Appendix

Supplementary Material for:
Towards a framework for reliable performance evaluation in defect prediction

Xutong Liu, Shiran Liu, Zhaoqiang Guo, Peng Zhang, Yibiao Yang,
Huihui Liu, Hongmin Lu, Yanhui Li, Lin Chen, and Yuming Zhou

A. The literature reviewing criteria and the meaning of baseline model b_i and the corresponding literature in which it is cited

The purpose of the literature review mentioned in Section 3.1 is to investigate which baseline models were used in the evaluation experiments of state-of-the-art (SOTA) SDP models. Therefore, we need to devise a literature selection strategy to choose representative SOTA SDP models for the literature review.

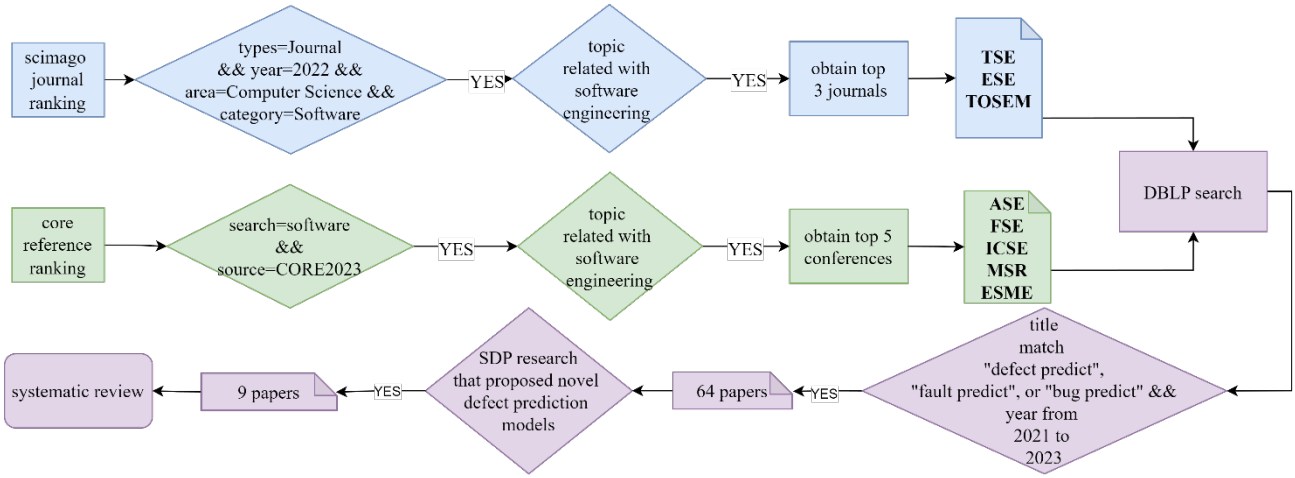


Figure 1. Overflow of literature selection to support our systematic review of representative SDP models.

As can be seen in Fig. 1, first, we obtain scimago journal ranking[1] and core reference ranking[2] in the field of software; then, we manually exclusive journals and conferences which topic is not mainly about software engineering; next, we obtain top three journals and top five conferences from ramianed lists. The included journals are IEEE Transactions on Software Engineering (TSE), Empirical Software Engineering (ESE), and ACM Transactions on Software Engineering and Methodology (TOSEM). The included conferences are Automated Software Engineering Conference (ASE), ACM International Conference on the Foundations of Software Engineering (FSE), International Conference on Software Engineering (ICSE), IEEE International Working Conference on Mining Software Repositories (MSR), International Symposium on Empirical Software Engineering and Measurement (ESEM). From those selected journals and conferences, we search SDP research through DBLP[3] with keyword “defect predict”, “bug predict”, or “fault predict” and manually check whether the research proposed novel defect prediction models. At last, we get nine papers that proposed novel SDP models in recent three years (2021~2023). Finally, we get nine papers as listed in Table 1.

Table 1: Baseline model b_i and the corresponding usage

		2021		2022				2023		
model	sym	KSETE	top-core	STABILIZER	MEG	EASC	FENSE	DSSDPP	TDTSR	ADA
TCA+	b1	x						x		x

[1] https://www.scimagojr.com/journalrank.php?category=1712&area=1700&type=j&year=2022
[2] https://portal.core.edu.au/conf-ranks/?search=software&by=all&source=CORE2023&sort=arank&page=1
[3] https://dblp.org/

TNB	b2	x								
CCA+	b3	x								
HDP-KS	b4	x							x	
NNFilter	b5	x						x		
Ree	b6		x							
Ree+BW	b7		x							
Ree+PR	b8		x							
Ree+degree	b9		x							
CTKCCA	b10	x							x	
HISNN	b11	x								
BellWether	b12	x		x			x			
CamargoCruz09-	b13					x				
Menzies11-RF	b14					x				
Turhan09-DT	b15					x				
Watanabe08-DT	b16					x				
ManualDown	b17					x				
ManualUp	b18					x				
TSEL	b19								x	
TPTL	b20			x						x
DIVACE	b21				x					
Stacking	b22				x					
NB	b23				x					
DT	b24				x					
KNN	b25				x					
SVM	b26				x					
random-ensemble	b27						x			
sim-ensemble	b28						x			
SSTCA+ISDA	b29							x		
DBA	b30							x		
LR	b31									x
TCNN	b32									x
Seml	b33									x

B. Evaluating MSMDA and top-core under MATTER

To investigate the progress in defect prediction achieved by new defect prediction models, we apply MATTER to evaluate two new defect prediction models, MSMDA [1] and top-core [2]. The evaluation of MSMDA and top-core are conducted on their original published data sets separately for the following reasons:

(1) **Data availability problem for top-core.** In top-core, for a module, the predicted defectiveness depends on its "coreness" that is computed from a graph extracted from the project's source code. In their original study, the authors of top-core provided such information for 8 test projects. However, for the other test projects used in our study, such information is unavailable. At the first glance, it seems that we could extract such information for each test project by ourselves. However, many data sets do not provide the corresponding source code and hence we must download their source code from their project websites. During this process, we find that there are two problems. First, since many test projects do not provide the exact version number, we are unable to find the corresponding correct source code. Second, for those test projects that provide the corresponding version number, we find that many modules in the test data sets are missing in the source code we download due to unknown reasons. This means we cannot compare top-core with other defect prediction models under the same modules in a test project. Therefore, we only use the same 8 test projects (shared by the authors of top-core) to compare ONE and top-core (see Table 2).

(2) **Computation complexity problem for MSMDA.** MSMDA is a multi-source selection based manifold discriminant alignment model. We use a 64GB RAM Windows machine to run single-source MDA, which is a simplified version of MSMDA and hence has a lower computation complexity. However, MDA is still a high memory usage program, which is mainly caused by its matrix computations and the "out-of-memory failure" occurs when larger datasets such as JURECZKO are used. This indicates that

MSMDA does not scale to large data sets due to the inherent high computation complexity. Therefore, we report their comparison on the same test sets (see Table 3) as used in the paper that MSMDA is originally proposed and evaluated.

Detailed experiment settings of top-core vs. ONE. In the original top-core study, their evaluation of top-core is conducted on (1) cross-validation data split strategy and (2) forward-release data split strategy. The former strategy randomly split the data set into training data and test data, which is considered to be unrealistic for a real-world scenario [3], for example, modules in a project that are developed earlier may be divided into test data while modules that are developed later may be divided into training data, then the prediction model will be built on the future knowledge that should not be known. The second strategy cannot be replicated by us due to the cross-version data sets with "coreness" are not available (i.e., the data availability problem stated before). Therefore, the comparison between top-core and ONE is conducted under the all-to-one data split strategy on projects in Table 2. For example, when Camel in Table 2 is the test project, all other seven projects are used to be the training data.

Detailed experiment settings of MSMDA vs. ONE. MSMDA is a multi-source selection-based model designed specifically for HDP (Heterogeneous Defect Prediction) scenario. In its original study, MSMDA uses all the projects from external datasets plus 10% modules in the test sets as the training data, and the remaining 90% modules in the test sets as the test data. For example, when EQ from the AEEEM dataset in Table 3 is the target project, then all other 23 projects outside the AEEEM dataset are used to be the training data, meanwhile, 10% of modules in EQ are plus to the training data and the remaining 90% of modules will be the test data. Since our goal is to evaluate the effectiveness of MSMDA, we decide to evaluate MSMDA under its original goal scenario by following its data split strategy to compare MSMDA with ONE on projects in Table 3. Note that ONE is also conducted on the same remaining 90% of modules to make a fair comparison.

Table 2: Details of data sets in the original top-core studies whose "coreness" of modules are publicly available

Study	Dataset	Project	#instance	%defective	#metrics
Top-core	tera-PROMISE	Camel	965	19%	20
		Ivy	352	11%	20
		Log4j	109	34%	20
		Poi	442	64%	20
		Synapse	256	34%	20
		Tomcat	858	9%	20
		Velocity	229	34%	20
		Xalan	885	46%	20

Table 3: Details of data sets used in the original MSMDA studies

Study	Dataset	Project	#instance	%defective	#metrics
MSMDA	NASA	CM1	327	12.84%	37
		MW1	253	10.67%	37
		PC1	705	8.65%	37
		PC3	1077	12.44%	37
		PC4	1458	12.21%	37
	SOFTLAB	AR1	121	7.44%	29
		AR3	63	12.70%	29
		AR4	107	18.69%	29
		AR5	36	22.22%	29
		AR6	101	14.85%	29
	ReLink	Apache	194	50.52%	26
		Safe	56	39.29%	26
		ZXing	399	29.57%	26
	AEEEM	EQ	324	39.81%	61
		JDT	997	20.66%	61
		LC	691	9.26%	61
		ML	1862	13.16%	61
		PDE	1497	13.96%	61
	PROMISE	ant1.3	125	16.00%	20
		arc	234	11.54%	20
		camel1.0	339	3.83%	20
		poi1.5	237	59.49%	20
		redaktor	176	15.34%	20
		skarbonka	45	20.00%	20
		tomcat	858	8.97%	20
		velocity1.4	196	75.00%	20
		xalan2.4	723	15.21%	20
		xerces1.2	440	16.14%	20

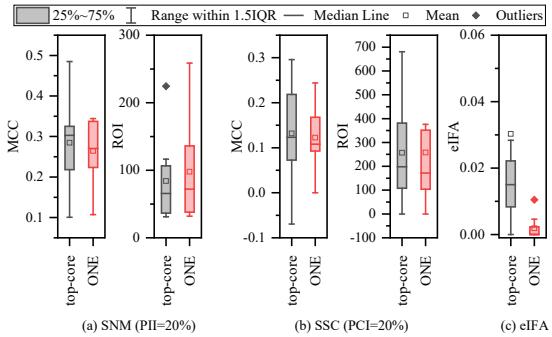


Figure 1: The performance distributions of top-core and ONE on the same target sets with the original study of top-core in terms of MCC, ROI, and eIFA under SNM and SSC

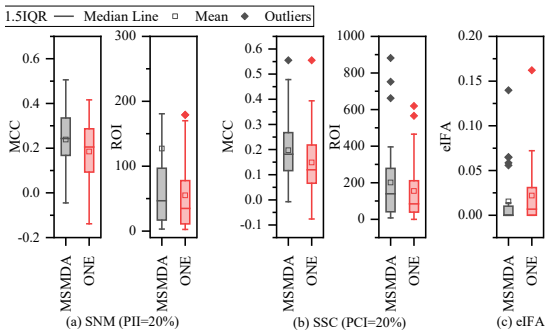


Figure 2: The performance distributions of MSMDA and ONE on the same target sets with the original study of top-core in terms of MCC, ROI, and eIFA under SNM and SSC

Fig. 1 reports the performance distributions of top-core vs. ONE. From Fig. 1, we can observe that:

- MCC: top-core exhibits a similar distribution compared with ONE (p-value = 0.641 under SNM, p-value = 0.742 under SSC);
- ROI: top-core exhibits a similar distribution compared with ONE (p-value = 0.055 under SNM, p-value = 0.945 under SSC);
- eIFA: top-core is significantly worse than ONE (p-value = 0.022) and the effect size is large (cliff's delta = 0.813).

By the above results, we can conclude that top-core underperforms ONE.

Fig. 2 reports the performance distributions of MSMDA vs. ONE. From Fig. 2, we can observe that:

- MCC: Compared with ONE, MSMDA performs slightly better under SNM (p-value = 0.021, cliff's delta = 0.212, a small effect size) and similarly under SSC (p-value = 0.057);
- ROI: Under SNM, no significant difference is observed (p-value = 0.264). MSMDA is significantly better (p-value = 0.036) than ONE but the effect size is trivial (cliff's delta = 0.102) under SSC;
- eIFA: there is no significant difference between MSMDA and ONE (p-value = 0.305).

By the above results, we can conclude that, from the viewpoint of practical application, MSMDA does not lead to an important progress in prediction performance.

(a) under SNM (PII=20%) (b) under SSC (PCI=20%) (c) eIFA

Figure 3: The distributions of rankings of multiple models' comparisons in terms of performance indicator and the non-parametric Scott-Knott ESD test result (the smaller the group number on the top of the plot, the better the performance rankings)

C. Comparisons between ONE and other baseline models on individual datasets

To evaluate whether ONE is "strong" enough as a baseline model for defect prediction, we compare its prediction performance with other defect prediction models that are recommended to be baseline models or have the potential to be baseline models (Bellwether [4], EASC_E [5], EASC_NE [5], ManualDown [6-8], ManualUp [6-8], SC [9], CLA [10], and FCM [11]). In this section, we report the comparison results on five individual datasets used in our experiment, AEEEM [12], JURECZKO [13], MA-SZZ-2020 [14], IND-JLMIV+R [15], and ReLink [16], respectively. Table 4 reports the mean and standard deviation values and Table 5 reports the median values in terms of MCC, ROI, and eIFA of each baseline model on five datasets, respectively. The best mean/median performance value of each indicator is marked in **bold** while the worst mean/median performance value is marked in underlined. In Fig. 3, the multiple models are grouped by the non-parametric Scott-Knott ESD test [17], and models in the same group are negligible in their performance ranking distributions. Note that we do not conduct the Scott-Knott ESD test on AEEEM and ReLink since they only contain five and three samples (i.e., test projects), respectively, and the statistical test on such a small sample is usually considered to be unreliable.

According to Table 4, Table 5, and Fig. 3, we have the following observations:

(1) According to Fig. 3, (1) on JURECZKO, ONE performs at the top-level under SSC and at the upper-middle level under SSC, meanwhile its eIFA is the best among models; (2) on MA-SZZ-2020, ONE performs top-level ROI under SNM, while performs middle-level on other indicators; (3) on IND-JLMIV+R, ONE performs top-level MCC under SSC, ROI under SNM, and eIFA, while the ROI under SSC and MCC under SNM are at the upper-middle-level.

(2) ONE achieves better prediction performance than ManualDown and ManualUp. First, ManualDown performs consistently badly in terms of ROI under SNM, since it requires a lot of code inspection effort to inspect the top largest modules when models are allowed to inspect the same number of modules. Second, for a total of 25 times multiple models' comparisons, ManualUp performs the worst median values for 21/25 comparisons and worst mean values for 20/25 comparisons, it is particularly not good at evaluations under SSC and the eIFA. As can be seen from Fig. 3, it is at the worst to the middle level in terms of ROI under SNM.

(3) As can be seen from Table 4, EASC_NE and Bellwether are the best supervised models among the multiple models' comparisons on multiple datasets. However, supervised models such as EASC_NE, EASC_E or Bellwether cannot provide a stable performance for target data when the training data changes. As the training data varies with the data split strategy or the data resampling algorithm, the prediction performance of a supervised model on the same target project may vary in a range, on the contrary, the performance of ONE on the same target will keep the same. Considering those supervised models are not often significantly better than ONE according to the model grouping of the Scott-Knott ESD test, we still recommend ONE, rather than those compared supervised models to be the baseline model in MATTER.

Based on the above observations, under both SNM and SSC, ONE has a competitive prediction performance in multiple models' comparisons on most of the five defect datasets. Although ManualDown and ManualUp are also simple in implementation and stable in prediction results for a given target data, ONE performs better and is preferred to be a global reference point for across-study comparison. For the other compared models, (1) the performance of supervised models depends on the choice of the training data and therefore they are inappropriate to be a global reference point for across-study model performance comparison; (2) although SC, CLA, and FCM are unsupervised (i.e., they are free of the influence of the training data), their prediction performance may vary with the feature set used for model building. Therefore, they are also inappropriate to be a global reference point for across-study comparison. In summary, the comparison results on five individual datasets support ONE to be the appropriate baseline model in evaluating defect prediction models.

Table 4. The mean(standard deviation) MCC, ROI, and eIFA values of each baseline model on five datasets

Dataset	Model	SNM (PII=20%)		SSC (PCI=20%)		eIFA
		MCC	ROI	MCC	ROI	
AEEEM	Bellwether	0.276(0.085)	133.0(63.9)	0.184(0.059)	541.2(301.6)	**0.000(0.000)**
	EASC-E	0.237(0.079)	157.0(103.3)	0.169(0.024)	420.4(219.5)	0.001(0.002)
	EASC-NE	**0.311(0.085)**	126.3(61.5)	0.126(0.065)	607.0(424.2)	0.012(0.018)
	SC	0.141(0.122)	188.1(89.3)	0.124(0.119)	310.1(230.3)	0.006(0.006)
	CLA	0.241(0.060)	127.3(43.1)	0.152(0.077)	428.3(296.2)	0.001(0.003)
	FCM	0.017(0.092)	126.0(62.1)	**0.192(0.098)**	464.1(251.4)	0.001(0.002)
	ManualDown	0.279(0.109)	113.1(60.1)	0.125(0.066)	**609.9(439.6)**	0.012(0.018)
	ManualUp	-0.149(0.111)	**1652.7(1018.4)**	-0.287(0.110)	96.9(33.6)	0.025(0.027)
	ONE	0.252(0.094)	141.5(72.9)	0.144(0.082)	455.9(267.9)	0.003(0.006)
JURECZKO	Bellwether	0.261(0.184)	53.4(72.3)	**0.144(0.120)**	**181.1(192.4)**	**0.011(0.035)**
	EASC-E	0.165(0.146)	78.6(160.8)	0.123(0.137)	140.5(160.6)	0.018(0.051)
	EASC-NE	0.263(0.161)	50.0(61.1)	0.115(0.119)	167.9(212.0)	0.021(0.047)
	SC	0.170(0.199)	96.5(224.1)	0.105(0.154)	159.1(179.4)	0.024(0.061)
	CLA	0.204(0.173)	66.8(100.9)	0.101(0.136)	145.1(174.9)	0.024(0.048)
	FCM	0.019(0.215)	61.6(94.2)	0.071(0.178)	149.7(198.9)	0.022(0.055)
	ManualDown	**0.277(0.170)**	45.4(51.0)	0.101(0.115)	160.7(206.3)	0.021(0.046)
	ManualUp	-0.191(0.140)	**2633.2(6377.9)**	-0.293(0.164)	78.6(137.6)	0.067(0.096)
	ONE	0.248(0.174)	56.4(65.5)	0.129(0.119)	158.5(196.2)	0.013(0.041)
IND-JLMIV+R	Bellwether	0.070(0.118)	30.3(22.9)	0.047(0.107)	55.0(62.7)	0.040(0.055)
	EASC-E	0.072(0.130)	49.9(145.4)	0.087(0.139)	85.7(139.6)	0.036(0.047)
	EASC-NE	0.245(0.122)	31.1(21.4)	0.197(0.129)	141.5(158.3)	0.027(0.051)
	SC	0.128(0.130)	29.6(21.6)	0.048(0.089)	53.9(59.4)	0.045(0.046)
	CLA	0.253(0.121)	29.7(21.2)	0.177(0.119)	144.1(152.5)	0.019(0.032)
	FCM	0.049(0.145)	44.4(86.3)	0.025(0.116)	45.7(58.9)	0.048(0.061)
	ManualDown	**0.307(0.127)**	28.5(19.1)	0.193(0.121)	**167.3(161.2)**	0.033(0.053)
	ManualUp	-0.147(0.048)	**3636.1(18902.9)**	-0.280(0.099)	14.2(18.5)	0.203(0.102)
	ONE	0.237(0.110)	32.4(23.7)	**0.202(0.113)**	148.9(167.8)	**0.017(0.027)**
MA-SZZ-2020	Bellwether	0.184(0.111)	82.1(55.3)	0.120(0.101)	169.8(98.7)	0.012(0.020)
	EASC-E	0.192(0.088)	84.8(59.5)	0.152(0.052)	210.5(171.1)	0.017(0.011)
	EASC-NE	0.238(0.077)	76.4(55.8)	**0.166(0.083)**	**294.1(190.3)**	0.008(0.020)
	SC	0.136(0.100)	88.0(62.3)	0.119(0.090)	204.0(195.3)	0.011(0.022)
	CLA	0.183(0.076)	89.2(65.7)	0.132(0.082)	174.4(138.5)	0.007(0.010)
	FCM	0.047(0.156)	55.9(54.3)	0.127(0.096)	184.6(162.3)	0.016(0.050)
	ManualDown	**0.263(0.090)**	66.0(48.4)	0.129(0.093)	257.5(223.8)	0.017(0.047)
	ManualUp	-0.159(0.062)	**278.3(356.6)**	-0.277(0.090)	60.9(68.4)	0.095(0.103)
	ONE	0.232(0.091)	78.7(60.7)	0.111(0.074)	182.7(174.6)	0.029(0.049)
ReLink	Bellwether	0.139(0.212)	66.7(41.6)	0.107(0.152)	115.8(87.0)	**0.000(0.000)**
	EASC-E	0.192(0.329)	122.9(86.1)	**0.212(0.184)**	116.1(74.7)	0.002(0.002)
	EASC-NE	**0.361(0.224)**	41.8(22.6)	0.161(0.068)	**157.2(99.0)**	**0.000(0.000)**
	SC	0.053(0.078)	65.4(38.0)	0.022(0.045)	88.8(60.5)	0.007(0.006)
	CLA	0.283(0.132)	46.2(27.7)	0.134(0.145)	116.5(67.3)	0.019(0.034)
	FCM	0.059(0.374)	208.8(306.3)	-0.013(0.366)	82.4(33.2)	0.007(0.012)
	ManualDown	0.338(0.253)	37.6(18.1)	0.150(0.079)	145.1(82.1)	**0.000(0.000)**
	ManualUp	-0.238(0.095)	**2047.0(1796.2)**	-0.372(0.179)	59.5(42.9)	0.032(0.027)
	ONE	0.272(0.163)	48.9(26.7)	0.170(0.111)	134.3(80.9)	0.006(0.006)

Table 5. The median MCC, ROI, and eIFA values of each baseline model on five datasets

Dataset	Model	SNM (PII=20%)		SSC (PCI=20%)		eIFA
		MCC	ROI	MCC	ROI	
AEEEM	Bellwether	0.223	150.8	0.151	575.8	**0.00**
	EASC-E	0.242	171.4	0.170	317	0.00
	EASC-NE	**0.262**	152.2	0.154	**592.6**	0.00
	SC	0.167	196.2	0.170	250.3	0.00
	CLA	0.252	146.5	0.177	276.6	0.00
	FCM	-0.039	153.9	**0.243**	298.8	0.00
	ManualDown	0.257	149.3	0.154	561.4	0.00
	ManualUp	-0.124	**1963.6**	-0.262	101.1	0.01
	ONE	0.218	189.5	0.156	526.4	0.00
JURECZKO	Bellwether	0.249	29.8	**0.145**	**112.8**	**0.00**
	EASC-E	0.165	34.5	0.138	96.4	0.00
	EASC-NE	0.263	29.6	0.089	87.2	0.00
	SC	0.146	36.5	0.095	104.5	0.00
	CLA	0.194	32.6	0.098	89.3	0.00
	FCM	0.002	24.7	0.090	73	0.00
	ManualDown	**0.271**	28.6	0.086	84.1	0.00
	ManualUp	-0.179	**340.3**	-0.291	26.8	0.03
	ONE	0.228	32.7	0.124	104.6	0.00
IND-JLMIV+R	Bellwether	0.053	25.6	0.032	33.2	0.02
	EASC-E	0.082	**29.5**	0.089	45.8	0.02
	EASC-NE	0.246	25.6	0.193	95.7	0.00
	SC	0.123	22.9	0.049	44.1	0.03
	CLA	0.248	24.6	0.182	97.9	**0.00**
	FCM	0.031	24.1	0.019	25.5	0.02
	ManualDown	**0.266**	24.7	**0.199**	**117.9**	0.01
	ManualUp	-0.142	0	-0.273	9.9	0.20
	ONE	0.206	26.2	0.196	94.6	0.00
MA-SZZ-2020	Bellwether	0.203	71.8	0.118	156.4	0.00
	EASC-E	0.183	69.1	**0.160**	173.3	0.01
	EASC-NE	0.259	61.8	0.146	**296.4**	**0.00**
	SC	0.132	80.4	0.137	137.2	0.00
	CLA	0.169	72.3	0.124	153.3	0.00
	FCM	0.097	44.7	0.137	204.4	0.00
	ManualDown	**0.271**	62.2	0.139	240.4	0.00
	ManualUp	-0.139	**109.5**	-0.285	33.6	0.07
	ONE	0.251	68.5	0.122	155.6	0.00
ReLink	Bellwether	0.160	69.3	0.103	89.9	**0.00**
	EASC-E	0.188	141.5	**0.197**	102.7	0.00
	EASC-NE	0.281	48.5	0.126	161.7	0.00
	SC	0.064	76.6	0.040	110.9	0.01
	CLA	0.243	51	0.087	104.5	0.00
	FCM	0.064	49.1	0.003	71.6	0.00
	ManualDown	0.281	47.7	0.117	**161.7**	0.00
	ManualUp	-0.214	**1024.9**	-0.387	71.6	0.02
	ONE	**0.281**	62.9	0.132	129.3	0.00

D. Evaluating representative models under MATTER on individual datasets

In this section, we report the effectiveness of four state-of-the-art defect prediction models (CamargoCruz09-NB [18], Amasaki15-NB [18], Peters15-NB [18], and KSETE [19]) under MATTER on five individual datasets, AEEEM [12], JURECZKO [13], MA-SZZ-2020 [14], IND-JLMIV+R [15], and ReLink [16], respectively. Table 6 reports the mean and standard deviation values and Table 7 report the median values in terms of MCC, ROI, and eIFA of each state-of-the-art defect prediction model and the baseline ONE. The

best mean/median performance value of each indicator is marked in **bold** while the worst mean/median performance value is marked in underlined. In Fig. 4, the multiple models are grouped by the non-parametric Scott-Knott ESD test [17], and models in the same group are negligible in their performance ranking distributions. Note that we do not conduct the Scott-Knott ESD test on AEEEM and ReLink for the same reason in Appendix C.

According to Table 6, Table 7, and Fig. 4, we have the following observations:

Table 6. The mean(standard deviation) MCC, ROI, and eIFA values of each state-of-the-art defect prediction model and ONE on five datasets

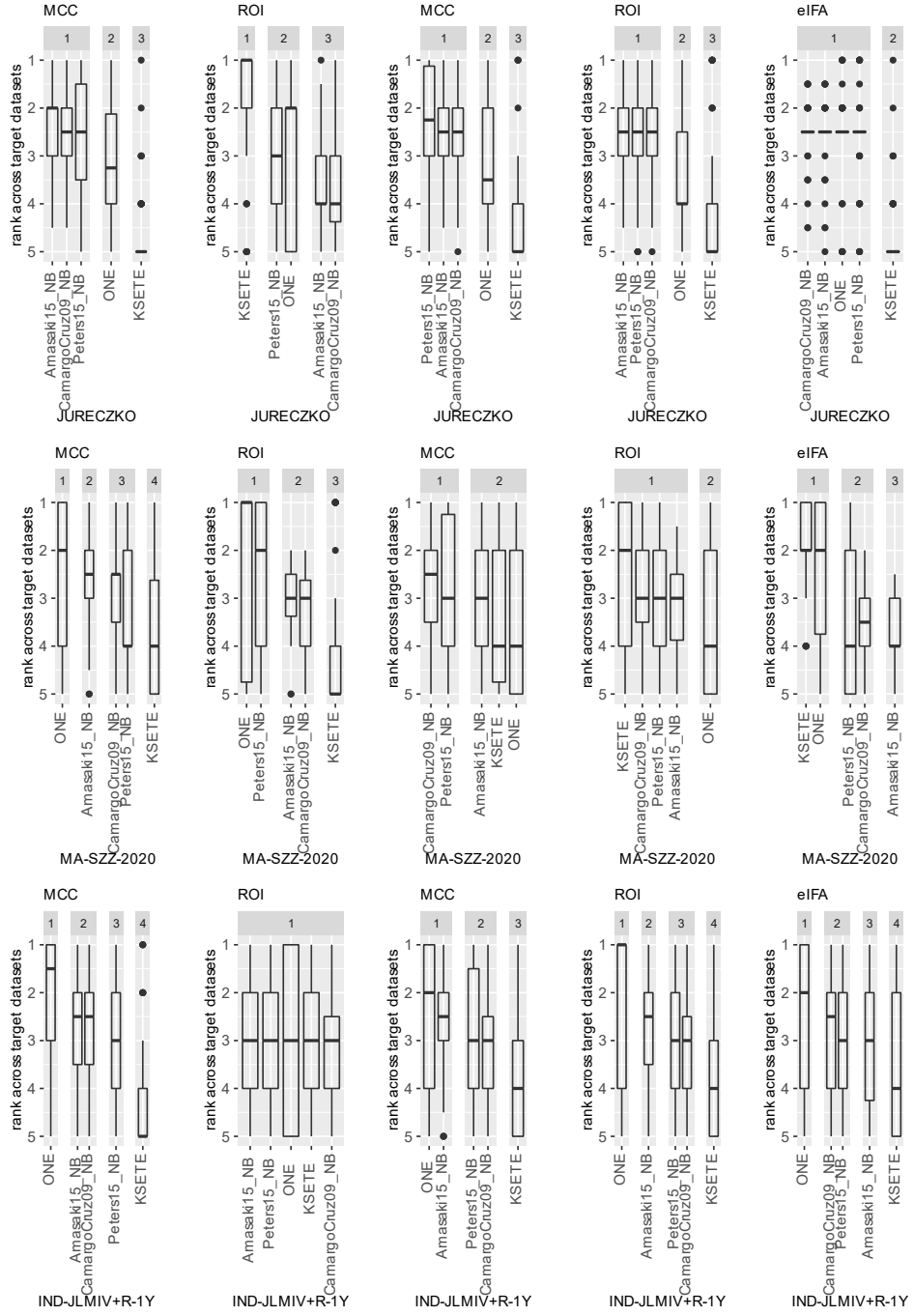
Dataset	Model	SNM (PII=20%)		SSC (PCI=20%)		eIFA
		MCC	ROI	MCC	ROI	
AEEEM	KSETE	0.284(0.086)	124.5(52.1)	0.181(0.049)	513.1(200.5)	**0.002(0.001)**
	CamargoCruz09-NB	**0.312(0.082)**	128.1(53.2)	**0.196(0.057)**	**664.1(322.9)**	0.012(0.021)
	Amasaki15-NB	0.308(0.092)	127.1(57.7)	0.194(0.069)	612.1(249.3)	0.009(0.011)
	Peters15-NB	0.303(0.077)	126.2(61.6)	0.172(0.036)	585.1(308.5)	0.015(0.018)
	ONE	0.252(0.094)	**141.5(72.9)**	0.144(0.082)	455.9(267.9)	0.003(0.006)
JURECZKO	KSETE	0.089(0.082)	**143.0(299.8)**	0.035(0.068)	137.5(166.4)	0.023(0.041)
	CamargoCruz09-NB	0.264(0.154)	57.5(84.3)	0.144(0.110)	195.0(203.9)	**0.008(0.022)**
	Amasaki15-NB	**0.267(0.154)**	57.4(83.7)	0.142(0.105)	**195.7(204.6)**	0.009(0.023)
	Peters15-NB	0.255(0.176)	60.5(85.7)	**0.148(0.150)**	189.3(196.8)	0.010(0.030)
	ONE	0.248(0.174)	56.4(65.5)	0.129(0.119)	158.5(196.2)	0.013(0.041)
IND-JLMIV+R	KSETE	0.150(0.093)	**34.5(24.7)**	0.117(0.079)	97.2(116.2)	0.024(0.022)
	CamargoCruz09-NB	0.191(0.119)	33.6(22.7)	0.159(0.130)	128.9(167.6)	0.028(0.046)
	Amasaki15-NB	0.195(0.114)	34.1(23.7)	0.164(0.120)	131.6(172.0)	0.030(0.044)
	Peters15-NB	0.157(0.136)	34.1(25.0)	0.153(0.163)	129.6(172.1)	0.033(0.059)
	ONE	**0.237(0.110)**	32.4(23.7)	**0.202(0.113)**	**148.9(167.8)**	**0.017(0.027)**
MA-SZZ-2020	KSETE	0.199(0.053)	71.7(60.0)	0.129(0.044)	232.1(178.0)	**0.012(0.014)**
	CamargoCruz09-NB	0.218(0.063)	79.3(55.3)	**0.167(0.084)**	**255.9(206.5)**	0.027(0.020)
	Amasaki15-NB	0.223(0.061)	79.4(55.0)	0.160(0.082)	245.5(194.0)	0.029(0.016)
	Peters15-NB	0.223(0.090)	**84.0(54.8)**	0.159(0.083)	226.5(174.2)	0.027(0.020)
	ONE	**0.232(0.091)**	78.7(60.7)	0.111(0.074)	182.7(174.6)	0.029(0.049)
ReLink	KSETE	0.152(0.065)	38.0(21.7)	0.130(0.096)	119.9(57.1)	**0.004(0.005)**
	CamargoCruz09-NB	0.299(0.198)	39.1(19.3)	0.050(0.170)	66.2(63.8)	0.056(0.053)
	Amasaki15-NB	**0.308(0.187)**	40.0(20.3)	0.093(0.096)	104.7(61.2)	0.048(0.024)
	ONE	0.272(0.163)	**48.9(26.7)**	**0.170(0.111)**	134.3(80.9)	0.006(0.006)

(1) In terms of eIFA, on all datasets (JURECZKO, MA-SZZ-2020, and IND-JLMIV+R) in Fig. 4, ONE achieves top-level according to the Scott-Knott ESD test, meanwhile, in Table 7, ONE performs the best median eIFA on three from five datasets. We can conclude that those four evaluated state-of-the-art defect prediction models are not able to cost less SQA-effort to find the first defective module than the baseline ONE.

(2) According to the mean and standard deviation values in Table 6, ONE wins for 8/25 comparisons, which is the best among compared models, and the second best is CamargoCruz09-NB who wins for 6/25 comparisons. According to the median values in Table 7, the best is ONE who wins for 10/25 comparisons and Peters15-NB is the second best who wins for 9/25 comparisons. Meanwhile, KSETE achieves 12/25 worst mean and 9/25 worst median values among multiple models' comparisons.

(3) According to the Scott-Knott ESD test result, we find that on the JURECZKO dataset, Peters15-NB performs the best among multiple models under both SNM and SSC; on the IND-JLMIV+R dataset, ONE performs the best among multiple models under both SNM and SSC; on the MA-SZZ-2020 dataset, CamargoCruz09-NB and Peters15-NB performs best under SSC while ONE performs best under SNM. Overall, among the comparisons on multiple datasets, we found Peters15-NB and CamargoCruz09-NB perform relatively well in comparison with those four representative defect prediction models. However, none of them are significantly better than ONE under MATTER on more than one dataset.

Conclusion. *In terms of defect datasets, ONE performs (1) top-level on IND-JLMIV+R, (2) top-level on MA-SZZ-2020 under SNM and bottom-level under SSC, (3) middle-level on JURECZKO, (3) and win the most time in terms of median and mean values. Overall, these models do not consistently outperform ONE on different datasets. This means that, if the practical prediction effectiveness is the goal, the real progress in defect prediction is not being achieved as has been reported in the literature.*



(a) under SNM (PII=20%) (b) under SSC (PCI=20%) (c) eIFA

Figure 4: The distributions of rankings of multiple models' comparisons in terms of performance indicator and the non-parametric Scott-Knott ESD test result (the smaller the group number on the top of the plot, the better the performance rankings)

Table 7. The median MCC, ROI, and eIFA values of each state-of-the-art defect prediction model and ONE on five datasets

Dataset	Model	SNM (PII=20%)		SSC (PCI=20%)		eIFA
		MCC	ROI	MCC	ROI	
AEEEM	KSETE	**0.290**	146.3	0.167	570.4	0.002
	CamargoCruz09-NB	0.277	154.3	0.180	**693.1**	**0.000**
	Amasaki15-NB	0.266	157.6	0.160	637.6	0.003
	Peters15-NB	0.281	152.5	**0.183**	613.5	0.009
	ONE	0.218	**189.5**	0.156	526.4	**0.000**
JURECZKO	KSETE	0.092	43.0	0.032	90.9	0.014
	CamargoCruz09-NB	0.243	30.5	0.157	121.8	**0.000**
	Amasaki15-NB	0.250	32.0	0.155	125.7	**0.000**
	Peters15-NB	**0.263**	33.3	**0.163**	**125.7**	**0.000**
	ONE	0.228	32.7	0.124	104.6	**0.000**
IND-JLMIV+R	KSETE	0.145	26.9	0.122	64.5	0.016
	CamargoCruz09-NB	0.179	27.1	0.162	76.9	0.010
	Amasaki15-NB	0.194	**28.5**	0.162	76.0	0.011
	Peters15-NB	0.162	28.1	0.156	67.6	0.011
	ONE	**0.206**	26.2	**0.196**	**94.6**	**0.008**
MA-SZZ-2020	KSETE	0.208	56.1	0.128	197.7	0.007
	CamargoCruz09-NB	0.223	64.1	0.154	197.9	0.024
	Amasaki15-NB	0.231	63.7	0.139	**201.4**	0.025
	Peters15-NB	0.232	71.0	**0.158**	195.0	0.022
	ONE	**0.251**	68.5	0.122	155.6	**0.006**
ReLink	KSETE	0.177	50.5	0.092	137.4	0.002
	CamargoCruz09-NB	0.229	46.0	0.081	42.0	0.027
	Amasaki15-NB	0.229	46.2	0.054	107.8	0.050
	Peters15-NB	0.203	44.2	**0.132**	**138.6**	**0.000**
	ONE	**0.281**	62.9	0.132	129.3	0.007

E. Coincidence of performance indicators in determining model superiority under SNM

Under SNM, the following performance indicators are coincident with each other in determining whether model A is superior to another model B on the same test data set:

- recall = TP / (TP + FN), also known as PD: the fraction of defective modules that are predicted as defective. A higher value indicates a better performance;
- precision = TP / (TP + FP): the fraction of predicted defective modules that are defective. A higher value indicates a better performance;
- F1 = 2 × precision × recall / (precision + recall): the harmonic mean of precision and recall. A higher value indicates a better performance;
- PF = FP / (FP + TN): the probability of False alarm, i.e., the fraction of not defective modules that are predicted as defective. A lower value indicates a better performance;
- $G1 = \frac{2\times \mathrm{PD}\times(1-\mathrm{PF})}{\mathrm{PD}+(1-\mathrm{PF})}$: the harmonic mean of recall and 1 – PF. A higher value indicates a better performance;
- $G2 = \sqrt{recall \times precision}$: the geometric mean of recall and precision. A higher value indicates a better performance;
- $G3 = \sqrt{recall \times (1 - PF)}$: the geometric mean of recall and 1 – PF. A higher value indicates a better performance;
- $balance = 1 - \frac{\sqrt{(0-PF)^2+(1-PD)^2}}{\sqrt{2}}$: the balance between PF and PD. A higher value indicates a better performance;
- $ED = \sqrt{\theta \times (1 - PD)^2 + (1 - \theta) \times PF^2}$: the distance between (PD, PF) and the ideal point on the ROC space (1, 0), weighted by cost function θ (θ = 0.6 in default). A lower value indicates a better performance;

- $MCC = \frac{\mathrm{TP}\times\mathrm{TN}-\mathrm{FP}\times\mathrm{FN}}{\sqrt{(TP+FP)(TP+FN)(TN+FP)(TN+FN)}}$: a correlation coefficient between the actual and predicted binary classifications. A higher value indicates a better performance.

Here, TP denotes the number of true positives, FP denotes the number of false positives, TN denotes the number of true negatives, and FN denotes the number of false negatives.

Proof. For the test set, let n be the total number of instances, n0 be the total number of actually clean instances, and n1 be the total number of actually defective instances. Furthermore, assume that, under SNM, the top k instances with the largest predicted values are predicted as defective. Then, we have:

$$n = n0 + n1$$

$$n0 = TN + FP$$

$$n1 = TP + FN$$

$$k = TP + FP$$

In the following, we show that: (1) each of recall, precision, F1, G1, G2, G3, balance, and MCC is a monotonically increasing function of TP; and (2) each of PF and ED is a monotonically decreasing function of TP. Note that, in this scenario, n, n0, n1, and k are constants, while TP is a variable.

- recall = TP/(TP+FN) = TP/n1. Therefore, TP↑ ⇒ recall↑
- precision = TP/(TP+FP) = TP/k. Therefore, TP↑ ⇒ precision↑
- F1 = 2×precision×recall/(precision+recall) =2×TP/(n1+k). Therefore, TP↑ ⇒ F1↑
- PF = FP/(FP+TN) = (k–TP)/n0 ⇒ TP↑ ⇒ FP↓
- $G1 = \frac{2\times\mathrm{PD}\times(1-\mathrm{PF})}{\mathrm{PD}+(1-\mathrm{PF})} = \frac{2\times TP^2+2(n0-k)\times TP}{n1(n0-k)+n\times TP}$. Since $\frac{dG1}{dTP} > 0$, TP↑ ⇒ G1↑
- $G2 = \sqrt{recall \times precision} = \frac{TP}{\sqrt{n1\times k}}$. Therefore, TP↑ ⇒ G2↑
- $G3 = \sqrt{recall \times (1-PF)} = \frac{\sqrt{TP\times(n0-k+TP)}}{\sqrt{n0\times n1}}$. Therefore, TP↑ ⇒ G3↑
- $balance = 1 - \frac{\sqrt{(0-PF)^2+(1-PD)^2}}{\sqrt{2}} = 1 - \sqrt{\frac{(k-TP)^2}{2\times n0^2} + \frac{(n1-TP)^2}{2\times n1^2}}$. Therefore, TP↑ ⇒ balance↑
- $ED = \sqrt{\theta \times (1-PD)^2 + (1-\theta)\times PF^2} = \sqrt{\theta \times (1-\frac{TP}{n1})^2 + (1-\theta)\times \frac{(k-TP)^2}{n0^2}}$. Therefore, TP↑ ⇒ ED↓
- $MCC = \frac{\mathrm{TP}\times\mathrm{TN}-\mathrm{FP}\times\mathrm{FN}}{\sqrt{(TP+FP)(TP+FN)(TN+FP)(TN+FN)}} = \frac{\mathrm{TP}\times(\mathrm{n0}-\mathrm{k}+\mathrm{TP})-(\mathrm{k}-\mathrm{TP})\times(\mathrm{n1}-\mathrm{TP})}{\sqrt{k\times n1\times n0\times(n-k)}} = \frac{\mathrm{n}\times\mathrm{TP}-\mathrm{n1}\times\mathrm{k}}{\sqrt{k\times n1\times n0\times(n-k)}}$. Therefore, TP↑ ⇒ MCC↑

For any two models A and B, due to the fact that they have the same k under SNM, whether A is superior to B indeed is up to their TP values. As can be seen, the above performance indicators depend only on one single variable TP. Therefore, for the above performance indicators, they must be coincident with each other in determining which one is superior in prediction performance.

F. A case study to quantitatively analyze why ONE performs well under effort-aware evaluation

In this section, we conduct a preliminary case study to quantitatively analyze why ONE performs well under effort-aware evaluation. We use models' prediction results on test set JURECZKO-redaktor as an example, and list module rankings before Amasaki15-NB, Camargo09-NB, Peters15-NB, and ONE find the first true negative module. As can be seen in Fig.5, on this test set, Amasaki15-NB ranks three large and clean modules at the top of the whole ranking, and it takes a lot of effort to find the first true negative module, consequencely, it performs the worst in terms of eIFA among four compared models. Peters15-NB performs four small and clean modules at the top of the whole ranking, although those false positive modules have small LOC, they take a lot of effort for context switch, consequencely, it performs the second worst in terms of eIFA among four models. CamargoCruz09-NB performs similarly to Amasaki15-NB, but offers one less false positive module to be inspected, therefore, its eIFA is smaller (better) than Amasaki15-NB.

The most suspicious module decided by ONE is true positive, that is to say, its ranking can save the inspection effort for SQA staff, and as a consequence, it performs the best in terms of eIFA among four compared models. From this case study, we have the following insights. First, ONE is a strong baseline that can be used to evaluate the effort-aware performance of models, as in this case, ONE saves the most effort in finding the first defective module compared to three SOTA models. Second, novel indicators such as eIFA provide valuable insights into the effectiveness of different models in prioritizing modules for inspection, contributing to the refinement of software quality assurance practices.

ONE

sloc	predicted label	actual label	eIFA
364	1	1	0

CamargoCruz09-NB

sloc	predicted label	actual label	eIFA
1139	1	0	
2423	1	0	0.0007
854	1	1	

Peters15-NB

sloc	predicted label	actual label	eIFA
819	1	0	
583	1	0	
732	1	0	0.0010
518	1	0	
529	1	1	

Amasaki15-NB

sloc	predicted label	actual label	eIFA
1139	1	0	
2423	1	0	0.0018
2781	1	0	
854	1	1	

Figure 5: Module rankings on JURECZKO-redaktor of Amasaki15-NB, Camargo09-NB, Peters15-NB, and ONE and the corresponding eIFA values.

G. Comparison results between ONE vs.GA and ONE vs. MODEP

Besides baseline models compared in our manuscript, we further compared ONE with other baseline models that did not release their source code. To compare with them, for each compared baseline, we run ONE on the test set (which are from publicly aviable defect datasets) and compare the performance of ONE with its reported performance in its original paper. Specifically, we report the comparison between ONE vs.GA [20] and ONE vs. MODEP [21].

Compared with GA, ONE performs better than their proposed models RT-GA and GLM-GA in terms of P_{error} on 11 of all 13 test sets, as can be seen in Table 8. P_{error} means 1-$delta_{error}$, and $delta_{error}$ is the area-under-curve difference between the optimal model and the evaluated model (the cumulative sloc as x-axis while the cumulative number of real bugs as y-axis).

Table 8. Comparison between ONE and [A] in terms of P_{error}

Project	Training Set	Test Set	RT-GA	GLM-GA	ONE
Log4j	1.0	1.1	0.7461	**0.8407**	0.6539
	1.1	1.2	0.5938	0.6728	**0.9502**
Lucene	2.0	2.2	**0.7947**	0.7711	0.7925
	2.2	2.4	0.6968	0.7660	**0.8573**
Poi	1.5	2.0	0.5283	0.6876	**0.7035**
	2.0	2.5	0.6250	0.8595	**0.8985**
Synapse	1.0	1.1	0.5691	0.5231	**0.6556**
	1.1	1.2	0.6802	0.6521	**0.7153**
Velocity	1.4	1.5	0.8698	0.9113	**0.9203**
	1.5	1.6	0.8082	0.8162	**0.8335**
Xalan	2.4	2.5	0.7319	0.8472	**0.8735**
	2.5	2.6	0.8175	0.8388	**0.8635**
	2.6	2.7	0.9141	0.9679	**0.9815**

Compared with MODEP (Multiobjective DEfect Predictor when optimizing inspection cost and number of predicted defect-prone classes), although MODEP performs better in terms of recall, ONE performs better in terms of balancing recall and precision, and as a result, ONE performs the best in terms of F1 on 5 of 8 test sets.

In conclusion, through the above comparisons, we further expand our validation of ONE's effectiveness as an SDP baseline model. ONE performs competitively with baseline models GA and MODEP.

Table 9. ONE vs. MODEP-Logistic and MODEP-DTree in terms of recall, precision, and F1

	Recall			Precision			F1		
Project	MODEP-Logistic	MODEP-DTree	ONE	MODEP-Logistic	MODEP-DTree	ONE	MODEP-Logistic	MODEP-DTree	ONE
Ant	0.74	0.66	**0.86**	0.28	0.17	**0.38**	0.41	0.27	**0.53**
Camel	0.82	**0.86**	0.62	0.18	0.17	**0.24**	0.30	0.28	**0.35**
Ivy	0.78	0.78	**0.88**	**0.20**	0.10	0.20	0.32	0.18	**0.32**
jEdit	**0.97**	0.85	0.75	0.24	0.22	**0.37**	0.38	0.35	**0.49**
Log4j	**0.94**	0.94	0.49	**0.92**	**0.92**	0.91	**0.93**	**0.93**	0.64
Lucene	**0.95**	0.95	0.58	0.58	0.59	**0.69**	0.72	**0.73**	0.63
Poi	0.66	**0.93**	0.64	0.62	0.59	**0.81**	0.64	**0.72**	0.72
Xalan	**0.81**	0.73	0.50	0.08	0.08	**1.00**	0.15	0.14	**0.67**

REFERENCES

[1] Z. Li, X. Y. Jing, X. Zhu, H. Zhang, B. Xu and S. Ying. 2019. On the Multiple Sources and Privacy Preservation Issues for Heterogeneous Defect Prediction. *IEEE Transactions on Software Engineering 45*, 4 (2019), 391-411. https://doi.org/10.1109/TSE.2017.2780222

[2] Yu Qu, Qinghua Zheng, Jianlei Chi, Yangxu Jin, Ancheng He, Di Cui, Hengshan Zhang and Ting Liu. 2021. Using K-core Decomposition on Class Dependency Networks to Improve Bug Prediction Model's Practical Performance. *IEEE Transactions on Software Engineering 47*, 2 (2021), 348-366. https://doi.org/10.1109/TSE.2019.2892959

[3] Duksan Ryu, Jong-In Jang and Jongmoon Baik. 2015. A Hybrid Instance Selection Using Nearest-Neighbor for Cross-Project Defect Prediction. *Journal of Computer Science and Technology 30*, 5 (2015), 969-980. https://doi.org/10.1007/s11390-015-1575-5

[4] Rahul Krishna and Tim Menzies. 2019. Bellwethers: A Baseline Method for Transfer Learning. *IEEE Transactions on Software Engineering 45*, 11 (2019), 1081-1105. https://doi.org/10.1109/TSE.2018.2821670

[5] Chao Ni, Xin Xia, David Lo, Xiang Chen and Qing Gu. 2022. Revisiting Supervised and Unsupervised Methods for Effort-Aware Cross-Project Defect Prediction. *IEEE Transactions on Software Engineering 48*, 3 (2022), 786-802. https://doi.org/10.1109/TSE.2020.3001739

[6] Akif Günes Koru, Khaled El Emam, Dongsong Zhang, Hongfang Liu and Divya Mathew. 2008. Theory of relative defect proneness. *Empirical Software Engineering 13*, 5 (2008), 473. https://doi.org/10.1007/s10664-008-9080-x

[7] Akif Günes Koru, Hongfang Liu, Dongsong Zhang and Khaled El Emam. 2010. Testing the theory of relative defect proneness for closed-source software. *Empirical Software Engineering 15*, 6 (2010), 577-598. https://doi.org/10.1007/s10664-010-9132-x

[8] Akif Günes Koru, Dongsong Zhang, Khaled El Emam and Hongfang Liu. 2009. An Investigation into the Functional Form of the Size-Defect Relationship for Software Modules. *IEEE Transactions on Software Engineering 35*, 2 (2009), 293-304. https://doi.org/10.1109/TSE.2008.90

[9] Feng Zhang, Quan Zheng, Ying Zou and Ahmed E. Hassan. 2016. Cross-Project Defect Prediction Using a Connectivity-Based Unsupervised Classifier. In *2016 IEEE/ACM 38th International Conference on Software Engineering (ICSE).* Austin, TX, USA, 309-320. https://doi.org/10.1145/2884781.2884839

[10] Jaechang Nam and Sunghun Kim. 2015. CLAMI: Defect Prediction on Unlabeled Datasets (T). In *2015 30th IEEE/ACM International Conference on Automated Software Engineering (ASE).* Lincoln, NE, USA, 452-463. https://doi.org/10.1109/ASE.2015.56

[11] Ning Li, Martin J. Shepperd and Yuchen Guo. 2020. A systematic review of unsupervised learning techniques for software defect prediction. *Information and Software Technology 122* (2020), 106287. https://doi.org/https://doi.org/10.1016/j.infsof.2020.106287

[12] Marco D'Ambros, Michele Lanza and Romain Robbes. 2010. An extensive comparison of bug prediction approaches. In *7th International Working Conference on Mining Software Repositories, MSR 2010 (Co-located with ICSE)*. Cape Town, South Africa, 31-41. https://doi.org/10.1109/MSR.2010.5463279

[13] Marian Jureczko and Lech Madeyski. 2010. Towards identifying software project clusters with regard to defect prediction. In *Proceedings of the 6th International Conference on Predictive Models in Software Engineering*. Association for Computing Machinery, Timişoara, Romania, Article 9. https://doi.org/10.1145/1868328.1868342

[14] Shiran Liu, Zhaoqiang Guo, Yanhui Li, Chuanqi Wang, Lin Chen, Zhongbin Sun, Yuming Zhou and Baowen Xu. 2022. Inconsistent defect labels: essence, causes, and influence. *IEEE Transactions on Software Engineering* (2022) https://doi.org/10.1109/TSE.2022.3156787

[15] Steffen Herbold, Alexander Trautsch, Fabian Trautsch and Benjamin Ledel. 2022. Problems with SZZ and Features: An empirical study of the state of practice of defect prediction data collection. *Empirical Software Engineering 27*, 2 (2022), 1-49. https://doi.org/10.1007/s10664-021-10092-4

[16] Rongxin Wu, Hongyu Zhang, Sunghun Kim and Shing-Chi Cheung. 2011. ReLink: recovering links between bugs and changes. In *Proceedings of the 19th ACM SIGSOFT symposium and the 13th European conference on Foundations of software engineering*. Association for Computing Machinery, Szeged, Hungary, 15–25. https://doi.org/10.1145/2025113.2025120

[17] Chakkrit Tantithamthavorn. 2017. Scottknottesd: The scott-knott effect size difference (esd) test. *R package version 2* (2017)

[18] Steffen Herbold, Alexander Trautsch and Jens Grabowski. 2018. A Comparative Study to Benchmark Cross-Project Defect Prediction Approaches. *IEEE Transactions on Software Engineering 44*, 9 (2018), 811-833. https://doi.org/10.1109/TSE.2017.2724538

[19] Haonan Tong, Bin Liu and Shihai Wang. 2021. Kernel Spectral Embedding Transfer Ensemble for Heterogeneous Defect Prediction. *IEEE Transactions on Software Engineering 47*, 9 (2021), 1886-1906. https://doi.org/10.1109/TSE.2019.2939303

[20] Annibale Panichella, Carol V. Alexandru, Sebastiano Panichella, Alberto Bacchelli and Harald C. Gall. 2016. A Search-based Training Algorithm for Cost-aware Defect Prediction. In *Proceedings of the Genetic and Evolutionary Computation Conference 2016*. Association for Computing Machinery, 1077–1084 , numpages = 1078. https://doi.org/10.1145/2908812.2908938

[21] Gerardo Canfora, Andrea De Lucia, Massimiliano Di Penta, Rocco Oliveto, Annibale Panichella and Sebastiano Panichella. 2015. Defect prediction as a multiobjective optimization problem. *Software Testing, Verification and Reliability 25*, 4 (2015), 426-459. https://doi.org/https://doi.org/10.1002/stvr.1570