RadiomicsFill-Mammo: Synthetic Mammogram Mass Manipulation with Radiomics Features

Supplementary Material

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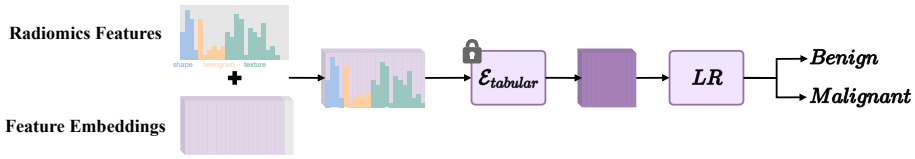

Fig. 1. Evaluating Framework for the Efficiency of the Pretrained Tabular Encoder. During the training phase, clinical variables were included alongside radiomics features. For evaluation, all clinical variables were masked, and only the 67 radiomics features were fed into the encoder. The encoder's output, once flattened, served as input for a logistic regression model tasked with a binary classification of BI-RADS into benign and malignant categories. The predictive performance of this model highlights the efficacy of MET in capturing clinically relevant information from radiomics features alone.

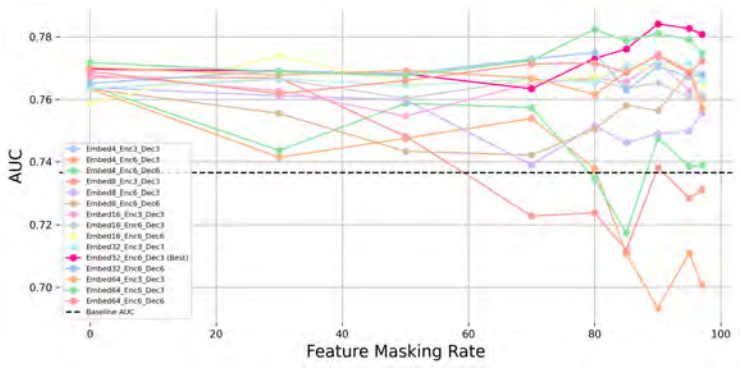

Fig. 2. Optimizing MET Parameters: AUC Performance Across Masking Rates. This graph tracks AUC scores for benign/malignant predictions at various feature masking rates to determine MET's optimal parameters. Highlighted in hot pink, the best-performing setup—featuring a 32-dimensional feature embedding, 6 encoder layers, and 3 decoder layers at a 90% masking rate—was chosen as the prompt encoder configuration for RadiomicsFill-MET.

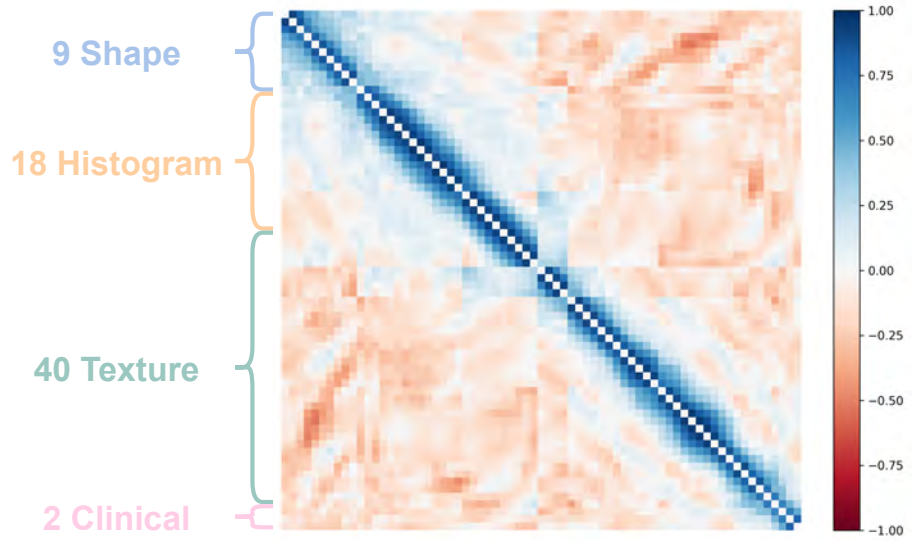

Fig. 3. Cosine Similarity between MET Feature Embeddings. This heatmap visualizes the cosine similarity for MET's 69 feature-specific embeddings, highlighting strong intra-group correlations within shape, histogram, and texture clusters. The clear block diagonal structure observed signifies the encoder's proficiency in grouping and differentiating feature categories.