



Machine Learning-based Estimation of Foot Parameters for Custom Insole Production: A Comprehensive Analysis of Structural Measurements

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ABSTRACT

Precise quantification of foot morphology is critical for clinical diagnostics, biomechanics, and personalized orthotic design. Conventional anthropometric methods often remain labor-intensive or dependent on specialized hardware, necessitating more efficient predictive frameworks. This study develops and validates a series of machine learning (ML) models to predict nine essential foot anthropometric parameters. Leveraging a dataset of 544 independent foot samples from 272 participants, encompassing high, normal, and flat arch types. The models were evaluated using a 10-fold cross-validation strategy to ensure robust generalizability. Our pipeline integrates correlation-based feature selection with hyperparameter-optimized regression algorithms, including XGBoost, Random Forest, Support Vector Regressors, Neural Networks, and Linear Regression. The results demonstrate high predictive fidelity, with Mean Absolute Errors (MAE) consistently remaining below 0.5 cm. This level of precision meets the 0.5 cm clinical tolerance threshold established through expert consultation for insole production, while simultaneously aligning with international footwear sizing increments, thereby confirming the framework's practical utility in real-world manufacturing. Although parameters such as the length from heel to midfoot area and the length from heel to distal metatarsal head achieved exceptional precision (MAE of 0.012 cm and 0.026 cm, respectively), predicting arch height remains a notable challenge. This research underscores the necessity of optimal feature engineering and algorithm selection in automating foot morphometric assessment.

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1. INTRODUCTION

Footwear is essential for postural stability and injury prevention [1], yet mass-produced designs often fail to accommodate structural variations such as pes planus and pes cavus. These morphologies alter gait mechanics and elevate injury risks across the kinetic chain [2]. While custom insoles effectively mitigate these issues by redistributing plantar pressure based on individual morphology [3], their production remains constrained by the necessity for clinical expertise and expensive 3D scanning hardware [4]. Consequently, these financial and technical requirements pose significant barriers to the scalability and accessibility of personalized orthotic solutions.

To address these limitations, we propose a machine learning (ML) framework designed to bridge the gap between high-fidelity clinical data and accessible home-based measurements. In this study, 3D scanning technology is utilized specifically as a standard to establish a high-precision ground truth dataset, ensuring that the ML models are trained on clinically-validated anatomical structures, allowing the system to transition toward predicting these complex parameters using only simple, cost-effective inputs (e.g., basic foot measurement, or using the photo as in [5]) in future applications. To ensure clinical validity, the experimental design and data collection were conducted in collaboration with orthotics and prosthetics ex-

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perts from the National Metal and Materials Technology Center (MTEC), Thailand. This research focuses on developing and evaluating ML models to predict nine essential foot parameters. Through a comprehensive analytical pipeline, we demonstrate the high predictability of these features and evaluate the efficacy of various modeling strategies.

The remainder of this paper is organized as follows. Section 2. reviews related work. Section 3. details the proposed methodology, including data acquisition, ground truth specification, and machine learning strategies for parameter prediction. Section 4. presents and analyzes the experimental results. Finally, Section 5. summarizes key findings and outlines directions for future research.

2. BACKGROUND AND RELATED WORKS

This section presents an overview of existing literature on foot anthropometry, its clinical significance, and the current challenges associated with foot measurement and personalized customization. This review also examines the use of machine learning in biomechanics, with a focus on predictive modeling of human body parameters. By synthesizing prior research, this review aims to establish the foundation for the present study and highlight the specific research gap it seeks to address.

2.1 Clinical significance of foot morphology

The human foot serves as a complex biomechanical system critical for weight-bearing and locomotion [6]. Morphological variations, particularly in the longitudinal arch, significantly impact biomechanical efficiency and injury susceptibility [7]. High arches (*pes cavus*) often exhibit rigidity and diminished shock absorption [8], whereas flat feet (*pes planus*) lead to excessive pronation and kinetic chain disruption, increasing risks for plantar fasciitis and joint degeneration [9].

Effective orthotic design and clinical evaluation depend on precise anthropometric assessment [10]. Key metrics, including foot dimensions, arch height, and heel to metatarsal pressure, are essential for optimizing pressure redistribution and biomechanical stability [11]. Understanding these parameters is therefore fundamental to developing personalized insole solutions that mitigate conditions such as metatarsalgia and diabetic foot ulcers.

2.2 Limitations of foot Measurement and Customization

Despite the established importance of precise foot assessment for personalized interventions, current measurement and customization methodologies face significant challenges regarding accessibility and efficiency. Traditionally, foot morphology has been captured through manual techniques, including calipers,

tapes, Brannock devices, and physical casting [10].

To capture complex three-dimensional contours such as toe alignment, the ball of the foot, and the heel cup—technological advancements have introduced 3D foot scanning and Computer-Aided Design (CAD) frameworks [12, 13]. While these systems improve the precision of foot shape analysis and streamline the translation of digital data into orthotic designs, they remain constrained by high hardware costs and the requirement for specialized technical expertise. Consequently, these financial and operational demands create significant barriers to the scalability and widespread adoption of personalized foot care solutions.

2.3 Machine Learning for anthropometric study

Machine Learning (ML) has transformed predictive analytics in biometrics and clinical diagnostics by identifying non-linear patterns within high-dimensional datasets [14]. While ML is widely applied to general body dimensions, its use in predicting comprehensive foot anthropometry for 3D morphing and orthotic production remains an emerging field.

Foot parameters, including arch height and pressure distribution, are fundamental to gait analysis and orthopedic diagnostics [15, 16]. Automated assessment has transitioned toward ML-based classification using footprint indices for morphology-BMI correlation [17]. Recent image-based algorithms have leveraged mobile camera data to extract feature points for insole profiling, achieving high precision in specific dimensions [5]. However, these 2D approaches often fail to achieve consistent accuracy across all anthropometric dimensions or capture the complex 3D geometry required for full customization.

To enhance accessibility, AI-driven models, including Decision Trees and Neural Networks, have been integrated to optimize 3D-printed orthopedic insoles through generative design [18, 19]. Among these techniques, regression remains a primary method for modeling anthropometric relationships due to its interpretability and capacity to handle diverse morphological patterns. The following subsection details the application of regression techniques in estimating functional body dimensions.

2.4 Regression techniques for anthropometric prediction

Despite advancements in ML-based anthropometry, a significant research gap remains in predicting the comprehensive foot parameters necessary for personalized insole manufacturing using accessible data. This study evaluates various regression techniques to estimate these dimensions, enhancing biomechanical modeling and ergonomic design.

Traditional linear regression has successfully predicted stature from facial and body segment met-

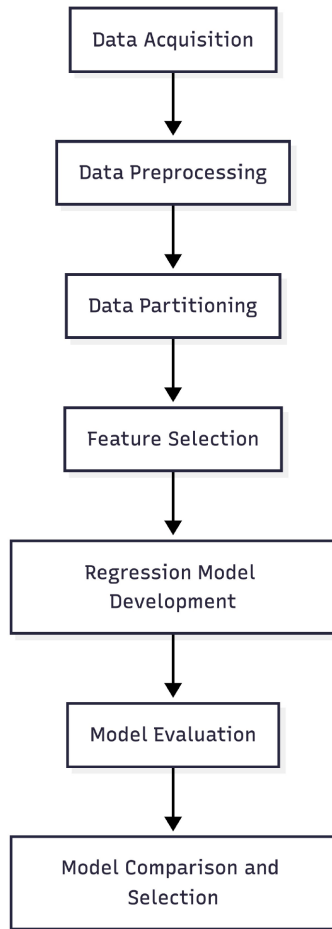


Fig.1: Methodology for foot parameter estimation using Machine Learning-based prediction.

rics [20]. Advanced statistical methods, such as conditional linear regression, further improve precision by leveraging variable covariance [21]. Additionally, regression models facilitate 3D shape reconstruction and the estimation of missing anthropometric data from sparse inputs in forensic and design contexts [22].

Modern ML approaches, such as Random Regression Forests, excel at capturing complex, non-linear relationships. By utilizing depth data, these models achieve robust, real-time anthropometric predictions with minimal error, often surpassing computationally intensive model-fitting by bypassing full 3D reconstruction [23]. Efficacy is further enhanced through multivariate analysis and segment-specific feature selection [24].

While regression is established in general ergonomics, its application to granular foot measurements for orthotics remains underexplored. Addressing this gap, our study develops targeted regression models trained on high-fidelity foot scanner data. The subsequent section details our methodology, including data acquisition, feature engineering, and model architecture.



Fig.2: Foot scanner used in the experiment, operated with expert assistance to ensure reliable and accurate data acquisition.

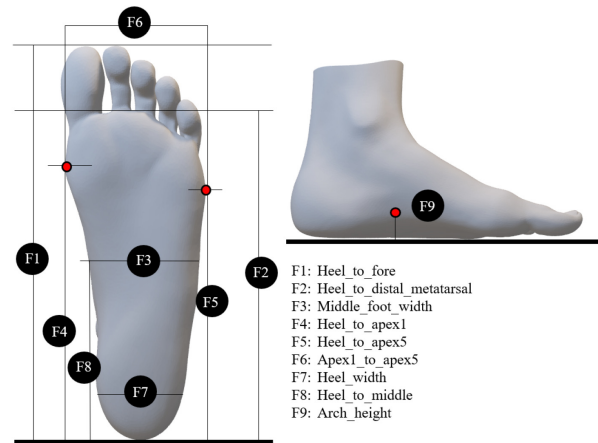


Fig.3: The important feature parameters (F1-F9) used for insole production were retrieved from the expert.

3. THE PROPOSED APPROACH

This section details the development of ML models to identify minimal feature subsets for custom orthotic design. Following a pipeline of correlation-based selection and benchmarking across diverse regression architectures—including linear models, tree-based ensembles, and neural networks—performance was quantified via MSE, MAE, and R^2 to determine optimal configurations for high-precision parameter prediction as shown in Figure 1.

3.1 Data acquisition

The dataset for this study was acquired in collaboration with orthotics and prosthetics experts from the National Metal and Materials Technology Center (MTEC), Thailand, comprising foot parameter measurements from 272 participants. This study received approval from Mahidol University, Thailand with COE No. MU-CIRB 2023/064.2404. The cohort was recruited from the local population via public announcements, with a strategic focus on achieving a balanced representation of diverse foot arch morphologies, including flat feet and high arch feet.

The age distribution was broadly categorized to capture physiological variability: 3 participants aged 60+ years, 26 aged 50-59, 101 aged 40-49, 93 aged 30-39, and 49 aged 20-29. This multi-generational demographic ensures that the resulting models account for age-related variations in foot anthropometry.

Each participant was instructed to position both the left and right feet on the foot scanner as shown in Figure 2. From 272 participants or 544 feet, the distribution of the foot type is 193 high arch feet, 178 normal feet, and 173 flat feet. Figure 3 illustrates the specific locations of 9 insole features we collected, which consist of:

- F1 Heel_to_fore: The foot length or the length from heel to forefoot area
- F2 Heel_to_distal_metatarsal: The length from heel to distal metatarsal head
- F3 Middle_foot_width: The width of the midfoot area
- F4 Heel_to_apex1: The length from heel to apex of 1st metatarsal head
- F5 Heel_to_apex5: The length from heel to apex of 5th metatarsal head
- F6 Apex1_to_apex5: The length from apex of 1st metatarsal head to apex of 5th metatarsal head
- F7 Heel_width: The width of the heel area
- F8 Heel_to_middle: The length from the heel to the midfoot area
- F9 Arch_height: The height of the foot's arch

Experts divided the foot into three functional regions: the forefoot (toes to metatarsals), midfoot (arch), and hindfoot (heel). To identify the apex of the 1st and 5th metatarsal heads, the most distal and prominent points beneath the hallux and the 5th digit were utilized, respectively. These features were also consistent with the other footwear production study.

Apart from these features, we chose to add the Staheli Index (SI) and the Chippaux-Smirak Index (CSI). The calculations for these indices are as follows:

- F10 The Staheli Index (SI) [25]: is calculated by dividing the width of the middle foot by the width of the heel, derived as:

$$SI = \frac{\text{Middle foot width}}{\text{Heel width}} = \frac{F3}{F7} \quad (1)$$

The resulting ratio provides an indication of the arch height, with higher values suggesting a flat foot and lower values indicating a high arch foot.

- F11 The Chippaux-Smirak Index (CSI) [26]: is calculated by dividing the middle foot width by the forefoot width, or to be more precise, the width measured from the apex of 1st metatarsal head (denoted as apex1) to the apex of 5th metatarsal head (denoted as apex5) derived as:

$$CSI = \frac{\text{Middle foot width}}{\text{Length from apex1 to apex5}} = \frac{F3}{F6} \quad (2)$$

Of the initial eleven parameters (F1-F11), the arch index was excluded to eliminate the need for specialized footprint area measurements and complex geometric calculations. This prioritizes directly measurable features, ensuring a more accessible and streamlined predictive framework.

3.2 Data Partitioning and feature selection

The dataset of 544 feet was randomized by treating each foot as a distinct anatomical entity. This methodological decision was substantiated by both professional consultations with orthotics experts and clinical evidence of bilateral asymmetry. Research indicates significant morphological variations between an individual's left and right feet, justifying the treatment of each foot as a unique individual sample to capture the full spectrum of anatomical diversity [27].

The processed data was subsequently partitioned using an 80/20 train-test split. We then calculated the inter-parameter dependencies using the Pearson correlation coefficient. This metric quantifies the linear relationship between two variables, x and y , and is defined as:

$$r_{xy} = \frac{\sum_{i=1}^n (x_i - \bar{x})(y_i - \bar{y})}{\sqrt{\sum_{i=1}^n (x_i - \bar{x})^2 \sum_{i=1}^n (y_i - \bar{y})^2}} \quad (3)$$

where r_{xy} is the correlation coefficient between two input datasets x and y ranged from -1 and 1, n is the size of sample, and x_i and y_i are the inputs of each dataset.

Python-based correlation analysis was performed exclusively on the 80% training set to identify dependencies with foot arch height while preventing data leakage. To enhance model robustness, outliers were subsequently removed using the Isolation Forest algorithm [28]. This unsupervised approach isolates anomalies through recursive partitioning, identifying distinct observations by their shorter path lengths compared to nominal data.

3.3 Regression model training

We employed nine off-the-shelf machine learning algorithms for the regression tasks, a selection consistent with previous comparative studies in anthropometric and biomechanical prediction [29-31]. These models span various computational strategies: traditional Linear Regression [32], hierarchical Decision Tree Regression [33], and regularized linear models including Lasso [34], Ridge [35], and ElasticNet [36]. Additionally, we utilized Support Vector Regression (SVR) [37] for margin maximization, and connectionist approaches via Neural Network Regression [38] to

capture non-linear dependencies. Ensemble methods, specifically XGBoost [39] and Random Forest Regression [40], were also integrated to mitigate overfitting and enhance generalization through sequential boosting and bagging strategies, respectively. All models were implemented in Python, leveraging its extensive ecosystem for high-performance data analytics.

3.4 Evaluation measures

Model performance was evaluated using three standard regression metrics to provide a comprehensive assessment of predictive accuracy and variance explanation:

- **Mean Square Error (MSE):** quantifies the average squared discrepancy between predicted and actual values, penalizing larger outliers more heavily.
- **Mean Absolute Error (MAE):** represents the average magnitude of prediction errors in the same units as the target parameters (cm), offering a direct measure of clinical precision
- **R^2 :** indicates the proportion of variance in the dependent variable predictable from the independent features, where a value of 1.0 represents a perfect fit.

Superior model performance is characterized by minimized MSE and MAE values, signifying higher predictive fidelity. Conversely, R^2 values approaching unity indicate that the model effectively captures the underlying morphological relationships within the dataset.

4. RESULTS AND DISCUSSION

This section evaluates ML models for foot parameter prediction, progressing from correlation-driven feature selection to regression benchmarking via R^2 scores and empirical validation. By comparing predicted versus empirical values across diverse feature subsets, we identify optimal configurations and provide a granular analysis of high-correlation features for each foot parameter.

4.1 Foot features correlation and analysis

Correlation coefficients (Figure 4) revealed a dominant cluster—comprising F1, F2, F3, F4, F6, and F8—with strong positive correlations ($|r| > 0.90$). This high collinearity suggests redundant anatomical constructs, necessitating the mitigation of multicollinearity during modeling. Conversely, the Staheli Index (SI) and Chippaux-Smirak Index (CSI) exhibited distinct, weaker relationships, capturing morphological dimensions divergent from the primary cluster. Based on these patterns, experiments were partitioned into subgroups to systematically evaluate the impact of diverse feature sets on model performance.

The experimental design followed an iterative feature selection strategy based on varying correlation thresholds. The specific feature sets and their associated correlation values are detailed in Tables 1-9.

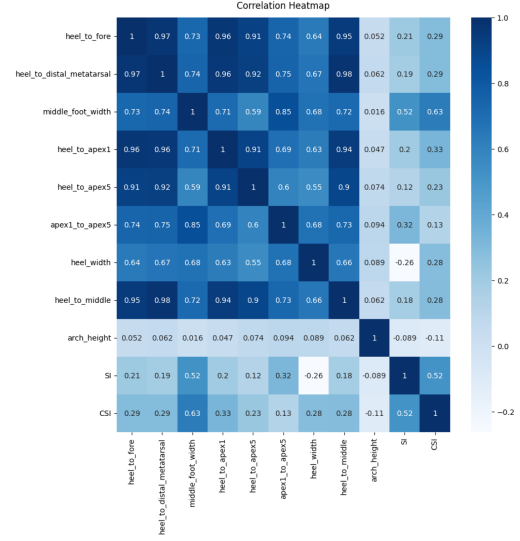


Fig.4: The heatmap illustrates the correlation coefficients among the 11 foot feature parameters.

Table 1: Feature set for the foot length (F1) estimation

Feature set	F2	F3	F4	F5	F6	F7	F8	F9	F10	F11
All	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Corr05	✓	✓	✓	✓	✓	✓	✓			
Corr07	✓	✓	✓	✓	✓		✓			
Corr09	✓		✓	✓			✓			

Feature selection thresholds utilized standard benchmarks ($|r| > 0.5, 0.7, 0.9$) derived from established statistical guidelines in medical research and machine learning [41, 42]. However, for F3 and F6 (Table 3 and Table 6, a 0.8 threshold was adopted as no predictors reached the 0.9 criterion, ensuring a balance between dimensionality reduction and information retention. For high-stochasticity targets like arch height (F9), thresholds were empirically lowered to 0.05–0.09. This exploratory measure, aligned with the granular increments of standard scales, aimed to capture latent morphological influences that would otherwise be excluded, ensuring the framework remained sensitive to the unique variance of each parameter.

Specifically, since F10 and F11 are derived features—calculated from F3, F7 (Equation 1) and F3, F6 (Equation 2), respectively—they were systematically excluded from the predictor sets of their constituent variables. This exclusion prevents data leakage and ensures model integrity by maintaining independence between the target parameters and their derived indices.

Table 2: Feature set for the length from heel to distal metatarsal head (F2) estimation

Feature set	F1	F3	F4	F5	F6	F7	F8	F9	F10	F11
All	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Corr05	✓	✓	✓	✓	✓	✓	✓			
Corr07	✓	✓	✓	✓	✓		✓			
Corr09	✓		✓	✓			✓			

Table 3: Feature set for the width of the midfoot area (F3) estimation

Feature set	F1	F2	F4	F5	F6	F7	F8	F9	F10	F11
All	✓	✓	✓	✓	✓	✓	✓	✓		
Corr05	✓	✓	✓	✓	✓	✓	✓			
Corr07	✓	✓	✓		✓		✓			
Corr08					✓					

Table 4: Feature set for the length from heel to apex of 1st metatarsal head (F4) estimation

Feature set	F1	F2	F3	F5	F6	F7	F8	F9	F10	F11
All	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Corr05	✓	✓	✓	✓	✓	✓	✓			
Corr07	✓	✓	✓	✓			✓			
Corr09	✓	✓		✓			✓			

4.2 Initial regression model performance (R² analysis)

Nine regression architectures were evaluated using 10-fold cross-validation to mitigate overfitting and ensure generalizability. Training results are summarized in Figure 5, with R² serving as the primary metric for identifying optimal feature-model configurations. Notably, Table 10 is analyzed independently due to the characteristically low feature correlations inherent to that specific parameter.

Most parameters (F1–F8) demonstrated robust explanatory power, with R² often exceeding 0.90. Notably, F2 achieved R² = 0.993 via Random Forest (‘All’ or ‘Corr09’ sets), while F8 maintained high stability (R² > 0.96) using Linear Regression. This performance divergence underscores the mix of linear and non-linear dependencies in foot morphology. Conversely, arch height (F9) yielded consistently negative R² values (peaking at -0.026 via SVR, ‘All’), indicating that current features are insufficient to outperform a simple mean-based baseline (Table 10). This R² screening identifies high-performing configurations for subsequent granular validation.

4.3 Detailed performance assessment of selected models

Following preliminary R² evaluation, Figure 6 illustrates comprehensive performance metrics (MSE,

Table 5: Feature set for the length from heel to apex of 5th metatarsal head (F5) estimation

Feature set	F1	F2	F3	F4	F6	F7	F8	F9	F10	F11
All	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Corr05	✓	✓	✓	✓	✓	✓	✓			
Corr07	✓	✓		✓			✓			
Corr09	✓	✓		✓			✓			

Table 6: Feature set for the length from apex of 1st metatarsal head to apex of 5th metatarsal head (F6) estimation

Feature set	F1	F2	F3	F4	F5	F7	F8	F9	F10	F11
All	✓	✓	✓	✓	✓	✓	✓	✓		
Corr05	✓	✓	✓	✓	✓	✓	✓			
Corr07	✓	✓	✓				✓			
Corr08			✓							

Table 7: Feature set for the width of the heel area (F7) estimation

Feature set	F1	F2	F3	F4	F5	F6	F8	F9	F10	F11
All	✓	✓	✓	✓	✓	✓	✓	✓		✓
Corr05	✓	✓	✓	✓	✓	✓	✓			

Table 8: Feature set for the length from the heel to the midfoot area (F8) estimation

Feature set	F1	F2	F3	F4	F5	F6	F7	F9	F10	F11
All	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Corr05	✓	✓	✓	✓	✓	✓	✓			
Corr07	✓	✓	✓	✓	✓	✓				
Corr09	✓	✓		✓	✓					

MAE, and R²) for optimal configurations across F1–F9. The models demonstrated robust predictive accuracy for most parameters, notably F2, which achieved an exceptional MAE of 0.011 cm and R² of 0.989 (Random Forest, ‘Corr09’). Similarly, F8 reported an MAE of 0.012 cm and R² of 0.990 (Linear, ‘Corr07’). Other dimensions, including F1 (XGBoost, ‘Corr07’), F4 (Linear, ‘Corr05’), F5 (Neural Network, ‘Corr05’), and F6 (SVR, ‘Corr05’), yielded strong R² values of 0.936, 0.926, 0.856, and 0.721, respectively.

In contrast, arch height (F9) presented significant modeling challenges, consistently yielding high errors (MAE up to 0.518 cm for Linear, ‘All’) and poor explanatory power, with a peak R² of only 0.108 (SVR, ‘All’). Negative R² values for F9 further indicate that model performance was inferior to a simple mean-based baseline, aligning with the large prediction variances reported across other metrics. These findings facilitated the selection of optimal regression frameworks, leading to the subsequent sample-level comparison of predicted versus ground-truth values.

Table 9: Feature set for the height of the foot’s arch (F9) estimation

Feature set	F1	F2	F3	F4	F5	F6	F7	F8	F10	F11
All	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Corr005	✓	✓			✓	✓	✓	✓		
Corr007					✓	✓	✓			

Table 10: Model training results (R² values) for feature parameters F9 using regression models, using sets of input features selected based on Table 9.

Regressor	Feature set		
	All	Corr005	Corr007
F9 Prediction			
Linear	-0.113	-0.177	-0.126
Decision Tree	-7.666	-0.179	-0.254
Lasso	-0.075	-0.163	-0.122
Ridge	-0.056	-0.123	-0.116
ElasticNet	-0.068	-0.110	-0.117
Neural Network	-0.199	-0.146	-0.145
SVR	-0.026	-0.103	-0.098
XGBoost	-0.423	-1.000	-1.017
Random Forest	-0.341	-0.455	-0.658

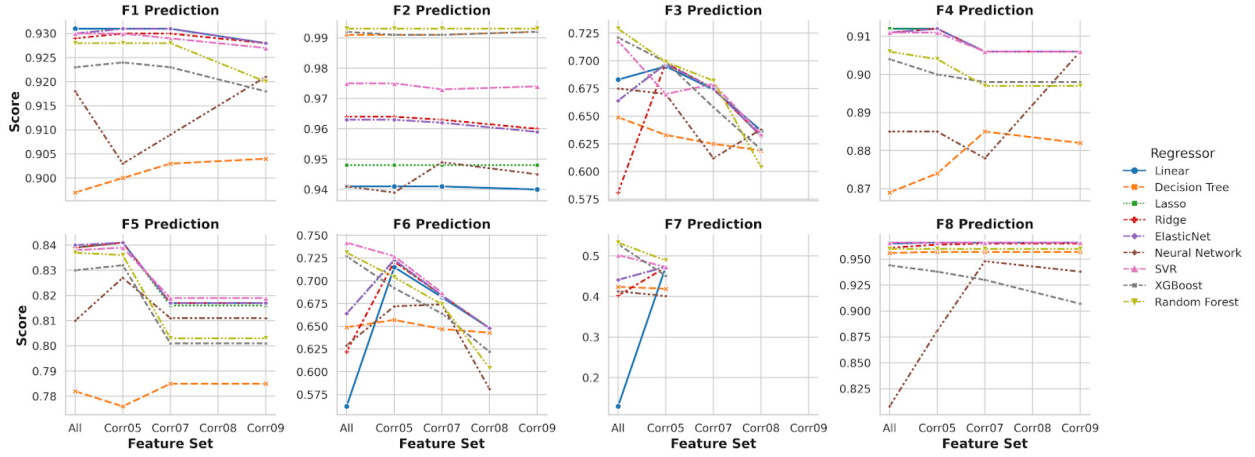


Fig.5: Model training results (R^2 values) for feature parameters F1-F8 using regression models. Only R^2 is reported here as a preliminary evaluation; additional performance metrics are applied in subsequent analyses.

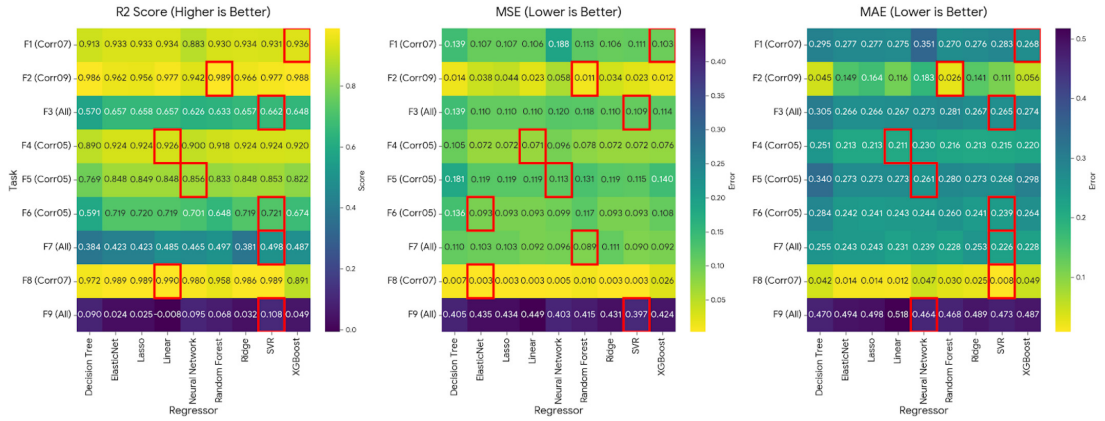


Fig.6: Model testing results for feature parameters F1-F9 using regression models. The highlighted red boxes denote the optimal performance achieved for each respective feature across the evaluated regression architectures.

4.4 Individual prediction performance on test data

Statistical summaries in Table 11 reveal high-fidelity predictions for F8 (0.012 cm, Linear, ‘Corr07’) and F2 (0.026 cm, Random Forest, ‘Corr09’), indicating superior model fidelity for these dimensions. These aggregate findings are corroborated by sample-level comparisons in Figure 7, where deviations for F2 and F8 are frequently confined to the third decimal place (< 0.1 cm), validating the robustness of the selected architectures. The diversity of optimal regressors—including XGBoost, Random Forest, SVR, Linear, and Neural Networks—underscores the heterogeneous predictive characteristics inherent to each foot parameter.

Conversely, arch height (F9) remains a significant challenge; Table 11 reports a peak average error of 0.473 cm (SVR, ‘All’), while Figure 7 exposes localized discrepancies as high as 1.567 cm (Sample 4). Such results underscore the inherent stochasticity and complexity of modeling 3D arch morphology

compared to longitudinal dimensions.

The optimal hyperparameters for these highest performing models, as determined during the tuning phase, are as follows:

- **F1 (XGBoost):** `colsample_bytree: 0.7;`
`learning_rate: 0.1;` `max_depth: 3;`
`n_estimators: 100;` `subsample: 0.9`
 - **F2 (Random Forest):** `max_depth: 20;`
`min_samples_leaf: 2;` `min_samples_split: 2;`
`n_estimators: 100`
 - **F3 (SVR):** `C: 10.0;` `epsilon: 0.001;` `kernel: rbf`
 - **F4 (Linear Regression):** `copy_X: True;`
`fit_intercept: False;` `n_jobs: 1;` `positive: False`
 - **F5 (Neural Network):** `activation: relu;`
`alpha: 0.1;` `hidden_layer_sizes: (50; 50)`
 - **F6 (SVR):** `C: 0.1;` `epsilon: 0.1;` `kernel: poly`
 - **F7 (SVR):** `C: 10.0;` `epsilon: 0.01;` `kernel: linear`
 - **F8 (Linear Regression):** `copy_X: True;`
`fit_intercept: False;` `n_jobs: 1;` `positive: True`
 - **F9 (SVR):** `C: 100.0;` `epsilon: 0.001;` `kernel: rbf`
- These specific configurations enabled the models

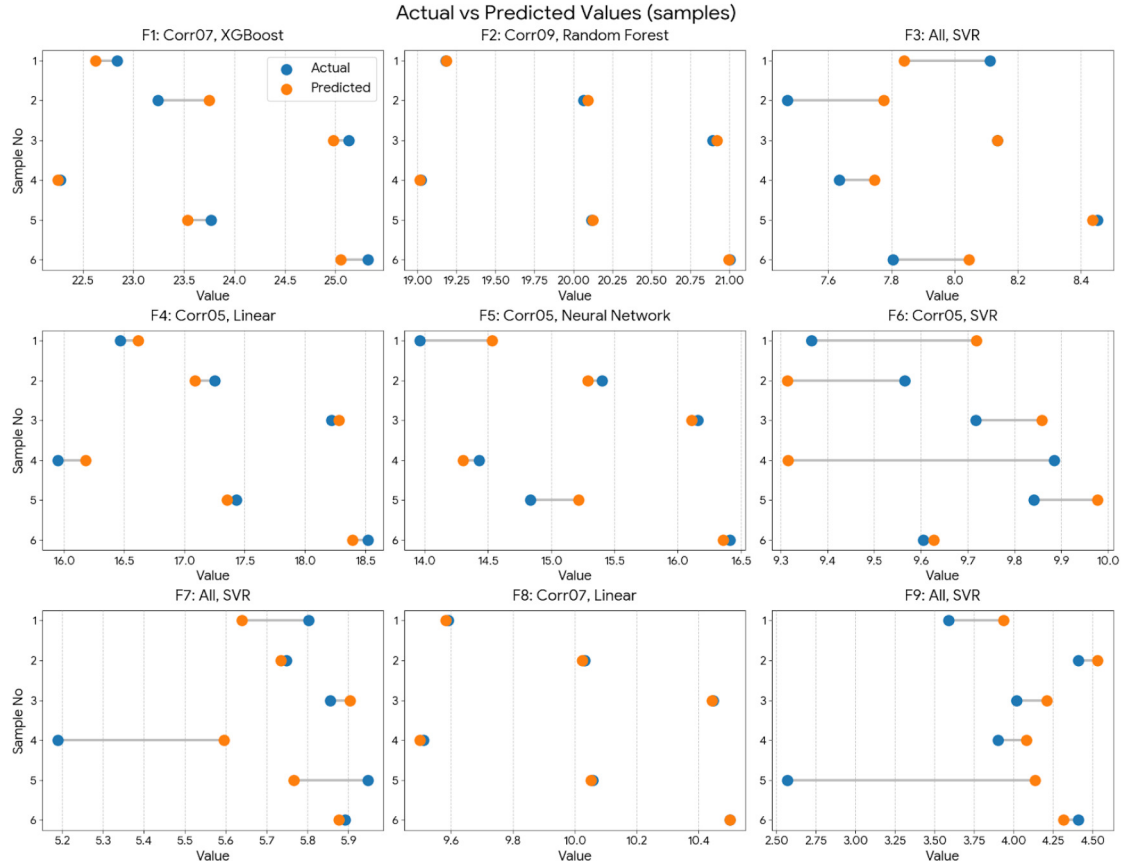


Fig.7: Comparison of predicted versus ground truth values (cm) for six test instances, utilizing the optimal feature set and regression model.

Table 11: Overall statistical results for the prediction of foot feature parameters using the most effective feature sets and regression models based on the list in Tables 1-9.

Target	Feature set	Regressor	Differences (cm)		
			Max	Min	Average
F1	Corr07	XGBoost	0.794	0.001	0.268
F2	Corr09	Random Forest	0.989	0.000	0.026
F3	All	SVR	1.012	0.000	0.249
F4	Corr05	Linear	0.617	0.000	0.211
F5	Corr05	Neural Network	0.977	0.011	0.261
F6	Corr05	SVR	0.844	0.007	0.239
F7	All	SVR	0.947	0.002	0.226
F8	Corr07	Linear	0.492	0.000	0.012
F9	All	SVR	2.176	0.009	0.473

to achieve the reported performance. The effectiveness of specific feature selection strategies, particularly those based on high correlation thresholds, warrants further detailed examination.

4.5 Performance evaluation with Corr09 feature set

The Corr09 feature set ($|r| > 0.9$) was utilized to evaluate predictive performance, focusing on parameters with high correlation. As detailed in Table 12, this subset maintains robust accuracy across most parameters. Linear Regression for F8 achieved the

Table 12: Overall statistical results using the Corr09, which includes feature parameters with correlation coefficients greater than 0.9.

Target	Feature set	Regressor	Differences (cm)		
			Max	Min	Average
F1	Corr09	XGBoost	0.862	0.006	0.285
F2	Corr09	Random Forest	0.989	0.000	0.026
F4	Corr09	Linear	0.670	0.001	0.221
F5	Corr09	Neural Network	1.106	0.001	0.302
F8	Corr09	Linear	0.492	0.000	0.012

Table 13: The prediction results obtained using linear regression models across all foot feature parameters with correlation coefficients greater than 0.9.

Target	Feature set	Regressor	Differences (cm)		
			Max	Min	Average
F1	Corr09	Linear	0.754	0.003	0.284
F2	Corr09	Linear	0.463	0.002	0.116
F4	Corr09	Linear	0.670	0.001	0.221
F5	Corr09	Linear	1.066	0.005	0.294
F8	Corr09	Linear	0.492	0.000	0.012

lowest average residual (0.012 cm), followed by Random Forest for F2 (0.026 cm), consistent with global optima in Table 11. Other longitudinal dimensions (F1, F4, F5) yielded competitive average residuals (0.221-0.302 cm) across XGBoost, Linear, and Neural Network models, with a maximum deviation of

Table 14: Summary of key features utilized for prediction. The symbols indicate included features, where $\bullet$ denotes primary predictors and $\blacktriangle$ identifies features with a mean(|SHAP|) value below 5% of the maximum importance.

Features	F1	F2	F3	F4	F5	F6	F7	F8	F9	F10	F11
F1											
F2	$\bullet$										
F3	$\blacktriangle$	$\blacktriangle$									
F4	$\blacktriangle$	$\blacktriangle$	$\blacktriangle$								
F5	$\blacktriangle$	$\blacktriangle$	$\blacktriangle$	$\blacktriangle$							
F6	$\blacktriangle$	$\blacktriangle$	$\blacktriangle$	$\blacktriangle$							
F7	$\blacktriangle$	$\blacktriangle$	$\blacktriangle$	$\bullet$	$\bullet$	$\blacktriangle$					
F8	$\bullet$	$\blacktriangle$	$\bullet$	$\bullet$	$\bullet$	$\bullet$					
F9	$\blacktriangle$	$\blacktriangle$	$\blacktriangle$	$\blacktriangle$	$\blacktriangle$	$\blacktriangle$	$\blacktriangle$	$\blacktriangle$		$\blacktriangle$	$\bullet$

1.106 cm for F5. These results validate that high-correlation subsets can achieve performance parity with exhaustive datasets, justifying the investigation of simplified architectures like Linear Regression in constrained feature contexts.

4.6 Justification for Linear Regression model with Corr09 feature set

Analyses conducted within the high-correlation subset ($|r| > 0.9$) underscore the clinical viability of Linear Regression despite its structural simplicity. Data summarized in Table 13 indicate that this architecture maintains high fidelity for F8 (0.012 cm) and F4 (0.221 cm), effectively matching the global optima reported in Table 11.

Furthermore, Linear Regression yielded competitive average residuals for F1 (0.284 cm) and F5 (0.294 cm), slightly outperforming alternative regressors under the ‘Corr09’ constraint. Conversely, a significant performance divergence was observed for F2; compared to the 0.026 cm residual achieved by Random Forest (Table 12), the Linear model produced a notably higher residual of 0.116 cm.

This discrepancy highlights that while high correlation provides a robust baseline, the selection of regressor architecture remains critical—specifically, tree-based ensembles appear necessary to capture the non-linear dependencies inherent in F2 morphology.

4.7 Overview of features, predictability, and optimal feature sets

This subsection evaluates the predictive performance for the nine foot parameters (F1-F9) based on training R^2 values (Figure 5, and Table 10), testing metrics (MSE, MAE, R^2 ; Figure 6), and aggregated statistical residuals (Tables 11-13). Based on these results, parameters are categorized into four distinct performance tiers:

- **Highly Predictable Features (F2, F8):** These features exhibited exceptional accuracy with test $R^2 > 0.99$ and negligible MAE. The stability of these models suggests linear or easily captured non-linear dependencies, making them highly reliable for orthotic customization.

- **Well Predictable Features (F1, F4, F5):** This group demonstrated robust predictability, generally achieving $R^2 > 0.86$. These results indicate effective capturing of underlying morphological relationships, though with slightly higher complexity than the first tier.

- **Moderately Predictable Features (F3, F6):** These features yielded useful but inconsistent results, with R^2 values typically ranging from 0.65 to 0.72. This performance suggests inherent anatomical variability or limitations in the current feature set’s ability to fully explain their variance.

- **Challenging Features (F7, F9):** Accuracy for these parameters was low ($R^2 < 0.5$ for F7) or negligible/negative (F9). Their high stochasticity and intricate definitions suggest a need for alternative data sources or more sophisticated non-linear architectures.

Notably, arch height (F9) required the full 11-feature set yet yielded negligible predictive power ($R^2 < 0.11$). This suggests F9 is a volumetric attribute influenced by internal bone alignment and soft tissue dynamics, which are not captured by surface-level 2D metrics. Consequently, while our framework excels in longitudinal dimensions, F9 remains a significant limitation, necessitating direct measurement or 3D-volumetric analysis for arch-specific customization.

4.8 Feature contribution analysis Using SHAP

To provide a more granular understanding of the decision-making mechanisms within the high-performing models, an interpretability analysis was conducted using the SHapley Additive exPlanations (SHAP) framework [43] among 9 models in Table 11 and 5 models in Table 12.

SHAP analysis reveals that longitudinal foot measurements exert the most significant predictive influence. F2 emerges as a primary predictor across multiple models, particularly for F1 (mean(|SHAP|) ≈ 0.405) and F8 (mean(|SHAP|) ≈ 0.397). A dominant reciprocal relationship is observed between F8 and F2 (mean(|SHAP|) ≈ 0.78), while distal features like F4 and F5 contribute minimally (≤ 0.01). These results underscore a strong structural coupling within the longitudinal foot dimension.

Regarding distal landmarks, F1 is the principal driver for predicting F4 (≈ 0.40), with F2 maintaining secondary importance. Transverse and structural parameters, such as F6 and F3, exhibit moderate interactions, suggesting a stable predictive link between longitudinal and transverse morphological dimensions.

Under a stricter correlation threshold ($|r| > 0.9$, Table 12), SHAP importance becomes more concentrated, with F2 and F8 dominating the predictive architecture. For instance, F8 remains the nearly exclusive predictor for F2 (mean(|SHAP|) ≈ 0.78), whereas secondary features show negligible influence.

This filtering emphasizes that a limited set of heel-referenced longitudinal measurements accounts for most of the variance in plantar landmarks, effectively isolating the primary morphological structure from minor variations.

Further experiments were conducted by applying a selection criterion where features with a mean $\text{mean}(|\text{SHAP}|) < 5\%$ of the maximum SHAP importance in each model were identified. Empirical results demonstrated that filtering features with this threshold yielded performance comparable to the original results, indicating that features with negligible contributions could be omitted without loss of predictive integrity. Results are summarized in Table 14.

5. CONCLUSION AND FUTURE WORK

This study evaluated nine regression architectures—ranging from linear and regularized models to ensemble and neural networks—to predict essential foot parameters (F1-F9) for personalized insole manufacturing. Through iterative correlation-based selection of 11 primary features, we established optimal subsets and rigorously benchmarked model performance. The analytical pipeline integrated R^2 , MSE, and MAE metrics with sample-level empirical validation across diverse algorithmic strategies to identify the most effective predictive configurations.

5.1 Discussion and limitation

The findings demonstrate high predictability for specific foot parameters, particularly the midfoot length (F8) and heel to distal metatarsal head length (F2), which achieved minimal average residuals (0.012 cm and 0.026 cm, respectively) and R^2 values up to 0.99. Strong predictive accuracy ($R^2 > 0.85$) was also observed for foot length (F1) and lengths to the apex of 1st (F4) and 5th (F5) metatarsal head apices. Notably, the top-performing predictors (F1, F2, F4, F5, and F8) are primarily longitudinal measurements, suggesting that longitudinal dimensions provide more robust predictive value than horizontal or volumetric metrics in foot modeling. Our evaluation also revealed that while Linear Regression is optimal for certain parameters (F4, F8), complex non-linear architectures like Random Forest are indispensable for others (F2), even when restricted to high-correlation subsets ($|r| > 0.9$).

Conversely, heel width (F7) and arch height (F9) proved more challenging, characterized by lower R^2 values and higher error margins. This divergence highlights the influence of feature selection; under the strict $|r| > 0.9$ filtering criterion, optimal input sets ranged from concise 4-feature subsets for F2 to a full 11-feature configuration for F9. Strategic exclusion of derived features (F10, F11) was essential to prevent data leakage and maintain model integrity. Furthermore, by employing SHAP (SHapley Additive ex-Planations), we were able to further perform feature

reduction in certain cases. For instance, the relationship between F2 and F8 was found to be nearly 1:1 (highly collinear), allowing us to streamline the feature set without losing significant predictive power.

However, the predictive performance for arch height (F9) was anticipated, as initial feature screening consistently revealed weak correlation trends ($|r| < 0.1$) with the available anthropometric predictors. This inherent difficulty in modeling arch height is corroborated by clinical literature, which emphasizes that arch height cannot be predicted by biomechanical variables but instead emerges from the interaction of several structural and functional factors, including plantar pressure distribution, postural stability, and lower-limb alignment [27].

5.2 Future directions and integration

While minimizing predictive error remains a primary objective, clinical and manufacturing workflows operate within established tolerance bounds. For practical context, standard footwear sizing increments—approximately 0.67 cm for the Paris Point system and 0.85 cm for full UK/US sizes—provide a critical benchmark for evaluating predictive accuracy. By maintaining a mean absolute error (MAE) consistently below the 0.5 cm threshold, our framework ensures that predictions remain well within a single size interval. This level of precision, established in consultation with field experts, is sufficient to prevent functional misfits in custom orthotics, as minor discrepancies can be effectively managed through material compression and padding during the manufacturing process. Furthermore, this accuracy aligns with the measurement variability reported in [44], where methodological discrepancies ranged from 0.06 to 0.43 cm, confirming that our machine learning approach matches the reliability of conventional clinical instruments. In addition, our predictive models offer a cost-effective alternative to expensive 3D scanning hardware, providing a foundation for scalable, automated production of assistive devices.

This study directly synergizes with the image-based methodologies in [5]. While previous research identified accuracy limitations in certain 2D-derived parameters, integrating our robust predictive insights into such image-processing pipelines can substantially enhance the fidelity of digital foot models without requiring 3D measurement values. Furthermore, the suboptimal prediction of arch height (F9) in this study suggests that augmenting our framework with alternative data sources—such as the image-based estimation from [5]—could potentially address current stochastic variances.

Future exploration should focus on ensemble architectures and the integration of dynamic gait data. By combining high-fidelity parameter prediction with parameter-driven 3D morphing tech-

niques [45, 46], we can streamline digital workflows, enabling hardware-independent, precise clinical assessments for diverse populations.

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AUTHOR CONTRIBUTIONS

Conceptualization, W.Saw., J.Kra., P.Pra., and P.Pan.; methodology, W.Saw., and P.Pan.; software, W.Saw.; validation, W.Saw., J.Kra., and P.Pan.; formal analysis, W.Saw., J.Kra., P.Pra., and P.Pan.; investigation, W.Saw., J.Kra., and P.Pan.; data curation, W.Saw., P.Pra., and P.Pan.; writing—original draft preparation, W.Saw. and P.Pan.; writing—review and editing, W.Saw., J.Kra., P.Pra., and P.Pan.; visualization, W.Saw. and P.Pan.; supervision, W.Saw.; funding acquisition, W.Saw. All authors have read and agreed to the published version of the manuscript.

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