Optimizing Enhanced Extended Topological Active Net Model Using Parallel Processing

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Abstract – *In numerous clinical applications that support the diagnosis and treatment planning of a broad variety of disorders, medical image segmentation is essential. Medical picture segmentation using the Enhanced Extended Topological Active Net (EETAN) model has proven to be successful in correctly identifying structures. This study suggests a novel way to combine the best clustering techniques and parallel processing approaches to maximize the segmentation performance of the EETAN model. The Probabilistic Depth Search Optimization (PDSO) Algorithm, which makes the parallel searching technique to find the ideal contour set, is responsible for this. This work implements parallel processing and ideal clustering to improve the EETAN model's performance in medical image segmentation. Performance metrics like accuracy, precision, recall, dice similarity, and computational time are used for a comparison study. The results demonstrate the notable enhancements attained by employing parallel processing and effective clustering.*

Keywords: *Image Segmentation, Parallel Computing, Probabilistic Depth Search Optimization (PDSO), Enhanced Extended Topological Active Net (EETAN)*

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1. INTRODUCTION

Medical picture segmentation is an essential part of diagnostic imaging that helps medical professionals identify exact anatomical structures and make clinical decisions based on those findings. The increase in volume and resolution of medical image datasets due to better medical imaging technology has made robust segmentation models necessary to handle the complexity of these datasets. Because it can capture complex structures in medical images, the Extended Topological Active Net (ETAN) model has emerged as a possible option [1]. However, it becomes more and more clear that more effective and scalable segmentation techniques are required as the size and complexity of medical datasets increase. Medical image data volume and resolution have increased exponentially as a result of the quick development of medical imaging technologies. For significant information to be extracted from these massive databases, effective segmentation techniques are crucial. A promising solution to the problems associated with medical image segmentation is the ETAN model, which is an extension of the Topological Active Net.

In contemporary healthcare, medical picture segmentation is an essential task that is critical to diagnosis, therapy planning, and image-guided therapies [2]. To extract relevant information from medical images and support healthcare practitioners in making decisions, accurate delineation of anatomical features is essential. The Extended Topological Active Net (ETAN) model is a useful tool for medical image segmentation because it is recognized for handling intricate anatomical components.

The amount and complexity of medical image data have significantly increased as a result of the growing use of high-resolution imaging modalities like computed tomography (CT) and magnetic resonance imaging (MRI). Although the ETAN model performs well in segmentation tasks, applying it to large-scale datasets may provide a challenge to its computing efficiency. The need for segmentation in real-time or almost real-time, especially in clinical contexts, makes it necessary to investigate novel approaches to improve the ETAN model's speed and scalability. The necessity to close the gap between the ETAN model's promise and the changing needs of modern medical imaging drives this research. We seek to overcome the computational issues with the ETAN model and advance it toward a more effective and scalable solution for medical picture segmentation by utilizing parallel processing capabilities and implementing optimal clustering algorithms. Through this investigation, we aim to provide a valuable contribution to the continuous endeavors aimed at refining segmentation techniques, which will promote progress in medical imaging technology and ultimately enhance patient care.

The idea for this study came from the realization that when dealing with large-scale medical picture datasets, the traditional sequential implementation of the ETAN model can run into processing difficulties. To overcome this difficulty, the incorporation of parallel processing methods is investigated as a way to improve the ETAN model's computational effectiveness. The potential to improve segmentation accuracy within the parallelized framework is another reason for including optimal clustering techniques. The combination of best clustering and parallel processing is meant to offer a fast and precise way to segment medical images, which could lead to better clinical results.

We explore the complexities of the ETAN model in this work, recognizing both its advantages and disadvantages. The next step of our trip is to investigate how parallel processing and optimum clustering strategies might work together to overcome computational bottlenecks and improve the EETAN model's performance. The particle weight search parallel model improves performance by cutting down on time without compromising system accuracy. The PDSO optimization algorithm handled this. The approaches used, the integration of parallel processing and optimal clustering, and the thorough assessment of the suggested strategy using pertinent performance measures are all covered in detail in the sections that follow. The research's conclusions have potential ramifications for improving medical picture segmentation in the larger healthcare context in addition to aiding in the ETAN model's optimization.

One significant difficulty is the exponential increase in volume and complexity of medical image databases brought about by advances in imaging technologies. When used on these larger datasets, conventional segmentation models—such as the ETAN model—may encounter scalability and processing speed issues. The need for segmentation techniques that can successfully manage the inherent complexity of contemporary medical images is growing as the need for more thorough and detailed medical imaging increases. The ETAN model's traditional sequential processing may make it more difficult for it to deliver findings quickly, particularly in situations where making decisions quickly is essential, like in clinical settings. The goal of enabling quicker and more effective segmentation capabilities within the EETAN framework is what drives the investigation of parallel processing techniques as a means of overcoming these constraints. Because the PDSO uses many optimization objectives to simplify contour searching and detect particles simultaneously, it also optimizes time consumption. Moreover, the realization that improving segmentation accuracy is just as important is what propels the incorporation of the best clustering approaches. Contour searching is the depiction of the boundaries or outlines of objects or shapes within an image. Contours are used to represent the structural information of objects within an image and are valuable in image segmentation. These are formed by connecting adjacent points with similar pixel intensity. So set of coordinates that outline the boundary of an object helps in segmenting objects from the background in an image.

In the ETAN algorithm contours are represented as a series of connected points in Cartesian coordinates. In the ETAN algorithm, Chan-Vese segmentation is applied to the image. Chan-Vese segmentation is a level set-based image segmentation method that partitions an image into regions based on intensity homogeneity. The Chan-Vese segmentation algorithm minimizes an energy function that consists of two terms: an internal term promoting smoothness within regions and an external term penalizing deviations from a given intensity or gray level. This is employed to evolve a contour or boundary that separates different regions in the image. We seek to improve the accuracy and consistency of the segmentation outputs generated by the EETAN model by integrating sophisticated clustering techniques, guaranteeing that the segmented structures closely match the ground truth.

2. ENHANCED EXTENDED TOPOLOGICAL ACTIVE NET MODEL

Building on the fundamental ideas of the classic Topological Active Net, the Enhanced Extended Topological Active Net (EETAN) model offers a comprehensive and flexible method for medical image segmentation. The EETAN model was created to address the difficulties presented by complex anatomical features and intensity variations in medical pictures. It accomplishes accurate and thorough segmentation results by combining topological geometry with dynamic contour evolution. The core idea of the EETAN model is the use of deformable contour representations that dynamically change across repetitions while successfully respecting anatomical structure boundaries. The EETAN model is unique in that it incorporates topological flexibility, which makes it possible to depict several interrelated components and makes it easier to delineate complicated systems subtly. The EETAN model is well-suited to the challenges presented by medical imaging datasets because it incorporates topological information into the segmentation process, which enhances its ability to capture fine-grained anatomical characteristics. The EETAN model's principal strength is its high degree of realism while handling complex anatomy. Multiple connected component scenarios may be difficult for typical active contour models to handle, but the topological adaptability of the EETAN model allows it to navigate and define such systems with accuracy. Because of its versatility, the EETAN model can be used for a variety of medical imaging tasks, such as organ, tissue, and lesion segmentation. The EETAN model has limits, especially concerning computational efficiency. The following sections of this paper explore these limitations and suggest creative solutions that make use of parallel processing and efficient clustering approaches. With these improvements, the EETAN model should be able to meet the changing needs of modern healthcare by being more computationally efficient, scalable, and adaptive for medical image segmentation. The EETAN model is an advanced framework in the field of medical image segmentation that was created to tackle the difficulties caused by intricate anatomical structures and different levels of intensity in medical images. By utilizing active contour evolution and topological geometry, the EETAN model achieves reliable and precise segmentation outcomes. Although the EETAN model performs admirably in segmentation, it is not without flaws. Its computational efficiency is one of its main limitations, particularly when dealing with large-scale medical imaging datasets. Traditional implementations' sequential design may cause extended processing times, which would make the model less applicable in situations where outcomes are crucial, including in healthcare settings. Furthermore, as medical datasets get more complex, the model may encounter difficulties with scalability and adaptability. To improve the performance of the EETAN model, this research attempts to investigate fresh methodologies, particularly parallel processing approaches and optimal clustering algorithms. Through the resolution of these issues, we want to fully realize the promise of the EETAN model and further the development of sophisticated segmentation techniques for medical imaging. The approaches used to include parallel processing and optimal clustering into the EETAN model are described in depth in the following sections, which aim to improve its usability in modern healthcare applications while reducing its drawbacks. The EETAN model's intrinsic dependency on sequential processing is one of its main drawbacks. Processing duration may be prolonged due to the computing demands resulting from the expansion of medical imaging collections with higher quality and complexity. This presents difficulties, especially in situations involving patients when outcomes are crucial for making well-informed decisions. Concerns about the EETAN model's scalability arise as medical datasets grow larger. The accuracy of segmentation can be affected by the EETAN model's sensitivity to initialization factors. In circumstances of unclear or difficult anatomy, suboptimal initialization might result in contour convergence problems that affect the model's capacity to precisely define structures. Several user-defined parameters in the EETAN model may need to be fine-tuned depending on the particulars of the medical imaging task at hand. Due to the model's sensitivity to these factors, precise calibration is required, which adds a level of subjectivity and may make it difficult to achieve the best results in various applications. Improving the EETAN model's performance requires addressing these constraints. To address these limitations, the following sections of this study investigate how parallel processing and appropriate clustering strategies might be combined to improve the overall effectiveness and suitability of the EETAN model for medical image segmentation.

3. PARALLEL PROCESSING TECHNIQUES

In response to the computational challenges posed by the EETAN model, parallel processing techniques are explored to harness the power of concurrent computation, accelerate segmentation tasks, and address the growing demands of large-scale medical image datasets. The parallelization of the EETAN model is essential to overcome computational bottlenecks and enhance its efficiency in handling large-scale medical image datasets. The parallelization of the EETAN model through multi-threading, GPU acceleration, task parallelism, and data parallelism collectively address the computational challenges. The subsequent integration with optimal clustering techniques further refines segmentation accuracy. In the multithreading approach, the segmentation algorithm is decomposed into concurrent threads allowing for the simultaneous execution of independent tasks. This approach enhances the utilization of multi-core processors resulting in faster iterations and reduced overall processing time.

The segmentation process within the EETAN model involves iterative tasks providing opportunities for task parallelism. Each iteration can be treated as an independent task enabling concurrent execution and reducing the overall processing time. Efficient load-balancing mechanisms are implemented to ensure optimal resource utilization and performance. Dynamic task scheduling mechanisms are employed to adaptively distribute computational tasks based on workload variations. This ensures that processing units remain engaged and productive throughout the segmentation process. The dynamic load balancing mitigates the risk of idle resources and maximizes the utilization of available computational power.

The data parallelism is achieved by partitioning the medical image dataset into smaller subsets and each subset is then processed independently by different processing units enabling parallel execution of segmentation tasks. The results from each subset are aggregated to produce the final segmented output. This approach enhances scalability and facilitates the efficient processing of large and high-resolution medical image datasets. The deformable contour evolution, a core component of the EETAN model is parallelized by distributing contour evolution tasks across processing units which accelerates the convergence of contours to anatomical boundaries contributing to faster and more efficient segmentation [3].

In conjunction with parallel processing, the integration of optimal clustering techniques into the EETAN model plays a crucial role in refining segmentation accuracy and addressing challenges associated with complex anatomical structures. Various clustering algorithms are explored to enhance the robustness of the segmentation process [4]. The k-means clustering is applied to group pixels based on intensity similarities. By partitioning the image into clusters with similar intensity levels the EETAN model benefits from improved discrimination between different tissue types. To mitigate sensitivity to initialization robust initialization strategies are employed for K-Means clustering. Smart initialization methods such as K-Means++ are implemented to improve convergence speed and ensure representative cluster assignments [5]. Hierarchical clustering is integrated to capture structural relationships within the image data. This method enhances the adaptability of the EETAN model to complex anatomies by incorporating information at different hierarchical levels contributing to more nuanced segmentation results.

The Fuzzy C-Means clustering is introduced to handle pixel memberships with degrees of uncertainty [5, 6]. This is particularly beneficial in regions where anatomical boundaries are ambiguous. The fuzzy clustering approach allows the model to represent partial memberships, enabling a more nuanced and accurate representation of anatomical structures. By combining optimal clustering with parallel processing, the segmentation algorithm gains the advantages of both enhanced accuracy from clustering and accelerated computation from parallelization. The resulting synergy creates a comprehensive solution for image segmentation demonstrating improved efficiency and adaptability across diverse datasets [7]. Clustering algorithms such as K-Means [8], hierarchical clustering, and fuzzy C-Means [9] are integrated into the parallelized segments of the EETAN model. A hybrid parallelization approach is implemented combining the strengths of both CPU and GPU architectures. CPU-based parallelization handles complex control logic, task scheduling, and communication, while GPU acceleration is employed for computationally intensive tasks within both clustering and segmentation components. Load balancing mechanisms dynamically adjust the workload distribution based on the capabilities of CPU and GPU units preventing resource underutilization and optimizing overall processing speed [10]. The performance metrics including segmentation accuracy, precision, recall, and computational time are employed to quantitatively assess the effectiveness of the integrated parallel processing and clustering approach.

4. METHODOLOGY

The methodology, which uses the Probabilistic Depth Search Optimization (PDSO) algorithm in Figure 1, describes the methodical approach used to include parallel processing techniques and effective clustering approaches in the EETAN model. PDSO algorithm is based on Particle swarm optimization (PSO) algorithm, where particles represent potential solutions that evolve over iterations. Particles for the optimization model are initialized with random coordinate positions within a specified range. The particles are split into random coordinates and start searching for updates. The completion time for each direction is estimated based on starting and finishing times. The difference between the traditional ETAN and the proposed EETAN is the implementation of contour updates by using PDSO. In the PDSO optimization, the Virtual Member set is initialized and processed as serial and parallel methods. The EETAN was implemented as a serial and parallel type of PDSO optimization to evaluate the time consumption. As per the implementation of PDSO in the EETAN model, this will enhance the performance level of segmentation. The actions made to improve segmentation accuracy and computing efficiency to create a comprehensive framework for advanced medical image analysis are covered in this part.

The main function of the PDSO optimization algorithm is to find the best particles for contour update. The estimation of contour update will be based on the update of particle weight value as calculated from the objective function. This will make the large searching process which leads to time consumption. In that, some of the parameters are independent to find the best contour. This we can compute by the separate thread which refers to parallel computing. This type of parallelization leads to reducing the time consumption for searching the best. This will update the weight and refer to the global parameters to validate the update of particles.

For the optimal searching process, the input of the function refers to the feature set, 'T' that was initialized as in equation (1).

$$T = \{T_1, T_2, \dots T_n\} \tag{1}$$

To achieve the parallel process of optimization, this initializes the virtual member set 'VM' which is represented in (2). The virtual member set (VM) represents the entities that interact with the feature set during the optimization process. In this algorithm, the virtual members are associated with different parameters for the processing of endoscopic images. These parameters include:

1. Contour Update Parameters:

- Parameters governing the update of contours in the images.

2. Optimization Parameters:

- Parameters controlling the behavior of the algorithm, such as swarm size, maximum iterations, and inertia weight.

$$VM = \{VM_1, VM_2, \dots VM_n\} \tag{2}$$

From these parameters, the particles for the optimization model can be initialized by the random coordinate positions as 'X_0'. This can be evaluated by the equation (3).

$$X_0 = X_{min} + (X_{max} - X_{min}) \times rand \tag{3}$$

From the particle update, the particles are now split in the random coordinates and start searching for the particle updates. For that, the particles are now updated in the right way by estimating the completion time for each direction to search for the update which means the particles take less time to update the parameters. This is referred to in (4).

$$T_{CT(ij)} = FT\big(T(j)\big) - ST\big(T(j)\big) \quad (4)$$

Where,

ST – Starting time

FT – Finishing Time

i=1,2,…n // Index of the feature list

j=1,2,…m // Index of VM list.

From the estimation of completion time in (4), the maximum value is estimated, and this is the reference for other particles to update the parameters as in (5).

$$M_T = max\{T_{CT(ij)}\} \quad (5)$$

The average utilization of particles for each 'VM' is calculated to find the amount of usage that is to perform the update. Equation (6) and (7) represents the average utilization and response time for iteration count respectively.

$$Average\ Utilization_{VM} = \frac{\sum_{i=1}^{n} T_{CT(ij)}}{M_T \times m} \quad (6)$$

$$Response\ Time\ (RT) = n \times T_{CT(0)} \quad (7)$$

Then calculate the value of process in each particle as from (8). This is to refer to the weight value of each particle to find the best update of contour.

$$L\big(VM_j, t\big) = \frac{NT(T,t)}{SR\big(VM_j,t\big)} \quad (8)$$

Where,

NT – Number of features in each VM at a time instant.

SR – Service Rate running in a VM.

The particles in the VM need to estimate the over process and under process to estimate the limit of particle movement for each iteration count. This can be evaluated from (9) and (10).

$$OL_{VM(j)} = \begin{cases} VM(j), & if\ (L(j) > S(j) \\ \phi, & otherwise \end{cases} \quad (9)$$

$$UL_{VM(j)} = \begin{cases} VM(j), & if\ (L(j) < (S(j) - B) \\ \phi, & otherwise \end{cases} \quad (10)$$

Where,

S(j) – Maximum size of each VM.

B – Boundary limit of VM.

OL – OverProcess of VM.

UL – UnderProcess of VM.

Based on this evaluation, the amount of resources that are scheduled and the available resources to apply search processes are estimated from (11) and (12).

$$T_{R_{Used}} = \sum_{i=1}^{n} T_i \quad (11)$$

$$T_{R_{Avail}} = \big(T_R - T_{R_{Used}}\big) \quad (12)$$

Arrange the logical Confirm List (CL) from the estimation of OL and UL. This is to eliminate the irrelevant features that are not updated in the contour validation. The list consists of logical values to represent the confirmed '1' and not allowed '0' respectively. This was represented in the equation (13).

$$CL = \begin{cases} 1, & if\ \big(OL_{VM(j)}(or)UL_{VM(j)}\ \neq \phi\big) \\ 0, & otherwise \end{cases} \quad (13)$$

Based on the evaluation factors, the particles are validated to perform the update of contour matrix that is to represent the relevant pixels that are matched with the neighboring. For that, the similarity between the patterns is referred to form the connected components that represent the contour for the current update. For the similarity measures, the angle of the findings 'θ' is estimated, and the similarity of particles. This was represented in (14) and (15).

$$\theta = \alpha \times angle + (1-\alpha) \times \frac{T_{CT(ij)}}{M_T} \quad (14)$$

Where α – Similarity constant is 0.5.

$$angle = \cos^{-1}\left(T_{CT(ij)} \times \frac{T_{R_{avail}}}{\big(|T_{CT(ij)}||T_{R_{avail}}|\big)}\right) \quad (15)$$

From the update of parameters, the fitness value is calculated as in (16).

$$Fitness = \frac{1}{M_T} \times Average\ Utilization_{VM} \quad (16)$$

The resource sequence are updated as in the format of elements in the array set by (17).

$$R_i^t = (R_i^1, R_i^2, R_i^3, \ldots, R_i^n) \quad (17)$$

Where,

$$R_i^1 = S_i^1 mod\ m \quad (18)$$

S_i^t – Discrete Permutation sequences for the feature-length 'n'.

The standard deviation of updated particles is to represent the evaluated points to update the particles for the next iteration position which is represented in (19).

$$\sigma = \sqrt{\frac{1}{m}\sum_{i=1}^{m}\big(PT_j - PT\big)^2} \quad (19)$$

$$\text{Where, } PT_j = \frac{L(VM_i,t)}{Average\ system\ process} \quad (20)$$

Equation (21) represents the normalized particle parameters for updating the coordinates of particles for the next iteration period.

$$PT = \sum_{i=1}^{m} PT_j \quad (21)$$

The detailed flowchart is presented in Fig. 1. The Kvasir-SEG dataset (size 46.2 MB) containing 1000 endoscopic gastrointestinal images and their corresponding ground truth from the Kvasir Dataset v2 is used. The resolution of the images contained in Kvasir-SEG varies from 332x487 to 1920x1072 pixels. Implementing the EETAN model incorporates topological processing on an image, including smoothening, adding borders, computing persistence diagrams, and segmenting components based on topological features. The basis for such advancements is a comprehensive description of the sequential EETAN model. To parallelize the EETAN model, the particle searches are done in batches. The parameters such as the VM weights, Average particle utilization for each VM, and time estimation to update the particles for iteration count. This makes the PDSO optimization parameters independent of estimating the prediction of contour update. Utilizing resources as efficiently as possible is the goal of load-balancing systems.

The ETAN and the PDSO optimization techniques were combined to form the parallelized EETAN model. To work concurrently on segmented regions, the clustering approaches leverage task and data parallelism. If the robust initialization and parameter adjustment techniques are applied, the clustering results are more trustworthy. Between the segments and clustering sections, a feedback loop is established. Findings from clustering techniques have an iterative impact on the segmentation process. Flexible responses to evolving anatomical configurations and imaging qualities are ensured by mechanisms for dynamic parameter adjustments.

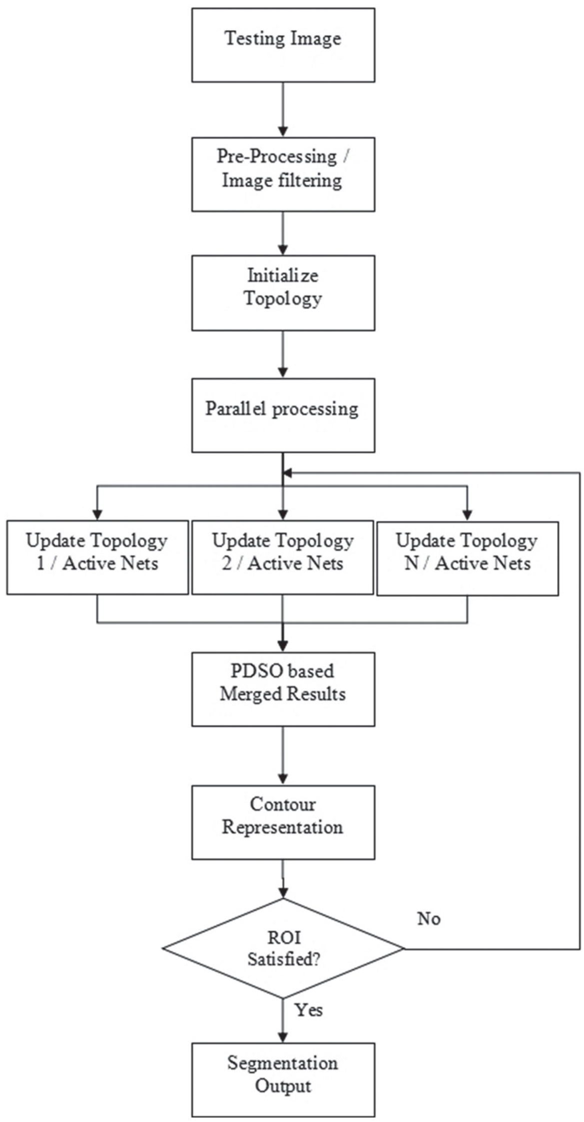

Fig 1. Flowchart for EETAN model

5. EXPERIMENTAL RESULTS

The experimental results provide a thorough assessment of the suggested methodology that integrates the best clustering algorithms and parallel processing techniques into the EETAN model for medical image segmentation. By showcasing increases in segmentation accuracy and processing efficiency, the trials hope to show how successful the integrated method is. The algorithm's output is compared to ground truth annotations to determine how accurate the segmentation results are. To measure segmentation accuracy, the Dice coefficient, and pixel-wise accuracy are calculated. We track and compare the segmentation computational time required with conventional ETAN models. Precision and Recall parameters are calculated by the pre-defined formula estimated from the confusion matrix which is framed by the difference estimation between the actual and predicted result from the algorithms. The actual result is represented as the ground truth and the predicted result is referred to as the clustered/segmented result from the result of simulation output. To assess the efficiency advantages attained through parallel processing, speedup ratios are computed. Consistency and reproducibility are ensured by the use of appropriate programming languages and frameworks in the implementation of the methodology. A thorough evaluation of the advancements made is possible through comparisons with alternative segmentation techniques and conventional EETAN models. A qualitative comprehension of the visual quality and correctness of the segmented structures is facilitated by visual inspection of the segmented findings, expert reviews, and comparisons against ground truth annotations. Python is used to implement the methodology for the EETAN model and parallel processing components.

Table 1 shows the time comparison of ETAN and EETAN for different methods on average time taken. For all these comparisons the EETAN statistics are best with the average time taken for EETAN_serial as 26.73 seconds and EETAN_parallel as 3.67 seconds so a reduction in time of image segmentation is nearly eight times whereas in Table 2 comparison based on percentage average accuracy, Kappa coefficients, MCC, TPR, and F1-macro is discussed and the various metrics in percentage resulted in accuracy as 95, Kappa coefficient as 73.96, MCC as 76.86, TPR as 96.87 and F1-macro as 86.87. These evaluation metrics are related to the quality of segmentation and found that in the proposed work they are improved so the quality of segmentation is improved. Values of parameters are same in serial and parallel because whether we run it in serial or parallel, it is not affecting the quality of segmentation. Table 3 compares the performance measures using the Kvasir-SEG dataset in precision, dice similarity, and recall with 98.24, 96.63, and 96.75 respectively. In Table 4 the comparison of segmentation results with the existing methods on the Kvasir-SEG dataset is presented in precision, dice similarity, and recall with 98.24, 96.19, and 96.75 respectively.

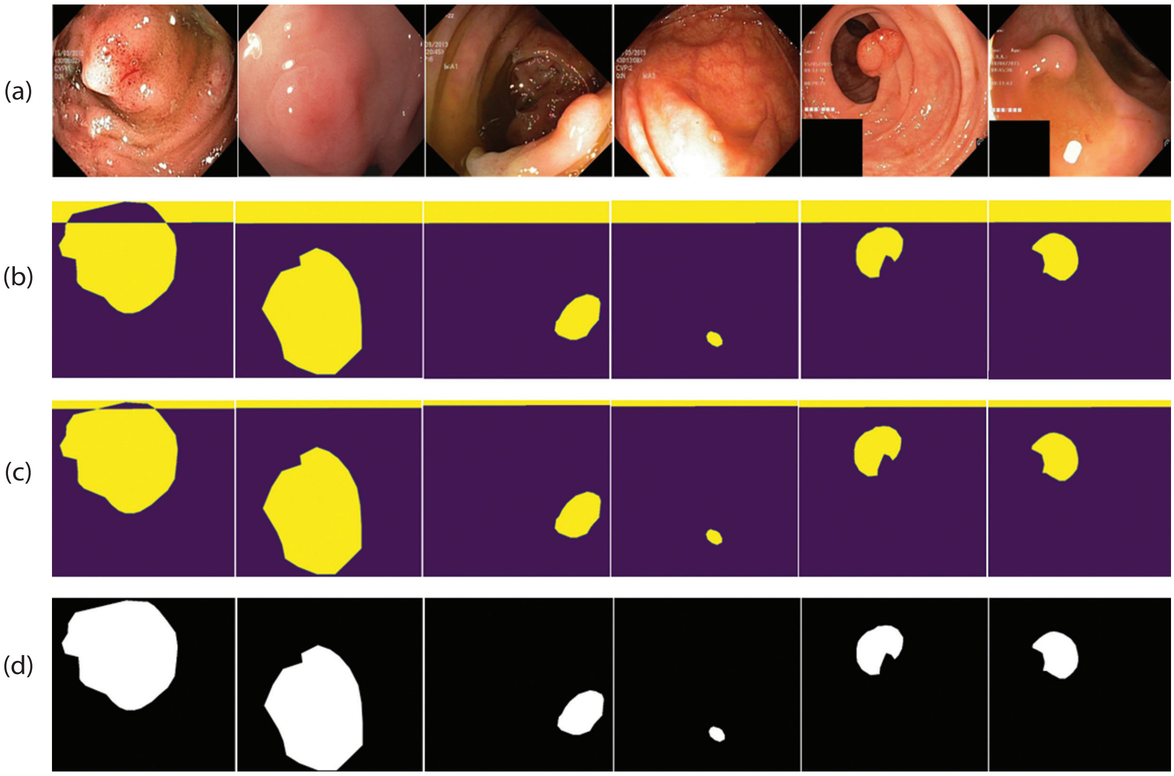

Fig. 2. Sample segmentation Results. (a) Input images, (b) Segmentation result from ETAN, (c) Segmentation result from EETAN, and (d) Ground-Truth

Table 1. Time Comparison of ETAN and EETAN

Methods	Average Time taken (Sec)
ETAN_Serial	26.73
ETAN_Parallel	5.73
EETAN_Serial	24.56
EETAN_Parallel	3.67

Table 2. Comparison of Parameters in Average

Methods	Average Accuracy (%)	Average Kappa Coefficient (%)	Average MCC (%)	Average TPR (%)	Average F1-Macro (%)
ETAN_ Serial	86.95	52.02	58.61	91.38	75.19
ETAN_ Parallel	86.95	52.02	58.61	91.38	75.19
EETAN_ Serial	95	73.96	76.86	96.87	86.87
EETAN_ Parallel	95	73.96	76.86	96.87	86.87

Table 3. Comparison of Performance Measures in Kvasir-Seg Dataset

Methods	Precision	Dice Similarity	Recall
CCS-Net [11]	92.47	90.89	91.41
CCS-Net with HFP [11]	96.81	92.93	90.01
MFRA-Net [12]	93.12	94.19	95.71
EETAN (Proposed)	98.24	96.63	96.75

Table 4. Comparing Segmentation Results with Existing Methods on The Kvasir-Seg Database

Methods	Precision	Dice Similarity	Recall
A-DenseUNet [13]	97.66	90.85	94.48
MSRF-Net [14]	96.66	92.17	91.98
ResUnet++ [11]	81.33	79.27	87.74
CCS-Net [11]	92.47	90.89	91.41
MFRA-Net [12]	93.12	94.19	95.71
EETAN (Proposed)	98.24	96.19	96.75

Visual inspection of segmented results supported by expert evaluations provides qualitative insights into the visual quality and accuracy of the segmentation outcomes. Comparative visualizations against traditional ETAN models and ground truth annotations help validate the improvements achieved through clustering and parallel processing. The experimental results provide a comprehensive evaluation of the proposed methodology, showcasing improvements in segmentation accuracy and computational efficiency. The subsequent sections of the research will discuss the implications of these findings, potential limitations, and avenues for future research in the context of medical image segmentation using the integrated approach. Comparative analyses in fig. 3-5 demonstrate improvements in segmentation accuracy achieved through the integration of optimal clustering techniques. PDSO optimization algorithm contributes to better discrimination of anatomical structures, reflected in higher Dice coefficient.

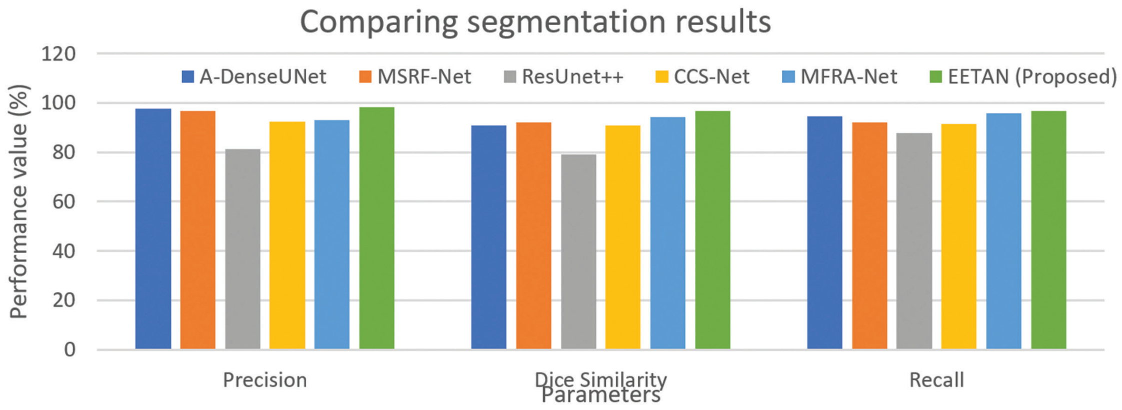

Fig. 3. Comparing segmentation results chart

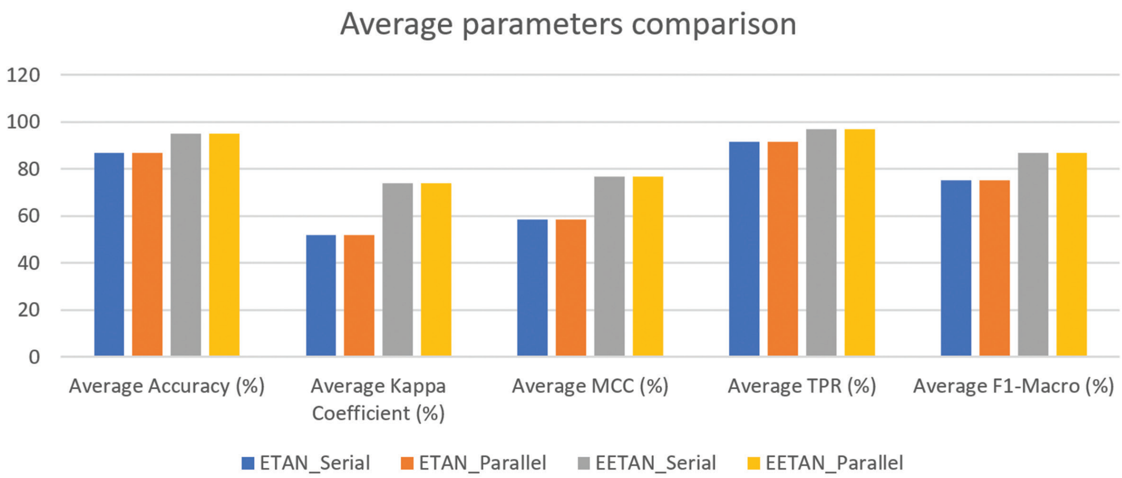

Fig. 4. Average parameters comparison chart

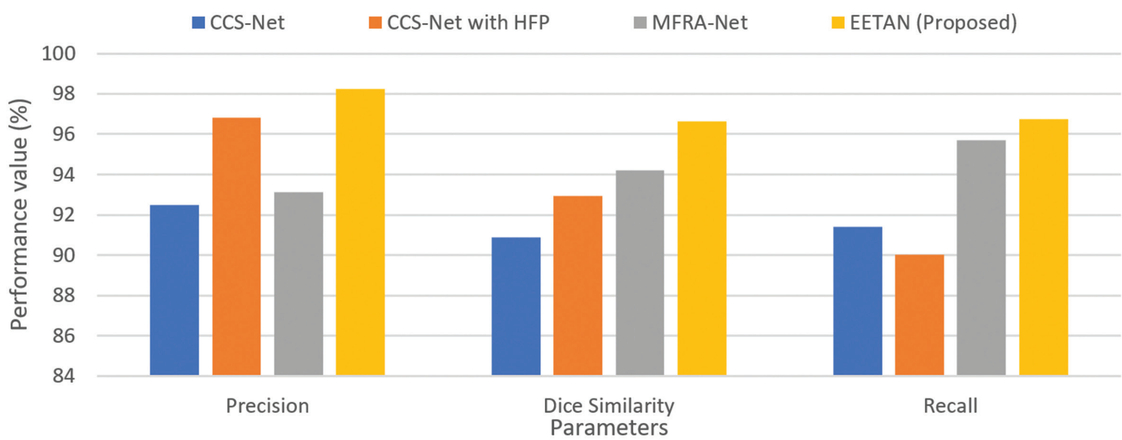

Fig. 5. Comparison of the performance chart

6. FUTURE CONSIDERATIONS

Even if the research to date shows encouraging developments, there is a need for more investigation and improvement. To achieve even greater efficiency and scalability, clustering algorithms and parallel processing techniques may be further optimized. Finally, the integration of deep learning approaches, such as convolutional neural networks, may be explored to improve the segmentation model's learning capacity. The study shows that the EETAN model's incorporation of optimal clustering and parallel processing provides a potent remedy for dealing with the difficulties presented by huge and intricate medical image collections. With this, the area of diagnostic imaging will benefit from more precise and efficient applications of image segmentation techniques.

7. CONCLUSION

This proposed work has investigated the incorporation of optimal clustering techniques and parallel processing techniques into the Enhanced Extended

Topological Active Nets model for medical image segmentation. The extensive studies and experimental results show notable improvements in segmentation accuracy and computing efficiency. The conclusions reached from this investigation are summed up in the following important elements. To increase the accuracy of segmentation, the PDSO optimization method is integrated and a concurrent process of particle searching for contour updates is carried out. A higher Dice coefficient is the outcome of improved anatomical structure discrimination made possible by these clustering techniques. The feedback loop that exists between segmentation and clustering makes it easier to develop the model iteratively, which improves its capacity to adapt to different anatomies. By using an integrated approach, segmentation accuracy is improved and a comprehensive framework that tackles the EETAN model's computational issues is created. When combined with appropriate clustering, the parallelized EETAN model has a synergistic impact that offers a comprehensive solution for advanced medical image segmentation.

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