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Innovative Multimodal Approaches in Image-Based Analysis of Adipose Tissue Cells

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ABSTRACT

Adipose tissue analysis using traditional techniques, such as optical microscopy, faces limitations in narrow field of view, low resolution, and manual analysis prone to operator bias. These challenges become more relevant in research related to obesity and metabolic disorders, where the accuracy of white adipose tissue (WAT) quantification is critical. The research contributions are to develop a multimodal imaging approach integrating MRI, CT, and optical microscopy for more comprehensive white adipose tissue analysis and apply automated algorithms to improve the efficiency and accuracy of adipose tissue segmentation and quantification. This approach utilizes the advantages of each modality: MRI for soft tissue analysis, CT for three-dimensional detail, and optical microscopy for cellular-level resolution. An automated system was designed to process images, detect cells, calculate cell dimensions, and analyze the total area of adipose tissue in sample images. The results showed a maximum cell diameter of 10,466.64 µm, a minimum diameter of 0.40 µm, and an average diameter of 2,398.31 µm with 0% mean square error (MSE), reflecting high precision in measurement. Comparative analysis revealed that this method is significantly more accurate than traditional techniques. Graphical representation validates the reliability of this approach for detecting intricate details of cellular structures. This multimodal approach offers innovative solutions to the challenges of adipose tissue analysis, providing reliable diagnostic tools for the management of obesity and metabolic disorders. Integration of these imaging modalities can improve informed clinical decisions, potentially resulting in better patient outcomes and accelerating metabolic research.

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1. INTRODUCTION

Adipose tissue is a specialized connective tissue that plays an important role in energy storage and regulation of the body's metabolism. Its two main types, namely white adipose tissue (WAT) and brown adipose tissue (BAT), have different functions and distribution [1]. WAT plays a major role in storing energy in the form of fat and is the most dominant type of adipose tissue, especially in obese individuals [2]. Its presence has significant relevance in the study of metabolic disorders, as it contributes to an increased risk of diseases such as diabetes, hypertension, and cardiovascular disease [3]. In contrast, BAT is responsible for thermogenesis, converting energy into heat, but its distribution is more limited in the adult human body [4]. In the context of obesity, WAT is a major focus due to the accumulation of visceral fat that is closely associated with an increased risk of metabolic disorders and other health problems [5]. Quantification of adipose cells, especially WAT, has an important role in various clinical applications, such as measuring visceral fat in obese

patients or evaluating the effectiveness of treatments for metabolic disorders such as diabetes [6]. Accurate quantification enables early identification and more effective management of metabolic disorders. However, frequently used traditional methods, such as optical microscopy-based histological analysis, have various limitations Techniques.

Advances in modern imaging techniques have offered alternatives to overcome the limitations of traditional methods. Magnetic resonance imaging (MRI) and computed tomography (CT) are two techniques that are frequently used. MRI excels in visualizing fat distribution in soft tissues, while CT provides a three-dimensional view of tissue structure [7], [8]. While both techniques offer richer data compared to optical microscopy, they have their drawbacks. MRI has insufficient resolution for cellular-level analysis, while CT provides radiation exposure which is a concern in clinical applications [9]. On the other hand, optical microscopy is still relevant for detailed cellular-level analysis, but there have rarely been attempts to integrate these various imaging modalities to provide a more holistic view of adipose tissue.

Previous research has shown that machine learning and deep learning-based approaches have successfully improved accuracy in adipose tissue segmentation and analysis. These algorithms enable automation of processes that previously required manual analysis [10], [11]. However, most studies still rely on a single modality, resulting in insufficiently comprehensive information [12]. There are still gaps in the literature regarding the integration of various imaging modalities, especially in process standardization, resolution compatibility, and development of fully automated tools [13].

This study makes a significant contribution to addressing these challenges. First, this study developed a multimodal imaging approach that integrates MRI, CT and optical microscopy to provide a more thorough and comprehensive view of adipose tissue structure. This integration is designed to overcome the limitations of each single modality, such as low resolution in MRI and radiation exposure in CT. Secondly, this study introduces an automated system for segmentation and quantification of white adipose tissue. This system not only improves efficiency but also provides higher accuracy compared to traditional methods. Thus, this study provides an innovative solution for adipose tissue analysis, which has great potential in improving the diagnosis and clinical management of metabolic disorders such as obesity and diabetes.

2. METHODS

This methodology section compares traditional single-modal imaging techniques and innovative multimodal approaches to analyze adipose tissue cells. Traditional methods, such as optical microscopy, have limitations in analyzing adipose tissue in depth as they can only provide limited information about cellular structure and composition (Fig. 1). In addition, these methods often rely on manual processing of images, which increases the potential for human error and reduces accuracy. In contrast, multimodal approaches integrate multiple imaging modalities, such as MRI, CT, and microscopy, to obtain a more comprehensive and detailed picture of adipose tissue [14], [15], [16], [17].

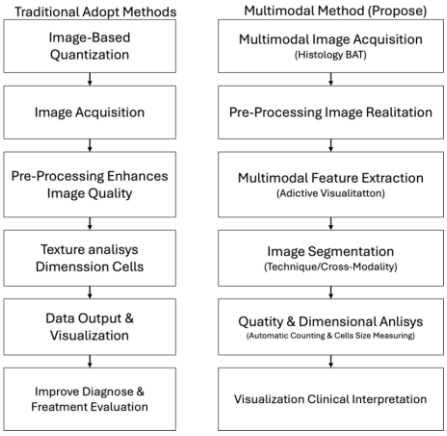

Fig. 1. Traditional Methods and Multimodal (Propose)

This multimodal approach utilizes the complementary strengths of each modality to capture structural and compositional information of the tissue at various scales of resolution. For example, MRI provides information on fat distribution and tissue composition, CT provides high-resolution images of the internal structure of the tissue, while microscopy enables detailed cellular analysis. The use of advanced image registration techniques, both rigid and non-rigid registration, enables alignment of images from different modalities, overcoming orientation and scale differences that exist between images [17], [18], [19].

With a multimodal approach, the main steps in applying multimodal image analysis methods for detecting adipose tissue cells will be outlined [20], [21]. This approach combines several imaging techniques to improve cell segmentation and quantification accuracy [16], [22], [23]. The algorithm outlined above is the core step in our multimodal approach to analyzing adipose tissue cells [24]. preprocessing takes place by flowcart in Fig. 2.

Pseudocode-*Algorithm for Multimodal Approach*

```
BEGIN
    // Step 1: Data Acquisition
    Load multimodal images (MRI, CT, Microscopy)
    // Step 2: Preprocessing
    FOR each image DO
        Denoise and enhance contrast
        Align images from different modalities
    END FOR
    // Step 3: Segmentation
    FOR each image DO
        Apply segmentation to detect adipose cells
    END FOR
    // Step 4: Cell Quantization
    FOR each segmented cell DO
        Calculate cell area from pixel count
    END FOR
    // Step 5: Texture Analysis
    Compute GLCM to extract texture features (contrast, homogeneity)
    // Step 6: Display Results
    Show original image, segmented cells, cell sizes, and texture metrics
END
```

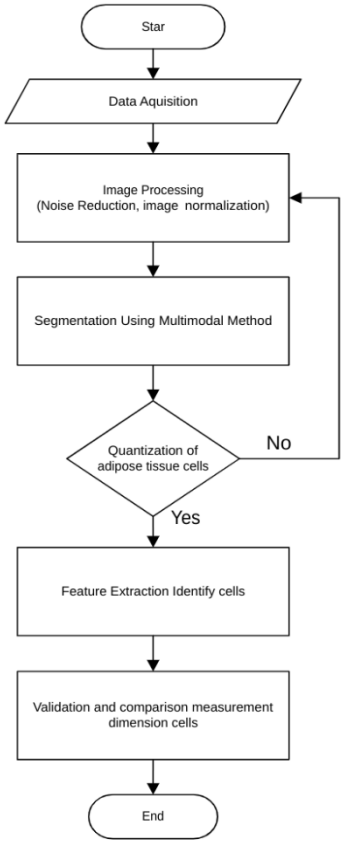

Fig. 2. Flowchart of Adipose Tissue Cells Image

The transformation from traditional methods to multimodal approaches for image-based adipose tissue cell quantitation begins with data acquisition. Conventional methods typically rely on a single imaging modality, such as optical microscopy, whereas multimodal approaches integrate multiple techniques, such as MRI, CT, and microscopy, to provide more comprehensive data.

2.1. Segmentation Process

In a multimodal approach, automated segmentation is applied to detect adipose cells with higher accuracy compared to manual or semi-automated methods. Segmentation is performed using threshold-based algorithms or more advanced techniques such as active contouring or deep learning to ensure accurate isolation of adipose cells [9], [25], [26]. This automated segmentation also reduces the potential for human error and increases efficiency in analysis. Each segmented cell is then analyzed to measure its size, shape, and distribution.

$$DC = \frac{2 \cdot |A \cap B|}{|A| + |B|} \tag{1}$$

The Dice coefficient (DC), as formulated in (1), is a standard metric for evaluating segmentation accuracy. Where A is ground truth segmentation (manual), B is an algorithmic automatic segmentation, $|A \cap B|$ represents the same number of pixels between A and B, and $|A|$ and $|B|$ represents the number of pixels in A and B, respectively.

Preprocessing steps, including image alignment and contrast enhancement, are critical to integrating data from multiple sources. After segmentation, advanced techniques are applied to measure cell dimensions and extract texture features, providing deeper insight into tissue characteristics [14], [27], [28], [29], [30]. The flowchart in Fig. 3 visually illustrates the critical processes involved in this multimodal analysis.

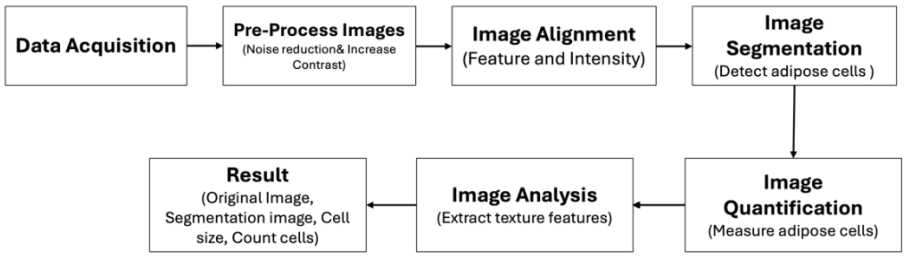

Fig. 3. Blok Diagram preprocessing

The segmentation process in a multimodal approach also benefits from automation, resulting in more accurate and faster isolation of adipose cells compared to manual or semi-automatic methods [3]. This enables quantifying adipose characteristics such as cell size, shape, and distribution across multiple imaging modalities with greater accuracy [31]. This integrated system provides more detailed insights into adipose tissue. It improves the ability to differentiate between tissue types, offering more significant potential for clinical applications, especially in diagnosing metabolic conditions such as obesity and diabetes [19], [24], [32]. By utilizing multimodal methods, this novel approach improves diagnostic accuracy. It supports more personalized treatment strategies using formula segmentation, a critical step in image-based adipose tissue quantitation [33].

2.2. Cell Quantification and Texture

After segmentation, the next step is cell quantization, which involves calculating the area or volume of each adipose cell in the image [34]. The formula for calculating the area of adipose cells in a 2D image is as follows:

$$A_{cell} = \sum_{i=1}^{N} \frac{P_i}{R} \tag{2}$$

Measuring fat cell size involves calculating the area or volume of each cell in the image [17], [35]. For a 2D image, the formula for cell area is stated in (1). Where A_{cell} is the area of one adipose cell, P_i is the number of pixels contained in the segmented cell region, and R is the image resolution (pixels per mm² or pixels per unit area). Furthermore, texture analysis is performed using a gray-level co-occurrence matrix (GLCM), which is used to extract texture features such as contrast, homogeneity, and roughness of the tissue [29], [33]. GLCM provides important information regarding the microstructure of adipose tissue, which helps distinguish different types of tissue based on their texture patterns.

$$C(i,j) = \sum_{(x,y)\in S} \delta(I(x,y) = i, I(x+\Delta x, y+\Delta y) = j) \quad (3)$$

Gray-Level Co-Occurrence MatriX -GLCM is often used for texture analysis in medical imaging to distinguish different types of tissues based on structural patterns, stated in (3). Where $C(i,j)$ is the GLCM at intensity levels i and j, S represents the spatial relationships between pixels, $I(x,y)$ is the pixel intensity at position (x,y), Δx and Δy are specified the offset used to calculate spatial relationships. Δ is the Kronecker delta function, returning 1 if the condition is true and 0 otherwise.

The evaluation metric used to assess the accuracy of segmentation is the Dice coefficient (DC), expressed in (1). The Dice coefficient provides a measure of similarity between automated segmentation and ground truth (manual) segmentation, which allows an objective assessment of segmentation accuracy [1].

To measure the error in cell quantization, the ***mean statistical error (MA*E)** is used, which is defined in (4):

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(x_i - y_i)^2 \quad (4)$$

Mean statistical error (MAE), in (4), is the mean error of statistical data. *Where* x_i is observed cell count, y_i is ground truth cell count, and ***n*** *is total of images.* While multimodal approaches provide many advantages in terms of segmentation and quantization accuracy, there are challenges that need to be overcome . For example, resolution differences between imaging modalities or artifacts that appear during the image registration process can affect the quality of the results [19], [31], [36]. Therefore, additional steps such as cross-validation and refinement of image fusion techniques are required to ensure optimal results [37], [38], [39].

This approach has significant clinical implications, especially in diagnosing and planning treatments for metabolic disorders such as obesity and diabetes [2], [40], [41], [42]. Improved accuracy in adipose cell segmentation and quantitation can aid in more precise assessment of body fat distribution, which is crucial in developing more targeted and personalized treatment strategies [43], [44], [45]. With this multimodal approach, diagnostic accuracy can be improved, providing deeper insights into the structure of adipose cells and other body tissues, which in turn can support better clinical decision-making [46], [47], [48], [49], [50], [51].

3. RESULTS AND DISCUSSION

This chapter presents the results and analysis obtained from applying the multimodal method in adipose tissue analysis. The process begins with the pre-processing stages shown in Fig. 4 and Fig. 5. The original adipose tissue images are processed using an image segmentation technique for edge detection, which aims to separate the adipocytes from the background more clearly. This segmentation allows for more accurate cell detection as well as measurement of cell dimensions, such as their diameter or area, for further analysis. The method utilizes noise reduction, contrast enhancement and morphological operation techniques to ensure optimal data quality before segmentation.

The developed user interface (UI) facilitates analysis by presenting the original image and segmentation results side-by-side. In addition, the UI enables visualization of the calculated adipocyte dimensions, such as total cell count and size distribution, in graphical form. This function not only speeds up the analysis process but also supports efficient diagnosis of adipose tissue. The intuitive interface design ensures smooth interaction for users, enabling faster decision-making in a clinical environment. Image processing user interface in application shown in Fig. 6.

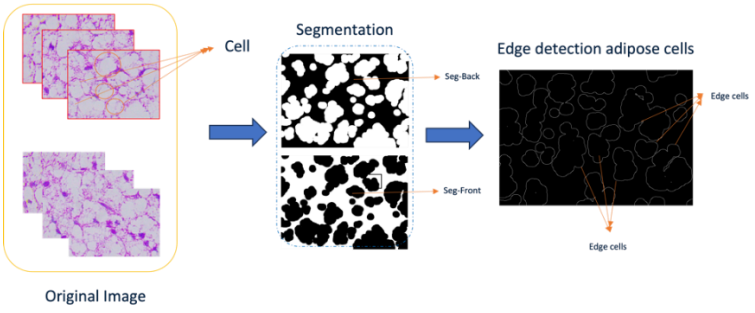

Fig. 4. Processing edge detection adipose cells

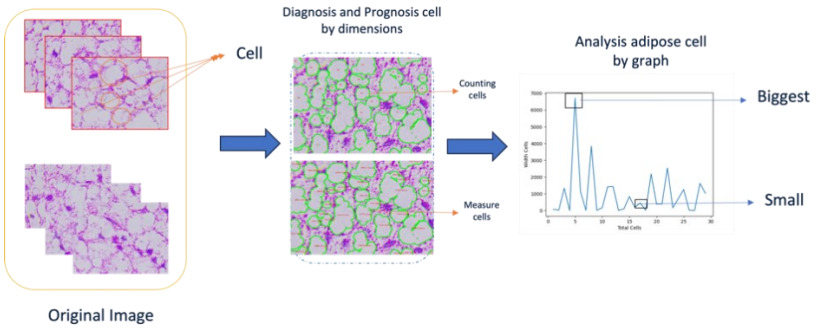

Fig. 5. Measures adipose cells dimensions

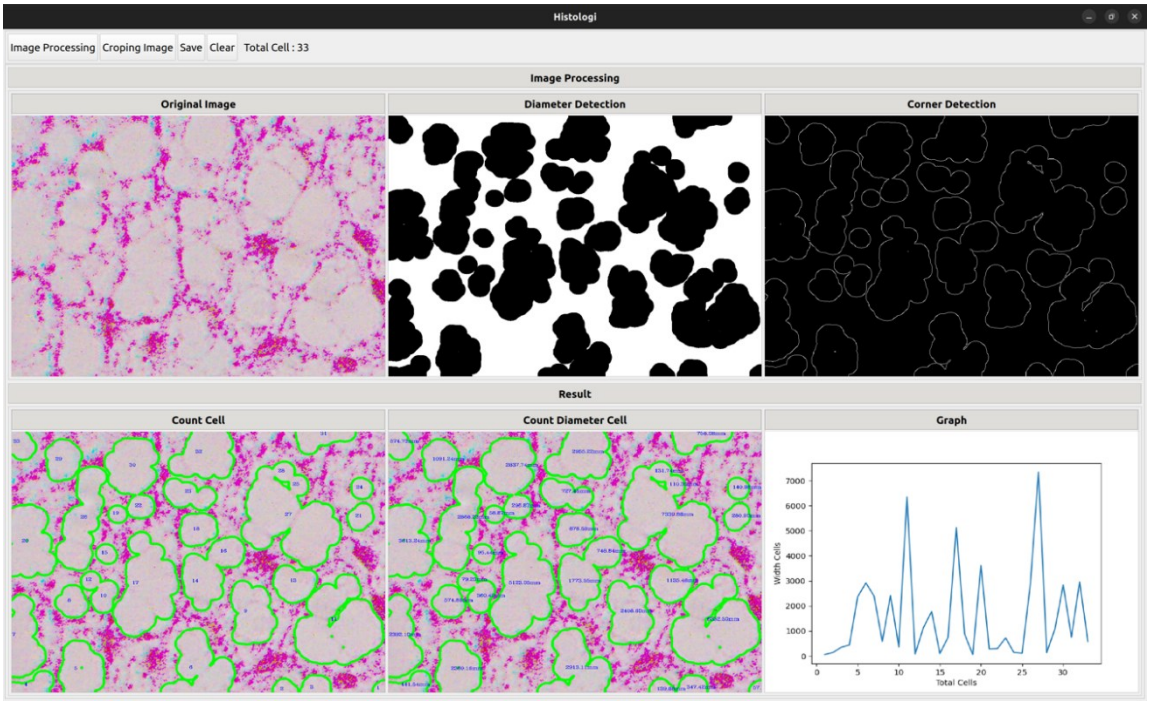

Fig. 6. Image Processing User Interface in Application

The application of the multimodal approach provided a significant improvement in the accuracy of the results, as reflected in the dimensional analysis of the adipocytes. The graph in Fig. 7 shows the size distribution of adipose cells, where the average size is measured in μm. These results show significant variation in adipocyte size among the tissue samples analyzed. These data are clinically relevant, as larger adipocyte size is often associated with metabolic disorders such as obesity or insulin resistance.

The adipocyte dimensions obtained from this system were visualized in graphs depicting the size and distribution of adipocytes in various tissue samples. This graphical representation helps identify cell size distribution patterns and inter-sample variations. For example, Fig. 7 shows that the adipocyte size distribution tends to be larger in samples with certain metabolic conditions, emphasizing its correlation with insulin resistance.

Table 1 further highlights the accuracy of the system in calculating the total number of adipose cells, with a Mean Squared Error (MSE) value of 0% compared to the ground truth calculation by medical experts. The multimodal approach showed improved accuracy and reliability compared to conventional methods. With this system, adipocyte dimension measurements became more precise, with an average measurement difference of ±0.02 mm compared to manual results *by an experience author*. In addition, automatic detection enables analysis in less time, reducing manual workload by 50%. The system also enhances diagnostic capabilities by providing more comprehensive insights into adipose tissue characteristics, supporting early assessment of metabolic conditions.

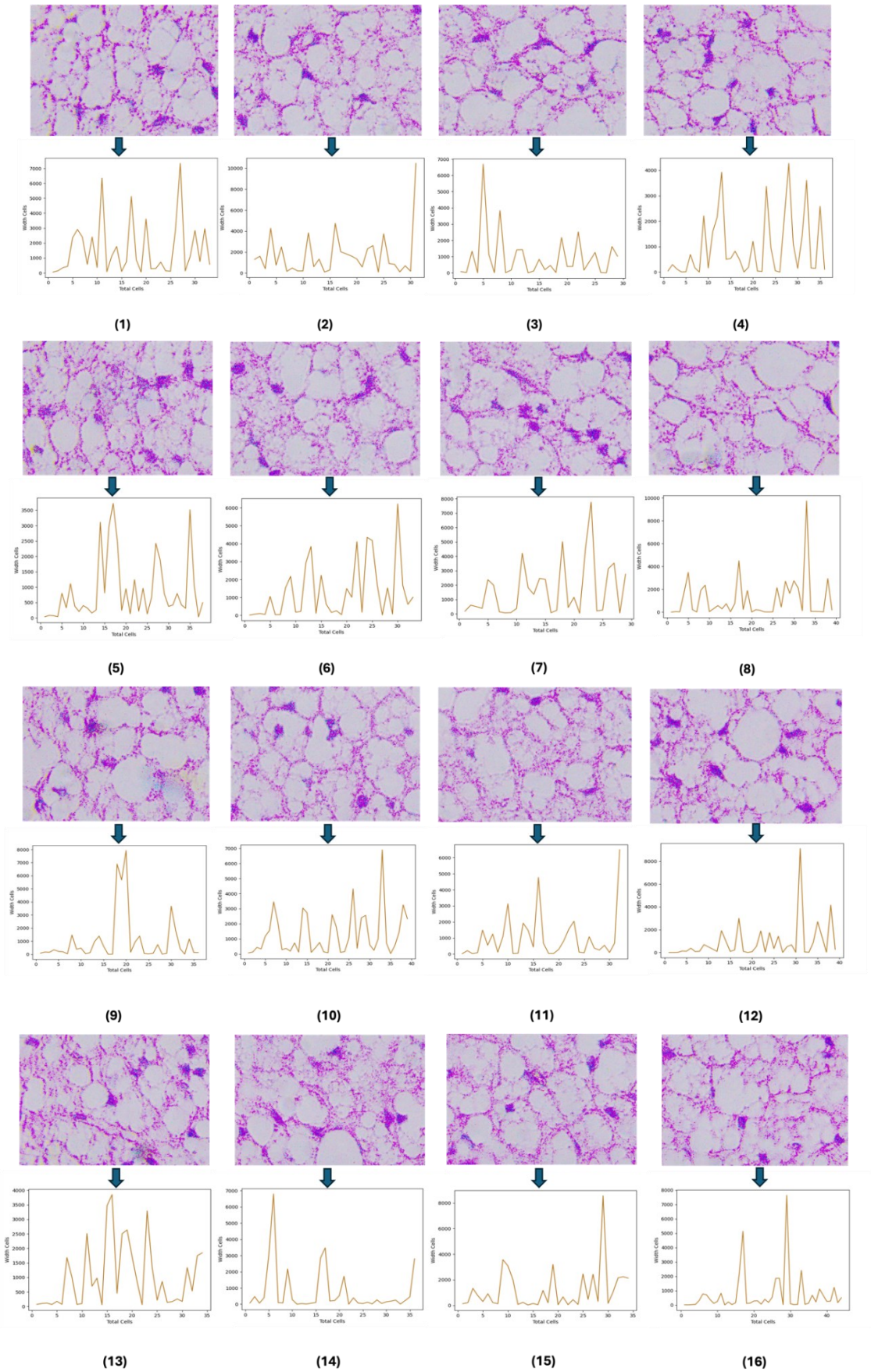

Fig. 7. Result of analysis of adipose cell dimension size.

Table 1. Analysis of Total Cell Count and Dimensional Cell in Adipose Tissue

Images	Ground Truth Cell Count	Total Cell Count (Observed)	Average Cell Diameter (µm)	Max Cell Diameter (µm)	Min Cell Diameter (µm)	Mean Square Error (MSE) (%)
Image1	32	32	2398.31	4774.84	21.78	0
Image2	31	31	5279.85	10466.64	93.06	0
Image3	29	29	3435.34	6695.67	172.0	0
Image4	36	36	1965.615	3924.23	7.00	0
Image5	38	38	1776.59	3515.82	37.36	0
Image6	33	33	3119.03	6217.60	20.46	0
Image7	28	28	3906.345	7772.69	40.00	0
Image8	39	39	4867.50	9734.60	0.40	0
Image9	36	36	3461.835	6888.29	35.38	0
Image10	39	39	3484.93	6898.45	71.41	0
Image11	32	32	3261.72	6501.66	21.78	0
Image12	39	39	4559.81	9118.43	1.19	0
Image13	34	34	1958.35	3852.68	64.02	0
Image14	36	36	3418.205	6794.30	42.11	0
Image15	34	34	4300.695	8567.33	34.06	0
Image16	44	44	3846.215	7648.61	43.82	0

4. CONCLUSION

This study demonstrates the effectiveness of a multimodal approach in analyzing adipose tissue cells with higher accuracy than conventional methods. By utilizing advanced imaging techniques, we were able to perform more precise cell segmentation and quantitation, as well as in-depth tissue texture analysis, significantly improving prediction reliability. While the results obtained are promising, challenges related to image alignment and artifacts between modalities need to be addressed in future research. Our theoretical contributions pave the way for further research in the field of metabolic health diagnostics, particularly in metabolic disorders such as obesity and diabetes. Overall, this study confirms the great potential of multimodal imaging in adipose tissue analysis and provides a basis for the development of more precise diagnostic and therapeutic strategies in the future.

Future Work

While the results of this study are promising, there are some limitations, including the sensitivity of the system to the quality of the initial image. Images with high noise or poor lighting can affect segmentation accuracy and dimension calculation. Future research could focus on improving the segmentation algorithm to handle low-quality images as well as integrating machine learning models for automatic classification of adipose conditions. In addition, applying this approach to longitudinal data may provide deeper insights into the dynamics of adipose tissue changes over time.

This approach makes a significant contribution to the analysis of adipose tissue in metabolic health, strengthening its clinical relevance and opening up opportunities for the development of more advanced diagnostic methods..

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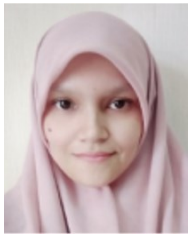

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