

Multi-Modal Deep Learning for the Thickness Prediction of Blood Clot

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Abstract— Carotid artery is an important vessel that supplies energy to the brain through the blood flow. However, if the blood flow in the carotid artery is blocked by blood clot, it can cause fatal damage to the brain. Therefore, it is essential to measure and predict the thickness of the blood clots. In this paper, we propose a method to measure the thickness of blood clot in blood vessels from self-produced ultrasound data. From the blood clot back scatter signal, one-dimensional data such as Bandwidth and Center Frequency information is obtained, and 2D image data is derived from the bandwidth by applying amplitude-frequency conversion. In order to improve the thickness prediction performance, we develop a deep learning model based on multi-modality that extracts a feature vector from the two types of data and infers the thickness of a blood clot. Through the proposed method, we show a meaningful result that achieved 96% accuracy for the thickness.

Keywords— Multiclass Classification, Blood Clot, Thickness Prediction, Multi-Modal Deep Learning

I. INTRODUCTION

Carotid artery is a blood vessel that has an important role that sends 80% of the blood to the brain to provide energy for the brain to function smoothly. Blood clot is formed by blood hardening in blood vessels for various reasons. When the carotid artery is narrowed by blood clot, blood supply decreases, and the risk of cerebrovascular disease due to blood clots increases [1].

Carotid ultrasound is a test to confirm the degree, location, and appropriateness of blood flow of the carotid and vertebral arteries around the neck. In carotid ultrasound, the degree of arteriosclerosis can be predicted through the thickness of the endometrial-intermediate complex of the common carotid artery, and this test can determine the risk of cardiovascular disease early. However, in order to analyse ultrasound data, expertise such as the ability to analyse ultrasound results and medical knowledge related to carotid arteries and blood clot is required.

Recently, deep learning studies have shown high performance for ultrasound medical data [2].

In this paper, we hypothesize that the thickness of blood clots in the vascular can be distinguished from the 2D transformed data by applying amplitude-frequency conversion to 1D raw ultrasound signal data. In order to predict the thickness of blood clot in vascular, we propose a method based on multi-modality by corroborating the extracted features from 1D and 2D data.

1. We propose a method to measure the thickness of blood clots in blood vessels from self-produced ultrasound data.

2. In order to improve the thickness prediction performance, we employ 1D raw ultrasound data together with 2D data applied amplitude-frequency conversion.

II. METHODOLOGY

A. Data description

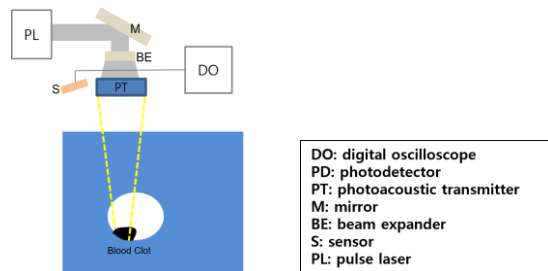


Figure 1. The experimental setup for obtaining waveforms of LGFU scattered from blood clot

The Figure 1 shows the experimental setup that was used to generate the blood clot-induced backscattered signal. The blood clot attached at the tissue-mimicking phantom targeting for the carotid artery was located at the focus of the laser-generated focused ultrasound (LGFU). The laser-generated focused ultrasound (LGFU) signal, which was scattered from blood clot attached to the tissue-mimicking phantom, was demonstrated. Blood clot samples with four different thickness (<100 , $100 \sim 200$, $200 \sim 500$, and >1000 μm) were fabricated by adding fibrinogen and thrombin which were obtained from bovine plasma (Sigma Aldrich, USA) to sheep blood (defibrinated; MB cells, Republic of Korea) [3],[4]. Then, the clotted blood was attached to a carotid artery-mimicked phantom (CAR healthcare, Canada). Even if the blood clot has minimal thickness (<100 μm), the LGFU incident to the blood clot was strongly scattered owing to the short wavelength (<100

μm) [5],[6]. Furthermore, the strong acoustic pressure (~ 70 MPa) of the LGFU enables the measurement of backscattered signal although the signal became weak due to the considerable scattering on the acoustic path in the phantom. The LGFU waveform was detected by 1-mm needle hydrophone (Precision Acoustics, UK). Obtained waveforms are visualized through fast Fourier transform(FFT). To predict the blood clot thickness of each sample, we used 1280 waveforms (1D data) for training data and 201 frequency spectra (2D data) for the validation.

B. Multi-Modal Architecture

As mentioned above, we use data from 1D raw ultrasound data and 2D visualized data to classify the thickness of blood clot in the vascular. In order to extract the features of 1D data, we conduct a 1D feature extractor which has four conv2d layers, ReLU activation function, and average pooling as shown in Fig. 2. After the 1D raw data which have 20002 ultrasound signal values are passed through the 1D feature extractor, the 1D feature vectors are finally obtained with (64×7) vectors.

For the 2D visualized data, in order to extract the meaningful features related to the thickness information, We conduct a 2D

and obtain the each probability of thickness class by applying softmax function [8],[9].

III. EXPERIMENTS

A. Implementation Detail

We trained Model with cross-entropy Loss for 4 classes classification. We set the batch size to 32, and use Adam optimizer with learning rates $1e-5$. We set 200 epoch for model training.

B. Thickness Prediction Results

Three experiments were conducted to infer the blood clot thickness value: 1D, 2D refer to the model trained with only 1D time-domain data, and 2D frequency-domain data, respectively. Multi-Modal refer to use the combined data of 1D and 2D. The experimental results are as follows.

To demonstrate the effectiveness of our proposal, we employ several metrics: precision (PRE), sensitivity (SEN), f1-score (F1), accuracy (ACC), and Area Under the ROC Curve(AUC).

TABLE 1. EXPERIMENTAL RESULTS FOR THICKNESS PREDICTION

METHOD	PRE	SEN	F1	ACC	AUC
1D	0.32	0.35	0.31	0.34	0.49
2D	0.82	0.81	0.81	0.81	0.94
Multi-Modal	0.97	0.97	0.97	0.96	0.99

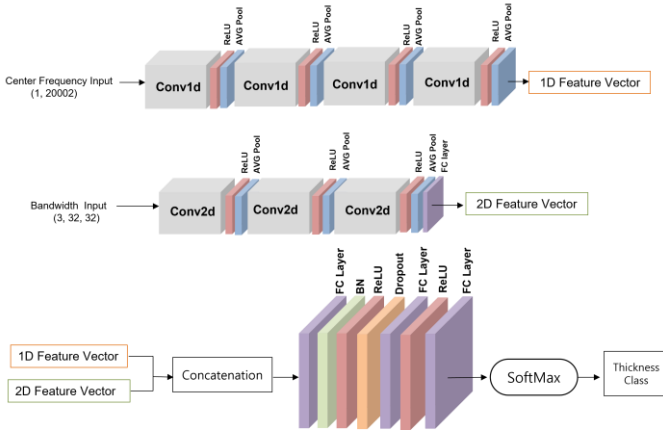


Figure 2. The architecture of proposed Multi-Modal model

feature extractor which have three 2D convolutional layers, ReLU activation functions, and average poolings as shown in Fig. 2, and obtain $(32 \times 1 \times 1)$ vectors from 2D visualized data through the 2D feature extractor.

In a bid to improve the thickness prediction performance, we employ multi-modal mechanism which can corroborate the difference types of features to make a synergy [7]. In order to do multi-modal, we need to integrate the outputs from each extractors, so we use feature concatenation as the integration method. Output of 1D is converted to (1×448) and output of 2D is converted to (1×32) , respectively and concatenate them into a (1×480) vectors. Then, we pass the concatenated vectors through the multi-modal layer as shown in Fig. 2.

Muti-Modal model is consist of Fully Connected Layer(FC), Batch Normalization(BN), ReLU and Dropout. By employing batch normalization and dropout layers to prevent overfitting

As shown in Table 1, the results of experiments with only 1D data show that the overall performance is low. This is because features of 1D raw data had little effect on classification performance for blood clot thickness.

When experimented with only 2D data, it shows relatively improved performance compared to 1D data, but still shows low performance. This shows that the features of the 2D data predicted the blood clot thickness better than the features of the 1D data.

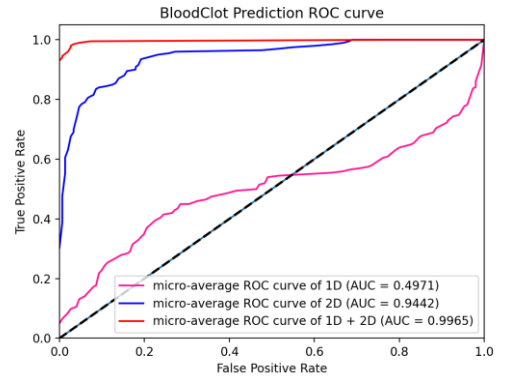


Figure 3. 1D, 2D and Multi-Modal roc curve result for thickness prediction

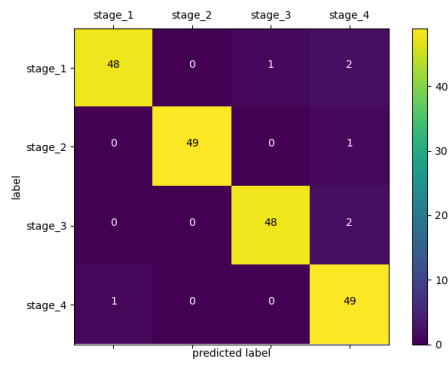


Figure 4. Multi-Modal Model confusion matrix result for thickness prediction

When 1D and 2D data are used together, it shows a significant improvement over the previous two experiments. Figure 3 is ROC curve for blood clot thickness prediction [10]. Figure 4 show the Multi-Modal Model result of the confusion matrix for blood clot thickness prediction [11]. When the x-axis is the predicted value and the y-axis is the correct value, Figure 4 shows that the predictive value and the correct answer are generally consistent, indicating that the discrimination performance is good.

Center frequency information of 1D data and bandwidth information of 2D data are used together to show the performance of an efficient prediction model using multiple modal data.

IV. CONCLUSIONS

In this paper, we proposed Multi-Modal deep learning for thickness prediction of blood clot. The flow of blood in the carotid artery is very important. If blood clot interferes with blood flow in the vascular, it can lead to dangerous situations. Therefore, it is important task to detect the thickness of blood clot. However, ultrasound, which is mainly used for blood clot detection, should be analysed based on expertise. To solve the above problem, we hypothesized that when amplitude-frequency conversion is applied to 1D raw data, a significant difference can occur for each thickness. In order to prove the hypothesis, a multi-modality-based deep learning model was constructed.

As a result of the analysis, we have demonstrated that the thickness can be distinguished from the transformed 2D data more efficiently than when using only 1D data.

In addition, when 1D raw data and 2D visualized data were used together, further improved results could be derived. However, since the above experiment was conducted based on self-produced data, additional research will be needed on whether clinically significant results can be derived.

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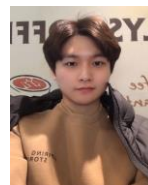
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