Pregnancy detection on a smartphone using deep learning

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***Abstract*—This study employed a smartphone to collect PPG signals, which were then used to train the TARNet model for non-invasive pregnancy detection. PPG signals (from both hands) were obtained from 63 pregnant participants and non-pregnant participants to train the model, resulting in an accuracy of 91.59%. Additionally, we examined the differences between first-trimester pregnant participants and non-pregnant participants. Using this data, the model achieved an accuracy of 97.16%. Furthermore, we observed that the RI values (the ratio of the diastolic peak to the systolic peak) differed significantly between non-pregnant and pregnant participants, which may potentially explain the model's prediction performance.**

I. Introduction

Early detection of pregnancy offers numerous benefits, aiding in clinical management and enhancing the control of pre-existing conditions during the prenatal period. This includes assessing the risk of Down syndrome fetus and predicting preeclampsia. Current common testing methods, such as Radioimmunoassays, can detect pregnancy within 8 to 12 days after conception, whereas ultrasounds provide confirmation approximately 2 to 3 weeks later. While these methods enable early pregnancy detection, Radioimmunoassays may not rule out the possibility of detecting uterine fibroids, and specific conditions must be met: (1) the embryo is larger than 0.4 cm, (2) hCG levels are greater than 1025 mIU/mL, and (3) there are no uterine-related diseases. While invasive Transvaginal ultrasounds can lead to unnecessary bleeding [3].

In recent years, Photoplethysmography (PPG) research has shown significant potential as a non-invasive approach for pregnancy detection. Studies indicate that pregnant women experience reduced heart rate variability (HRV) during pregnancy, with most physiological indicators being lower compared to non-pregnant states [7]. By utilizing non-invasive PPG data, pregnancy status could potentially be identified through comparative analysis.

Recently, we designed a cost-effective PPG sensing system based on smartphones, which incorporates a PPG sensor and a galvanic skin response (GSR) sensor. We employ a fully connected neural network (FCN) to establish a binary classifier capable of detecting the "wiry pulse," a frequently observed Traditional Chinese Medicine (TCM) pulse type often associated with liver diseases [4]. Pregnancy, according to TCM, is associated with unique pulse qualities, often described as "slippery" or "soft." These pulse characteristics correspond to changes in blood volume, hormonal fluctuations, and cardiovascular dynamics during pregnancy, which can be captured through PPG and galvanic skin response (GSR) signals. Given that the previously developed system has successfully detected subtle pulse variations associated with specific conditions, such as the wiry pulse, it is plausible that the same sensing technology could identify the distinct pulse patterns characteristic of pregnancy.

The sensor platform captures GSR and PPG signals from the subject and transmits them to a smartphone via an OTG (On-The-Go) cable. The data is then wirelessly forwarded to a cloud server (refer to Figure 1). The GSR and PPG sensors are linked to an Arduino Beetle board, powered by the smartphone, which also serves as the interface for data transmission. Both systems run on the Android platform, utilizing UART communication to transfer data between the smartphone and the sensors.

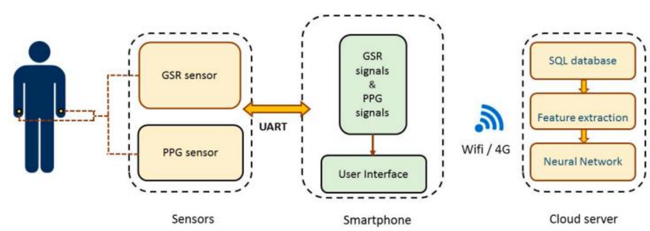

Figure 1. Sensor platform in our previous system [4].

The PPG measurement process is depicted in Figure 2. The PPG sensor is placed near the central location of the radial bone prominence and secured to the wrist using tape to minimize interference during the measurement process. We collected PPG data at a frequency of 500Hz and retained all the raw data.

Given that GSR relies on injecting a small electrical current to measure skin impedance, even though this current is imperceptible to most individuals, the concept of injecting current may be perceived as invasive by pregnant women and healthcare providers. This perception could limit the acceptance of GSR as a diagnostic tool during pregnancy. Therefore, this study focuses solely on collecting PPG signals using smartphone-based PPG sensing technology and employing deep learning models to determine pregnancy status. To the best of our knowledge, this is the first study to leverage PPG signals combined with an AI model for pregnancy detection on a smartphone.

Figure 2. Placement of the PPG sensors [4].

II. Related work

A. Photoplethysmography Signal (PPG)

P PPG is a non-invasive method that measures the amount of light reflected or absorbed by tissue to calculate changes in blood volume within capillaries. Leveraging this principle, PPG can estimate various physiological signals, including heart rate, heart rate variability (HRV), respiratory rate, and blood pressure. For instance, PPG signals are commonly used to derive key pulse characteristics such as pulse transit time (PTT) and pulse wave velocity (PWV), which are then utilized to infer blood pressure [1]. In this work, we used PPG data to detect pregnancy with an AI model.

B. Pulse Wave and Pregnancy

Pregnancy is typically divided into three stages: the first trimester (weeks 1–12), the second trimester (weeks 13–27), and the third trimester (weeks 28–40). Previous research [5] has confirmed a correlation between the waveform characteristics of radial pulses and pregnancy In the early stages of pregnancy, particularly between weeks 12 and 15, pregnant women experience a gradual increase in heart rate, which typically peaks around weeks 24 to 27. In contrast, blood pressure tends to decrease gradually during this period. Figure 3 illustrates these variations: Figure 3(a) shows heart rate changes across different trimesters, while systolic and diastolic blood pressure variations at various weeks of pregnancy are depicted in Figures 3(b) and 3(c), respectively.

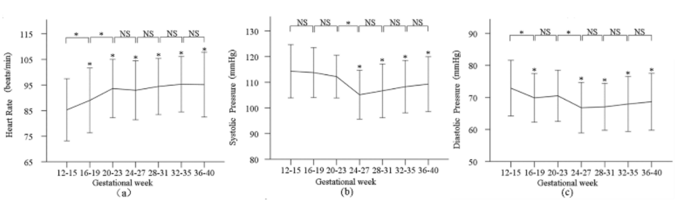

Figure 3. Heart rate and blood pressure at different trimesters [5].

Previous studies [5,8] have identified several PPG waveform characteristics that may help distinguish different stages of pregnancy. For example, indicators such as the Reflection Index (RI), Notch point (Tn), and Total Pulse Area have been highlighted, as they are significantly influenced by the progression of each trimester [5]. Additionally, other indicators, including the Photoplethysmographic Augmentation Index (PAI), RI, Pulse Transit Time (PTT), Area Under the Curve (AUC), and the barycenter of AUC (bcAUC), have been shown to be useful in determining pregnancy stages [8]. Among these, RI stands out due to its significant changes and frequent use. RI is widely recognized as a measure of arterial stiffness, with higher values indicating stiffer arteries and lower values suggesting greater elasticity. RI is calculated using Equation (1), where P2P2P2 represents the amplitude of the diastolic peak and P1P1P1 denotes the amplitude of the systolic peak, as illustrated in Figure 4.

$$RI = P2 / P1. \tag{1}$$

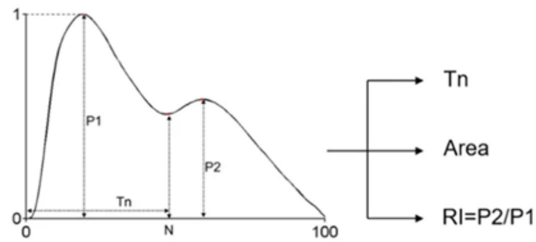

Figure 4. Arterial pulse waveform characteristics extracted from normalized PPG waveforms. [5].

Based on prior findings [5,8], it is clear that RI exhibits a significant decreasing trend during pregnancy and is comparatively lower compared to non-pregnant women. For instance, one study [8] reported that the average RI for non-pregnant individuals is 0.623±0.082, while for women in the first trimester of pregnancy, the average RI is 0.588±0.113.

C. Detection of pregnancy with AI models

Building on previous observations, Li et al. [6] utilized a commercial pressure sensor-based system to record arterial pulse data and employed a 1D convolutional neural network (1D CNN) combined with a gated recurrent unit (GRU) to classify pregnancy pulses across three stages of pregnancy. They achieved classification accuracies of 85%, 88%, and 86% for the respective stages. Inspired by their work, we adopted a transformer-based model for pregnancy detection and achieved an accuracy of 97.16%. Additionally, our sensing system is cost-effective, utilizing a smartphone integrated with a PPG sensor costing less than $10. It is worth noting that while their study focused on classifying different pregnancy stages, our research is aimed at distinguishing pregnancy from non-pregnancy.

III. Methodology

We utilized a deep learning model named TARNet (Task-Aware Reconstruction Network) for pregnancy detection. Built on the Transformer architecture, TARNet is designed to learn task-aware data reconstruction, with the goal of improving end-task performance [2]. The learning process of TARNet is illustrated in Figure 4. In the first step, the relevant information of interest is mean-standardized. Then it passes through an Embedding and a positional encoding layer, followed by the N-layer Transformer Encoders and Fully Connected (FC) Layer. This model collects attention maps for each time-series data generated by the Transformer Encoder. It computes a set of crucial timestamps to be masked during task-aware reconstruction and applies this mask to the input data reconstruction. Parameters are shared among various layers, except for the FC Layer [2].

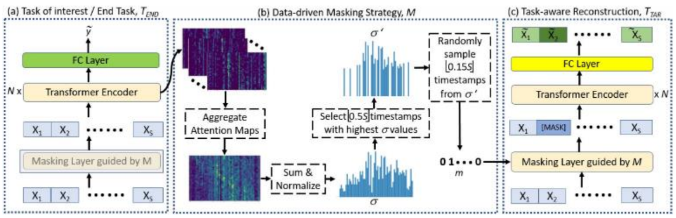

Figure 4. TARNet Overview [2].

IV. RESULT

We collected PPG data from 33 pregnant women and 30 non-pregnant women, totaling 63 participants, for pulse wave analysis. The distribution of the number of participants in every trimester is shown in Figure 5.

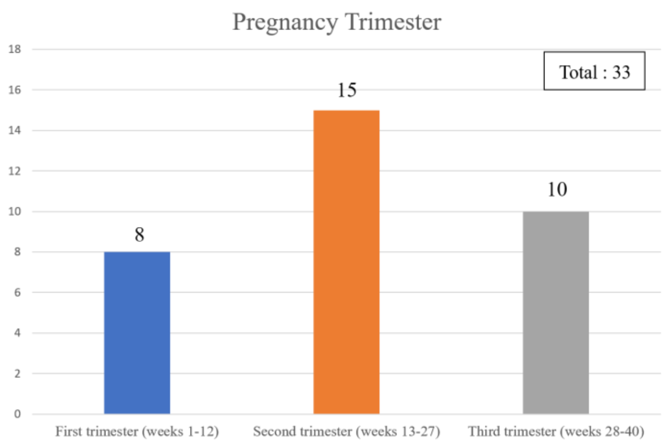

Figure 5. Numbers of participants in every trimester.

Data were collected at a sampling rate of 500 Hz, with each participant contributing five minutes of recordings. The data were preprocessed using a 5:1 downsampling ratio for peak-to-peak single-wave sampling, yielding approximately 300–400 waves per participant. Following preprocessing, the data were split into training and testing sets in an 8:2 ratio for model training. We used a batch size of 300 and trained the model for 300 epochs, achieving an accuracy of 91.59% under these settings. A sliding-window approach with a window size of 5 seconds was applied to segment the PPG data prior to inputting it into the neural network.

Once women reach the second and third trimesters of pregnancy, their physical appearance undergoes noticeable changes, eliminating the need for pregnancy detection. As a result, the use of PPG for detection and early identification becomes unnecessary beyond the first trimester. Consequently, we focused our research on detecting pregnancy during the first trimester. Specifically, we analyzed data from 8 pregnant women in their first trimester, comparing it with data from non-pregnant individuals. Prior to comparison, the data were preprocessed as described earlier. Given the limited size of the first trimester group (8 participants) compared to the 30 non-pregnant participants, we applied data augmentation techniques, including jittering and scaling, and replicated the pregnancy data four times. This approach led to a final testing accuracy of 97.16%.

To interpret these results, and in reference to prior studies [5,8], we calculated the RI values for the 8 pregnant women in their first trimester (including the augmented data) and compared them to those of the non-pregnant participants using equation (1). The physiological waveforms of all participants were normalized, and the diastolic peak value (P2) and systolic peak value (P1) were extracted to compute the RI value for each waveform, following the methodology outlined in previous work [5]. After performing the calculations, we determined the median and mean RI values for the first-trimester group to be 0.306 and 0.325, respectively, and for the non-pregnant group to be 0.354 and 0.422, as illustrated in Figure 6.

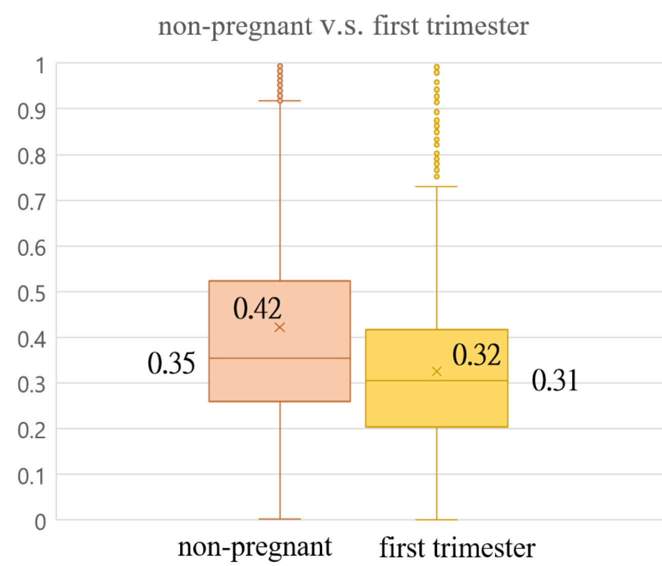

Figure 6. Comparison of RI Values between Non-Pregnant Individuals and First-Trimester Pregnancies

Statistical analysis revealed that the RI values of non-pregnant women were generally higher than those of women in the first trimester, with the difference between the two groups being statistically significant (p = 0.0028). This finding aligns with previous literature. Figure 11 illustrates a comparison of representative pulse waveforms (from the systolic peak to the endpoint) after normalization for 8 women in the first trimester and 8 non-pregnant women. The visualization clearly shows that the P2 values of non-pregnant women (red arrow) are significantly higher than those of first-trimester pregnant women (blue arrow), while the P1 values remain nearly identical. The magnitude of the P2 values closely corresponds to the observed differences in RI values. Thus, it can be concluded that the RI values of non-pregnant women are generally higher than those of women in the first trimester.

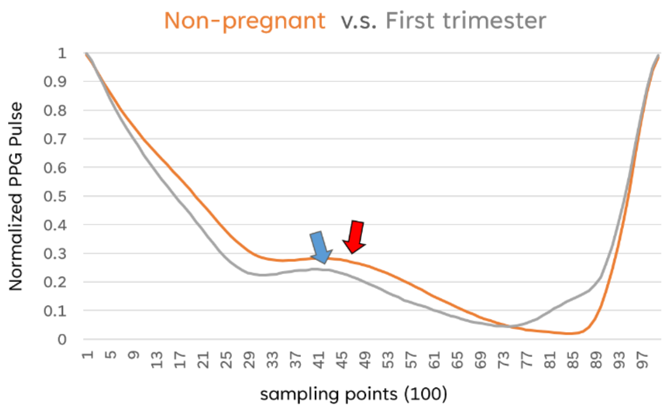

Figure 7. Comparison of PPG Pulse Waveforms Between Non-Pregnant Individuals and First-Trimester Pregnancies.

V. Conclusion and Future Work

This study employed smartphones paired with PPG sensing devices to collect PPG signals from both pregnant and non-pregnant individuals. These signals were used as training data to develop a model for determining pregnancy status, achieving an accuracy of 91.59%. Additionally, for early detection during the first trimester, the model achieved an accuracy rate of 97.16%.

The data used in this study is limited, and an obvious direction for future work is to expand the dataset to validate the results obtained here. Additionally, pulse diagnosis is a crucial component of Traditional Chinese Medicine (TCM), with a history spanning thousands of years. TCM practitioners have long used pulse feeling to diagnose pregnancy, referring to the pulse during pregnancy as the 'slippery pulse.' One potential application of this research is to examine the characteristics of the slippery pulse by collecting a large dataset from both pregnant and non-pregnant individuals, as TCM theory also notes that slippery pulse can occur in non-pregnant individuals.

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