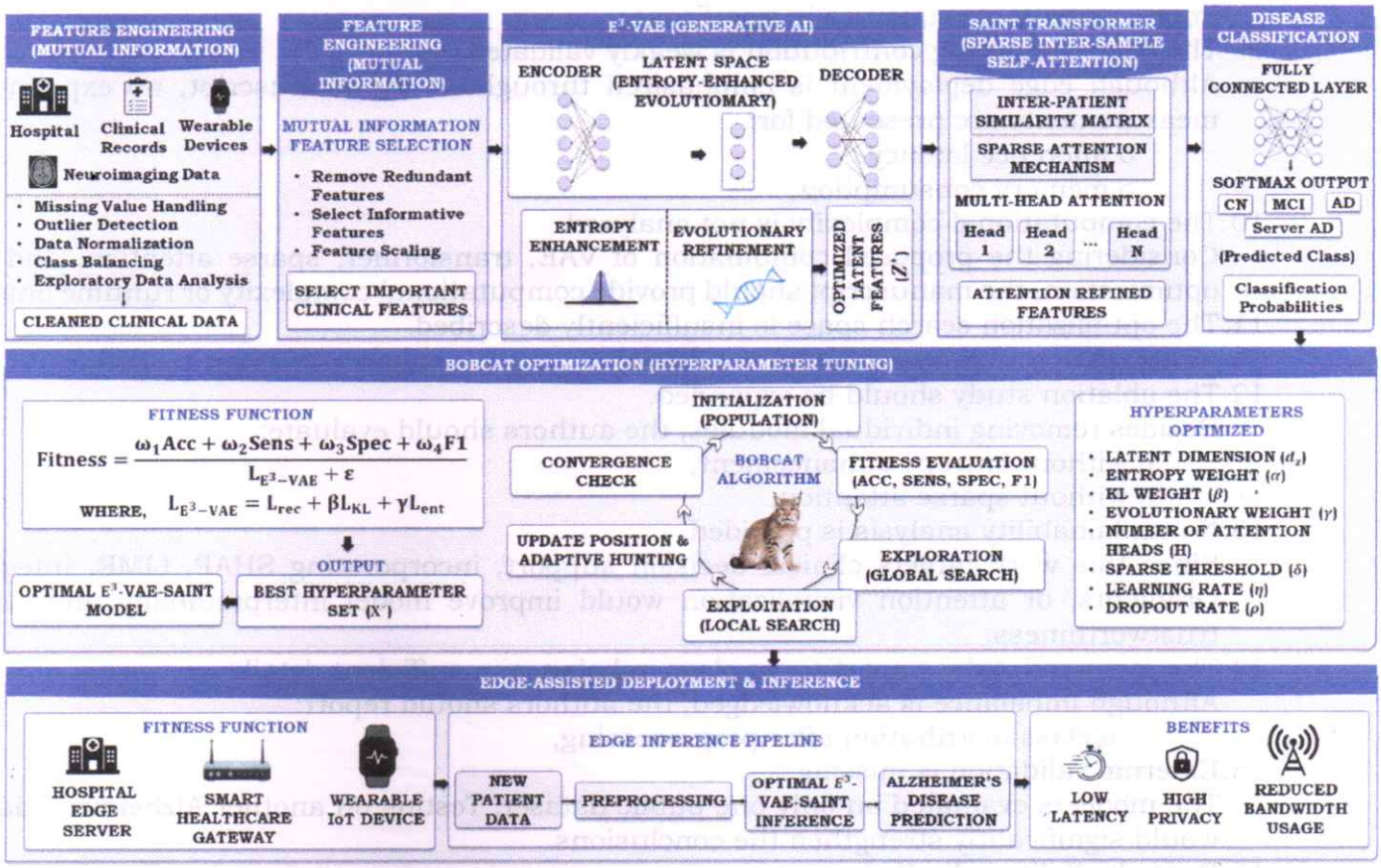
AB TECHNOLOGIES
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ABT_R&D_EX11_RCRRF01 REVIEW COMMENTS

RESULT REQUIREMENT FORM-SCI

RF NUMBER	:	ABT_R&D_EX11_RCRRF01_**53**	**PREPARED DATE**	09/11/2026
REGISTRATION CODE	:	ABT_NGL_5943	**DELIVERY DATE**	12/11/2026
SCHOLAR NAME	:	Ms. ASHMIN RUBY J M	**DEPT. NAME**	ICE
UNIVERSITY NAME	:	SAVEETHA ENGINEERING COLLEGE		
TITLE	:	EDGE-BASED GENERATIVE AI FRAMEWORK FOR ALZHEIMER DISEASE CLASSIFICATION USING BOBCAT-OPTIMIZED E³-VAE-SAINT MODEL		
REVISION NO.	:	1		
ALLOTTED STAFF NAME WITH ID	:	M Mr. DHILAHARIS T (ABT_NGL_029)		
STAFF IN CHARGE	:	Ms. LIBNA SHANU R (ABT_NGL_089)		

BLOCK DIAGRAM



REVIEW COMMENTS

1. The proposed methodology is excessively mathematical but lacks implementation details.
2. The manuscript introduces many equations, but important implementation information is missing, including: encoder/decoder architecture, number of hidden layers,
3. The dataset is relatively small (2,149 samples) for training a complex deep generative transformer model.
4. The authors should justify why such a sophisticated architecture is appropriate for this dataset and discuss possible overfitting.
5. Only five training epochs were used.
   According to Table 3, the model is trained for only 5 epochs, which is surprisingly low for a VAE and transformer-based framework. The authors should justify this choice and provide convergence analysis.
6. The manuscript reports extremely high performance (99.30% accuracy), which raises concerns about overfitting or data leakage. The authors should explain why such performance is achievable on this dataset and provide stronger evidence that no information leakage occurred during preprocessing or feature selection.
7. The evaluation relies on a single experimental setup. A k-fold cross-validation (e.g., 5-fold or 10-fold) would provide stronger evidence of model robustness.
8. Statistical significance analysis is absent.
   The authors should report statistical tests (paired t-test, Wilcoxon signed-rank test, confidence intervals, or multiple independent runs) to demonstrate that the observed improvements are statistically significant.
9. The edge computing contribution is weakly validated.
   Although edge deployment is emphasized throughout the manuscript, no experimental measurements are presented for:
   - o inference latency,
   - o memory consumption,
10. The computational complexity is not analyzed.
    Considering the proposed combination of VAE, transformer, sparse attention, and BOA optimization, the manuscript should provide computational complexity or runtime analysis.
11. The optimization search space is insufficiently described.
    Although optimized parameters are listed,
12. The ablation study should be expanded.
    Besides removing individual modules, the authors should evaluate:
    - o without entropy enhancement,
    - o without sparse attention,
13. No explainability analysis is provided.
    Since this work targets clinical decision support, incorporating SHAP, LIME, Integrated Gradients, or attention visualization would improve model interpretability and clinical trustworthiness.
14. The manuscript does not discuss class imbalance in sufficient detail.
    Although imbalance is acknowledged, the authors should report:
    - o class distribution after preprocessing,
15. External validation is missing.
    The model is evaluated on only one public dataset. Testing on another Alzheimer's dataset would significantly strengthen the conclusions.
16. Reproducibility is limited.
    The manuscript should provide:
    - o source code,
    - o random seeds,
    - o details,

    to enable reproducibility.

17. The train/validation/test splitting strategy is not clearly described.
    The manuscript should specify:
    - o percentage of each split,
    - o whether stratified sampling was used,
18. Cross-validation is missing.
19. Experimental validation: The reported 99.30% accuracy on 2,149 patient records is encouraging. However, the authors should provide clearer details on the training and testing splits, repeated experiments, and statistical reliability.
20. Data leakage: Please clarify how data preprocessing, feature selection, and inter-sample attention were implemented to prevent information leakage between training and testing datasets.
21. Performance comparison: Additional comparisons with established machine learning and tabular deep learning models would strengthen the evaluation.
22. Ablation study: The existing ablation results are useful, but further analysis of individual components would help demonstrate their effectiveness.
23. Edge deployment: The authors should provide actual inference latency, hardware specifications, memory usage, and computational requirements to support the edge-deployment claims.
24. The paper would benefit from further discussion of clinical applicability, external validation, and limitations of the proposed approach.

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