ISSN 2362–0412

ABS-043

Machine Learning-Based Tumor Grade Classification Using ADC Maps in Breast MRI

G.A.D. Dewminda[1], W.M.K. De Silva[1], M.L. Jayathilake[2], A.D.S. Suranga[3], B.S. Weerakoon[2], S.M. Vijithananda[4], P.D.S. H. Upul[5]*

[1] Department of Physics, Faculty of Science, University of Ruhuna
[2] Department of Radiography/Radiotherapy, Faculty of Allied Health Sciences, University of Peradeniya
[3] Department of Anatomy, Faculty of Medicine, University of Ruhuna
[4] Department of Radiology, Faculty of Medicine, University of Peradeniya
[5] Senior Medical Physicist (Sri Lanka Scientific Service), Department of Physics, National Cancer Institute, Maharagama

**Corresponding author:* dewminda12345@gmail.com

Breast cancer grading plays a critical role in treatment planning and prognosis, yet manual histopathological assessment is invasive, time-consuming, and subject to inter-observer variability. Diffusion-Weighted Imaging (DWI) and Apparent Diffusion Coefficient (ADC) maps provide quantitative information on tissue microstructure and offer potential for non-invasive tumor characterization. This study focused on developing and evaluating a machine learning (ML)-based radiomic framework for classifying low-intermediate grade (Grade 1–2) and high-grade (Grade 3) breast tumors from ADC-derived features. This study was carried out using 846 labeled ADC maps from breast cancer patients who were radiologically confirmed using the SBR (Scarff-Bloom-Richardson) grading system. Tumor regions of interest were manually segmented, and first-order, textural, and wavelet radiomic features were extracted. Feature redundancy and selection were performed using Pearson/Spearman correlation and ANOVA F-test. Dataset imbalance due to fewer low-intermediate-grade tumors was addressed using weighted class learning, SMOTE, SMOTE-Tomek, and SMOTE-ENN. Logistic Regression, Support Vector Machine (SVM), Random Forest, CatBoost, and XGBoost models were trained using patient-wise splitting and cross-validation to prevent data leakage. Performance was evaluated using accuracy, F1-score, and area under the ROC curve (AUC). SVM combined with SMOTE-Tomek achieved the best performance, yielding 68% accuracy and an AUC of 0.71, with improved sensitivity for detecting high-grade tumors. These findings show that ADC-based radiomic features capture clinically relevant markers for tumor aggressiveness. This proposed framework provides a reproducible, non-invasive decision support tool that may improve the diagnostic decision-making process. However, manual segmentation may limit generalizability. Future studies should incorporate automated segmentation and multimodal MRI features to enhance the robustness of the framework.

Keywords: Magnetic resonance imaging, Apparent diffusion coefficient, Diffusion-weighted imaging, Support vector machine, Machine learning