Cardiovascular Age Detection

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***Abstract*—A healthy heart contributes to a longer and healthier life. But how old is our heart really? Our research looks into that question by estimating cardiovascular age using two noninvasive techniques, tonometry and ballistocardiography (BCG). Although tonometry has long been used in hospitals to assess arterial stiffness, it typically requires direct contact and a trained professional. Ballistocardiography (BCG), in contrast, detects subtle body movements caused by the heartbeat and can be measured passively, even while a person stands on an ordinary scale. In this study, we compare these two approaches to assess whether BCG can provide a more accessible yet accurate method for estimating arterial aging. Surprisingly, our BCG-based models performed similarly to those based on tonometry, with the best model achieving a mean absolute error of just 9.59 years.**

I. Introduction

Arterial stiffness, the flexibility of the arteries, is a significant health concern as it is closely linked to the progression of cardiovascular events, dementia, renal disease, and ultimately, increased mortality [1]–[3]. With advancing age, the arterial system undergoes a natural deterioration characterised by luminal enlargement, wall thickening, and reduced elasticity—particularly in large elastic arteries—which in turn elevates systolic and pulse pressures [4], [5]. Given that cardiovascular disease (CVD) remains the leading cause of death worldwide, early identification of arterial stiffening serves as a sensitive marker for vascular pathology and is critical for effective primary prevention and early intervention [6]. A recent global meta-analysis reinforced this view by emphasizing pulse wave velocity (PWV) as a validated non-invasive measure of arterial stiffness that powerfully predicts both cardiovascular disease and all-cause mortality, independent of traditional risk factors [6].

A key measure of arterial stiffness is pulse wave velocity (PWV), which quantifies how rapidly pressure waves propagate along the arteries. Clinically, higher PWV values indicate stiffer arteries and, consequently, a heightened risk of cardiovascular events. Commonly employed non-invasive methods include carotid-femoral PWV (cfPWV) and brachial-ankle PWV (baPWV), with cfPWV often considered the gold standard due to its close reflection of aortic health [6], [7]. However, measuring cfPWV can be technically challenging and cause discomfort, as it requires placing sensors near the groin area [8]. To address this, simplified techniques like finger-toe PWV have been introduced as less invasive alternatives. Studies show that this method provides comparable results to standard PWV measurements in young adults [8].

Recent research has explored the use of artificial intelligence to improve the accessibility and predictive power of PWV-based measurements. One study [9] introduced a deep learning model using convolutional neural networks to analyze arterial pressure waveforms and estimate PWV. The predicted values were then converted through linear regression into a metric called artificial intelligence vascular age (AI-VA), which reflects the biological age of the vascular system. This AI-derived index not only captured arterial stiffness accurately but also showed strong potential for forecasting future cardiovascular events, making it a promising tool for non-invasive vascular health assessment. In another study [10], a more straightforward approach was taken—heart rate and stroke volume were used as input features in a random forest algorithm to predict "pulse wave age." While the model achieved perfect training accuracy, it was developed on a limited sample, raising questions about overfitting and whether heart rate and stroke volume alone are sufficient indicators of vascular aging.

Despite PWV's reliability as a non-invasive method for assessing arterial stiffness, its clinical application is often constrained by the need for specialized equipment and trained professionals. Similarly, traditional methods for measuring stroke volume involve either invasive catheter-based techniques or advanced echocardiography, both of which can be complex and less accessible in routine practice. These limitations underscore the necessity for more streamlined and scalable solutions for monitoring vascular health across broader populations.

In this context, ballistocardiography (BCG) emerges as a promising alternative. BCG is a non-invasive technique that measures the subtle oscillations of the body caused by the cardiac cycle, offering accurate insights into cardiovascular aging. In the last ten years, new measurement techniques have been developed that do not disturb the person. Two distinct signals kinds have been created by the researchers: seismocardiograms (SCG) and ballistocardiograms (BCG). This makes it possible to take measurements not just in medical facilities but also at home, outside, and even in space [11]. With innovations such as BCG-VARS, an embedded real-time software capable of evaluating vital parameters from various equipment (e.g. wheelchairs, vehicle seats, hospital beds) [12] and even wearable devices tested in animal models [13], BCG presents a

more practical and patient-friendly replacement for traditional electrocardiography (ECG) methods [14]. Using sensors in an electronic weighing scale to determine pulse transit time (PTT) is the most straightforward technique. This technique links PTT to the I and J waves in the ballistocardiogram (BCG) signal, which are the temporal differences between two places [15]. However, long-term monitoring via BCG requires the collection of extensive datasets. Since we have the dataset, we can mitigate this issue. Some researchers have faced the same challenge and addressed it through machine learning approaches, such as BCGNET, which uses RNN and CNN architectures to enhance data processing and predictive accuracy. BCGNET employs deep learning models to automatically process raw BCG signals, eliminate noise, and extract important cardiovascular health-related features [16].

***Index Terms*—cardiovascular aging, arterial stiffness, pulse wave velocity, ballistocardiography, tonometry, machine learning**

II. Materials and Methods

A. Overview of Modalities

This study compares two non-invasive signal modalities for cardiovascular age prediction like carotid-femoral tonometry and ballistocardiography (BCG). Both approaches informs us about arterial stiffness and vascular aging, but differ in terms of acquisition complexity, patient comfort, and scalability. In particular, BCG signals were recorded through an electronic weighing scale, making it possible to detect tiny body movements from the heartbeat without geting in contact with the person.

B. Dataset Description

This study is based on data collected from 80 subjects, each of whom underwent a two-minute non-invasive cardiovascular monitoring session. For each subject, three categories of data were recorded: (1) metadata, (2) beatwise physiological features, and (3) ensemble-averaged waveforms.

Metadata consists of patient-level information such as age, height, weight, gender, carotid-femoral distance (`CF_dist`), and the sampling frequency (`fs`) used during signal acquisition. These variables serve as physiological covariates and were retained for all modeling pipelines.

Beatwise data includes detailed cardiovascular features recorded on a per-heartbeat basis, measured continuously over a two-minute window. These columns include time intervals such as RR (beat-to-beat interval), RI, RJ, RK, and IJ (from the ECG R-peak to the I, J, and K points of the BCG waveform), as well as amplitude values AI, AJ, and AK corresponding to those peaks. The number of rows per subject in this table varies depending on their heart rate—patients with higher heart rates generate more beatwise rows within the fixed two-minute acquisition period.

Ensemble-averaged signals include waveform segments from the carotid (`tonc_mean`), femoral (`tonf_mean`), and BCG (`bcg_mean`) channels. These waveforms are time-aligned to the ECG R-peak and sampled at 1000 Hz for 600 milliseconds (resulting in 600 points per waveform). Although these ensemble signals were used for quality inspection, they were excluded from modeling to focus on beatwise signal dynamics.

C. Data Cleaning

High-fidelity cardiovascular modeling requires robust preprocessing to mitigate the effects of noise, misaligned data, and physiological outliers. Prior to modeling, we applied a structured cleaning pipeline to all parts of the dataset, including metadata, beatwise features, and ensemble-averaged signals.

We began by manually inspecting the raw metadata tables, where several CSV files contained misaligned or malformed entries—for instance, patient metadata such as `Height`, `Gender`, or `Weight` were occasionally shifted or swapped across columns. These discrepancies were manually corrected to ensure consistent schema alignment across all subjects.

For the beatwise data—which includes per-beat features such as RR intervals, BCG timing intervals (RI, RJ, RK, IJ), and amplitudes (AI, AJ, AK)—we observed considerable physiological variability, as well as occasional measurement artifacts (e.g., extreme spikes, flat lines). To address this, we applied column-wise outlier filtering using the interquartile range (IQR) method with a conservative multiplier of 3.0. This approach was implemented in a custom function that computed Q1, Q3, and IQR per feature, and flagged any values falling outside the range $[Q1 - 3 \cdot \text{IQR},\ Q3 + 3 \cdot \text{IQR}]$. Rather than deleting entire rows, we used a fine-grained, cell-level filtering strategy—outlier values were set to `NaN`, preserving the rest of the beat data from the same heartbeat. This allowed us to retain more valid observations per subject while still filtering out clear anomalies.

After filtering, we retained only beatwise columns with at least five valid (non-`NaN`) values per subject. Subjects with fewer than five usable values across all beatwise features were excluded entirely due to insufficient signal quality. Additionally, for ensemble-averaged waveforms (such as `tonc_mean`, `tonf_mean`, `tond_mean`, and `bcg_mean`), we visually inspected plots for each patient to flag those with implausible morphologies or noise-corrupted recordings. While these ensemble signals were excluded from the modeling pipeline, they served as a useful quality control reference.

Missing values introduced during cleaning were imputed later during preprocessing: numerical features were imputed with the mean, and categorical ones (e.g., gender) with the mode. Importantly, we saved the cleaned metadata, beatwise data, and ensemble waveform data into separate files for traceability and reproducibility.

This rigorous yet conservative cleaning strategy allowed us to suppress noise and artifacts without over-sanitizing the data—maintaining important physiological variability while ensuring data reliability for downstream modeling.

D. Feature Engineering

As noted in the dataset description, each subject's beatwise physiological data varied in length depending on heart

rate—higher heart rates produced more rows within the fixed two-minute recording window. Following the cleaning process described above, we performed feature engineering on the cleaned beatwise dataset to ensure consistency across subjects. To standardize the variable-length data across patients, we computed a suite of summary statistics (mean, standard deviation, range, median, skewness, kurtosis, etc.) for each beatwise feature [17]. These statistics were calculated for all relevant beatwise columns, including timing intervals (e.g., RI, RJ, RK, IJ) and amplitude features (e.g., AI, AJ, AK), as well as a count of non-missing values. This summarization process effectively transformed each subject's beatwise cardiovascular recordings into a consistent, fixed-length feature vector—what we term a physiological fingerprint—suitable for use in tabular machine learning models.

In addition to summary statistics, we derived classical Heart Rate Variability (HRV) metrics—such as SDNN, RMSSD, SDSD, pNN20, pNN50, and the coefficient of variation—from the cleaned RR interval series. While these features were retained for future analysis and may inform studies of autonomic function, they were excluded from the BCG-only modeling pipeline to ensure the model relied exclusively on mechanical signal characteristics.

This summarization strategy allowed us to preserve rich information about per-beat dynamics (timing intervals, amplitudes, and beat-to-beat variability), while generating a uniform feature structure across all patients. It also improved robustness by smoothing out noise and anomalies, many of which had already been masked during the cleaning phase.

III. Modelling Approaches

A. PWV-Based Modeling Pipeline

The tonometry dataset contained ensemble-averaged waveforms from carotid and femoral sites, alongside subject-level metadata such as age, height, weight, and sampling frequency. Features included `tonc_mean`, `tonf_mean`, `pattonc`, `pattonf`, and the computed Pulse Wave Velocity (PWV). PWV was derived using:

$$\text{PWV} = \frac{\text{CF\_dist}}{\text{PTT\_cf}} \tag{1}$$

where `CF_dist` is the distance between carotid and femoral sensors and `PTT_cf` is the pulse transit time. Carotid-femoral PWV remains the clinical gold standard for assessing arterial stiffness [18]. To isolate the impact of tonometry, all BCG-derived features were excluded. Additionally, feature selection was performed based on importance scores from Random Forests [19], discarding low-contribution features. In addition to waveform-derived features, subject height and weight were included as physiologically relevant covariates. After calculating PWV, it was manually added to the dataset as a new column, improving the dataset's sensitivity to arterial stiffness. BCG-related features and pulse shape descriptors (e.g., `Aj_skew`, `Ak_mean`) were removed to maintain modality purity. Importantly, to preserve modality separation and avoid data leakage, we explicitly removed all features originating from ballistocardiography (e.g., `Aj_skew`, `Ak_mean`), retaining only features directly derived from the carotid and femoral waveforms. Low-importance features were discarded using a Random Forest-based feature importance threshold of 0.02 to reduce dimensionality and improve generalization.

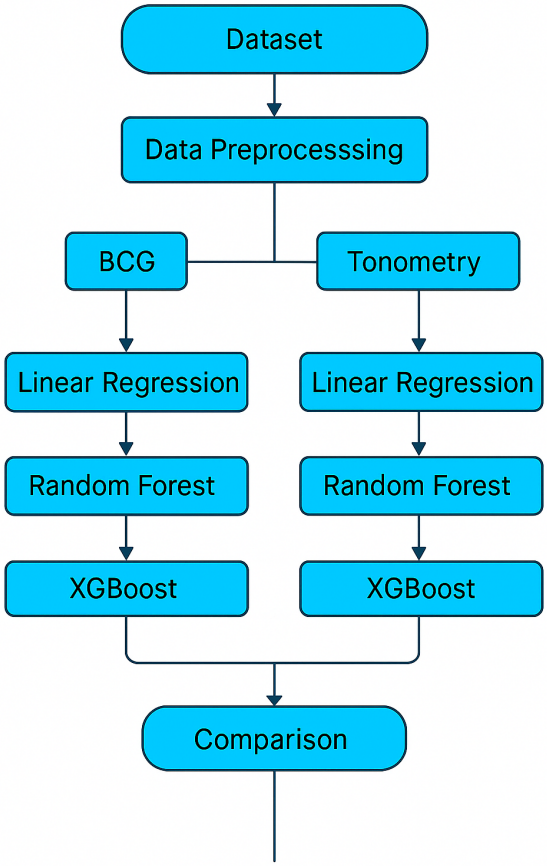

Fig. 1: Overview of the modeling pipeline applied to both modalities (BCG and Tonometry). Each dataset underwent separate training with three machine learning models: Linear Regression, Random Forest, and XGBoost, followed by performance comparison.

Figure 1 Description: This diagram summarizes the full pipeline used in our study. After preprocessing the dataset, we split it into two branches—BCG and tonometry—and trained three models per modality. The results from each model were then compared to assess performance across signal types.

B. BCG-Based Modeling Pipeline

The BCG-based modeling pipeline focused on predicting chronological age using features derived solely from mechanical BCG signals, alongside basic demographic metadata. All features related to ECG, heart rate variability (HRV), and tonometry were excluded to ensure a purely BCG-driven model. Only beatwise features describing the timing and amplitude characteristics of the BCG waveform were

retained—specifically the RI, RJ, RK, IJ, AI, AJ, and AK intervals.

As described in the Feature Engineering section, we computed statistical descriptors—such as mean, standard deviation, median, range, skewness, kurtosis, and count—over these beatwise signals to generate a consistent, subject-level feature representation. This process yielded 63 BCG-based features per individual, effectively capturing inter-beat variability and waveform morphology in a fixed-length physiological fingerprint.

Four additional metadata variables (Height, Weight, Gender, and sampling frequency `fs`) were included as covariates. The resulting dataset consisted of 67 features per subject, fully constrained to the mechanical modality.

We trained three machine learning models—Linear Regression, Random Forest, and XGBoost—on this dataset. These were chosen to reflect a range of complexity and generalization capabilities. Model evaluation was conducted using a 5×5 nested cross-validation framework, providing unbiased estimates of predictive accuracy while enabling hyperparameter tuning within inner folds. This setup ensured fair comparison with the tonometry-based pipeline and accounted for the modest sample size ($n = 80$).

C. Machine Learning Pipeline

We trained three regressors—Random Forest, XGBoost, and Linear Regression—on both modalities. For BCG, models were evaluated using a 5×5 nested cross-validation framework. Hyperparameter tuning was handled by grid search in the inner loop, while the outer loop provided unbiased performance estimates. Both BCG and tonometry pipelines were evaluated using identical nested 5×5 cross-validation schemes, with hyperparameter tuning implemented via Scikit-learn's GridSearchCV. Categorical features such as gender were one-hot encoded using Scikit-learn's OneHotEncoder prior to training. Additionally, the Random Forest regressor utilized out-of-bag (OOB) error estimates to validate generalization performance [20]. All models were trained and evaluated on data from a total of 80 unique subjects, drawn from two datasets that provided both tonometry and BCG signals. Subjects with fewer than five valid beatwise entries were excluded from BCG training, ensuring reliable learning from mechanical signal features.

IV. Model Evaluation and Results

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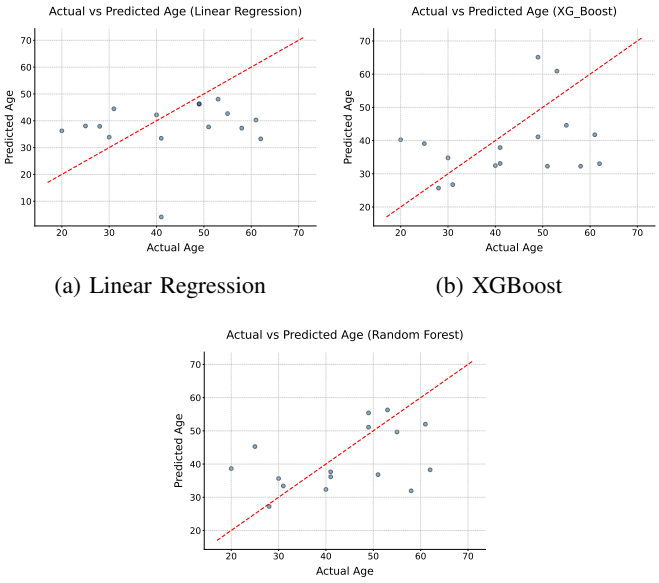
A. Tonometry-Based Model Performance

TABLE I: Tonometry Model Performance

Model	MAE (years)	R^2 Score
Random Forest	9.60	0.07
XGBoost	12.45	-0.30
Linear Regression	13.09	-0.56



(a) Linear Regression (b) XGBoost

(c) Random Forest

Fig. 2: Actual vs. Predicted cardiovascular age for each tonometry-based model. The red dashed line represents ideal predictions.

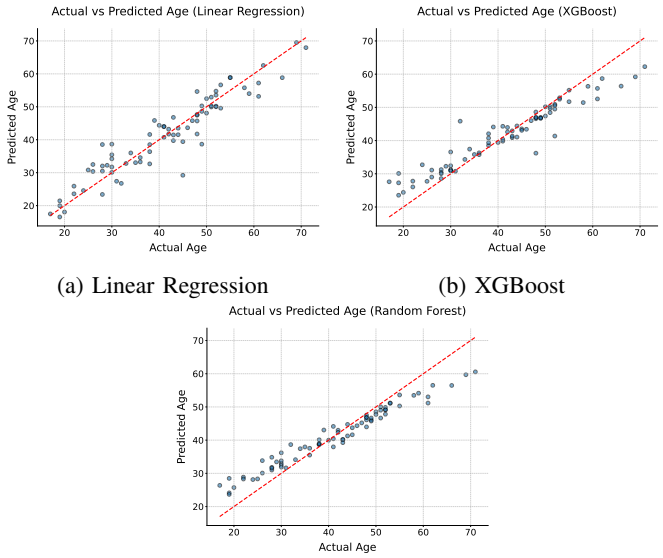
Figure 2 Description: Panel (a) shows the linear regression model struggling to fit the tonometry-derived features, with many predictions far from the ideal. Panel (b) shows XGBoost capturing some structure but with poor generalization. Panel (c) demonstrates that Random Forest produces predictions that better align with the actual values, supporting its stronger performance metrics.

Among the three models tested, **Random Forest** performed best, achieving a mean absolute error (MAE) of 9.60 years and an R^2 score of 0.07. This suggests it was more effective at capturing patterns in the tonometry-derived features than the other models. **XGBoost** performed worse (MAE = 12.45 years), possibly due to overfitting or difficulty generalizing to this specific feature set. **Linear Regression** showed the weakest performance (MAE = 13.09 years, $R^2 = -0.56$), emphasizing the need for nonlinear models when working with complex physiological waveforms.

B. BCG-Based Model Performance

TABLE II: BCG Model Performance

Model	MAE (years)	Notes
XGBoost	9.59 ± 0.88	Best performance overall
Random Forest	9.69 ± 1.44	OOB estimate: 9.63
Linear Regression	13.27	Weakest model



(a) Linear Regression (b) XGBoost

(c) Random Forest

Fig. 3: Actual vs. Predicted cardiovascular age for each BCG-based model. The red dashed line represents perfect prediction.

Linear Regression showed the weakest performance, with a mean absolute error (MAE) of 13.27 years. This aligns with expectations, as linear models struggle to capture the nonlinear dependencies present in beatwise physiological features. Nonetheless, the prediction plot for Linear Regression reveals that many predictions still follow the red diagonal line, suggesting the model captures a general upward trend between predicted and actual age despite its high error.

In contrast, tree-based models like XGBoost and Random Forest demonstrated significantly better generalization, with XGBoost slightly outperforming Random Forest in terms of both mean error and fold-to-fold consistency. BCG-derived features led to improved robustness, as seen by the relatively low standard deviation across outer folds.

Although XGBoost achieved the lowest MAE, visual inspection of the prediction plots (Figure 3) reveals some limitations. Notably, the XGBoost model exhibits a number of outlier points—especially for younger subjects around 30 years old—where predicted age can be as high as 47. Moreover, for older subjects (above 55 years), the model consistently underestimates age, as shown by the systematic deviation of points below the red diagonal line.

In contrast, Random Forest yields a visually cleaner and more uniform spread around the ideal prediction line. It avoids extreme overpredictions and appears more balanced across the full age range. However, similar to XGBoost, it also shows a tendency to underpredict for subjects over 60 years old, though the deviations are less severe.

This visual contrast reflects known trade-offs between the models: XGBoost excels in optimizing average error by correcting its bias iteratively [21], but can produce sharper localized errors. Random Forest, on the other hand, benefits from ensemble averaging, leading to more conservative but smoother predictions [19].

These observations complement the numerical results and support the selection of tree-based methods as viable models for cardiovascular age estimation using beatwise BCG features. Moreover, as illustrated in Figure 3, the consistent alignment between predicted and actual values—even across model types—suggests that BCG signals encode relevant physiological information, making them a promising non-invasive indicator of cardiovascular age.

C. Cross-Modality Comparison

Both modalities achieved similar error levels when using Random Forest, with tonometry and BCG yielding mean absolute errors (MAEs) of approximately 9.6–9.7 years. However, BCG outperformed tonometry under XGBoost, with an MAE of 9.59 years compared to 12.45 years. This suggests that the beatwise features in BCG offer richer information for machine learning models. Moreover, BCG's contactless and scalable nature makes it well-suited for use in home-based or continuous monitoring applications [11]. These findings support the idea that BCG captures meaningful physiological signals related to vascular aging, even in relatively small datasets [22]. The close performance across modalities, paired with BCG's practical advantages, highlights its potential as a viable alternative to traditional tonometry in broader healthcare contexts.

V. Conclusion

This study dived into whether it's possible to estimate a person's cardiovascular age using two noninvasive methods: carotid-femoral tonometry and ballistocardiography (BCG). While both modalities showed comparable accuracy using Random Forests, BCG slightly outperformed tonometry when using XGBoost, achieving a lower MAE and greater consistency. Because BCG can collect data without physical contact and works well over long periods, it shows promise as a scalable tool for monitoring heart health outside the clinic. Future work will focus on integrating ensemble waveform features, expanding the sample size, and exploring hybrid models that combine both modalities. We also plan to review recent advances in BCG-based monitoring to place our findings within the broader landscape of contactless health technologies. Although the results are promising, limitations of the study, include the reliance on manual data cleaning and a relatively small dataset.

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