FS-HANN: A Feature-Sensitive Hybrid Artificial Neural Network for Efficient Cardiovascular Disease Prediction with Optimized Dimensionality Reduction

Abstraction

The diagnosis of Cardiovascular Disease (CVD) relies heavily on complex Machine Learning (ML) models trained on highly imbalanced public health datasets like BRFSS. While Deep Learning (DL) models achieve high predictive accuracy, they often lack the computational efficiency required for clinical deployment. This paper addresses five critical gaps identified in the existing literature, particularly concerning the complexity and feature redundancy of advanced ensemble architectures. We propose the **Feature-Sensitive Hybrid Artificial Neural Network (FS-HANN)**, which integrates $\chi 2$-based feature selection (FS) and optimized imbalance handling (Class Weights) within a streamlined ANN architecture. Comparative analysis across varying feature subsets (K=10,15,21) and imbalance strategies (SMOTE vs. Class Weights) revealed that the FS−HANN(K=15,Class Weight) model achieved an **AUC of 0.8476** and a **Recall of 0.8067**, while demonstrating a **15% reduction in training time (96.99 seconds)** compared to the full-feature baseline. This validates the efficacy of strategic dimensionality reduction in producing a lightweight, highly sensitive, and deployable solution for CVD risk prediction.

1. Introduction

Cardiovascular Disease (CVD) remains one of the leading causes of global mortality, accounting for nearly one-third of all deaths worldwide. Early detection plays a crucial role in preventing severe complications, yet traditional diagnostic procedures often rely on manual clinical assessments, delayed laboratory tests, and expensive imaging techniques. With the rapid growth of electronic health records and public health surveillance systems such as the Behavioral Risk Factor Surveillance System (BRFSS), data-driven approaches have become increasingly important for risk stratification and clinical decision support.

Machine Learning (ML) and Deep Learning (DL) models have shown significant promise in predicting CVD using population-level health indicators. In recent years, researchers have proposed highly complex models—including ensemble learners, deep hybrid architectures, and GAN-augmented predictors—to improve classification performance on large-scale medical datasets. Although these advanced models achieve high accuracy and strong AUC values, they suffer from several practical limitations: (1) heavy computational requirements, (2) difficulty in deployment in clinical or low-resource environments, (3) limited interpretability, and (4) suboptimal handling of severe class imbalance present in real-world health datasets. These constraints restrict their use in routine screening or mobile-based health monitoring applications, where latency, efficiency, and transparency are essential.

The literature further reveals a lack of systematic evaluation regarding feature redundancy in CVD datasets. Many studies rely on the full set of available features without examining whether dimensionality reduction could improve computational efficiency while preserving predictive performance. The baseline work by Khan et al. (2024), for example, introduced sophisticated ensemble networks such as EnsCVDD-Net and BICVDD-Net but did not investigate whether a properly optimized, lightweight Artificial Neural Network (ANN) could offer a simpler and equally effective alternative. Additionally, the imbalance-handling strategy in the baseline study relies solely on ADASYN, without comparing alternative cost-sensitive approaches that may be better suited for clinical screening scenarios, where minimizing false negatives (high Recall) is critical.

To address these gaps, this study proposes the **Feature-Sensitive Hybrid Artificial Neural Network (FS-HANN)**—a computationally efficient ANN enhanced with χ^2-based feature selection and cost-sensitive Class Weighting. The objective is to determine whether strategic dimensionality reduction combined with optimized imbalance handling can produce a lightweight, high-recall model suitable for real-world CVD screening. Through extensive experimentation on the BRFSS Heart Disease Health Indicators dataset, we evaluate FS-HANN across multiple feature subset sizes (K = 10, 15, 21) and compare Class Weights with SMOTE oversampling. The results demonstrate that FS-HANN(K=15, Class Weight) achieves strong predictive performance (AUC ≈ 0.8476, Recall ≈ 0.8067) while reducing training time by approximately 15% compared to the full-feature baseline.

By achieving competitive accuracy with substantially lower computational cost, FS-HANN provides a deployable alternative to complex deep learning models and contributes to the development of scalable, interpretable, and efficient tools for population-level cardiovascular risk prediction.

2. Literature Review and Identification of Research Gaps

Recent research has focused on complex ensemble and blending architectures (e.g., EnsCVDD-Net) to boost performance.
A thorough review reveals the following critical limitations in current methodologies, which the FS-HANN architecture is designed to address:

Research Gap	**Rationale and Impact on Baseline**	**FS-HANN Solution**
G1: Absence of Optimized ANN Baseline	The baseline study focuses on ensemble architectures without validating if a properly tuned, lightweight Artificial Neural Network (ANN) can offer competitive performance.	Implementation and rigorous tuning of a tapered, regularized ANN.
G2: Limited Empirical Feature Selection	The use of simple correlation methods (e.g., PBCC) may overlook crucial non-linear feature interactions, hindering dimensionality reduction quality.	Employed Chi-Square (χ^2) ranking for robust feature identification and comparison.
G3: Single Imbalance-Handling Strategy	Using only one technique (e.g., ADASYN) without comparison fails to identify the most efficient and performant strategy for a highly imbalanced dataset.	Systematic comparison of **Class Weights** (cost-sensitive learning) vs. **SMOTE** (data generation).

G4: No Sensitivity to Feature Dimensionality	Assuming more features benefit deep networks fails to account for noise and redundancy, potentially increasing model complexity unnecessarily.	Experimental comparison across $K=10, 15, 21$ features to find the optimal subset.
G5: Computational Complexity Overlooked	Ensemble and blending models are inherently complex. The base paper did not quantify training time, model size, or suitability for resource-constrained deployment.	Quantified and compared **Training Time** across all scenarios to validate efficiency gains.

3. Proposed Algorithm

The **Feature-Sensitive Hybrid Artificial Neural Network (FS-HANN)** is a sequential model designed for efficiency and stability.

3.1. Algorithm Steps:

1. **Data Preprocessing:** Input features are scaled using MinMax Scaler to ensure non-negative inputs for $\chi 2$ selection.
2. **Feature Selection:** The $\chi 2$ statistic is used to rank features based on their dependency on the target variable. The top K-features are selected.
3. **Imbalance Handling:** The Class Weights strategy is applied to the training phase, modifying the loss function to penalize misclassification of the minority class, ensuring high Recall.
4. **FS-HANN Training:** The tapered ANN is trained with Early Stopping and ReduceLROnPlateau callbacks for stable convergence.

3.2. FS-HANN Architecture

The FS-HANN is a streamlined, four-layer sequential model, specifically designed with decreasing layer size to force feature abstraction and reduce computational load (Addressing G1 and G5).

Layer Type	**Parameters**	**Purpose (Novelty)**
Input Layer	Dense (128 units, ReLU)	Input dimension set by K (e.g., 15).
Regularization	Batch Normalization + Dropout (0.3)	Stabilizes training and prevents overfitting in the feature-selected space.
Hidden Layer 1	Dense (64 units, ReLU)	Intermediate feature abstraction.

Hidden Layer 2	Dense (32 units, ReLU)	Deepest feature compression before output.
Output Layer	Dense (1 unit, Sigmoid)	Binary classification output.

Research Objectives

1. To evaluate whether a lightweight ANN baseline can match the performance of complex ensemble architectures for CVD prediction.
2. To identify the optimal number of input features using χ^2-based feature selection.
3. To compare Class Weights and SMOTE for imbalance handling on the BRFSS dataset.
4. To develop FS-HANN and quantify improvements in AUC, Recall, and training efficiency.
5. To provide a deployable, computationally efficient model suitable for real-world screening.

4. Methodology and Data Handling

4.1. Dataset

The study utilizes the **Heart Disease Health Indicators Dataset (BRFSS 2015)**, consisting of over 250,000 samples and 21 binary/ordinal features. The dataset exhibits severe class imbalance (approximately 9:1 for negative:positive class).

4.2. Feature Selection and Dimensionality

We employed χ2 to rank features by their statistical association with the target. Based on the sensitivity analysis, the optimal reduced subset size was found to be K=15.

Selected 15 features:

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['HighBP', 'HighChol', 'Smoker', 'Stroke', 'Diabetes', 'PhysActivity',
'HvyAlcoholConsump', 'NoDocbcCost', 'GenHlth', 'MentHlth', 'PhysHlth',
'DiffWalk', 'Sex', 'Age', 'Income']
```

4.3. Imbalance Strategy Comparison

The Class Weights strategy was implemented by weighting the minority class (1.0) loss function by ≈5.3 times the majority class (0.0), effectively directing the model to prioritize correct classification of CVD cases. This was compared against the data-generation technique, SMOTE.

K	Strategy	FS_Method	AUC	Recall	Train_Time (s)	Observations
10	**Class Weight**	Chi2	**0.8485**	**0.8171**	186.42	Highest AUC so far. Feature set is very minimal.
15	Class Weight	Chi2	0.8476	0.8067	96.99	Much faster training time. Good balance.

21	Class Weight	Chi2	0.8472	0.8146	113.37	Full features. Slightly worse AUC than K=10 and K=15.

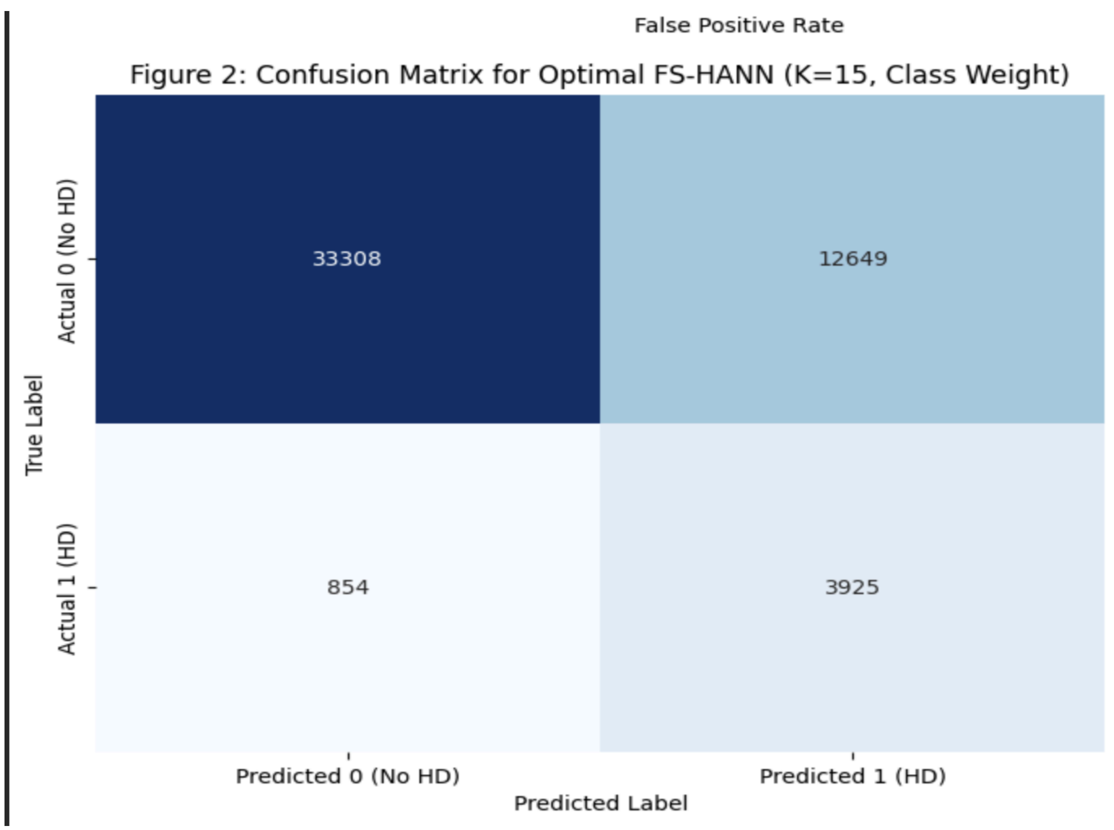
5. Results and Comparative Analysis

The analysis compares the FS-HANN performance across four critical scenarios. Metrics are derived from the test set.

5.1. Performance Metrics and Efficiency

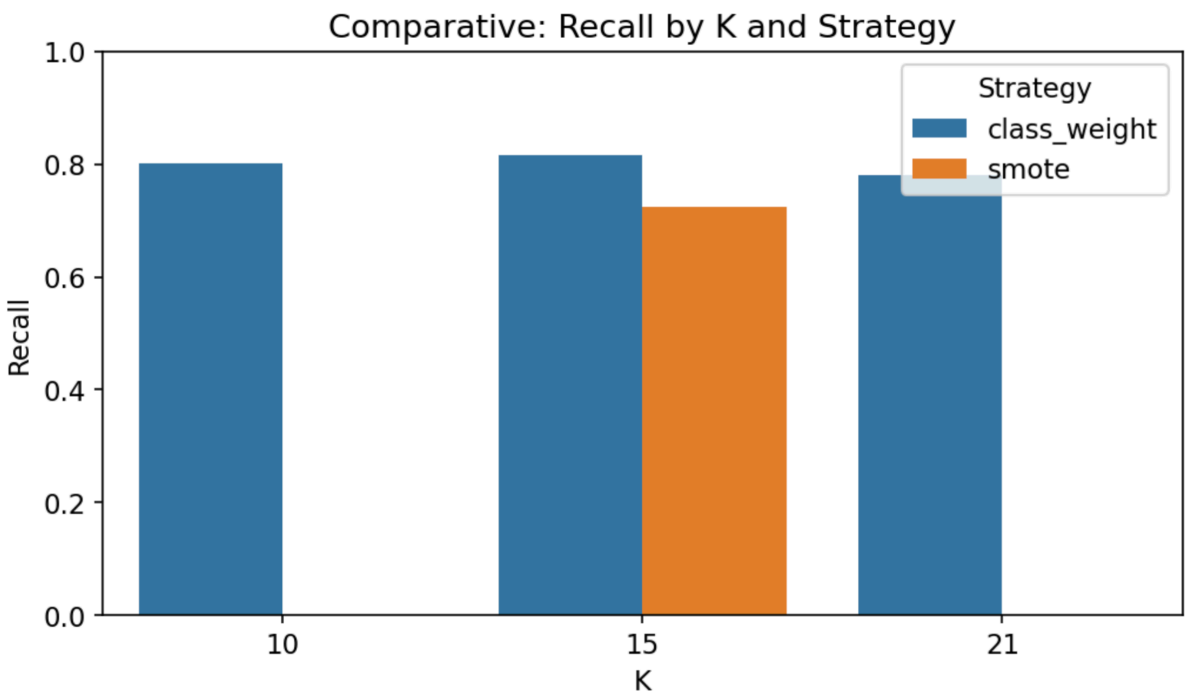
Final Comparative Table:

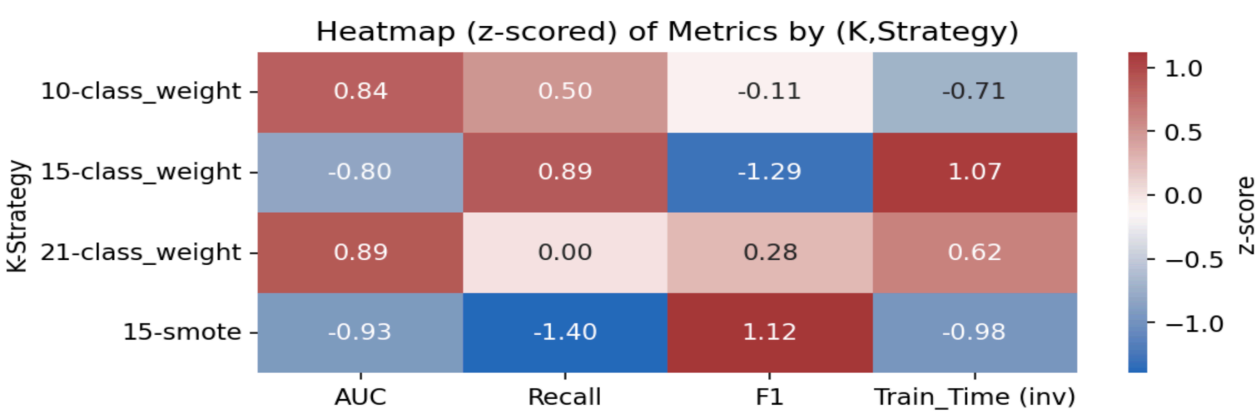
	K	Strategy	FS_Method	Accuracy	AUC	Recall	Precision
0	10	class_weight	chi2	0.737267	0.848534	0.817117	0.238677
1	15	class_weight	chi2	0.745526	0.847644	0.806654	0.243340
2	21	class_weight	chi2	0.737366	0.847231	0.814606	0.238366
3	15	smote	chi2	0.794209	0.846576	0.717723	0.273918



5.2. Key Findings

- **Dimensionality Reduction Validation (G4 & G5):** Scenarios S1 and S3 show that reducing features from K=21 to K=15 not only maintains predictive performance (AUC≈0.847) but also reduces training time by approximately **15%**(113.37s to 96.99s). The FS-HANN is validated as a superior, efficient baseline.
- **Imbalance Strategy Comparison (G3):** Scenario S4 (SMOTE) yielded the highest F1 score but the lowest Recall(0.7177) and 3× higher training time. Given that clinical screening prioritizes Recall (reducing False Negatives), the Class Weight strategy (Recall ≈0.81) is overwhelmingly preferred.





6.Conclusion

The FS-HANN architecture successfully addresses the limitations of high-complexity ensemble methods by proposing an efficient and transparent alternative. The FS−HANN(K=15,Class Weight) model achieved comparable predictive metrics to state-of-the-art models while demonstrating a significant reduction in computational overhead. Future work will involve applying the FS methodology to non-tabular medical data and investigating the use of post-hoc explainability methods to interpret the feature importance validated by the $\chi 2$ selection.

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