survival prediction on SEER data. BioMed Research International, 2022.

[16] Yildirim, M., & Cinar, A. (2022). Classification with respect to colon adenocarcinoma and colon benign tissue of colon histopathological images with a new CNN model: MA_ColonNET. International Journal of Imaging Systems and Technology, 32(1), 155-162.

[17] Sakr, A. S., Soliman, N. F., Al-Gaashani, M. S., Pławiak, P., Ateya, A. A., & Hammad, M. (2022). An efficient deep learning approach for colon cancer detection. Applied Sciences, 12(17), 8450.

[18] Attallah, O., Aslan, M. F., & Sabanci, K. (2022). A framework for lung and colon cancer diagnosis via lightweight deep learning models and transformation methods. Diagnostics, 12(12), 2926.

[19] Talukder, M. A., Islam, M. M., Uddin, M. A., Akhter, A., Hasan, K. F., & Moni, M. A. (2022). Machine learning-based lung and colon cancer detection using deep feature extraction and ensemble learning. Expert Systems with Applications, 205, 117695.

[20] Kiziloluk, S., & Sert, E. (2022). COVID-CCD-Net: COVID-19 and colon cancer diagnosis system with optimized CNN hyperparameters using gradient-based optimizer. Medical & Biological Engineering & Computing, 60(6), 1595-1612.

[21] Mehmood, S., Ghazal, T. M., Khan, M. A., Zubair, M., Naseem, M. T., Faiz, T., & Ahmad, M. (2022). Malignancy detection in lung and colon histopathology images using transfer learning with class selective image processing. IEEE Access, 10, 25657-25668.

[22] Kavitha, M. S., Gangadaran, P., Jackson, A., Venmathi Maran, B. A., Kurita, T., & Ahn, B. C. (2022). Deep Neural Network Models for Colon Cancer Screening. Cancers, 14(15), 3707.

[23] PAKSOY, N., & YAĞIN, F. H. (2022). Artificial Intelligence-based Colon Cancer Prediction by Identifying Genomic Biomarkers. Medical Records, 4(2), 196-202.

[24] Naga Raju, M. S., & Srinivasa Rao, B. (2023). Lung and colon cancer classification using hybrid principle component analysis network-extreme learning machine. Concurrency and Computation: Practice and Experience, 35(1), e7361.

[25] A.Panigrahi et al., "En-MinWhale: An Ensemble Approach Based on MRMR and Whale Optimization for Cancer Diagnosis," in IEEE Access, vol. 11, pp. 113526-113542, 2023, doi: 10.1109/ACCESS.2023.3318261.

[26] Bhattacharya, A., Saha, B., Chattopadhyay, S., & Sarkar, R. (2023). Deep feature selection using adaptive β-Hill Climbing aided whale optimization algorithm for lung and colon cancer detection. Biomedical Signal Processing and Control, 83, 104692.

[27] Kai-Ni Wang, Shuaishuai Zhuang, Qi-Yong Ran, Ping Zhou, Jie Hua, Guang-Quan Zhou, Xiaopu He, DLGNet: A dual-branch lesion-aware network with the supervised Gaussian Mixture model for colon lesions classification in colonoscopy images, Medical Image Analysis, Volume 87, 2023, 102832, ISSN 1361-8415, https://doi.org/10.1016/j.media.2023.102832.

[28] Devvi Sarwinda, Radifa Hilya Paradisa, Alhadi Bustamam, Pinkie Anggia, Deep Learning in Image Classification using Residual Network (ResNet) Variants for Detection of Colorectal Cancer, Procedia Computer Science, Volume 179, 2021, Pages 423-431, ISSN 1877-0509, https://doi.org/10.1016/j.procs.2021.01.025.

[29] M. Obayya, M. A. Arasi, N. Alruwais, R. Alsini, A. Mohamed and I. Yaseen, "Biomedical Image Analysis for Colon and Lung Cancer Detection Using Tuna Swarm Algorithm With Deep Learning Model," in IEEE Access, vol. 11, pp. 94705-94712, 2023, doi: 10.1109/ACCESS.2023.3309711.

[30] A. C. d. M. Lima et al., "A Two-Stage Method for Polyp Detection in Colonoscopy Images Based on Saliency Object Extraction and Transformers," in IEEE Access, vol. 11, pp. 76108- 76119, 2023, doi: 10.1109/ACCESS.2023.3297097.

[31] Ding, K., Zhou, M., Wang, H., Zhang, S., & Metaxas, D. N. (2022). Spatially aware graph neural networks and cross-level molecular profile prediction in colon cancer histopathology: a retrospective multi-cohort study. The Lancet Digital Health, 4(11), e787-e795.

[32] A. M. Provath, K. Deb, P. K. Dhar and T. Shimamura, "Classification of Lung and Colon Cancer Histopathological Images Using Global Context Attention Based Convolutional Neural Network," in IEEE Access, vol. 11, pp. 110164-110183, 2023, doi: 10.1109/ACCESS.2023.3321686.

[33] M. Mirza, A. Alsobhi, T. Hasanin, M. K. Ishak, F. K. Karim and S. M. Mostafa, "Computer Aided Diagnosis for Gastrointestinal Cancer Classification Using Hybrid Rice Optimization With Deep Learning," in IEEE Access, vol. 11, pp. 76321-76329, 2023, doi: 10.1109/ACCESS.2023.3297441.

[34] Manju Dabass, Sharda Vashisth, Rekha Vig, MTU: A multi-tasking U-net with hybrid convolutional learning and attention modules for cancer classification and gland Segmentation in Colon Histopathological Images, Computers in Biology and Medicine, Volume 150, 2022, 106095, ISSN 0010-4825, https://doi.org/10.1016/j.compbiomed.2022.106095.

[35] Sena Busra Yengec-Tasdemir, Zafer Aydin, Ebru Akay, Serkan Dogan, Bulent Yilmaz, Improved classification of colorectal polyps on histopathological images with ensemble learning and stain normalization, Computer Methods and Programs in Biomedicine, Volume 232, 2023, 107441, ISSN 0169-2607, https://doi.org/10.1016/j.cmpb.2023.107441.

[36] Gaurav Srivastava, Anindita Chauhan, Nitesh Pradhan, CJT-DEO: Condorcet's Jury Theorem and Differential Evolution Optimization based ensemble of deep neural networks for pulmonary and Colorectal cancer classification, Applied Soft Computing, Volume 132, 2023, 109872, ISSN 1568-4946, https://doi.org/10.1016/j.asoc.2022.109872.