Tabular Learning for Biomedical Data

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Abstract

Foundation models trained on tabular data, such as TabPFN and TabICL, have demonstrated strong classification performance on synthetic and benchmark datasets. Applications to biological datasets are emerging but remain comparatively underexplored, as such data are often high-dimensional, noisy, and limited in sample size. In this paper, we present the first comprehensive evaluation of TabPFN and TabICL across diverse biology-specific classification tasks, including healthcare, mass spectrometry, gene splicing, and gene expression datasets. Across all datasets, tabular foundation models outperformed traditional classifiers such as XGBoost and SVC, demonstrating strong generalization to biological data. Models trained on raw features resulted in the best accuracies in all datasets except the high-dimensional, noisy gene expression dataset, where TabICL combined with dimensionality reduction (PCA and cPCA) achieved the highest accuracies. These findings provide the systematic evidence that tabular foundation models are effective for biological classification tasks and establish a foundation for their broader application in biomedicine.

1 Introduction

Classification tasks in biomedical datasets are a challenging problem, as modern neural network-based approaches typically struggle with tabular tasks that can contain a large number of features. [5] Traditional machine learning classifiers such as support vector machines, random forests, and XGBoost are commonly used for tabular dataset classification due to their ability to quickly converge to a desirable classification solution [12]. However, following the introduction of the transformer architecture [15], researchers have explored re-purposing transformers for tabular classification tasks. Notable transformer-based models include TabPFN [7, 6] and TabICL [10] - both of which can outperform traditional machine learning methods in terms of classification accuracy. Tabular-based foundational models are typically trained on datasets with a low feature count (i.e. under 500 for TabPFN). Biomedical datasets often contain a large number of features, which presents a challenge for such tabular foundational models. [8]

Dimensionality reduction is a promising method to reduce feature count while preserving the dataset's inherent characteristics. Notably, principal component analysis (PCA) has been widely used in biomedical research to project high-dimensional data onto its principal components for more interpretable biological insights. Abid et al. introduced the contrastive principal component analysis (cPCA) that considers two distributions: X_i which is the foreground data, and Y_i which is the background data. Subsequently, the cPCA method aims to find a parameter α that increases the variance (the "expressivity") of the foreground data distribution, while minimizing the variance of the

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background data distribution. By maximizing foreground variance relative to the background, cPCA produces a compact embedding in which heterogeneity that is common for tabular data is largely removed and class-discriminative structure is amplified. [1]

In this study, we evaluate the performance of tabular foundation models on biomedical classification tasks and examine how dimensionality reduction techniques, including PCA and cPCA, affect their predictive performance. Our empirical results show that tabular-based foundational models outperform traditional classifiers on a wide array of biomedical classification tasks. Furthermore, we identified cost-performance trade-offs when applying PCA and cPCA as dimensionality reduction methods. Through an ablation of different background datasets and related compression parameters, this paper identifies cases where cPCA-compressed data enables better classification accuracy than PCA-compressed data. This paper also identifies cases where cPCA and PCA both outperform uncompressed features, thus introducing dimensionality reduction as a valuable enhancement for tabular foundational models.

2 Methods

2.1 Classification Models

We used four models for tabular classification: TabPFN and TabICL (two transformer-based foundation models that have demonstrated strong empirical performance in recent studies), along with two traditional machine learning methods, SVC and XGBoost, which served as a baseline for comparison.

- **TabPFN (Tabular Prior-Data Fitting Network):** TabPFN is a transformer-based foundation model specifically designed for rapid and accurate predictions on tabular datasets [7, 6]. It leverages prior knowledge from a large corpus of tabular tasks, enabling it to perform competitively even on small datasets without extensive fine-tuning.
- **TabICL (Tabular In-Context Learning):** TabICL is a transformer-based model tailored for in-context learning tasks on tabular data [10]. By conditioning predictions directly on relevant examples from the dataset (context), TabICL efficiently generalizes to new tabular classification tasks with minimal data.
- **SVC (Support Vector Classifier):** SVC is a supervised learning algorithm that identifies the optimal separating hyperplane between classes by maximizing the margin around decision boundaries, leading to robust generalization on unseen data [4].
- **XGBoost (Extreme Gradient Boosting):** XGBoost is a gradient boosting algorithm that builds an ensemble of decision trees sequentially, where each new tree corrects the errors of the previous ones using a regularized objective to prevent overfitting [3].

2.2 Preprocessing

We performed an ablation study with three conditions: (i) using the raw features with no dimensionality reduction, (ii) applying PCA for dimensionality reduction, and (iii) applying cPCA for dimensionality reduction. All experiments were conducted using a consistent selection of 2, 10, 20, and 50 (if available) components. For cPCA, the regularization parameter α was set to 1, 10, and 100.

For each experiment, we selected multi-class datasets and chose the labels for classification as the features of interest, which served as the foreground data (X_i), while the remaining data were treated as the background data (Y_i). We used an 80/20 train-test split and evaluated model performance on the test set using accuracy, F1-score, and computation time (in seconds) as the performance metrics.

3 Dataset

We used the following datasets, accessed from OpenML and the UCI Machine Learning Repository:

1. **MicroMass (Pure Spectra Version).** This dataset contains 571 mass spectrometry samples, each described by 1,300 intensity features corresponding to spectral peaks. The samples represent 20 distinct microorganism species, and the task is to classify the species based on their characteristic mass-spectrometry profiles. [14, 9]

Table 1: Foreground Data Classification Accuracy without Dimensionality Reduction

Model	Micro-Mass	DNA	Thyroid	Diabetes	HBTRC
TabPFN	**1.000 ± 0.000**	0.986 ± 0.005	**0.885 ± 0.001**	**0.997 ± 0.002**	**0.956 ± 0.007**
TabICL	0.984 ± 0.016	**0.992 ± 0.004**	**0.885 ± 0.001**	0.994 ± 0.003	0.953 ± 0.006
XGBoost	0.984 ± 0.016	0.986 ± 0.005	0.884 ± 0.002	0.996 ± 0.002	0.916 ± 0.014
SVC	0.839 ± 0.047	0.988 ± 0.005	0.883 ± 0.001	0.952 ± 0.006	0.913 ± 0.002

2. **Primate Splice-Junction Gene Sequences (DNA).** This genomic dataset contains 3,186 rows with 180 unique binary features and three target labels. The classification task is to identify the type of splice junction-intron-exon boundary (IE), exon-intron boundary (EI), or neither (N), which correspond to regions that are retained or removed during RNA splicing. [13]
3. **Thyroid Disease.** Collected by the Garvan Institute of Medical Research (Sydney), this dataset includes 3,771 patient records with 26 clinical and hormonal features, such as TSH, T3, and T4 levels, as well as indicators of thyroid surgery and goitre. We focused on distinguishing hypothyroid from hyperthyroid patients (foreground) using healthy individuals as the background group. [11]
4. **Diabetes Disease.** This dataset was obtained from the Medical City Hospital and the Specialized Center for Endocrinology and Diabetes-Al-Kindy Teaching Hospital in Iraq. It contains medical and biochemical data from 1,000 patients, including 12 features such as blood glucose, BMI, cholesterol, triglycerides, creatinine ratio, and HbA1c. We used it to classify pre-diabetic versus diabetic individuals, with non-diabetic participants serving as the background group. [2]
5. **Harvard Brain Tissue Resource Center (HBTRC).** This dataset contains gene expression profiles of 500 highly variable genes measured in the dorsolateral prefrontal cortex of 736 individuals. The cohort includes 379 individuals with late-onset Alzheimer's disease, 184 with Huntington's disease, and 173 non-demented controls. Post-mortem samples were collected through the Harvard Brain Tissue Resource Center (HBTRC) and accessed via the Gene Expression Omnibus (GEO, accession number GSE44770). Our task was to distinguish patients with Alzheimer's disease from those with Huntington's disease, with non-demented subjects serving as the background group. [16]

4 Results

4.1 Foundational Models Outperform Traditional Classifiers Across Biomedical Domains

As shown in Table 1, tabular transformer-based foundation models (TabPFN and TabICL) consistently outperform traditional classifiers such as XGBoost and SVC across a wide range of biological and biomedical datasets. These datasets span multiple domains — from healthcare records (Thyroid, Diabetes) and mass spectrometry (Micro-Mass) to gene expression (HBTRC) and gene splicing data (DNA). Notably, both TabPFN and TabICL achieve the highest or near-highest accuracy across all datasets, indicating strong generalization to diverse biological feature spaces without the need for dimensionality reduction.

While traditional models like XGBoost and SVC remain competitive, especially on simpler feature sets, the transformer-based approaches provide a consistent empirical advantage, suggesting that tabular foundation models may capture complex nonlinear and cross-feature relationships relevant for biological data that classical models may struggle with. However, as detailed in the Appendix, this performance gain comes with a computational trade-off: TabPFN in particular requires substantially longer runtimes compared to XGBoost and SVC.

4.2 Dimensionality Reduction Improves Performance in High-Dimensional, Noisy Data

As shown in Table 2, models trained on raw features achieved the highest accuracy across most datasets, including healthcare, mass spectrometry, and gene splicing data. The only exception was the gene expression dataset (HBTRC), which contains a large number of noisy and correlated features.

Table 2: TabPFN Accuracy with Dimensionality Reduction

Method	N	Micro-Mass (†)	DNA (‡)	Thyroid	Diabetes	HBTRC	HBTRC (TabICL)
PCA	2	0.532 ± 0.064	0.876 ± 0.015	**0.885 ± 0.001**	0.947 ± 0.004	0.764 ± 0.013	0.751 ± 0.013
PCA	10	0.806 ± 0.051	0.952 ± 0.010	**0.885 ± 0.001**	0.953 ± 0.005	0.893 ± 0.013	0.880 ± 0.011
PCA	20	0.952 ± 0.027	0.957 ± 0.009	**0.885 ± 0.001**	-	0.920 ± 0.012	0.927 ± 0.011
PCA	50	0.952 ± 0.027	0.973 ± 0.007	-	-	0.953 ± 0.008	**0.967 ± 0.009**
cPCA	2	0.355 ± 0.061	0.779 ± 0.019	**0.885 ± 0.001**	0.952 ± 0.007	0.771 ± 0.011	0.769 ± 0.025
cPCA	10	0.806 ± 0.051	0.888 ± 0.014	0.884 ± 0.001	0.985 ± 0.004	0.898 ± 0.012	0.880 ± 0.015
cPCA	20	0.790 ± 0.052	0.895 ± 0.014	0.884 ± 0.001	-	0.927 ± 0.011	0.933 ± 0.011
cPCA	50	0.806 ± 0.051	0.932 ± 0.011	-	-	0.942 ± 0.011	**0.960 ± 0.008**
None	-	**1.000 ± 0.000**	**0.986 ± 0.005**	**0.885 ± 0.001**	**0.997 ± 0.002**	**0.956 ± 0.007**	0.953 ± 0.006

(†) and (‡) represent experiments where the foreground and background were randomly selected. The right-most column denoted with (TabICL) was run with a TabICL classifier, while all other columns used TabPFN.

In this case, TabICL combined with dimensionality reduction achieved the best results (0.967 with PCA and 0.960 with cPCA), outperforming TabPFN on raw features (0.956). This suggests that in high-dimensional, noisy biological data, feature compression and contrastive learning can improve classification accuracy by filtering redundant signals.

Other datasets did not show this pattern likely because their feature spaces were smaller, cleaner, or already biologically constrained, making dimensionality reduction less beneficial. While PCA-based methods offer favorable speed-performance tradeoffs, it does not consistently preserve TabPFN's accuracy across datasets. Dimensionality reduction thus remains a relevant consideration for tabular foundation models, which are typically trained on a limited number of features (e.g., 500 for TabPFN). Both excessive compression and overly large input spaces can hinder model efficiency and accuracy, underscoring the need for a data-driven approach to managing feature dimensionality.

4.3 Ablation Study of PCA and Contrastive PCA

There are three parameters that we can ablate in our work: (i) the number of components, (ii) the alpha (α) parameter for cPCA and (iii) the foreground-background dataset selection. Our results suggest that the choice of foreground and background datasets is the most important parameter to identify.

As shown in Table 2, classifier accuracy decreases as the number of dimensions decreases. However, the accuracy gap introduced by dimensionality reduction is larger when the foreground and background datasets are chosen randomly, as denoted by (†) and (‡) in Table 2. Accordingly, for datasets where the background dataset was chosen as a "true" background dataset, the accuracy drop tends to be smaller. Interestingly, "true" background datasets can also improve downstream classifier performance on cPCA-compressed data. This effect is noticeably visible in the Diabetes and HBTRC columns in Table 2, where cPCA-compressed data has a classification accuracy improvement from 0.0% to 3.2% over PCA for all except one case.

The choice of the α for cPCA requires tuning to compress dataset dimensionality for optimal classification accuracy. The effects of α are further shown in Appendix B.

5 Conclusion

This paper analyzes the effectiveness of tabular-based foundational models on biological and biomedical classification tasks. Our results show that transformer-based models such as TabPFN and TabICL consistently exceed the accuracy of traditional classifiers across diverse biology-relevant datasets. In most cases, models trained on raw features achieved the highest accuracy, demonstrating that these foundation models can serve as effective "out-of-the-box" classifiers for tabular datasets with moderate feature sizes. However, in high-dimensional and noisy datasets such as gene expression data, combining dimensionality reduction with contrastive learning (e.g., cPCA with TabICL) improved classification performance, suggesting that feature compression could be beneficial for high-dimensional omics data. Relevant future directions include investigating further dimensionality

reduction methods that preserve or improve classifier accuracy, as well as expanding evaluation to a broader range of tabular foundation models and biology-relevant classification tasks on tabular data.

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A Reproducibility Statement

The codebase used to run the experiments can be accessed at the following GitHub repository: `https://github.com/TheFloatingString/additional-cpca-experiments`.

The authors used a random seed of 42 to ensure that the results can be reproduced. All of the datasets and models used in this paper are openly accessible.

B Additional Data

This section contains the full experimental results. “se" is the standard error, and “std" is the standard deviation. Time elapsed is recorded in seconds.

Table 3: Dimensionality Reduction Results on the Micro-Mass Classification Task

model	preprocessing	n_components	alpha	accuracy	f1_score	std_accuracy	std_f1	se_accuracy	se_f1	time_elapsed
tabpfn	None	1300	N/A	1.000	1.000	0.000	0.000	0.000	0.000	7.590
tabicl	None	1300	N/A	0.984	0.985	0.126	0.126	0.016	0.016	7.588
xgboost	None	1300	N/A	0.984	0.984	0.126	0.126	0.016	0.016	0.831
svc	None	1300	N/A	0.839	0.827	0.368	0.368	0.047	0.047	0.037
tabpfn	PCA	2	N/A	0.532	0.471	0.499	0.499	0.064	0.064	0.341
tabicl	PCA	2	N/A	0.516	0.457	0.500	0.500	0.064	0.064	0.442
xgboost	PCA	2	N/A	0.435	0.420	0.496	0.496	0.063	0.063	0.270
svc	PCA	2	N/A	0.371	0.265	0.483	0.483	0.062	0.062	0.004
tabpfn	PCA	10	N/A	0.806	0.796	0.395	0.395	0.051	0.051	0.331
tabicl	PCA	10	N/A	0.806	0.797	0.395	0.395	0.051	0.051	0.485
xgboost	PCA	10	N/A	0.774	0.764	0.418	0.418	0.054	0.054	0.242
svc	PCA	10	N/A	0.629	0.589	0.483	0.483	0.062	0.062	0.004
tabpfn	PCA	20	N/A	0.952	0.952	0.215	0.215	0.027	0.027	0.371
tabicl	PCA	20	N/A	0.952	0.952	0.215	0.215	0.027	0.027	0.561
xgboost	PCA	20	N/A	0.903	0.903	0.296	0.296	0.038	0.038	0.263
svc	PCA	20	N/A	0.742	0.702	0.438	0.438	0.056	0.056	0.004
tabpfn	PCA	50	N/A	0.952	0.952	0.215	0.215	0.027	0.027	0.393
tabicl	PCA	50	N/A	0.935	0.935	0.246	0.246	0.031	0.031	0.688
xgboost	PCA	50	N/A	0.919	0.918	0.272	0.272	0.035	0.035	0.377
svc	PCA	50	N/A	0.823	0.817	0.382	0.382	0.049	0.049	0.005
tabpfn	cPCA	2	1	0.290	0.206	0.454	0.454	0.058	0.058	0.327
tabicl	cPCA	2	1	0.371	0.310	0.483	0.483	0.062	0.062	0.435
xgboost	cPCA	2	1	0.258	0.260	0.438	0.438	0.056	0.056	0.354
svc	cPCA	2	1	0.339	0.234	0.473	0.473	0.061	0.061	0.004
tabpfn	cPCA	2	10	0.355	0.261	0.478	0.478	0.061	0.061	0.327
tabicl	cPCA	2	10	0.339	0.243	0.473	0.473	0.061	0.061	0.433
xgboost	cPCA	2	10	0.355	0.325	0.478	0.478	0.061	0.061	0.357
svc	cPCA	2	10	0.339	0.223	0.473	0.473	0.061	0.061	0.004
tabpfn	cPCA	2	100	0.290	0.223	0.454	0.454	0.058	0.058	0.316
tabicl	cPCA	2	100	0.306	0.260	0.461	0.461	0.059	0.059	0.422
xgboost	cPCA	2	100	0.226	0.225	0.418	0.418	0.054	0.054	0.337
svc	cPCA	2	100	0.355	0.248	0.478	0.478	0.061	0.061	0.004
tabpfn	cPCA	10	1	0.726	0.706	0.446	0.446	0.057	0.057	0.320
tabicl	cPCA	10	1	0.726	0.712	0.446	0.446	0.057	0.057	0.470
xgboost	cPCA	10	1	0.435	0.416	0.496	0.496	0.063	0.063	0.314
svc	cPCA	10	1	0.548	0.517	0.498	0.498	0.064	0.064	0.005
tabpfn	cPCA	10	10	0.726	0.717	0.446	0.446	0.057	0.057	0.329
tabicl	cPCA	10	10	0.694	0.688	0.461	0.461	0.059	0.059	0.477
xgboost	cPCA	10	10	0.597	0.568	0.491	0.491	0.063	0.063	0.310
svc	cPCA	10	10	0.613	0.589	0.487	0.487	0.062	0.062	0.005
tabpfn	cPCA	10	100	0.806	0.797	0.395	0.395	0.051	0.051	0.320
tabicl	cPCA	10	100	0.823	0.816	0.382	0.382	0.049	0.049	0.465
xgboost	cPCA	10	100	0.645	0.627	0.478	0.478	0.061	0.061	0.299
svc	cPCA	10	100	0.548	0.542	0.498	0.498	0.064	0.064	0.005
tabpfn	cPCA	20	1	0.710	0.698	0.454	0.454	0.058	0.058	0.339
tabicl	cPCA	20	1	0.758	0.755	0.428	0.428	0.055	0.055	0.516
xgboost	cPCA	20	1	0.581	0.562	0.493	0.493	0.063	0.063	0.357
svc	cPCA	20	1	0.581	0.565	0.493	0.493	0.063	0.063	0.006
tabpfn	cPCA	20	10	0.758	0.752	0.428	0.428	0.055	0.055	0.333
tabicl	cPCA	20	10	0.758	0.755	0.428	0.428	0.055	0.055	0.524
xgboost	cPCA	20	10	0.677	0.673	0.467	0.467	0.060	0.060	0.363
svc	cPCA	20	10	0.629	0.621	0.483	0.483	0.062	0.062	0.005
tabpfn	cPCA	20	100	0.790	0.779	0.407	0.407	0.052	0.052	0.343
tabicl	cPCA	20	100	0.887	0.886	0.316	0.316	0.041	0.041	0.521
xgboost	cPCA	20	100	0.597	0.597	0.491	0.491	0.063	0.063	0.373
svc	cPCA	20	100	0.597	0.583	0.491	0.491	0.063	0.063	0.005
tabpfn	cPCA	50	1	0.742	0.728	0.438	0.438	0.056	0.056	0.389
tabicl	cPCA	50	1	0.823	0.821	0.382	0.382	0.049	0.049	0.658
xgboost	cPCA	50	1	0.516	0.477	0.500	0.500	0.064	0.064	0.586
svc	cPCA	50	1	0.548	0.528	0.498	0.498	0.064	0.064	0.006
tabpfn	cPCA	50	10	0.790	0.787	0.407	0.407	0.052	0.052	0.391
tabicl	cPCA	50	10	0.823	0.822	0.382	0.382	0.049	0.049	0.672
xgboost	cPCA	50	10	0.677	0.668	0.467	0.467	0.060	0.060	0.576
svc	cPCA	50	10	0.565	0.551	0.496	0.496	0.063	0.063	0.007
tabpfn	cPCA	50	100	0.806	0.801	0.395	0.395	0.051	0.051	0.387
tabicl	cPCA	50	100	0.887	0.883	0.316	0.316	0.041	0.041	0.665
xgboost	cPCA	50	100	0.661	0.637	0.473	0.473	0.061	0.061	0.567
svc	cPCA	50	100	0.581	0.575	0.493	0.493	0.063	0.063	0.006

Table 4: Dimensionality Reduction Results on the DNA Classification Task

model	preprocessing	n_components	alpha	accuracy	f1_score	std_accuracy	std_f1	se_accuracy	se_f1	time_elapsed
tabpfn	None	180	N/A	0.986	0.989	0.119	0.119	0.005	0.005	6.196
tabicl	None	180	N/A	0.992	0.994	0.091	0.091	0.004	0.004	5.246
xgboost	None	180	N/A	0.986	0.989	0.119	0.119	0.005	0.005	0.114
svc	None	180	N/A	0.988	0.991	0.111	0.111	0.005	0.005	0.122
tabpfn	PCA	2	N/A	0.876	0.911	0.330	0.330	0.015	0.015	0.363
tabicl	PCA	2	N/A	0.884	0.918	0.320	0.320	0.015	0.015	0.512
xgboost	PCA	2	N/A	0.882	0.916	0.322	0.322	0.015	0.015	0.067
svc	PCA	2	N/A	0.882	0.917	0.322	0.322	0.015	0.015	0.041
tabpfn	PCA	10	N/A	0.952	0.965	0.213	0.213	0.010	0.010	0.382
tabicl	PCA	10	N/A	0.957	0.968	0.204	0.204	0.009	0.009	0.849
xgboost	PCA	10	N/A	0.942	0.957	0.233	0.233	0.011	0.011	0.099
svc	PCA	10	N/A	0.952	0.965	0.213	0.213	0.010	0.010	0.025
tabpfn	PCA	20	N/A	0.957	0.968	0.204	0.204	0.009	0.009	0.471
tabicl	PCA	20	N/A	0.961	0.971	0.194	0.194	0.009	0.009	1.068
xgboost	PCA	20	N/A	0.950	0.964	0.217	0.217	0.010	0.010	0.144
svc	PCA	20	N/A	0.948	0.962	0.221	0.221	0.010	0.010	0.034
tabpfn	PCA	50	N/A	0.973	0.980	0.162	0.162	0.007	0.007	0.878
tabicl	PCA	50	N/A	0.973	0.980	0.162	0.162	0.007	0.007	3.352
xgboost	PCA	50	N/A	0.950	0.964	0.217	0.217	0.010	0.010	0.274
svc	PCA	50	N/A	0.973	0.980	0.162	0.162	0.007	0.007	0.055
tabpfn	cPCA	2	1	0.779	0.846	0.415	0.415	0.019	0.019	0.421
tabicl	cPCA	2	1	0.783	0.849	0.412	0.412	0.019	0.019	0.455
xgboost	cPCA	2	1	0.779	0.841	0.415	0.415	0.019	0.019	0.061
svc	cPCA	2	1	0.711	0.820	0.453	0.453	0.021	0.021	0.074
tabpfn	cPCA	2	10	0.719	0.816	0.449	0.449	0.020	0.020	0.353
tabicl	cPCA	2	10	0.729	0.820	0.444	0.444	0.020	0.020	0.465
xgboost	cPCA	2	10	0.692	0.788	0.462	0.462	0.021	0.021	0.061
svc	cPCA	2	10	0.684	0.812	0.465	0.465	0.021	0.021	0.094
tabpfn	cPCA	2	100	0.738	0.824	0.440	0.440	0.020	0.020	0.357
tabicl	cPCA	2	100	0.729	0.818	0.444	0.444	0.020	0.020	0.413
xgboost	cPCA	2	100	0.711	0.800	0.453	0.453	0.021	0.021	0.058
svc	cPCA	2	100	0.684	0.812	0.465	0.465	0.021	0.021	0.069
tabpfn	cPCA	10	1	0.876	0.909	0.330	0.330	0.015	0.015	0.373
tabicl	cPCA	10	1	0.853	0.893	0.354	0.354	0.016	0.016	0.826
xgboost	cPCA	10	1	0.868	0.903	0.339	0.339	0.015	0.015	0.133
svc	cPCA	10	1	0.824	0.873	0.380	0.380	0.017	0.017	0.063
tabpfn	cPCA	10	10	0.880	0.912	0.325	0.325	0.015	0.015	0.380
tabicl	cPCA	10	10	0.853	0.895	0.354	0.354	0.016	0.016	0.822
xgboost	cPCA	10	10	0.837	0.883	0.370	0.370	0.017	0.017	0.127
svc	cPCA	10	10	0.812	0.869	0.391	0.391	0.018	0.018	0.069
tabpfn	cPCA	10	100	0.888	0.918	0.315	0.315	0.014	0.014	0.378
tabicl	cPCA	10	100	0.868	0.906	0.339	0.339	0.015	0.015	0.817
xgboost	cPCA	10	100	0.851	0.893	0.356	0.356	0.016	0.016	0.132
svc	cPCA	10	100	0.814	0.871	0.389	0.389	0.018	0.018	0.070
tabpfn	cPCA	20	1	0.890	0.919	0.312	0.312	0.014	0.014	0.483
tabicl	cPCA	20	1	0.882	0.915	0.322	0.322	0.015	0.015	1.035
xgboost	cPCA	20	1	0.870	0.905	0.336	0.336	0.015	0.015	0.215
svc	cPCA	20	1	0.860	0.899	0.348	0.348	0.016	0.016	0.076
tabpfn	cPCA	20	10	0.890	0.921	0.312	0.312	0.014	0.014	0.481
tabicl	cPCA	20	10	0.870	0.907	0.336	0.336	0.015	0.015	1.062
xgboost	cPCA	20	10	0.860	0.899	0.348	0.348	0.016	0.016	0.219
svc	cPCA	20	10	0.843	0.888	0.364	0.364	0.017	0.017	0.080
tabpfn	cPCA	20	100	0.895	0.924	0.307	0.307	0.014	0.014	0.468
tabicl	cPCA	20	100	0.888	0.919	0.315	0.315	0.014	0.014	1.015
xgboost	cPCA	20	100	0.853	0.895	0.354	0.354	0.016	0.016	0.210
svc	cPCA	20	100	0.855	0.897	0.352	0.352	0.016	0.016	0.080
tabpfn	cPCA	50	1	0.932	0.950	0.252	0.252	0.011	0.011	0.864
tabicl	cPCA	50	1	0.938	0.955	0.241	0.241	0.011	0.011	3.301
xgboost	cPCA	50	1	0.907	0.933	0.290	0.290	0.013	0.013	0.436
svc	cPCA	50	1	0.932	0.951	0.252	0.252	0.011	0.011	0.090
tabpfn	cPCA	50	10	0.924	0.944	0.266	0.266	0.012	0.012	1.026
tabicl	cPCA	50	10	0.942	0.958	0.233	0.233	0.011	0.011	3.628
xgboost	cPCA	50	10	0.884	0.918	0.320	0.320	0.015	0.015	0.771
svc	cPCA	50	10	0.930	0.949	0.256	0.256	0.012	0.012	0.153
tabpfn	cPCA	50	100	0.926	0.946	0.262	0.262	0.012	0.012	1.219
tabicl	cPCA	50	100	0.944	0.959	0.230	0.230	0.010	0.010	3.518
xgboost	cPCA	50	100	0.907	0.934	0.290	0.290	0.013	0.013	0.422
svc	cPCA	50	100	0.930	0.949	0.256	0.256	0.012	0.012	0.090

Table 5: Dimensionality Reduction Results on the Thyroid Classification Task

model	preprocessing	n_components	alpha	accuracy	f1_score	std_accuracy	std_f1	se_accuracy	se_f1	time_elapsed
TabPFN	None	0	N/A	0.885	0.833	0.003	0.005	0.001	0.002	47.012
TabPFN	PCA	2	N/A	0.885	0.832	0.001	0.002	0.001	0.001	10.854
TabPFN	PCA	10	N/A	0.885	0.833	0.001	0.002	0.001	0.001	28.046
TabPFN	PCA	20	N/A	0.885	0.833	0.002	0.004	0.001	0.002	49.394
TabPFN	cPCA	2	1	0.885	0.832	0.001	0.002	0.001	0.001	11.093
TabPFN	cPCA	2	10	0.885	0.832	0.001	0.002	0.001	0.001	10.891
TabPFN	cPCA	2	100	0.885	0.832	0.001	0.002	0.001	0.001	10.746
TabPFN	cPCA	10	1	0.884	0.832	0.002	0.003	0.001	0.001	27.697
TabPFN	cPCA	10	10	0.884	0.832	0.002	0.003	0.001	0.001	28.162
TabPFN	cPCA	10	100	0.884	0.832	0.002	0.003	0.001	0.001	27.738
TabPFN	cPCA	20	1	0.884	0.831	0.003	0.004	0.001	0.002	49.953
TabPFN	cPCA	20	10	0.884	0.831	0.003	0.004	0.001	0.002	49.600
TabPFN	cPCA	20	100	0.884	0.831	0.003	0.004	0.001	0.002	49.318
TabICL	None	0	N/A	0.885	0.832	0.001	0.003	0.001	0.001	2.706
TabICL	PCA	2	N/A	0.884	0.830	0.001	0.001	0.000	0.000	0.788
TabICL	PCA	10	N/A	0.884	0.830	0.001	0.001	0.001	0.000	1.878
TabICL	PCA	20	N/A	0.884	0.830	0.001	0.001	0.000	0.000	2.486
TabICL	cPCA	2	1	0.885	0.831	0.001	0.001	0.000	0.000	0.780
TabICL	cPCA	2	10	0.885	0.831	0.001	0.001	0.000	0.000	0.778
TabICL	cPCA	2	100	0.885	0.831	0.001	0.001	0.000	0.000	0.819
TabICL	cPCA	10	1	0.884	0.832	0.002	0.003	0.001	0.001	1.869
TabICL	cPCA	10	10	0.884	0.832	0.002	0.003	0.001	0.001	1.868
TabICL	cPCA	10	100	0.884	0.832	0.002	0.003	0.001	0.001	1.874
XGBoost	None	0	N/A	0.884	0.841	0.004	0.006	0.002	0.003	0.897
XGBoost	PCA	2	N/A	0.883	0.836	0.002	0.003	0.001	0.002	0.296
XGBoost	PCA	10	N/A	0.880	0.837	0.005	0.004	0.002	0.002	0.536
XGBoost	PCA	20	N/A	0.880	0.838	0.004	0.004	0.002	0.002	0.781
SVC	None	0	N/A	0.883	0.830	0.001	0.001	0.001	0.001	0.206
SVC	PCA	2	N/A	0.885	0.831	0.001	0.001	0.000	0.000	0.102
SVC	PCA	10	N/A	0.884	0.830	0.001	0.001	0.001	0.001	0.167
SVC	PCA	20	N/A	0.883	0.830	0.001	0.001	0.001	0.001	0.190

Table 6: Dimensionality Reduction Results on the Diabetes Classification Task

model	preprocessing	n_components	alpha	accuracy	f1_score	std_accuracy	std_f1	se_accuracy	se_f1	time_elapsed
TabPFN	None	0	N/A	0.997	0.997	0.003	0.004	0.002	0.002	6.752
TabPFN	PCA	2	N/A	0.947	0.93	0.008	0.016	0.004	0.008	3.304
TabPFN	PCA	10	N/A	0.983	0.982	0.01	0.01	0.005	0.005	6.247
TabPFN	cPCA	2	1.0	0.952	0.939	0.014	0.02	0.007	0.01	3.188
TabPFN	cPCA	2	10.0	0.952	0.939	0.014	0.02	0.007	0.01	3.243
TabPFN	cPCA	2	100.0	0.952	0.939	0.014	0.02	0.007	0.01	3.201
TabPFN	cPCA	10	1.0	0.985	0.984	0.008	0.009	0.004	0.004	6.252
TabPFN	cPCA	10	10.0	0.985	0.984	0.008	0.009	0.004	0.004	6.025
TabPFN	cPCA	10	100.0	0.985	0.984	0.008	0.009	0.004	0.004	6.094
TabICL	None	0	N/A	0.994	0.994	0.005	0.005	0.003	0.003	1.36
TabICL	PCA	2	N/A	0.959	0.954	0.01	0.013	0.005	0.007	0.531
TabICL	PCA	10	N/A	0.982	0.98	0.008	0.01	0.004	0.005	0.752
TabICL	cPCA	2	1.0	0.971	0.968	0.017	0.019	0.009	0.009	0.498
TabICL	cPCA	2	10.0	0.971	0.968	0.017	0.019	0.009	0.009	0.484
TabICL	cPCA	2	100.0	0.971	0.968	0.017	0.019	0.009	0.009	0.489
TabICL	cPCA	10	1.0	0.979	0.978	0.006	0.007	0.003	0.004	0.751
TabICL	cPCA	10	10.0	0.979	0.978	0.006	0.007	0.003	0.004	0.754
TabICL	cPCA	10	100.0	0.979	0.978	0.006	0.007	0.003	0.004	0.753
XGBoost	None	0	N/A	0.996	0.996	0.003	0.004	0.002	0.002	0.054
XGBoost	PCA	2	N/A	0.945	0.94	0.012	0.014	0.006	0.007	0.082
XGBoost	PCA	10	N/A	0.971	0.968	0.011	0.013	0.006	0.007	0.084
XGBoost	cPCA	2	1.0	0.948	0.941	0.011	0.016	0.006	0.008	0.081
XGBoost	cPCA	2	10.0	0.948	0.941	0.011	0.016	0.006	0.008	0.075
XGBoost	cPCA	2	100.0	0.948	0.941	0.011	0.016	0.006	0.008	0.075
XGBoost	cPCA	10	1.0	0.969	0.967	0.011	0.013	0.006	0.006	0.089
XGBoost	cPCA	10	10.0	0.969	0.967	0.011	0.013	0.006	0.006	0.085
XGBoost	cPCA	10	100.0	0.969	0.967	0.011	0.013	0.006	0.006	0.088
SVC	None	0	N/A	0.952	0.944	0.008	0.012	0.004	0.006	0.004
SVC	PCA	2	N/A	0.94	0.912	0.006	0.006	0.003	0.003	0.006
SVC	PCA	10	N/A	0.952	0.944	0.008	0.012	0.004	0.006	0.004
SVC	cPCA	2	1.0	0.94	0.912	0.006	0.006	0.003	0.003	0.007
SVC	cPCA	2	10.0	0.94	0.912	0.006	0.006	0.003	0.003	0.007
SVC	cPCA	2	100.0	0.94	0.912	0.006	0.006	0.003	0.003	0.007
SVC	cPCA	10	1.0	0.952	0.944	0.008	0.012	0.004	0.006	0.004
SVC	cPCA	10	10.0	0.952	0.944	0.008	0.012	0.004	0.006	0.004
SVC	cPCA	10	100.0	0.952	0.944	0.008	0.012	0.004	0.006	0.004

Table 7: Dimensionality Reduction Results on the HBTRC Classification Task

model	preprocessing	n_components	alpha	accuracy	f1_score	std_accuracy	std_f1	se_accuracy	se_f1	time_elapsed
TabPFN	None	0	N/A	0.956	0.956	0.014	0.014	0.007	0.007	57.523
TabPFN	PCA	2	N/A	0.764	0.761	0.026	0.025	0.013	0.013	1.593
TabPFN	PCA	10	N/A	0.893	0.894	0.027	0.027	0.013	0.013	4.83
TabPFN	PCA	20	N/A	0.92	0.92	0.025	0.024	0.012	0.012	5.938
TabPFN	PCA	50	N/A	0.953	0.953	0.016	0.016	0.008	0.008	10.402
TabPFN	cPCA	2	1.0	0.771	0.768	0.023	0.024	0.011	0.012	1.542
TabPFN	cPCA	2	10.0	0.771	0.768	0.023	0.024	0.011	0.012	1.613
TabPFN	cPCA	2	100.0	0.771	0.768	0.023	0.024	0.011	0.012	1.657
TabPFN	cPCA	10	1.0	0.898	0.898	0.025	0.024	0.012	0.012	4.427
TabPFN	cPCA	10	10.0	0.898	0.898	0.025	0.024	0.012	0.012	4.536
TabPFN	cPCA	10	100.0	0.898	0.898	0.025	0.024	0.012	0.012	4.527
TabPFN	cPCA	20	1.0	0.927	0.927	0.022	0.021	0.011	0.011	5.992
TabPFN	cPCA	20	10.0	0.927	0.927	0.022	0.021	0.011	0.011	6.023
TabPFN	cPCA	20	100.0	0.927	0.927	0.022	0.021	0.011	0.011	6.046
TabPFN	cPCA	50	1.0	0.942	0.942	0.022	0.022	0.011	0.011	10.805
TabPFN	cPCA	50	10.0	0.942	0.942	0.022	0.022	0.011	0.011	10.298
TabPFN	cPCA	50	100.0	0.942	0.942	0.022	0.022	0.011	0.011	10.435
TabICL	None	0	N/A	0.953	0.953	0.013	0.013	0.006	0.006	6.048
TabICL	PCA	2	N/A	0.751	0.751	0.026	0.025	0.013	0.012	0.488
TabICL	PCA	10	N/A	0.88	0.88	0.022	0.022	0.011	0.011	0.656
TabICL	PCA	20	N/A	0.927	0.926	0.023	0.023	0.011	0.011	0.787
TabICL	PCA	50	N/A	0.967	0.967	0.019	0.018	0.009	0.009	1.092
TabICL	cPCA	2	1.0	0.769	0.769	0.05	0.05	0.025	0.025	0.487
TabICL	cPCA	2	10.0	0.769	0.769	0.05	0.05	0.025	0.025	0.485
TabICL	cPCA	2	100.0	0.769	0.769	0.05	0.05	0.025	0.025	0.528
TabICL	cPCA	10	1.0	0.88	0.879	0.029	0.029	0.015	0.015	0.662
TabICL	cPCA	10	10.0	0.88	0.879	0.029	0.029	0.015	0.015	0.664
TabICL	cPCA	10	100.0	0.88	0.879	0.029	0.029	0.015	0.015	0.654
TabICL	cPCA	20	1.0	0.933	0.933	0.021	0.021	0.011	0.011	0.775
TabICL	cPCA	20	10.0	0.933	0.933	0.021	0.021	0.011	0.011	0.785
TabICL	cPCA	20	100.0	0.933	0.933	0.021	0.021	0.011	0.011	0.776
TabICL	cPCA	50	1.0	0.96	0.96	0.015	0.015	0.008	0.008	1.089
TabICL	cPCA	50	10.0	0.96	0.96	0.015	0.015	0.008	0.008	1.09
TabICL	cPCA	50	100.0	0.96	0.96	0.015	0.015	0.008	0.008	1.086
XGBoost	None	0	N/A	0.916	0.915	0.029	0.029	0.014	0.015	1.55
XGBoost	PCA	2	N/A	0.731	0.727	0.039	0.039	0.019	0.019	0.082
XGBoost	PCA	10	N/A	0.862	0.861	0.027	0.027	0.013	0.013	0.113
XGBoost	PCA	20	N/A	0.887	0.886	0.033	0.032	0.016	0.016	0.149
XGBoost	PCA	50	N/A	0.904	0.903	0.011	0.011	0.006	0.006	0.75
XGBoost	cPCA	2	1.0	0.733	0.729	0.031	0.032	0.015	0.016	0.081
XGBoost	cPCA	2	10.0	0.733	0.729	0.031	0.032	0.015	0.016	0.085
XGBoost	cPCA	2	100.0	0.733	0.729	0.031	0.032	0.015	0.016	0.082
XGBoost	cPCA	10	1.0	0.856	0.855	0.02	0.019	0.01	0.01	0.115
XGBoost	cPCA	10	10.0	0.856	0.855	0.02	0.019	0.01	0.01	0.119
XGBoost	cPCA	10	100.0	0.856	0.855	0.02	0.019	0.01	0.01	0.119
XGBoost	cPCA	20	1.0	0.887	0.885	0.049	0.05	0.025	0.025	0.146
XGBoost	cPCA	20	10.0	0.887	0.885	0.049	0.05	0.025	0.025	0.14
XGBoost	cPCA	20	100.0	0.887	0.885	0.049	0.05	0.025	0.025	0.147
XGBoost	cPCA	50	1.0	0.896	0.893	0.037	0.038	0.018	0.019	0.246
XGBoost	cPCA	50	10.0	0.896	0.893	0.037	0.038	0.018	0.019	0.252
XGBoost	cPCA	50	100.0	0.896	0.893	0.037	0.038	0.018	0.019	0.259
SVC	None	0	N/A	0.913	0.911	0.04	0.042	0.02	0.021	0.033
SVC	PCA	2	N/A	0.76	0.754	0.026	0.027	0.013	0.013	0.005
SVC	PCA	10	N/A	0.882	0.88	0.044	0.045	0.022	0.023	0.005
SVC	PCA	20	N/A	0.898	0.896	0.042	0.044	0.021	0.022	0.006
SVC	PCA	50	N/A	0.911	0.909	0.031	0.033	0.016	0.017	0.008
SVC	cPCA	2	1.0	0.76	0.754	0.029	0.031	0.015	0.016	0.004
SVC	cPCA	2	10.0	0.76	0.754	0.029	0.031	0.015	0.016	0.004
SVC	cPCA	2	100.0	0.76	0.754	0.029	0.031	0.015	0.016	0.005
SVC	cPCA	10	1.0	0.882	0.881	0.038	0.039	0.019	0.02	0.005
SVC	cPCA	10	10.0	0.882	0.881	0.038	0.039	0.019	0.02	0.005
SVC	cPCA	10	100.0	0.882	0.881	0.038	0.039	0.019	0.02	0.005
SVC	cPCA	20	1.0	0.9	0.897	0.04	0.042	0.02	0.021	0.006
SVC	cPCA	20	10.0	0.9	0.897	0.04	0.042	0.02	0.021	0.005
SVC	cPCA	20	100.0	0.9	0.897	0.04	0.042	0.02	0.021	0.005
SVC	cPCA	50	1.0	0.913	0.911	0.028	0.03	0.014	0.015	0.008
SVC	cPCA	50	10.0	0.913	0.911	0.028	0.03	0.014	0.015	0.007
SVC	cPCA	50	100.0	0.913	0.911	0.028	0.03	0.014	0.015	0.008