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Abstract

Intramuscular fat (IMF) is a principal determinant of pork loin quality and a critical factor in meat grading and consumer preference. This study proposes a Transformer-based deep learning framework for noninvasive quantitative estimation of porcine IMF from B-mode ultrasonographic images. A total of 9,409 single-channel ultrasound frames were acquired using a 3.5-MHz system targeting the *longissimus thoracis et lumborum* and subcostal regions. The dataset comprised 3,949 pigs, including 47 animals with directly measured IMF values and 3,902 animals with IMF estimates generated by the Biosoft ultrasound analysis program. To address the limited availability of measured ground-truth data, we adopted a Vision Transformer–Huge (ViT-H) regression model and incorporated a teacher–student knowledge distillation strategy. The teacher model was trained using large-scale Biosoft-derived IMF estimates, and the student model was trained using measured IMF values while simultaneously learning from the teacher's soft predictions. An uncertainty-aware distillation loss was introduced to adaptively weight the distillation signal based on the teacher model's predictive variance, thereby mitigating the transfer of unreliable knowledge. In addition, RandAugment was applied during training to enhance generalization under limited data conditions. Model performance was evaluated using mean absolute percentage error (MAPE) with five-fold cross-validation. Compared with the conventional Biosoft-based regression baseline (MAPE: 43.61%), the ViT-H regression model substantially reduced prediction error (34.78%). Incorporating knowledge distillation further improved performance (34.361%), and uncertainty-aware distillation yielded additional gains (33.859%). The best performance was achieved by combining uncertainty-aware distillation with RandAugment, yielding a MAPE of 31.313%. These findings demonstrate that Transformer-based regression combined with uncertainty-aware knowledge distillation provides a robust and scalable solution for IMF estimation from ultrasound images and may help distinguish IMF differences relevant to commercial pork quality grading, although further validation is required. The proposed framework effectively leverages both limited measured data and large-scale predicted data, enabling accurate, practical, and noninvasive IMF assessment suitable for on-farm and near-real-time applications in precision livestock production.

Keywords: Deep learning; meat quality; noninvasive estimation; porcine intramuscular fat; ultrasonography

Introduction

Pork is the most widely consumed meat in South Korea [1], and meat quality is a primary determinant of consumer purchasing decisions [2]. Within the Korean livestock product grading system, intramuscular fat (IMF) content is one of several factors considered in determining pork quality grade [3]. It is considered alongside other critical attributes, such as fat thickness, meat color, and texture, because it is closely linked to palatability. In particular, higher IMF levels are associated with improved tenderness, juiciness, and flavor, which in turn shape consumer satisfaction and their willingness to purchase. Accordingly, a reliable and practical IMF assessment is essential, not only for producers seeking to align products with market expectations but also for sustaining competitiveness throughout the supply chain. These considerations have motivated the development of methods that can accurately and consistently quantify the IMF at low operational cost, thereby supporting quality-focused decision-making from the point of production to retail outlets. In commercial settings, methods that minimize invasiveness, such as noninvasive imaging techniques, and reduce turnaround time are particularly desirable.

Despite their utility in grading and research, the prevailing methods for IMF estimation face practical, methodological, and ethical constraints. Carcass-based chemical analyses provide reference values but are inherently postmortem, preventing assessment during the rearing process and increasing the turnaround time and cost; consequently, such analyses cannot support longitudinal management decisions at the farm level. They also rely on destructive sampling of specific muscles, for example, the *longissimus thoracis et lumborum* and, by definition, yield a single cross-section per carcass, offering no opportunity for repeated measurements in the same animal. The inability to obtain IMF estimates during the rearing process remains a major operational barrier for producers seeking to stratify animals before shipment, adjust feeding regimes, or evaluate genetic lines *in vivo*.

To enable live animal assessment of IMF, three main approaches have been investigated: biopsy-based sampling [4], CT imaging [6], and ultrasonography (US) [7].

In a large-scale study of 216 pigs (732 samples), Bosch et al. [4] showed that the sampling strategy significantly affected IMF and fatty acid (FA) estimates. Biopsies from live animals tended to overestimate IMF and polyunsaturated FA, while smaller samples underestimated monounsaturated FA, indicating systematic sampling bias. Although analytically reliable, biopsy methods are invasive and raise welfare and productivity concerns [5], limiting their suitability for repeated or large-scale on-farm use.

CT imaging has been evaluated as a noninvasive alternative in 104 pigs [6], where IMF was predicted from filtered CT images using partial least squares regression. Despite its technical feasibility, CT requires ionizing radiation, expensive, immobile equipment, and specialized facilities, limiting its scalability in commercial settings.

Ultrasound provides a portable and radiation-free option. In a study of 574 pigs [7], IMF was estimated from segmented B-mode images using mean grayscale intensity, achieving RMSE of 0.54% and R^2 of 0.56. However, there was no clear explanation regarding external validation or data splitting, and the model was trained and evaluated on the same dataset. The reference values for backfat and loin depth were not based on actual carcass measurements, but rather on readings from another ultrasound-based semi-automated software called Biosoft. Additionally, the IMF estimation model had a strong breed effect, so a significant portion of the IMF variance may have been explained by breed differences. This suggests that the model may have predicted the average IMF level based on breed information rather than learning subtle tissue signals from ultrasound images.

Collectively, prior work demonstrates that biopsy is accurate but invasive, CT is noninvasive but impractical for routine use, and ultrasound is deployable yet constrained by feature engineering. A remaining gap is the need for a portable, noninvasive framework that leverages learning-based models to capture multiscale image patterns directly from data. The present study addresses this limitation.

US images can be inherently challenging to analyze because of speckle noise, heterogeneous tissue echogenicity, and anatomical variability, underscoring the need for more sophisticated techniques. Consequently, advanced computational methods—most notably deep learning models—have been actively explored to improve the accuracy and reliability of IMF estimation. Accordingly, deep-learning-based computer-aided diagnosis (CADx) for US has gained momentum in diverse clinical applications [8]. By learning task-specific representations directly from data, deep models can automatically extract features relevant to IMF, capture complex spatial patterns, and deliver rapid inference, which is beneficial for large cohorts and near-real-time use. These properties also support scalability and adaptation to industrial settings with a focus on pork quality assessments. A recent study used data from 945 commercial pigs to estimate the IMF [9]. The proposed prediction of intramuscular fat percentage (PIMFP) model converted images to grayscale, selected regions of interest, applied contrast enhancement, and then trained a ResNet-50-based deep neural network to output the IMF. An RMSE of 0.59% was reported, demonstrating the feasibility of deep-learning models for IMF estimation from US. Moreover, the reliance on predefined preprocessing (grayscale conversion, ROI selection, and contrast heuristics)

highlights the opportunity for an end-to-end methodology that jointly learns representations and predictions, potentially improving the model's robustness across operators and acquisition settings.

Prior IMF estimation methods balance accuracy, practicality, and noninvasiveness. Carcass chemistry and biopsies provide reference values but are invasive and unsuitable for longitudinal use, while CT offers improved imaging yet is costly, nonportable, and uses ionizing radiation. Accordingly, recent studies have explored ultrasonography with deep learning, though comprehensive evaluations remain limited. In actual farm environments, precise IMF measurements are limited by cost and procedural constraints, making it difficult to secure sufficiently accurate data. These data shortages have acted as structural limitations to improving the performance of ultrasound-based IMF estimation models. Research that achieves high regression performance using limited measurement data is relatively rare.

In this study, we proposed a method for quantitatively estimating intramuscular fat using B-mode ultrasound data. We developed a knowledge distillation-based model to complement limited measured data by utilizing soft labels generated by Biosoft, a previously developed ultrasound-based intramuscular fat estimation program [10]. We also introduced an uncertainty-aware knowledge distillation loss to reflect prediction uncertainty, thereby improving model performance. To address the issue of insufficient measured data, we further applied RandAugment. The main performance evaluation metric was mean absolute percentage error (MAPE), which is intuitively interpretable in livestock farming settings. We ultimately achieved an MAPE of approximately 31.313%.

Our objective was to identify an accurate, practical, and noninvasive method suitable for on-farm, near-real-time monitoring of IMF during the rearing process. Such capabilities could support quality-focused management and selection, improve process efficiency across the production chain, and enhance consumer satisfaction and market competitiveness.

Materials and Methods

Dataset

The study was approved by the IACUC of the Rural Development Administration, Korea (Approval No. NIAS2020-0478), and the dataset used in this study was provided by the Research Department at the National Institute of Animal Science in Cheonan-si, Chungnam, South Korea. The data used in this study were collected from 3,949 pigs (including Duroc and Woori Heukdon breeds). Among them, 47 pigs were slaughtered to obtain direct measurements of intramuscular fat (IMF). For the remaining 3,902 pigs, IMF values were estimated using

the ultrasound image analysis software, Biosoft [10]. For each pig, one to three ultrasound images were collected. All splits used for five-fold cross-validation were performed at the individual ID level, ensuring that images from the same pig were included in only one fold. Further details are provided in Table 1.

The images were acquired using the Exago US system (IMV Imaging) operating at 3.5 MHz, with a depth of 140 mm and a focal length of 60 mm [11]. The target acquisition sites were the *longissimus thoracis et lumborum* and subcostal region (beneath the last rib), both of which are commonly used to evaluate the IMF. Representative raw frames are shown in Figure 1.

Deep-learning-based regression models for IMF estimation

This study aimed to quantitatively estimate the IMF in B-mode US images using supervised regression. Conventional image classification models assign images to predefined categories, which can be useful for learning generic visual patterns; however, they are suboptimal for predicting continuous targets. Accordingly, we adapted the classification backbones by replacing the final classification head with a single-output regression head to predict the IMF as a continuous value. This modification enabled end-to-end training on pixel-level textures and anatomical cues that correlated with the IMF, yielding precise quantitative estimates under regression loss.

We adopted a Transformer-based architecture for IMF estimation from ultrasound (US) images, specifically utilizing the ViT-H (Vision Transformer Huge) model. To match the model's input requirements, single-channel B-mode US frames were replicated across three channels. The ViT-H model tokenizes an image into fixed-size patches and leverages self-attention mechanisms to capture long-range dependencies across the entire spatial domain [12]. This global attention enables the model to integrate contextual information from distant regions within the image, which is particularly beneficial for understanding distributed texture patterns and morphological variations in US data. Such characteristics are crucial in the context of intramuscular fat estimation, where subtle and spatially distributed visual cues can influence prediction accuracy. By leveraging the Transformer architecture's global receptive field and data-driven inductive bias, the model effectively learns complex visual patterns associated with IMF. Model performance was evaluated using MAPE under standardized experimental conditions.

Knowledge Distillation-Based Teacher-Student Learning

In this study, we applied the teacher-student-based knowledge distillation [13]. Knowledge distillation transfers predictive information from a pretrained teacher model to a student model, encouraging the student to learn representations with improved generalization.

The teacher model was trained using only intramuscular fat data derived from Biosoft values. The teacher model was sufficiently trained using this IMF information, and its weights were fixed during the subsequent student training stage.

The student model was trained using measured data collected in real field conditions as input. During student training, two types of losses were applied simultaneously. First, a supervised loss was computed using the measured values as ground truth. Second, a distillation loss was introduced to minimize the discrepancy between the teacher and student models' predictions for the same input. The distillation loss was calculated as the error between the teacher and student predictions. The final loss was defined as a linear combination of the supervised and distillation losses, with their respective weighting factors. Through this training strategy, the student model was designed to reflect not only the direct supervision from measured data but also the predictive tendencies of the teacher model trained on Biosoft-based IMF information. Consequently, the student model preserves the characteristics of the measured data while indirectly absorbing knowledge transferred from reliable IMF-based information.

Also, because the available training data were limited, K-fold cross-validation was used to enhance the robustness of the student model. In this study, a 5-fold cross-validation strategy was adopted, dividing the dataset into 5 mutually exclusive subsets. For each iteration, four subsets were used for training, and the remaining subset was used for validation. This process was repeated five times so that each subset served as the validation set once.

Uncertainty-Aware Knowledge Distillation

In addition to the standard knowledge distillation framework, we further introduce an uncertainty-aware distillation strategy to improve training stability and predictive accuracy [14]. In conventional knowledge distillation, the distillation loss is applied uniformly to all samples, regardless of the reliability of the teacher's predictions. However, when the teacher model exhibits high uncertainty for certain samples, enforcing strong distillation on those samples may transfer unreliable knowledge to the student model, thereby degrading performance. To address this issue, we estimate the teacher model's predictive uncertainty via dropout during inference. Specifically, eight stochastic forward passes are performed with dropout activated, and the variance of the teacher predictions is computed as a measure of uncertainty.

Samples with higher predictive variance are considered more uncertain. Based on this uncertainty estimate, the distillation loss contribution is adaptively adjusted for each sample. When the teacher's uncertainty is high, the weight assigned to the distillation loss is reduced, thereby weakening the influence of unreliable teacher predictions. Conversely, when the teacher's uncertainty is low, the distillation loss is emphasized to effectively

transfer reliable knowledge. The final training objective is formulated as a weighted combination of the supervised loss and the uncertainty-modulated distillation loss. This uncertainty-aware knowledge distillation strategy allows the student model to selectively learn from confident teacher predictions while relying more on ground truth supervision for ambiguous samples. As a result, compared with fixed weight distillation, the proposed method provides more stable optimization and achieves improved prediction accuracy.

RandAugment Augmentation Method

Finally, we applied RandAugment only during training as a data augmentation strategy [15]. RandAugment is a simplified automatic data augmentation method that randomly selects a fixed number of augmentation operations from a predefined set (e.g., rotation, translation, color adjustment, shear) and applies them with a uniformly controlled magnitude. Unlike earlier policy-search-based approaches such as AutoAugment, RandAugment eliminates the need for computationally expensive searches over augmentation policies by using only two hyperparameters: the number of transformations (N) and the magnitude (M). This design enables efficient and scalable augmentation while maintaining strong performance. In this study, N and M were set to 2 and 9, respectively.

RandAugment provides diverse and effective transformations without requiring an extensive search for optimal augmentation policies, thereby improving generalization performance. It enhances robustness by exposing the model to a wide range of appearance variations. In this study, we applied RandAugment specifically because the amount of measured data were limited. By artificially increasing data diversity through random transformations, we aimed to compensate for the insufficient number of measured samples and to mitigate overfitting caused by the scarcity of training data. The overall research flow chart is shown in Figure 2.

The experiments were executed on an Intel Core i9-10920X CPU running at 3.50 GHz with an NVIDIA GeForce RTX 3090 and 64 GB RAM using Python 3.11.7, PyTorch 2.1.2, and CUDA 12.1. All training ran for 100 epochs with a batch size of eight using the Adam optimizer (learning rate 0.0001). Early stopping was triggered when the validation loss plateaued to mitigate overfitting.

Results and Discussion

Quantitative performance metrics

In this study, the predictive performance of the ultrasonographic IMF regression model was evaluated using the mean absolute percentage error (MAPE). MAPE is defined as the mean of the absolute percentage differences between predicted and reference values and quantifies model error on a relative scale. Unlike scale-dependent

metrics, MAPE expresses deviations as percentages of the true values, enabling direct interpretability and facilitating comparison across experimental conditions. This property is particularly relevant for IMF estimation, where relative prediction error is often more meaningful for production decisions than absolute error magnitude. Moreover, MAPE provides a balanced and robust summary of prediction performance without disproportionately amplifying large deviations, thereby offering a stable estimate of generalization performance in practical settings.

Baseline Model results

As described in the Materials and Methods section, the mean absolute percentage error was calculated for 47 animals for which both the predicted values generated by Biosoft and the corresponding measured values were available. The mean absolute percentage error of the conventional Biosoft-based prediction model was 43.61%, which was defined as the baseline in this study. For the same 47 animals, the ViT-H model was applied, and K-fold cross-validation was performed, resulting in a mean absolute percentage error of 34.78%. This result indicates a substantial reduction in prediction error compared with the baseline.

The conventional Biosoft system selects eight texture variables using stepwise regression and constructs a multiple linear regression model, which relies on predefined variable combinations and linear assumptions. In contrast, the ViT-H model automatically extracts high-dimensional image features via a Vision Transformer architecture and learns both global contextual information and local patterns simultaneously. In addition, it directly models nonlinear relationships, enabling more effective representation of complex tissue structures and interactions among pixels. These structural differences are interpreted as contributing to improved predictive performance compared with the traditional regression approach that depends on variable selection.

Overall, the ViT-H model reduced prediction error relative to the conventional method and demonstrated more stable, consistent performance across the dataset. Although a mean absolute percentage error of 34.78% still indicates a discrepancy between predicted and actual values, this study's results suggest that a transformer-based deep learning approach has the potential to replace or complement conventional statistical models for estimating intramuscular fat in pigs.

Knowledge Distillation-Based Model results

Additional experiments were conducted using Knowledge Distillation on the ViT-H model. The model with Knowledge Distillation achieved a MAPE of 34.361%, representing a reduction of 0.419 percentage points compared to the baseline model without Knowledge Distillation, which recorded 34.78%. This result

demonstrates that, under identical training data conditions, the Knowledge Distillation strategy further reduced prediction error.

Through Knowledge Distillation, the student model learned the teacher model's continuous prediction distribution, enabling it to exploit richer representational information beyond simple regression to ground-truth values. This study utilized not only 47 samples with measured values but also large-scale prediction data generated by Biosoft as auxiliary supervision signals. As a result, the approach alleviated the issue of limited information arising from the constrained measured dataset and more effectively captured the distributional characteristics and latent patterns of intramuscular fat.

This semi-supervised learning framework is highly practical, as it enables the use of accumulated prediction data from existing systems even when obtaining measured data is challenging. Furthermore, the model with Knowledge Distillation consistently reduced error compared to the baseline, indicating that the proposed training strategy further improved the model's generalization performance.

Uncertainty-Aware Knowledge Distillation-Based Model Results

Next, we describe the performance evaluation results of the proposed Uncertainty-aware Knowledge Distillation method. The proposed method is designed to effectively distill reliable knowledge into the student model by accounting for the teacher model's predictive uncertainty. When conventional Knowledge Distillation was applied, the MAPE was 34.361%, whereas the proposed uncertainty-aware method achieved 33.859%, resulting in an improvement of 0.502 percentage points.

Although the absolute difference may appear marginal, its significance extends beyond a simple improvement in accuracy. The proposed method reduces reliance on unreliable soft targets and mitigates error propagation during training. These results demonstrate that properly leveraging uncertainty information can address the limitations of conventional knowledge distillation methods and enable the training of a more stable and generalized student model. Consequently, the proposed method is experimentally validated as an effective approach that improves both the reliability and efficiency of the knowledge distillation process.

Proposed Model results

Finally, we describe the results obtained by applying RandAugment to the uncertainty-based knowledge distillation framework during training. RandAugment was used only during training, and the resulting model achieved a Mean Absolute Percentage Error of 31.313%. Compared with the best performance from the previous experiment (33.859%), this represents an improvement of approximately 2.546 percentage points, the best result among all proposed methods in this study.

The performance gain can be attributed to the student model's enhanced generalization, enabled by RandAugment, which exposed it to a broader range of input distributions. In particular, because the soft targets from the teacher model had already been adjusted to incorporate uncertainty information, the additional data diversity likely enabled the student model to learn more robustly under uncertain prediction scenarios. In other words, the uncertainty-controlled distillation signals and the increased input diversity acted in a complementary manner, contributing to improved predictive accuracy. Furthermore, given the inherently speckle-rich nature of ultrasound imaging, the augmentation policies also improve robustness against noise-related variations. By exposing the student model to intensity perturbations, contrast variations, and geometric transformations, RandAugment implicitly simulates fluctuations in speckle patterns and acquisition-dependent noise characteristics. This encourages the model to focus on anatomically meaningful structural cues rather than overfitting stochastic speckle artifacts, thereby enhancing noise tolerance and stability under real-world ultrasound conditions. The overall performance of this study is shown in Table 2.

These findings also provide important practical implications. In precision analysis tasks such as intramuscular fat prediction in pigs, which is a primary application of this study, model generalization is a critical factor that determines real-world applicability. With improved predictive accuracy, we can more precisely estimate individual quality prior to slaughter, thereby enhancing decision-making in meat grading, feed efficiency management, and genetic selection. Therefore, the results demonstrate that the proposed method not only improves performance but also achieves a level of reliability and practicality suitable for real livestock production environments.

Conclusions

This study proposed a Transformer-based regression framework for IMF estimation in B-mode ultrasound images of pigs and systematically enhanced its performance through knowledge distillation, uncertainty-aware distillation, and data augmentation. Compared with the conventional Biosoft-based regression approach, the ViT-H model substantially reduced the mean absolute percentage error, demonstrating the effectiveness of deep learning–based feature extraction and nonlinear modeling for IMF prediction.

The teacher–student knowledge distillation framework enabled the student model to leverage large-scale IMF prediction data derived from Biosoft, thereby alleviating the limitations imposed by the small number of measured samples. Incorporating predictive uncertainty into the distillation process further improved training stability by selectively transferring reliable knowledge from the teacher model. The addition of RandAugment significantly enhanced generalization performance, yielding the best predictive accuracy among all evaluated configurations.

Nevertheless, this study has important limitations. All ultrasound data were acquired under a single acquisition environment, including a fixed device, imaging parameters, and protocol. Although this controlled setting ensured experimental consistency, it restricts the external validity of the model. In real-world livestock production, variations in ultrasound systems, operators, and farm conditions may introduce domain shifts that were not explicitly addressed in this study. Furthermore, the number of samples with directly measured IMF values was limited, which may constrain the model's ability to fully capture biological variability despite the use of knowledge distillation.

Future research should therefore focus on validating the proposed framework across multi-center datasets collected under heterogeneous acquisition conditions. Incorporating domain adaptation or domain generalization techniques may improve robustness against distribution shifts. Expanding the number of directly measured IMF samples would further strengthen model reliability. Additionally, integrating multimodal information and exploring lightweight or compressed model architectures could facilitate practical deployment in on-farm environments.

Overall, the proposed uncertainty-aware knowledge distillation framework combined with Transformer-based regression provides a promising approach for quantitative IMF estimation from ultrasound images. Compared with conventional statistical models that rely on predefined variables and linear assumptions, the proposed approach leverages global contextual modeling, nonlinear representation learning, uncertainty-guided knowledge transfer, and data-driven augmentation within a unified framework. While the proposed method improved MAPE relative to the Biosoft-based regression baseline in this study, further validation on multi-environment datasets with more directly measured IMF samples is required to confirm robustness before routine large-scale deployment.

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Competing Interests

No potential conflict of interest relevant to this article was reported.

Author's Contributions

Conceptualization: HCC, JSK, YSK, JKH
Data curation: JSK, SHB
Formal analysis: HCC
Methodology: TKK, HCC, YSK, JKH
Software: TKK, HCC
Validation: JSK, HCC, YSK, JKH
Investigation: TKK, HCC, SHB
Writing - original draft: TKK, JSK, HCC, YSK, SHB. JKH

Ethics Approval and Consent to Participate

This study was approved by IACUC of Rural Development Administration (No. NIAS2020-0478), Korea.

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386 # Tables

387 **Table 1**. Detail of dataset

Dataset Type	Number of pigs	Number of images	Mean and standard deviation of intramuscular fat
Biosoft	3,902	9,329	2.966±0.919
Actual measurement	47	80	3.233±1.472

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389 **Table 2**. The overall performance of this study

Method	Mean Absolute Percentage Error (%)
Biosoft versus actual measurement	43.610
Original Model	34.780
Knowledge Distillation-Based Model	34.361
Uncertainty-Aware Knowledge Distillation Based Model	33.859
RandAugment with Uncertainty-Aware Knowledge Distillation Based Model	31.313

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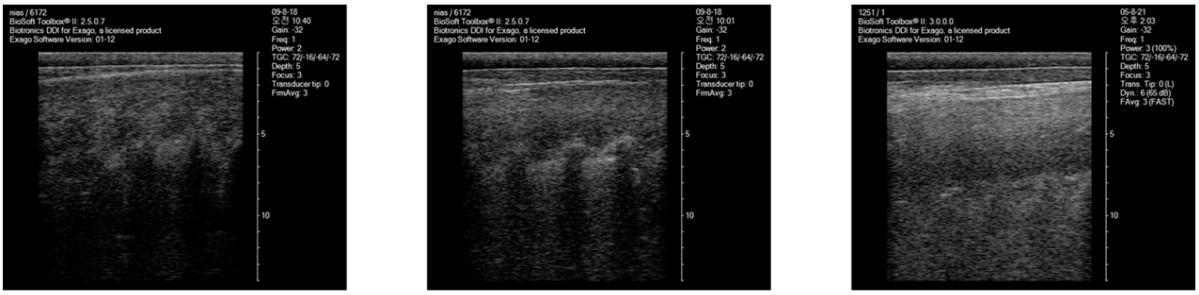
391 **Figure 1**. Examples of B-mode ultrasound frames at low (A), mid (B), and high (C) IMF; numbers indicate

392 reference IMF (%)



393

Figure 2. Flowchart of the proposed methodology for intramuscular fat estimation