MULTI-PARAMETRIC ANALYSIS OF BREAST COMPRESSION IN FULL-FIELD DIGITAL MAMMOGRAPHY: DOSIMETRIC MODELING AND MACHINE LEARNING-BASED PAIN TOLERANCE CLASSIFICATION

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Abstract – **To develop and evaluate multiparametric models relating breast compression, mean glandular dose (MGD), and patient-reported pain tolerance in full-field digital mammography (FFDM) using multivariable regression and machine-learning techniques. A retrospective dataset comprising 208 women examined with a Fujifilm Amulet Innovality FFDM system operating under automatic exposure control was analyzed. Demographic, anatomical, mechanical, acquisition and dosimetric variables were included. To improve model training, a balanced synthetic dataset (n = 468) was generated. MGD was modeled using Linear Regression, third-order Polynomial Regression, and Gaussian Process Regression (GPR) with a Matérn 5/2 kernel. Correlation analysis and Principal Component Analysis (PCA) were performed to characterize variable relationships and reduce dimensionality. Pain tolerance was classified into three categories using supervised machine-learning algorithms evaluated by five-fold cross-validation and independent external validation. MGD showed its strongest association with tube current–time product (mAs) (r = 0.96), followed by tube voltage (r = 0.53) and compressed breast thickness (r = 0.52), whereas compression force exhibited only a weak correlation (r = 0.14). The multivariable GPR model achieved the highest predictive performance (R^2 = 0.687; RMSE = 0.410 mGy) and demonstrated agreement during external validation (R^2 = 0.950; RMSE = 0.168 mGy). For pain-tolerance classification, Fine KNN showed the highest cross-validation accuracy (86.5%), whereas Ensemble Bagged Trees demonstrated the most consistent performance across internal and external validation. MGD is determined by the combined effects of breast anatomy, mechanical characteristics, and acquisition parameters rather than by any single variable. GPR enabled accurate patient-specific dose estimation, while Ensemble Bagged Trees provided the most robust prediction of pain tolerance. These findings support the development of personalized mammographic protocols that jointly optimize radiation dose, image quality, and patient comfort.**

Keywords- **Full-field digital mammography; Mean glandular dose; Breast compression; Gaussian Process Regression; Machine learning; Pain tolerance.**

I. INTRODUCTION

Breast cancer remains one of the most frequently diagnosed malignancies worldwide, and mammographic screening plays a central role in early detection and mortality reduction [1,2]. Full-field digital mammography (FFDM) is widely used in both screening and diagnostic, where optimization of image quality and radiation exposure remains a fundamental objective [3].

Breast compression is an essential component of FFDM because it reduces tissue overlap, improves image quality, minimizes motion artifacts, and optimizes radiation dose by decreasing breast thickness and improving exposure efficiency [3,4]. However, it is also the main source of patient discomfort and may negatively affect the patient experience and participation in breast cancer screening programs [5,6].

Mean glandular dose (MGD), the standard dosimetric quantity for mammography, is influenced by multiple factors, including breast thickness, tissue composition, compression parameters, tube voltage (kVp), and tube current–time product (mAs) [4]. Similarly, pain perception during mammographic compression is a multifactorial process influenced by anatomical, mechanical, and patient-related variables, although the combined contribution of these factors remains incompletely understood [5,6].

The interaction among breast anatomy, compression, acquisition parameters, and patient response is difficult to characterize using conventional statistical approaches. Machine-learning techniques provide an effective framework for modeling complex nonlinear relationships and identifying interactions that may not be captured by traditional methods [7].

This study aimed to perform a multiparametric analysis of breast compression in FFDM by investigating relationships among anatomical, mechanical, and acquisition variables using correlation analysis and Principal Component Analysis (PCA); developing multivariable regression models for MGD estimation; and evaluating supervised machine-learning algorithms for predicting patient-reported pain tolerance.

II. MATERIALS AND METHODS

Study Dataset

A retrospective dataset comprising 208 women who underwent FFDM examinations using a Fujifilm Amulet Innovality system operating under automatic exposure control (AEC) was analyzed. Recorded variables included age, compressed and uncompressed breast thickness, compression force, compression percentage, kVp, mAs, breast type, chest wall-to-nipple distance, and MGD.

Patient-reported pain tolerance was categorized into three levels (low, moderate, and high), and breast type was encoded into three tissue-composition classes.

Data Preprocessing

Class imbalance was addressed using a customized Synthetic Minority Oversampling Technique (SMOTE) applied exclusively to the training data within each five-fold cross-validation split. Synthetic samples were generated using k-nearest-neighbor interpolation with controlled Gaussian perturbations while preserving clinically plausible ranges and physically consistent relationships among variables. Test sets remained unchanged to prevent information leakage.

Pain-Tolerance Classification

Supervised machine-learning algorithms were initially performed using the MATLAB Classification Learner toolbox. Based on five-fold cross-validation performance, the three best-performing classifiers: Fine KNN, Ensemble Bagged Trees, and KNN with PCA, were selected for detailed evaluation.

Performance was assessed using five-fold cross-validation (80% training and 20% testing). Feature normalization parameters were estimated from the training data and applied to the corresponding test set. SMOTE was applied only to the training subset of each fold. Classification performance was evaluated using accuracy, precision, recall, F1-score, and confusion matrices.

Correlation Analysis and Principal Component Analysis

Pearson correlation coefficients were calculated to evaluate relationships among anatomical, mechanical, acquisition, and dosimetric variables.

PCA was performed after z-score standardization to characterize the multivariate structure of the dataset, evaluate variable contributions, and generate PCA-derived predictors. The first five principal components were retained for regression modeling.

Dosimetric Regression Modeling

Three predictor configurations were evaluated:

- Dance Model: compressed breast thickness, mAs, kVp, and breast type.
- Full Model: age, compressed and uncompressed breast thickness, compression force, mAs, kVp, chest wall-to-nipple distance, and breast type.
- PCA Model: the first five principal components derived from the Full Model predictors.

Each predictor configuration was evaluated using Linear Regression (LR), third-order Polynomial Regression (Poly3), and GPR with a Matérn 5/2 kernel. Predictive performance was assessed using five-fold cross-validation with R^2 and RMSE.

External Validation

Model generalization was evaluated using an independent dataset of 30 FFDM examinations acquired with the same mammography system. Following model selection, the optimal regression models were retrained using the complete development dataset and applied to the external cohort. Performance was quantified using R^2, RMSE and measured-versus-predicted MGD comparisons.

III. RESULTS

Correlation Analysis

Pearson correlation analysis identified mAs as the variable most strongly associated with MGD ($r = 0.96$), followed by kVp ($r = 0.53$), compressed breast thickness ($r = 0.52$), and uncompressed breast thickness ($r = 0.45$) (Figure 1). In contrast, compression force showed only a weak correlation with MGD ($r = 0.14$).

Compressed breast thickness was strongly correlated with kVp ($r = 0.93$), mAs ($r = 0.56$), and uncompressed breast thickness ($r = 0.85$), reflecting the expected behavior of the AEC system.

Overall, MGD was primarily influenced by breast geometry and acquisition parameters, whereas demographic and mechanical variables had limited effects.

Principal Component Analysis

The first three principal components (PC1–PC3) explained 76.2% of the total variance, while the first five components accounted for 92.6%, indicating that most dataset variability was preserved in a reduced-dimensional space. PC1 was primarily associated with breast thickness and acquisition parameters, PC2 with anatomical and mechanical variables, and PC3 with breast tissue composition (Figure 2).

PCA Projection

The three-dimensional PCA projection (Figure 3) showed substantial overlap among pain-tolerance categories, with no distinct class separation despite the high proportion of explained variance. These findings indicate that linear combinations of the original variables were insufficient to discriminate pain-tolerance levels, supporting the use of nonlinear machine-learning methods.

Dosimetric Regression Modeling

Three dosimetric predictor configurations were evaluated using five-fold cross-validation (Table 1): the Dance Model (compressed breast thickness, mAs, kVp, and breast type), the Full Model (eight anatomical and acquisition variables), and the PCA Model (the first five principal components).

The Full Model achieved the highest predictive accuracy, with GPR achieving the best performance ($R^2 = 0.687$; RMSE = 0.410 mGy). The Dance Model performed similarly ($R^2 = 0.681$; RMSE = 0.414 mGy), whereas the PCA Model showed lower accuracy, suggesting that dimensionality reduction removed information relevant for dose estimation.

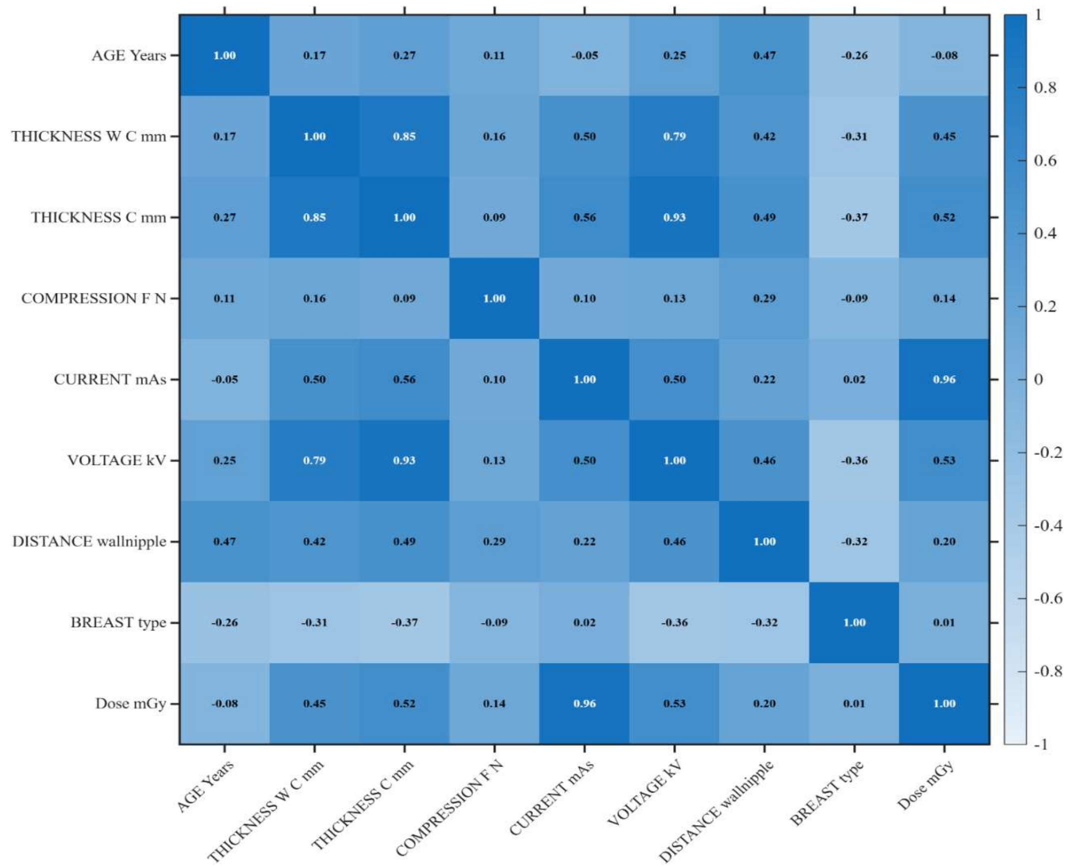

Figure 1. Pearson correlation matrix showing relationships among demographic, anatomical, mechanical, acquisition, and dosimetric variables

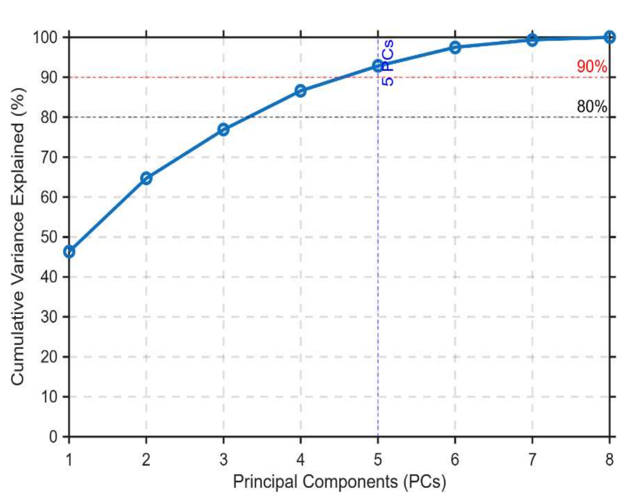

Figure 2. Variable loadings of the first five principal components

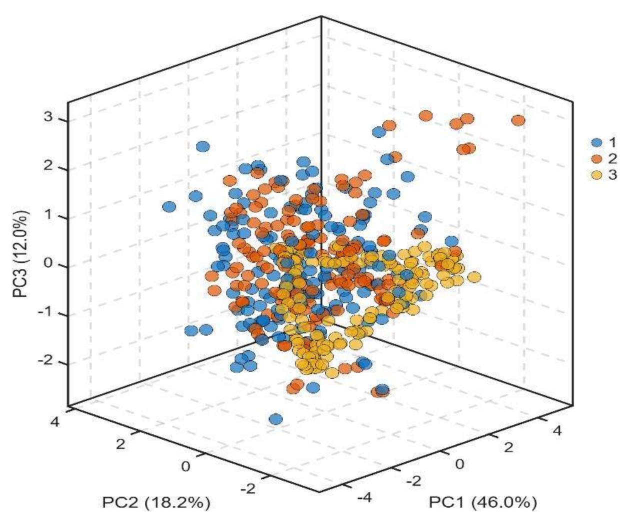

Figure 3. Three-dimensional PCA projection of the study dataset using the first three principal components

Table 1. Predictive performance of the Dance, Full, and PCA dosimetric models evaluated using five-fold cross-validation

Predictor configuration	Regression method	R^2	RMSE (mGy)
Dance Model	Gaussian Process Regression (Matérn 5/2)	0.681	0.414
Dance Model	Linear Regression	0.680	0.414
Dance Model	Third-Order Polynomial Regression	0.665	0.424
Full Model	Gaussian Process Regression (Matérn 5/2)	0.687	0.410
Full Model	Linear Regression	0.675	0.420
Full Model	Third-Order Polynomial Regression	0.670	0.414
PCA Model	Gaussian Process Regression (Matérn 5/2)	0.617	0.453
PCA Model	Linear Regression	0.601	0.463
PCA Model	Third-Order Polynomial Regression	0.603	0.461

External Validation

The selected GPR models were evaluated using an independent dataset of 30 FFDM examinations acquired with the same mammography system. As shown in Figure 4, the Dance and Full models achieved similar predictive performance (R^2 = 0.957 and 0.951; RMSE = 0.155 and 0.166 mGy, respectively), both outperforming the PCA Model (R^2 = 0.890; RMSE = 0.248 mGy). Predicted and measured MGD values showed close agreement across the external dataset, confirming the robustness of the proposed regression models.

Feature Importance Analysis

Automatic Relevance Determination (ARD) within the GPR framework was used to estimate the relative contribution of predictors included in the Full Model. The mAs was the most influential predictor (42.1%), followed by compressed breast thickness. Compression force, kVp, chest wall-to-nipple distance, and breast type showed smaller contributions, whereas age and uncompressed breast thickness had minimal influence. These findings are consistent with the correlation and PCA analyses, highlighting the dominant role of acquisition parameters and breast geometry in dose estimation.

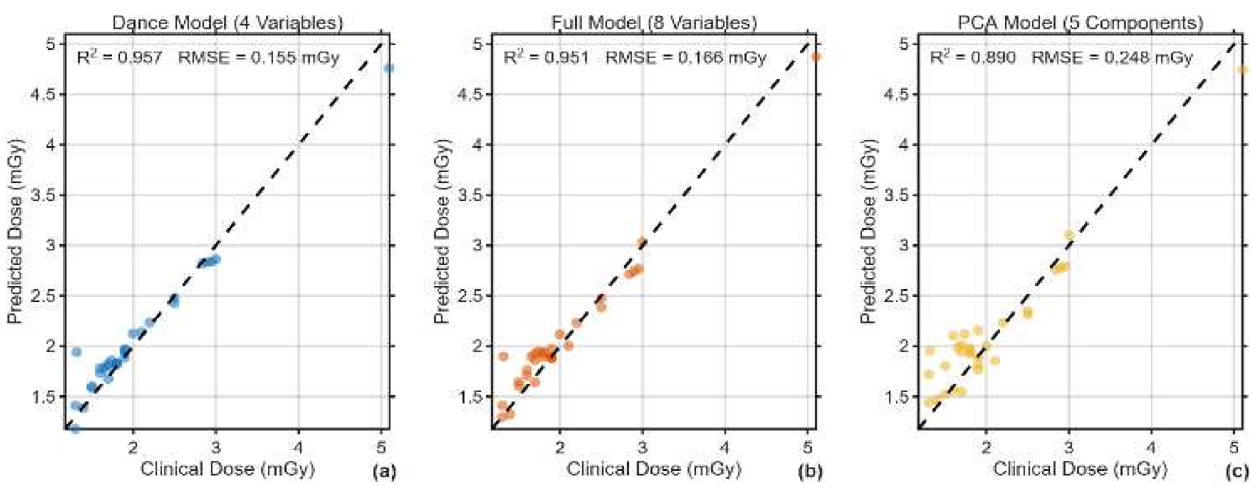

Figure 4. Predicted versus measured mean glandular dose (MGD) for the independent external validation dataset using the Dance, Full, and PCA Gaussian Process Regression (GPR) models. The dashed line represents the line of identity

Pain-Tolerance Classification

Classification results are summarized in Table 2. During five-fold cross-validation, Fine KNN achieved the highest overall accuracy (87.4%), followed by Ensemble Bagged Trees (82.3%) and KNN + PCA (79.3%). During external validation, however, Fine KNN showed poor generalization (26.7%), whereas Ensemble Bagged Trees and KNN + PCA achieved accuracies of 93.3% and 96.7%, respectively.

Although KNN + PCA achieved the highest external accuracy, Ensemble Bagged Trees classifier provided the most balanced performance across pain-tolerance categories and the most consistent behavior between cross-validation and external validation (Figure 5). Overall, pain perception was influenced by multiple interacting anatomical and acquisition variables and could be effectively modeled using machine-learning methods.

Predictor Sensitivity Analysis

A leave-one-variable-out sensitivity analysis using the Ensemble Bagged Trees classifier to evaluate the contribution of individual predictors to pain-tolerance classification. Removal of age produced the largest reduction in accuracy, decreasing performance from 84.1% to 77.2%. Chest wall-to-nipple distance was the second most influential predictor, with accuracy decreasing to 81.0% when excluded. In contrast, removing the remaining variables, including breast thickness parameters, compression force, tube current–time product, tube voltage, and breast type, produced minimal changes in classification performance (≤1 percentage point).

These results suggest that pain perception during mammographic compression is not determined by a single acquisition parameter but rather by the combined contribution of multiple anatomical, mechanical, and patient-related factors.

IV. DISCUSSION

The present study investigated the relationships among breast compression, MGD, and patient-reported pain tolerance in full-field digital mammography using multivariable regression and machine-learning approaches. The findings demonstrate that both radiation dose and pain perception depend on the interaction of anatomical, mechanical, and acquisition-related variables rather than on any single predictor.

Table 2. Classification performance of the evaluated classifiers during five-fold cross-validation (CV) and independent external validation (Ext). Precision, recall, and F1-score are reported for each pain-tolerance category.

Classifier	Evaluation	Pain tolerance	Precision (%)	Recall (%)	F1-score
Ensemble Bagged Trees	CV (Accuracy 82.3%)	Class 1	75.5	77.6	76.5
		Class 2	78.9	71.2	74.9
		Class 3	92.5	98.1	95.2
Fine KNN	CV (Accuracy 87.4%)	Class 1	86.8	75.6	80.8
		Class 2	80.9	88.5	84.5
		Class 3	94.7	98.1	96.4
KNN + PCA	CV (Accuracy 79.3%)	Class 1	77.8	62.8	69.5
		Class 2	71.0	76.3	73.5
		Class 3	92.4	98.7	95.4
Ensemble Bagged Trees	Ext (Accuracy 93.3%)	Class 1	90.0	90.0	90.0
		Class 2	100.0	90.0	94.7
		Class 3	100.0	100.0	100.0
Fine KNN	Ext (Accuracy 26.7%)	Class 1	25.0	10.0	14.3
		Class 2	31.8	70.0	43.8
		Class 3	0.0	0.0	0.0
KNN + PCA	Ext (Accuracy 96.7%)	Class 1	90.0	90.0	90.0
		Class 2	100.0	100.0	100.0
		Class 3	100.0	100.0	100.0

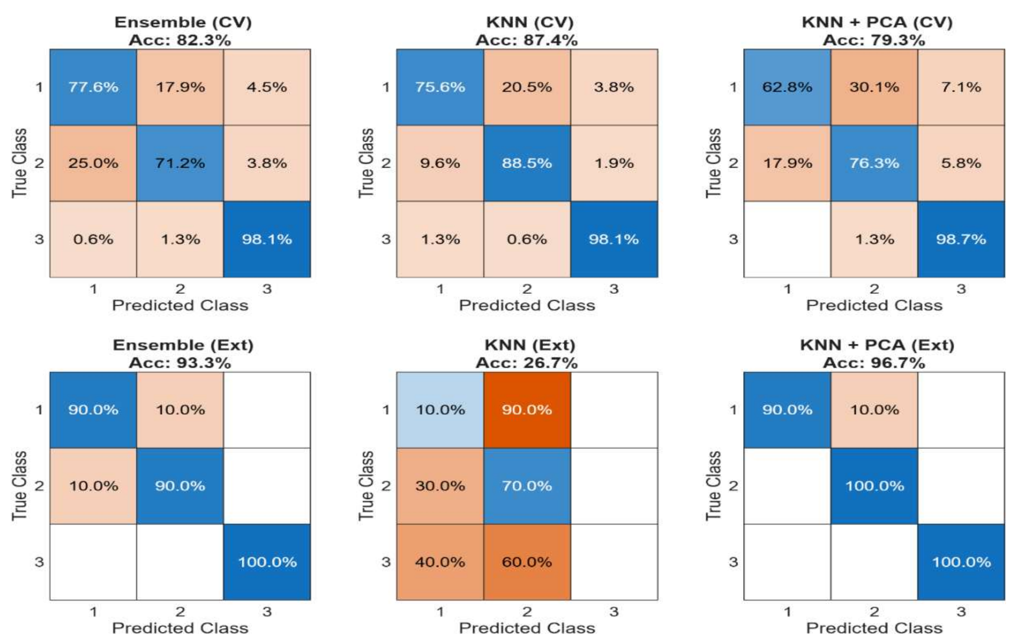

Figure 5. Confusion matrices for the Ensemble Bagged Trees, Fine KNN, and KNN + PCA classifiers obtained during five-fold cross-validation (upper row) and independent external validation (lower row)

Dosimetric Modeling

Among the evaluated regression approaches, GPR provided the best predictive performance, particularly when combined with the Full Model predictor configuration. However, the Dance Model achieved comparable accuracy, indicating that a reduced number of clinically relevant variables may be sufficient for reliable MGD estimation.

Feature importance analysis identified mAs and compressed breast thickness as the dominant predictors, consistent with the correlation and PCA findings. This observation agrees with previous reports indicating that breast thickness and exposure parameters are major determinants of mammographic dose [4]. External validation demonstrated close agreement between predicted and measured MGD values, supporting the applicability of the proposed regression framework under consistent acquisition conditions.

Principal Component Analysis

PCA showed that most dataset variability could be represented by a reduced number of components, mainly associated with breast geometry, acquisition parameters, and tissue composition. However, the persistent overlap among pain-tolerance categories indicated that linear combinations of variables were insufficient for class separation, supporting the use of nonlinear machine-learning approaches.

Pain-Tolerance Classification

Machine-learning classifiers predicted pain tolerance with good overall performance. Although Fine KNN achieved the highest cross-validation accuracy, its marked decrease during external validation indicated limited generalization. In contrast, Ensemble Bagged Trees showed the most consistent performance across internal and external evaluations.

Sensitivity analysis identified age and chest wall-to-nipple distance as the most influential predictors, whereas removing individual acquisition parameters produced only minor changes in performance. These findings support the multifactorial nature of pain perception and agree with previous studies showing that mammographic discomfort is influenced by multiple anatomical and mechanical factors rather than compression force alone [5,6,10-12]

Clinical Implications

Optimization of mammographic examinations should consider not only radiation dose and image quality but also patient comfort [4,5]. The proposed dosimetric models enable MGD estimation from routinely available variables, while supervised classification may assist in predicting patient tolerance to compression. Machine-learning approaches have increasingly been applied in medicine to model complex interactions and support personalized decision-making [7]. Together, these approaches may facilitate personalized mammographic protocols that optimize radiation exposure, diagnostic performance, and patient experience.

Limitations

This study has several limitations. Data was obtained from a single institution using one mammography system, which may limit generalizability. External validation was performed on a relatively small independent cohort acquired under the same clinical conditions, and larger multicenter studies are required to confirm model generalization.

Although SMOTE improved class balance during training, synthetic samples may influence the performance of distance-based classifiers. In addition, pain perception is inherently subjective and may be affected by psychological, emotional, and contextual factors not included in the present dataset.

V. CONCLUSION

This study demonstrated that mean glandular dose is primarily determined by the combined effects of breast geometry and acquisition parameters, whereas pain tolerance arises from complex interactions among anatomical, demographic, and imaging-related factors.

Among the evaluated regression approaches, Gaussian Process Regression with the Full Model provided the most accurate MGD estimation. For pain-tolerance classification, Ensemble Bagged Trees showed the most consistent performance across internal and external validation, despite the higher cross-validation accuracy of Fine KNN.

Although PCA effectively summarized dataset variability, its use as a predictive input reduced model performance, suggesting that dimensionality reduction removed information relevant for dose estimation.

Overall, these findings support the integration of regression modeling and machine-learning techniques to develop personalized mammographic protocols that optimize radiation dose, image quality, and patient comfort.

VI. REFERENCES

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