VLSI IMPLEMENTATION OF CHEST X-RAY IMAGE SEGMENTATION USING HYBRID CLUSTERING

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Abstract - Medical image segmentation plays a crucial role in various clinical applications, facilitating accurate diagnosis and treatment planning. In communication systems, particularly telemedicine and remote healthcare monitoring, real-time processing and transmission of medical images are essential for timely diagnosis and intervention. Leveraging VLSI technology for implementing K-means offers a promising solution to address the computational demands of image segmentation while meeting the stringent requirements of communication systems. Existing systems often rely on software-based implementations such as threshold segmentation, leading to significant computational overhead and latency, particularly in resource-constrained environments. Moreover, these implementations struggle to achieve real-time performance, hindering their practical utility in communication systems for healthcare. So, this work proposed VLSI-based approach aims to overcome these challenges by offloading the computational burden from the software to hardware, enabling parallel processing and efficient utilization of resources. By exploiting the inherent parallelism of the K-means algorithm and optimizing hardware architecture, our design ensures high throughput and low latency, making it suitable for real-time medical image segmentation in communication systems.
Keywords: Hybrid clustering, X-ray, Image Segmentation

1 INTRODUCTION

Nowadays, Chest Diseases have become a significant threat to human health. These diseases in Various types. Each with its own set of symptoms and severity levels. To diagnose chest diseases, medical professionals rely heavily on diagnostic imaging techniques, with X-ray being the most commonly used due to its speed and affordability. X-ray has become a primary tool for screening and identifying various chest ailments such as pneumonia, pneumothorax, and masses among these diseases, about half a billion persons are suffered from pneumonia and about 4 million people die from it per year. For example, lung cancer is one of the tumors, which has the highest incidence and mortality in the world, since the 5-year survival rate of the patient is around 16%. Early diagnosis and treatment can significantly reduce mortality resulting from chest diseases. However, understanding chest X-ray needs a lot of professional knowledge. So far, X-ray images are typically explained by radiologists. But misdiagnosis always happens, because of the diverse chest pathological features and the potential fatigue or lack of experience of radiologists. Therefore, there is a crucial need to develop chest X-ray-assisted diagnostic algorithms that can aid radiologists in providing timely and effective treatment to patients with chest diseases. Recently, the emergence of artificial intelligence techniques has attracted popularity worldwide because they can be applied in the biomedical fields, including skin cancer diagnosis, standard plane detection and localization in fetal ultrasound, lung nodule detection, etc.

1.1 Proposed System

Clustering is a method of unsupervised learning in machine learning, used for grouping similar data points into clusters based on certain characteristics or features. The goal of clustering is to partition the data into groups such that data points within the same group are more similar to each other than to those in other groups. Clustering is widely used in various applications such as customer segmentation, image segmentation, anomaly detection, and document categorization, among others. It helps in discovering patterns and insights within data without the need for labeled examples. In chest X-ray image segmentation, clustering plays a crucial role in identifying key regions such as lung fields, heart, ribs, and potential abnormalities like tumors or infections. Various clustering algorithms, including k-means, hierarchical clustering, and density-based clustering, can be utilized to partition the image pixels into distinct clusters representing different anatomical structures or pathologies. These algorithms leverage the intensity, texture, and spatial information present in the X-ray image to accurately delineate regions of interest, facilitating diagnostic interpretation and treatment planning.

The ultimate goal of clustering in chest X-ray image segmentation is to assist radiologists and clinicians in efficiently analyzing and interpreting medical images for accurate diagnosis and treatment. By automating the segmentation process, clustering algorithms help reduce the time and effort required for manual interpretation while ensuring consistency and reproducibility in the segmentation results. Additionally, clustering-based segmentation techniques enable quantitative analysis of chest X-ray images, providing valuable insights into disease progression, treatment efficacy, and patient outcomes.

1.2 Hybrid Clustering

Step-1: Read the input pixels data and store them into memory.

In the first step of a hybrid clustering approach, the input pixels data are read and stored into memory. This process involves retrieving the pixel values from the source, which could be an image file, a database, or any other data repository containing the pixel information. The pixel data typically include attributes such as color values (e.g., RGB or grayscale intensity), spatial coordinates, or other relevant features depending on the specific application. These pixel values are then loaded into memory, usually in the form of arrays or matrices, to facilitate subsequent processing. the algorithm begins by reading the input image data and storing it into the computer's memory. This process involves loading the image pixel by pixel, where each pixel typically contains information about its color or intensity.

Step-2: Automated No of Clusters Selection

In the second step of hybrid clustering, the algorithm focuses on automatically determining the optimal number of clusters to be created based on the characteristics of the input image data. This is a crucial step as it ensures the segmentation process is adaptive and tailored to the specific complexities and variations present in human images. Various techniques can be employed to automatically select the number of clusters, such as statistical methods, density-based approaches, or heuristics based on image properties like texture, color distribution, or edge detection.

Step-3: Cluster Analysis with cluster-to-cluster similarity measurement

In the third step of hybrid clustering, the algorithm performs cluster analysis on the pixel data to identify distinct groups or clusters that represent different parts of the image. This involves applying clustering techniques such as k-means, hierarchical clustering, or density-based clustering to partition the pixels into cohesive groups based on their similarities in color, texture, or other features. Additionally, the algorithm evaluates the similarity between clusters to understand how different regions or individuals in the image relate to each other spatially and visually.

During this step, the algorithm also examines cluster-to-cluster similarity to identify commonalities or overlaps between different clusters.

Step-4: Internal Cluster Values Analysis With pixel to pixel difference estimation

In the fourth step of hybrid clustering, the algorithm focuses on analyzing the internal values of each cluster and assessing whether there are significant differences between pixel values within clusters. By examining the internal characteristics of clusters, such as the distribution of pixel intensities or color values, the algorithm gains insights into the homogeneity or coherence of each cluster. This analysis helps ensure that each cluster represents a distinct and coherent region or individual within the image, enhancing the accuracy and reliability of the segmentation results.

Step-5: Resultant Two Clusters Generation

In the fifth step of hybrid clustering, the algorithm finalizes the clustering process by reducing the number of clusters to a predefined quantity, such as two clusters for binary segmentation representing foreground and background. This reduction is often achieved through cluster elimination or merging similar clusters. The goal is to simplify the segmentation while preserving the essential features and details of the image. By maintaining a smaller number of clusters, the segmentation result becomes more interpretable and easier to analyze.

During this step, the algorithm may also perform cluster-to-cluster eliminations, where redundant or overlapping clusters are identified and merged to improve segmentation accuracy.

Step-6: Maximum pixel values Based regions finalization

In the sixth step of hybrid clustering, the algorithm focuses on maintaining maximum pixel values for color difference. This involves adjusting the cluster centroids or boundaries to ensure that the color differences between clusters are maximized, thereby enhancing the visual distinction between different segments of the image. The hybrid clustering algorithm iteratively refines the segmentation process by iteratively considering the maximum pixel values within each cluster to delineate regions.

Step-7: Generate output text file

In the seventh step of hybrid clustering, the algorithm generates an output text file containing the segmented regions or individuals. This text file typically includes information about the location, size, and characteristics of each segment, allowing for easy access and interpretation of the segmentation results. By storing the segmentation output in a text format, the algorithm enables further analysis or processing of the segmented image data using various software tools or programming languages.

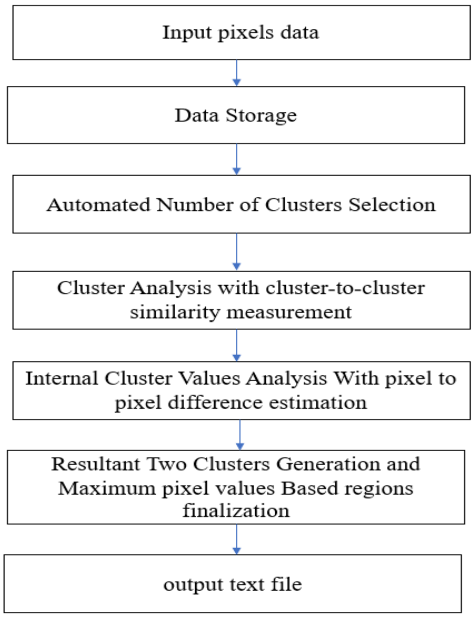

Fig 1: Flow chart of Hybrid clustering process

Image to Text and Text to Image Conversion Using MATLAB

In MATLAB, performing image-to-text and text-to-image conversions involves utilizing various functionalities available in the Image Processing Toolbox, Signal Processing Toolbox, and other relevant toolboxes. For image-to-text conversion, one common approach is using Optical Character Recognition (OCR) techniques to extract text from images. MATLAB offers the ocr function, enabling users to perform OCR on images and extract textual information. This function allows for customization through parameters such as language, character set, and text layout, ensuring accurate extraction of text from images.

For text-to-image conversion in MATLAB, various techniques can be employed depending on the desired output. Users can create graphical representations of text data by generating images with text annotations, visualizing textual data using plots or graphs, or generating images based on textual descriptions. MATLAB's image processing capabilities allow for the creation and manipulation of images, including functions for displaying images (imshow), saving images to files (imwrite), and drawing shapes, text, and annotations on images. These functionalities enable users to generate visual representations of textual data efficiently, facilitating communication and visualization of information in different formats.

2 PROPOSED METHOD

VLSI Implementation of chest x-Ray image segmentation using hybrid clustering

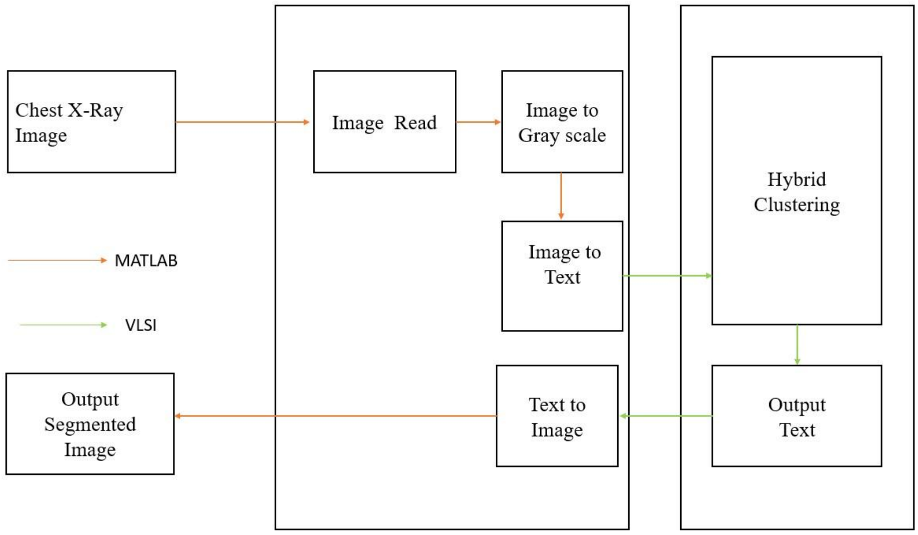

Fig 2: Block Diagram of Proposed System

The block diagram illustrates a process starting with the input of a chest X-ray image, followed by its reading into MATLAB for further analysis. Once the image is imported, MATLAB performs preprocessing tasks to enhance its quality and reduce noise. Subsequently, the preprocessed image undergoes conversion into text format within MATLAB. This step involves extracting relevant features or characteristics from the image and representing them as text data, potentially aiding in further computational analysis or integration with other systems.

The text data obtained from the previous step is then input into a hybrid clustering algorithm implemented in VLSI. Hybrid clustering combines multiple clustering techniques to achieve more accurate and efficient segmentation. Once clustering is performed, the resulting segmented text data is output from the VLSI system. Following this, MATLAB takes over again by converting the segmented text data back into an image format, reconstructing the segmented regions based on the clustering results. Finally, the output of this process is the segmented chest X-ray image, where different anatomical structures or abnormalities are delineated, potentially aiding medical professionals in diagnosis and treatment planning.

3 RESULTS

Figure 3 shows the existing Results for Sample Image-1. Here, we can observe the difference between the Original Image and existing k-means Chest x-ray image for the Sample Image-1.

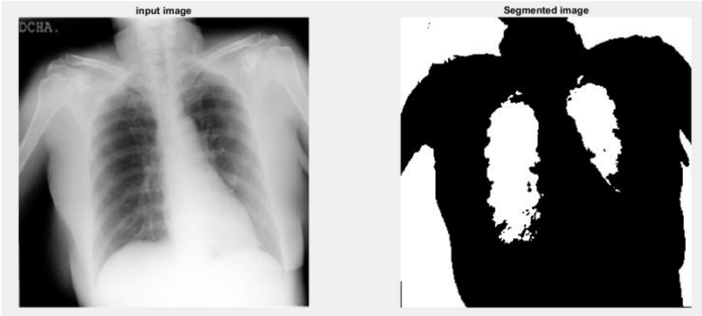

Fig 3: Existing results for sample image-1

Figure 4 shows the existing Results for Sample Image-2. Here, we can observe the difference between the Original Image and existing k-means Chest x-ray image for the Sample Image-2.

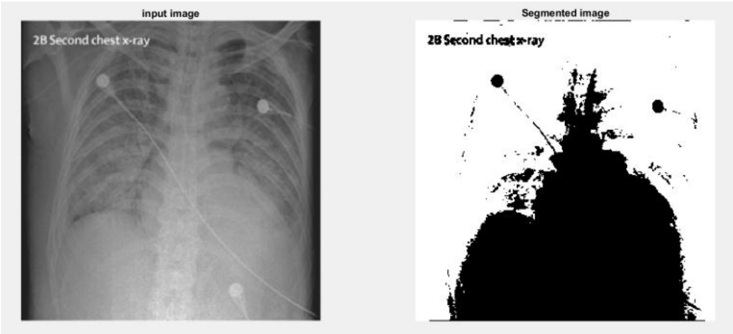

Fig 4: Existing results for sample image-2

Figure 5 shows the existing Results for Sample Image-3. Here, we can observe the difference between the Original Image and existing k-means Chest x-ray image for the Sample Image-3.

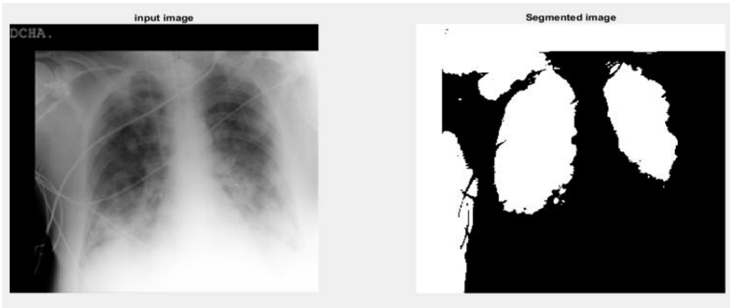

Fig 5: Existing results for sample image-3

Table 7.1 shows the existing Results. Here, we calculated the Accuracy, Sensitivity, F-measure, Precision, MCC, Dice, Jaccard, Specificity values for Sample Image-1, Sample Image-2, Sample Image-3. And finally estimated the Average Values.

Table 1: Existing Results for Sample image-1, Sample image-2, Sample image-3

Parameter	Image-1	Image-2	Image-3	Average
Accuracy	65.9288	81.3772	64.176	70.494
Sensitivity	10.1212	76.38	47.7671	44.7561
F-measure	15.2004	83.4751	53.7376	50.8043
Precision	30.513	92.0234	61.4138	61.3167
MCC	0.24863	63.9945	25.7778	30.0069
Dice	15.2004	83.4751	53.7376	50.8043
Jaccard	8.2254	71.6371	36.7405	38.8676
Specificity	90.0413	89.3874	76.8391	85.4226

Proposed Result

Figure 6 shows the Proposed Results for Sample Image-1. Here, we can observe the difference between the Original Image and Proposed Chest x-ray Segmented image for the Sample Image-1

Fig 6: Proposed results for sample image-1

Figure 7 shows the Proposed Results for Sample Image-2. Here, we can observe the difference between the Original Image and Proposed Chest x-ray Segmented image for the Sample Image-2.

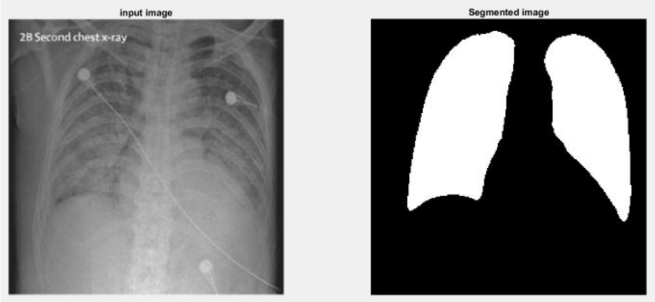

Fig. 7 Proposed results for sample image-2

Figure 8 shows the Proposed Results for Sample Image-3. Here, we can observe the difference between the Original Image and Proposed Chest x-ray Segmented image for the Sample Image-3

Fig 8: Proposed results for sample image-3

Table 2 shows the proposed Results. Here, we calculated the Accuracy, Sensitivity, F-measure, Precision, MCC, Dice, Jaccard, Specificity values for Sample Image-1, Sample Image-2, Sample Image-3. And finally estimated the Average Values.

Table 2: Proposed Results for Sample image-1, Sample image-2, Sample image-3

Parameter	Image-1	Image-2	Image-3	Average
Accuracy	99.9939	99.9985	99.9954	99.9959
Sensitivity	100	100	99.9895	99.9965
F-measure	99.9868	99.9974	99.9921	99.9921
Precision	99.9735	99.9948	99.9948	99.9877
MCC	99.9828	99.9963	99.9889	99.9893

Dice	99.9868	99.9974	99.9921	99.9921
Jaccard	99.9735	99.9948	99.9843	99.9842
Specificity	99.9921	99.9978	99.9978	99.9959

4 VLSI RESULTS

4.1 Simulation Output

Figure 9 shows the proposed simulation result. Here, the input parameters denoted as input_file1[31:0], input_file2[31:0] represents various characteristics used in the simulation process. The Ultimate output labeled as output_ file [31:0], signifies the results of the Chest x-ray segmented image algorithm. This output provides a binary representation, showcasing the effectiveness of the simulation in extracting relevant visual information for VLSI applications.

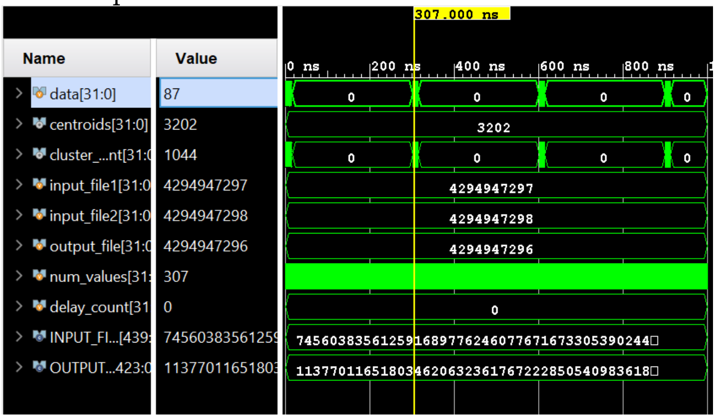

Fig 9: Proposed Simulation Output

Area Output

Table 3 shows the proposed area measurements. Here 29 number of LUT's are used out of available 32600, which consumes 0.09% of utilization, 94 number of IO's are used out of available 150, which consumes 62.67% of utilization.

Table 3: Area Output

Resource	Utilization	Available	Utilization...
LUT	29	32600	0.09
IO	94	150	62.67

Power Output

Figure 10 shows the proposed Power measurements. Here total Dynamic power Utilization is 21.216w and it includes signal power utilization is 1.178w, Logic power utilization is 0.109w and IO power utilization is 19.929w and also Total static power Utilization is 0.485w.

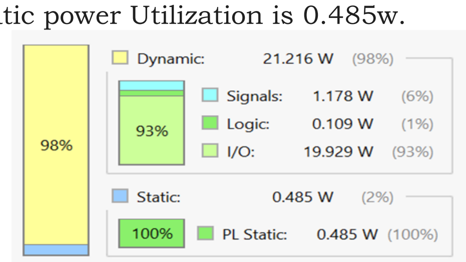

Fig 10: Power Output

5 CONCLUSION

The VLSI implementation of chest X-ray image segmentation using hybrid clustering represents a significant advancement in medical imaging technology, poised to revolutionize diagnostic processes in healthcare. By combining the power of VLSI chips with innovative hybrid clustering techniques, this approach offers a promising solution for automatically segmenting chest X-ray images into meaningful regions for medical analysis. The integration of hybrid clustering algorithms, such as k-means, hierarchical clustering, and density-based clustering, allows for more accurate and robust segmentation, catering to the complex and variable characteristics of chest X-ray images. This groundbreaking implementation harnesses the parallel processing capabilities of VLSI chips to efficiently perform the computationally intensive tasks involved in image segmentation. By distributing the workload across multiple processing units on the VLSI chip, the segmentation process can be accelerated, enabling real-time or near-real-time analysis of chest X-ray images. This not only enhances the efficiency of medical diagnosis but also facilitates timely interventions and treatments for patients, potentially leading to improved patient outcomes and healthcare delivery.

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