APPENDIX A

Relevant Proofs

Lemma A.1 $\sum_{i=1}^{m} \alpha_i \left\| \mathbf{E}\mathbf{x}_i - \mathbf{c} \right\|^2 = n$

Proof: For $\mathbf{E} \succ 0$, according to (2.12), at optimality, we have $\mathbf{c} = \dfrac{\mathbf{EX\alpha}}{\mathbf{e}^T\boldsymbol{\alpha}}$. Hence,

$$
\begin{aligned}
\sum_{i=1}^{m} \alpha_i \left\| \mathbf{E}\mathbf{x}_i - \mathbf{c} \right\|^2 &= \mathrm{tr}\left(\sum_{i=1}^{m} \alpha_i \left(\mathbf{E}\mathbf{x}_i - \mathbf{c}\right)^T \left(\mathbf{E}\mathbf{x}_i - \mathbf{c}\right) \right) \\
&= \mathrm{tr}\left(\sum_{i=1}^{m} \alpha_i \left(\mathbf{E}\mathbf{x}_i - \mathbf{c}\right) \left(\mathbf{E}\mathbf{x}_i - \mathbf{c}\right)^T \right) \\
&= \mathrm{tr}\left(\sum_{i=1}^{m} \alpha_i \left(\mathbf{E}\mathbf{x}_i - \frac{\mathbf{EX\alpha}}{\mathbf{e}^T\boldsymbol{\alpha}} \right) \left(\mathbf{E}\mathbf{x}_i - \frac{\mathbf{EX\alpha}}{\mathbf{e}^T\boldsymbol{\alpha}} \right)^T \right) \\
&= \mathrm{tr}\left(\mathbf{E} \sum_{i=1}^{m} \alpha_i \left(\mathbf{x}_i - \frac{\mathbf{X\alpha}}{\mathbf{e}^T\boldsymbol{\alpha}} \right) \left(\mathbf{x}_i - \frac{\mathbf{X\alpha}}{\mathbf{e}^T\boldsymbol{\alpha}} \right)^T \mathbf{E}^T \right) \\
&= \mathrm{tr}\left(\mathbf{E} \left[\sum_{i=1}^{m} \alpha_i \mathbf{x}_i \mathbf{x}_i^T - \sum_{i=1}^{m} \alpha_i \mathbf{x}_i \left(\frac{\mathbf{X\alpha}}{\mathbf{e}^T\boldsymbol{\alpha}} \right)^T - \left(\frac{\mathbf{X\alpha}}{\mathbf{e}^T\boldsymbol{\alpha}} \right) \sum_{i=1}^{m} \alpha_i \mathbf{x}_i^T + \sum_{i=1}^{m} \alpha_i \frac{\mathbf{X}\boldsymbol{\alpha}\boldsymbol{\alpha}^T\mathbf{X}^T}{(\mathbf{e}^T\boldsymbol{\alpha})^2} \right] \mathbf{E}^T \right).
\end{aligned}
$$

By using (2.11), we can rewrite the above expression in a matrix form as

$$
\sum_{i=1}^{m} \alpha_i \left\| \mathbf{E}\mathbf{x}_i - \mathbf{c} \right\|^2 = \mathrm{tr}\left(\mathbf{E} \left[\mathbf{XAX}^T - \frac{\mathbf{X}\boldsymbol{\alpha}\boldsymbol{\alpha}^T\mathbf{X}^T}{\mathbf{e}^T\boldsymbol{\alpha}} \right] \mathbf{E}^T \right) .
$$

Since $\mathbf{E}^{-2} = \left(\mathbf{XAX}^T - \dfrac{\mathbf{X}\boldsymbol{\alpha}\boldsymbol{\alpha}^T\mathbf{X}^T}{\mathbf{e}^T\boldsymbol{\alpha}} \right)$ according to (2.15), we then have

$$
\sum_{i=1}^{m} \alpha_i \left\| \mathbf{E}\mathbf{x}_i - \mathbf{c} \right\|^2 = \mathrm{tr}\left(\mathbf{E}(\mathbf{E}^T\mathbf{E})^{-1}\mathbf{E}^T \right) = n \qquad \square
$$

Lemma A.2

The dual problem (3.13) is the outcome of the primal problem

$$\begin{aligned} \min_{\mathbf{E},\mathbf{c},r,\boldsymbol{\xi}} \quad & nr^2 + 2\log\det(\mathbf{E}^{-1}) + \frac{C}{m}\sum_{i=1}^{m}\xi_i \\ \text{s.t.} \quad & y_i \left\|\mathbf{E}\mathbf{x}_i - \mathbf{c}\right\|^2 \le y_i r^2 + \xi_i, \quad \xi_i \ge 0, \quad i = 1,\ldots,m. \end{aligned} \tag{A.1}$$

Proof: From (A.1), the Lagrangian is

$$\begin{aligned} L(\mathbf{E},\mathbf{c},r,\boldsymbol{\xi},\boldsymbol{\alpha},\boldsymbol{\beta}) = {} & nr^2 - 2\log\det(\mathbf{E}) + \frac{C}{m}\sum_{i=1}^{m}\xi_i \\ & + \sum_{i=1}^{m}\alpha_i\left(y_i\left\|\mathbf{E}\mathbf{x}_i - \mathbf{c}\right\|^2 - y_i r^2 - \xi_i\right) - \sum_{i=1}^{m}\beta_i\xi_i \end{aligned} \tag{A.2}$$

where the Lagrange multiplier $\alpha_i, \beta_i \ge 0$ for i = 1, 2, …, m. By simply rearranging, we have

$$\begin{aligned} L(\mathbf{E},\mathbf{c},r,\boldsymbol{\xi},\boldsymbol{\alpha},\boldsymbol{\beta}) = {} & nr^2 - 2\log\det(\mathbf{E}) \\ & + \sum_{i=1}^{m}\left(\frac{C}{m} - \alpha_i - \beta_i\right)\xi_i + \sum_{i=1}^{m} y_i\alpha_i\left(\left\|\mathbf{E}\mathbf{x}_i - \mathbf{c}\right\|^2 - r^2\right). \end{aligned} \tag{A.3}$$

Suppose $\mathbf{y} = [y_1, y_2, ..., y_m]$ and $\mathbf{Y} = \operatorname{diag}(\mathbf{y})$ with $y_i \in \{1,-1\}$ for i = 1, 2, ..., m. The first-order derivatives are

$$\frac{\partial L}{\partial \xi_i} = \frac{C}{m} - \alpha_i - \beta_i \tag{A.4}$$

$$\frac{\partial L}{\partial r} = 2r\left(n - \sum_{i=1}^{m} y_i\alpha_i\right) = 2r(n - \mathbf{y}^T\boldsymbol{\alpha}) \tag{A.5}$$

$$\frac{\partial L}{\partial \mathbf{c}} = 2\left(\mathbf{c}\sum_{i=1}^{m}\alpha_i y_i - \mathbf{E}\sum_{i=1}^{m}\alpha_i y_i \mathbf{x}_i\right) = 2\left(\mathbf{c}\mathbf{y}^T\boldsymbol{\alpha} - \mathbf{E}\mathbf{X}\mathbf{Y}\boldsymbol{\alpha}\right) \tag{A.6}$$

$$\frac{\partial L}{\partial \mathbf{E}} = -\mathbf{E}^{-1} + \sum_{i=1}^{m}\alpha_i y_i\left[(\mathbf{E}\mathbf{x}_i - \mathbf{c})\mathbf{x}_i^T + \mathbf{x}_i(\mathbf{E}\mathbf{x}_i - \mathbf{c})^T\right]. \tag{A.7}$$

Under the first-order necessary condition of optimality, we have $0 \le \alpha_i \le C/m$ from (A.4) and the condition $\alpha_i, \beta_i \ge 0$. Equation (A.5) also yields $\mathbf{y}^T\boldsymbol{\alpha} = n$. The optimal $\mathbf{c}$ can be obtained from (A.6) as

$$\mathbf{c} = \frac{\mathbf{EXY\alpha}}{\mathbf{y}^T\boldsymbol{\alpha}}. \tag{A.8}$$

Substituting (A.8) into (A.7) and, (A.7) can be rewritten as

$$\mathbf{E}^{-1} = \frac{1}{2}(\mathbf{ES}+\mathbf{SE}) \tag{A.9}$$

where

$$\mathbf{S} = \mathbf{XAYX}^T - \frac{\mathbf{XY\alpha\alpha}^T\mathbf{YX}^T}{\mathbf{y}^T\boldsymbol{\alpha}}. \tag{A.10}$$

It is possible that **E** is not unique since **S** is not positive definite, however, we will assume that $\mathbf{E} = \mathbf{S}^{-1/2}$, similar to the solution in (2.15) and let the logarithm term in the objective of (A.1) act as a natural barrier function to drive the solution **E** to be positive definite. After further rewriting the Lagrangian (A.3) with $\sum_{i=1}^{m} y_i\alpha_i \|\mathbf{Ex}_i - \mathbf{c}\|^2 = n$, we obtain

$$L(\boldsymbol{\alpha}) = \log\det(\mathbf{XAYX}^T - \frac{\mathbf{XY\alpha\alpha}^T\mathbf{YX}^T}{\mathbf{y}^T\boldsymbol{\alpha}}). \tag{A.11}$$

Finally, by letting $\tilde{\mathbf{X}} = \begin{bmatrix}\mathbf{X}\\ \mathbf{e}^T\end{bmatrix}$ as in (2.22), we arrive the dual problem (3.13),

$$\begin{aligned} \max_{\boldsymbol{\alpha}} \quad & \log\det \tilde{\mathbf{X}}\mathbf{AY}\tilde{\mathbf{X}}^T \\ \text{s.t.} \quad & \mathbf{y}^T\boldsymbol{\alpha} = n \\ & \mathbf{0} \le \boldsymbol{\alpha} \le \frac{C}{m}. \end{aligned}$$

□

APPENDIX B

Additional Experimental Results

B.1 Supplementary Results for neSVDD

The following results in Table B.1 were obtained from training neSVDD's optimization model (3.13) but using the wrong classification rule (3.14).

Table B.1 The comparison of the area under ROC for one-class classification

Dataset		Spherical SVDD		Ellipsoidal SVDD	
		SVDD	nSVDD	eSVDD	neSVDD
1	Balance-scale (left)	0.9665 (0.0204)	0.9671 (0.0201)*	**0.9858 (0.0108)**	0.9780 (0.0158)
2	Balance-scale (middle)	0.8009 (0.1099)	0.8014 (0.1082)*	0.9224 (0.0475)	**0.9884 (0.0371)***
3	Balance-scale (right)	0.9665 (0.0188)	0.9676 (0.0184)*	**0.9853 (0.0108)**	0.9770 (0.0152)
4	Cancer wpbc (nonret)	**0.5433 (0.1233)**	0.5362 (0.1305)	0.5254 (0.1373)	0.5177 (0.1456)
5	Cancer wpbc (ret)	0.6128 (0.1509)	0.6283 (0.1578)*	**0.6449 (0.1291)**	0.6100 (0.1508)
6	Ecoli (periplasm)	0.9580 (0.0608)	**0.9599 (0.0586)***	0.9414 (0.0592)	0.9472 (0.0585)*
7	Glass (bldg. float)	0.8000 (0.0943)	0.8008 (0.0893)*	**0.8317 (0.0824)**	0.8021 (0.1125)
8	Glass (bldg. nonfloat)	0.6541 (0.1244)	0.6841 (0.1281)*	**0.7509 (0.1125)**	0.7097 (0.1269)
9	Glass (containers)	0.8269 (0.3286)	0.8269 (0.3286)	**0.9802 (0.0371)**	0.9665 (0.0872)
10	Glass (headlamps)	**0.9425 (0.0808)**	**0.9425 (0.0808)**	0.8925 (0.1220)	0.9108 (0.1247)*
11	Glass (vehicle float)	0.7116 (0.1230)	0.7324 (0.1258)*	0.8600 (0.1430)	**0.8853 (0.1540)***
12	Hepatitis (live)	0.8183 (0.1252)	0.8183 (0.1252)	0.8182 (0.1369)	**0.8258 (0.1273)***
13	Housing (MEDV>35)	0.8523 (0.0936)	0.8604 (0.0935)*	**0.8905 (0.0766)**	0.8862 (0.0853)
14	Imports (low risk)	0.8338 (0.0968)	0.8351 (0.0964)*	0.7678 (0.1368)	**0.8606 (0.0948)***
15	Iris (setosa)	**1.0000 (0.0000)**	**1.0000 (0.0000)**	**1.0000 (0.0000)**	**1.0000 (0.0000)**
16	Iris (versicolor)	0.9708 (0.0353)	0.9796 (0.0322)*	**0.9920 (0.0194)**	0.9888 (0.0233)
17	Iris (virginica)	0.9688 (0.0456)	0.9692 (0.0459)*	**0.9788 (0.0356)**	0.9708 (0.0394)
18	Liver (1)	0.5614 (0.0770)	0.5670 (0.0927)*	**0.6155 (0.0782)**	0.5928 (0.0847)
19	Liver (2)	0.5485 (0.1068)	0.6057 (0.0972)*	0.5533 (0.0862)	**0.6216 (0.0942)***
20	Sonar (mines)	0.7394 (0.0987)	0.7429 (0.0992)*	0.7879 (0.0919)	**0.8015 (0.0918)***
21	Sonar (rocks)	0.7179 (0.1109)	**0.7209 (0.1103)***	0.6273 (0.1296)	0.7063 (0.1281)*
22	Spectf (0)	0.8978 (0.0570)	0.9008 (0.0564)*	**0.9435 (0.0585)**	0.9420 (0.0532)
23	Spectf (1)	0.7153 (0.0845)	**0.7327 (0.0834)***	0.6453 (0.0744)	0.6474 (0.0471)*
24	Thyroid (normal)	0.7928 (0.0735)	0.8453 (0.0676)*	**0.9454 (0.0450)**	0.9127 (0.0794)
25	Wine (1)	0.9989 (0.0047)	0.9989 (0.0047)	0.9983 (0.0054)	**0.9991 (0.0037)***
26	Wine (2)	0.9011 (0.0703)	0.9011 (0.0703)	0.9491 (0.0504)	**0.9687 (0.0412)***
27	Wine (3)	0.9949 (0.0181)	0.9949 (0.0181)	**0.9986 (0.0062)**	**0.9986 (0.0062)**

Table B.1 shows that the numbers of datasets where each method is the best are 14, 10, 5, and 3 datasets, for eSVDD, neSVDD, nSVDD, and SVDD, respectively. In fact, eSVDD provides better results than SVDD for 18 out of 26 datasets, and neSVDD is

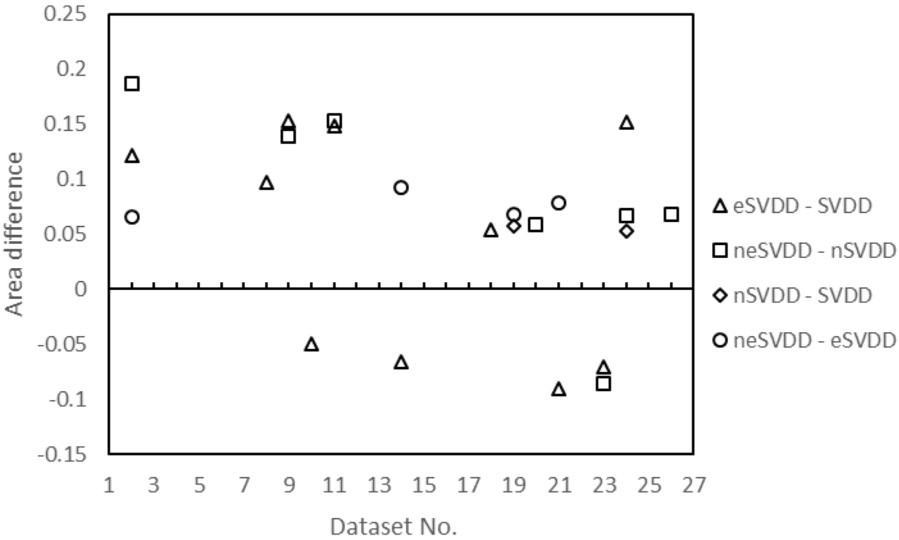

Figure B.1 Differences of the area under the ROC curve

also better than nSVDD for 20 out of 26 datasets. Hence, changing the descriptive boundary from a hypersphere to a hyperellipsoid help improve the results. Specifically, according to Table B.1, the ellipsoidal boundary yields superior results to the spherical one for 21 out of 26 datasets which is in line with the results in Table 4.2.

Nevertheless, it can be observed that some results in the table are only slightly different and the gaps between these results are depicted in Figure B.1. Suppose that we neglect the cases where the differences of the absolute area are less than 0.05 (or 5%) because of their less significance. According to the figure, we observe that using ellipsoidal boundaries degrades the performance for 4 datasets when comparing SVDD with eSVDD as can be from the number of "△" markers which are below -0.05. For nSVDD vs. neSVDD, the performances are reduced for one dataset as depicted by one "☐" marker below -0.05. Furthermore, according to the figure, the performance of SVDD and eSVDD did not degrade more than 5% when negative examples were introduced as depicted by none of the "◇" and "◯" markers are above -0.05.

B.2 Accuracy Ranking Summary for TESVM

This section summarizes, as presented in Table B.2 to Table B.5, the ranks of TESVM against the other algorithms in term of accuracy on each dataset. The ranks are displayed in the column "#". It is important to note that the accuracies reported in this section are the same as the results in Section 4.2; however, the ranks are provided here for the sake of convenience in comparing those algorithms. The last row of each table also shows the average accuracy as well as the average rank.

Table B.2 Accuracy ranking for Table 4.6

Dataset	Scenario I				Scenario II			
	TESVM	#	THSVM	#	TESVM	#	THSVM	#
Bupa	67.73 (1.23)	2	56.95 (1.02)	4	68.69 (1.05)	1	57.39 (1.16)	3
Diabetes	72.18 (0.61)	4	73.17 (1.53)	3	75.84 (0.74)	1	74.27 (0.54)	2
Haberman	69.05 (1.12)	4	71.17 (2.36)	3	75.32 (0.51)	1	73.03 (0.97)	2
Heart	81.29 (1.10)	2	79.96 (1.64)	4	81.85 (1.15)	1	80.40 (2.28)	3
Hepatitis	82.90 (1.90)	2	79.03 (1.02)	4	82.96 (1.80)	1	80.19 (1.94)	3
Ionosphere	68.74 (0.76)	3	37.74 (0.45)	4	92.19 (0.33)	1	87.72 (0.63)	2
Iris (1)	100.00 (0.00)	1	100.00 (0.00)	1	100.00 (0.00)	1	100.00 (0.00)	1
Iris (2)	82.93 (0.64)	3	66.80 (0.42)	4	88.06 (1.45)	1	86.66 (1.53)	2
Iris (3)	96.66 (0.00)	3	93.40 (0.66)	4	96.73 (0.66)	2	96.80 (0.81)	1
Postop	61.39 (2.03)	3	55.46 (3.46)	4	69.30 (1.99)	1	69.18 (1.57)	2
Sonar	75.86 (1.44)	2	69.32 (1.29)	4	77.16 (1.71)	1	69.56 (1.84)	3
Thyroid (1)	83.67 (1.08)	3	34.51 (1.70)	4	92.18 (0.78)	1	87.95 (3.11)	2
Thyroid (2)	98.04 (0.19)	4	98.37 (0.82)	3	98.46 (0.44)	2	98.93 (0.49)	1
Thyroid (3)	97.62 (0.26)	3	97.39 (1.61)	4	98.04 (0.19)	2	98.69 (0.75)	1
Transfusion	74.15 (0.51)	4	75.93 (0.73)	2	76.59 (0.49)	1	75.58 (0.47)	3
WDBC	95.44 (0.40)	2	94.21 (0.47)	4	95.78 (0.34)	1	94.71 (0.87)	3
Average	81.72	2.8	73.96	3.5	85.57	1.2	83.19	2.1

Table B.3 Accuracy ranking for Table 4.7

Dataset	Scenario I				Scenario II			
	TESVM	#	THSVM	#	TESVM	#	THSVM	#
Bupa	69.79 (1.28)	1	69.73 (1.19)	2	69.79 (1.28)	1	69.73 (1.40)	2
Diabetes	76.18 (0.54)	3	76.34 (0.57)	2	76.83 (0.31)	1	76.34 (0.57)	2
Haberman	76.14 (0.37)	2	74.11 (2.39)	3	76.20 (0.68)	1	71.47 (4.01)	4
Heart	83.92 (0.60)	1	83.00 (0.91)	3	83.92 (0.60)	1	83.66 (0.53)	2
Hepatitis	83.48 (1.26)	3	81.61 (2.56)	4	84.70 (1.25)	2	85.22 (0.71)	1
Ionosphere	94.30 (0.32)	3	95.15 (0.65)	1	94.44 (0.30)	2	95.15 (0.65)	1
Iris (1)	100.00 (0.00)	1	100.00 (0.00)	1	100.00 (0.00)	1	100.00 (0.00)	1
Iris (2)	97.46 (0.28)	3	96.93 (0.56)	4	97.66 (0.64)	1	97.60 (0.71)	2
Iris (3)	98.06 (0.49)	1	96.73 (0.73)	2	98.06 (0.49)	1	96.33 (1.05)	3
Postop	71.74 (1.23)	2	69.18 (1.83)	4	72.79 (0.98)	1	70.34 (1.47)	3
Sonar	89.66 (1.32)	1	87.21 (1.28)	3	89.66 (1.32)	1	88.17 (0.91)	2
Thyroid (1)	96.93 (0.44)	3	96.46 (0.90)	4	97.20 (0.53)	2	97.25 (0.40)	1
Thyroid (2)	99.48 (0.14)	1	98.83 (0.32)	2	99.48 (0.14)	1	98.51 (0.75)	3
Thyroid (3)	98.65 (0.34)	1	98.51 (0.89)	2	98.65 (0.34)	1	98.37 (1.03)	3
Transfusion	77.31 (0.70)	3	76.79 (1.09)	4	77.43 (0.13)	1	77.39 (0.56)	2
WDBC	97.18 (0.11)	1	96.50 (0.39)	3	97.18 (0.20)	1	96.80 (0.38)	2
Average	88.14	1.9	87.31	2.8	88.37	1.2	87.64	2.1

Table B.4 Accuracy ranking for Table 4.8

Dataset	TESVM	#	THSVM	#	TWSVM	#	SVM	#
Bupa	68.69 (1.05)	2	57.39 (1.16)	4	66.66 (0.61)	3	69.10 (0.83)	1
Diabetes	75.84 (0.74)	3	74.27 (0.54)	4	76.94 (0.38)	1	76.92 (0.31)	2
Haberman	75.32 (0.51)	2	73.03 (0.97)	4	75.45 (0.58)	1	73.52 (0.00)	3
Heart	81.85 (1.15)	3	80.40 (2.29)	4	83.85 (0.58)	2	84.14 (0.51)	1
Hepatitis	82.96 (1.80)	1	80.19 (1.94)	2	80.12 (2.31)	3	79.48 (1.51)	4
Ionosphere	92.19 (0.33)	1	87.72 (0.63)	2	82.07 (0.72)	4	87.54 (0.87)	3
Iris (1)	100.00 (0.00)	1	100.00 (0.00)	1	100.00 (0.00)	1	100.00 (0.00)	1
Iris (2)	88.06 (1.45)	1	86.66 (1.53)	2	74.86 (1.37)	3	72.00 (1.40)	4
Iris (3)	96.73 (0.66)	2	96.80 (0.81)	1	94.80 (0.87)	4	95.80 (0.63)	3
Postop	69.30 (1.99)	3	69.18 (1.57)	4	70.58 (1.23)	2	72.09 (0.00)	1
Sonar	77.16 (1.71)	2	69.56 (1.84)	4	75.52 (1.99)	3	78.26 (2.06)	1
Thyroid (1)	92.18 (0.78)	1	87.95 (3.11)	2	81.34 (0.46)	4	86.65 (0.44)	3
Thyroid (2)	98.46 (0.44)	3	98.93 (0.49)	1	92.27 (0.82)	4	98.60 (0.00)	2
Thyroid (3)	98.04 (0.19)	2	98.69 (0.75)	1	97.34 (0.22)	3	98.04 (0.42)	2
Transfusion	76.59 (0.49)	2	75.93 (0.73)	4	77.92 (0.62)	1	76.20 (0.00)	3
WDBC	95.78 (0.34)	2	94.71 (0.87)	3	94.67 (0.32)	4	97.69 (0.19)	1
Average	85.57	2.0	83.21	2.7	82.78	2.7	84.13	2.2

Table B.5 Accuracy ranking for Table 4.9

Dataset	TESVM	#	THSVM	#	TWSVM	#	SVM	#
Bupa	69.79 (1.28)	3	69.73 (1.40)	4	73.21 (0.58)	1	72.60 (0.85)	2
Diabetes	76.83 (0.31)	3	76.34 (0.57)	4	77.09 (0.77)	2	77.39 (0.33)	1
Haberman	76.20 (0.68)	1	74.11 (2.39)	3	73.20 (1.40)	4	74.24 (0.71)	2
Heart	83.92 (0.60)	2	83.66 (0.53)	4	83.77 (0.62)	3	84.37 (0.45)	1
Hepatitis	84.70 (1.25)	2	85.22 (0.71)	1	84.38 (1.57)	3	83.48 (1.95)	4
Ionosphere	94.44 (0.30)	3	95.15 (0.65)	2	93.90 (0.81)	4	95.21 (0.39)	1
Iris (1)	100.00 (0.00)	1	100.00 (0.00)	1	100.00 (0.00)	1	100.00 (0.00)	1
Iris (2)	97.66 (0.64)	1	97.60 (0.71)	2	97.26 (0.58)	3	97.26 (0.21)	3
Iris (3)	98.06 (0.49)	1	96.73 (0.73)	3	97.20 (0.52)	2	95.86 (0.52)	4
Postop	72.79 (0.98)	1	70.34 (1.47)	3	69.06 (3.29)	4	72.67 (1.25)	2
Sonar	89.66 (1.32)	2	88.17 (0.91)	4	88.79 (1.22)	3	89.75 (1.28)	1
Thyroid (1)	97.20 (0.53)	2	97.25 (0.40)	1	95.16 (0.96)	4	96.04 (0.54)	3
Thyroid (2)	99.48 (0.14)	1	98.83 (0.32)	3	99.48 (0.14)	1	98.97 (0.19)	2
Thyroid (3)	98.65 (0.34)	1	98.51 (0.89)	2	97.86 (0.24)	3	97.81 (0.69)	4
Transfusion	77.43 (0.13)	3	77.39 (0.56)	4	79.21 (0.43)	1	78.97 (0.63)	2
WDBC	97.18 (0.20)	3	96.80 (0.38)	4	98.04 (0.19)	1	97.83 (0.18)	2
Average	88.38	1.9	87.86	2.8	87.98	2.5	88.28	2.2

Table B.6 Accuracy ranking for Table 4.16

Dataset	TESVM	#	THSVM	#	TWSVM	#	SVM	#
Adult	80.7411	4	81.5703	2	82.7481	1	81.5279	3
Banana	90.3453	2	88.1321	4	89.4642	3	90.3717	1
Checkerboard	93.6000	2	94.9400	1	91.4500	4	93.5700	3
German	71.3300	3	70.8500	4	74.3200	1	73.6000	2
HTRU2	97.9070	1	97.8333	4	97.8634	3	97.9009	2
Occupancy	98.8205	1	98.0034	4	98.6629	3	98.7359	2
Pen-based (1)	99.7972	1	99.7732	2	99.7251	4	99.7451	3
Pen-based (2)	99.3355	2	99.2060	3	98.7950	4	99.5850	1
Pen-based (3)	99.6410	2	99.5103	3	99.4876	4	99.8225	1
Pen-based (4)	99.6771	2	99.6130	3	99.4489	4	99.7585	1
Pen-based (5)	99.8706	1	99.6744	4	99.6851	3	99.8612	2
Pen-based (6)	99.7838	1	99.7638	3	98.8671	4	99.7758	2
Pen-based (7)	99.7825	3	99.8479	2	99.7638	4	99.8812	1
Pen-based (8)	99.5957	2	99.5250	3	98.9685	4	99.7758	1
Pen-based (9)	99.7251	2	99.6878	3	99.5036	4	99.7758	1
Pen-based (10)	99.6531	2	99.6437	3	99.2167	4	99.8305	1
Page-blocks0	96.3359	1	92.7814	4	95.6232	3	95.8553	2
Phoneme	74.9112	1	74.7150	2	69.3949	4	73.0477	3
Shuttle (1)	99.7175	1	95.4816	4	97.9097	3	99.7149	2
Shuttle (4)	99.8246	3	99.8531	2	95.9285	4	99.9559	1
Shuttle (5)	99.9269	2	99.8947	3	99.4186	4	99.9434	1
Skin	99.9045	1	98.2431	4	99.6005	2	99.5800	3
Twonorm	94.6000	4	96.5838	2	95.1203	3	96.6419	1
Wilt	99.2279	3	99.4031	2	99.0873	4	99.4330	1
Average	95.5856	2.0	95.1888	3.0	95.0022	3.4	95.7371	1.7

Table B.7 Accuracy ranking for Table 4.17

Dataset	TESVM	#	THSVM	#	TWSVM	#	SVM	#
Bupa	68.3768	2	64.6667	4	67.9130	3	68.8406	1
Diabetes	74.8047	3	72.4219	4	76.0938	2	76.6406	1
Haberman	74.4771	1	70.9150	4	73.2026	3	73.4641	2
Heart	80.3704	3	78.1852	4	83.5185	2	83.6667	1
Hepatitis	81.0968	2	80.4516	3	81.2258	1	78.9677	4
Ionosphere	68.3191	2	40.2279	4	60.6553	3	87.3504	1
Sonar	83.9904	1	75.7212	4	78.9904	3	82.6442	2
Thyroid (1)	95.2093	2	82.8372	4	93.4419	3	95.6744	1
Thyroid (2)	97.6744	2	93.0233	3	92.7442	4	98.3721	1
Thyroid (3)	95.8140	1	91.3953	4	94.5116	2	94.1860	3
Transfusion	73.8235	2	73.3021	3	72.2326	4	77.1123	1
WDBC	95.7645	3	84.0598	4	96.4851	2	96.6784	1
Average	82.4768	2.0	75.6006	3.8	80.9179	2.7	84.4665	1.6

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