Augmented Chains to Ensemble of Classifier Chains

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Abstract. Multi-label classification (MLC) problems, where instances are associated with multiple labels, are commonly employed in everyday applications. There are several approaches to solving MLC problems and the ensemble of classifier chains (ECC) is one such method used as the basis of this article. ECC uses a binary classifier for each label and creates a chain of these classifiers in a specific sequence. However, the method has issues related to the order of the chain and the number of labels. Many studies try to find the best chain order or reduce the number of labels to improve results. This article aims to evaluate whether the insertion of meta-labels, created from combinations of the original labels, can enhance ECC prediction results. The approach involves creating combinations of labels through similarity correlation, selecting the most relevant labels based on these correlations, incorporating them into the dataset, and subsequently evaluating the model and prediction results. Results obtained in experiments with 19 well-known multi-label datasets and evaluated with 12 different measures show that the proposed approach improves Micro-Precision, Precision, Hamming-Loss, and Subset-Accuracy.

CCS Concepts: • **Computing methodologies** → **Machine learning algorithms**.

Keywords: machine learning, classifier, multi-label classifier

1. INTRODUCTION

Multi-label classification (MLC) has gained significant attention in recent years due to its relevance in various applications where instances are associated with multiple labels, such as protein function classification and music categorization [Tsoumakas and Katakis 2009]. Most approaches to solving this problem involve associating multiple binary class labels with a single instance [Read et al. 2019]. A typical example is the binary relevance method [Zhang et al. 2017], which decomposes multi-label problems into single-label and tries to predict one label at a time using the dataset. However, binary relevance (BR) does not consider the correlation between labels.

Classifier chain (CC) emerged to address the limitations of the binary relevance (BR) method [Read et al. 2009]. CC builds upon BR by partitioning the dataset into n binary classifiers, one for each label, and organizing them in a chain, where the output prediction of the previous classifier is used as an additional input feature of subsequent classifiers [Read et al. 2019]. However, CC has performance issues because it depends on the random selection of the chain order. If the sequential choice is suboptimal, the prediction can be negatively affected [Read et al. 2009]. To mitigate this issue, the ensemble classifier chain (ECC) was developed. ECC creates m models of CC, each with a different random chain, built from a fraction of instances and attributes. The final prediction is obtained by averaging the predictions from these m models [Moyano et al. 2018]. The ECC is among those presenting the best results for multi-label classification [Bogatinovski et al. 2022].

The current study evaluates the performance of the ECC algorithm when the label space is augmented with artificially generated labels, from hereafter named meta-labels. The term meta-labels refers to combinations of original labels. In other words, associations between labels are combined to form new labels. The values of instances for meta-labels depend on the corresponding binary values of the original labels' instances. It is important to note that creating meta-labels requires a method to measure the similarity or distance between original labels, as this forms the basis for their construction because if the number of labels inserted into the chain increases, the algorithm can be negatively affected and consume a significant amount of computational memory. Another factor that can limit the use of augmented chains is the low density and cardinality of the original labels, making it impossible to generate a relevant number of artificial labels in some cases.

2. CORRELATED WORKS

Nowadays, many studies aim to enhance the performance of Classifier Chains (CC) and Ensemble of Classifier Chains (ECC). Typically, these approaches focus on methods to improve how labels are inserted into the chain. The generic algorithm proposed by [Gonçalves et al. 2015] can solve the sequential labeling problem because the process can perform extreme permutation among labels. In this specific case, the research approach produces simpler and more accurate models. Another approach studied by [Li et al. 2016] considers the classifier through multi-label importance ranking. In other words, it ranks multi-label classifiers based on their correlation and inserts them into the chain according to their importance.

Still, in the area of correlation studies, there are label dependencies, where it is possible to create groups based on these dependencies. The k-means algorithm was used by [Huang et al. 2015] to cluster similar examples that share the same correlations between labels and have the same labels describing the examples. This approach was proposed to solve the misclassification problem of examples with similar features. Following the same line of reasoning for label dependencies, [Sun and Kudo 2019] used label dependencies to construct and couple a polytree structure that effectively models the relationships between labels. The incorporation of label-dependent features allows for improving the generalization and predictive accuracy of multi-label classification methods.

In addition to the sequence in which the labels are inserted into the chain, another factor that strongly influences the performance is the number of labels in the classifier chain. [Tsoumakas et al. 2008] introduced the HOMER method, which is responsible for grouping the labels correlated to smaller groups, called meta-labels. For each meta-label, a classifier is built to predict which group the examples belong to, thus decreasing the number of labels inserted in multi-label classification.

Given the information presented, it is clear that the sequence of labels in CC and ECC can lead to significant results. However, the sequence does not always impact the results. Sometimes, having similarity between the labels is essential to create groups and reduce complexity and computational expense. Therefore, this article integrates several concepts related to studies and research that aim to improve ECC through the introduction of meta-labels in the chain.

3. PROPOSED METHOD

The proposed method consists of principles and approaches from the area of multi-label classification. More specifically, it uses the ECC algorithm as a basis, created to improve upon the CC algorithm problem of depending on the random choice of the chain, potentially worsening the results [Read et al. 2009]. Knowing that ECC is based on CC, one can imagine a dataset represented as $D = \{(x_i, Y_i) \mid 1 \leq i \leq m\}$, where m represents the total number of instances, and i is associated with a feature vector $x_i = \{(x_1, \ldots, x_d)\}$, where d represents the number of instance attributes, and a subset of labels $Y_i \subseteq L$. Here, $L = \{l_1, \ldots, l_q\}$, with $q \geq 2$, and $Y_i = \{y_1, \ldots, y_q\}$ [Silva et al. 2014].

Considering the dataset D with $L = \{l_1, l_2\}$ in which each instance x_i is associated with the labels $Y_i = \{(y_1, y_2)\}$, the Figure (1a) represents CC algorithm that will be composed of two binary models, one for each label, and is important to notice that subsequent models are using the labels from previous models as features creating a chain of classifiers. Figure (1b) represents the CC algorithm with the addition of a meta-label $MY_1\_Y_2$ creating an augmented chain. This is a very simplified sample with only two labels and as the chains are aleatory generated, the meta-labels will not necessarily be as last in the chains.

As represented in Figure (1), in the augmented chains, the idea of creating combinations between

X	Y_1
x_1	0
x_2	1
x_3	0
x_4	1
x_5	0

X	Y_1	Y_2
x_1	0	1
x_2	1	0
x_3	0	0
x_4	1	1
x_5	0	0

(a) CC Algorithm

X	Y_1
x_1	0
x_2	1
x_3	0
x_4	1
x_5	0

X	Y_1	Y_2
x_1	0	1
x_2	1	0
x_3	0	0
x_4	1	1
x_5	0	0

X	Y_1	Y_2	$MY_1\_Y_2$
x_1	0	1	0
x_2	1	0	0
x_3	0	0	0
x_4	1	1	1
x_5	0	0	0

(b) CC Algorithm with augmented chain

Fig. 1: ECC x Augmented ECC representations.

labels through correlations and inserting them into the chain was explored to verify whether the performance of ECC improves as the number of inserted meta-labels increases.

Meta-labels can be created through correlations between labels. Considering two original labels l_a and l_b, the corresponding instances labels can be represented as binary vectors y_a and y_b, the meta-label $\mu(y_a, y_b)$ is defined through the logical AND operation ($\wedge$) between the values of y_a and y_b as represented in Equation (1).

$$\mu(y_a, y_b) = \begin{cases} 1 & \text{if } y_{ia} = 1 \text{ and } y_{ib} = 1 \\ 0 & \text{otherwise} \end{cases} \tag{1}$$

These meta-labels are then incorporated into the chain alongside the original labels to evaluate their impact on ECC performance. However, there are two main issues concerning the creation of meta-labels. The first is the presence of many zeros in the meta-labels due to the low density and cardinality of the dataset, if many zeros are present, it indicates that the original labels have low correlations. The second issue concerns the number of possible meta-labels generated from the original labels. For instance, if the dataset contains many labels, the resulting meta-labels can be 2^q, which can lead to challenges increasing complexity and computational costs.

To solve this problem, Jaccard's Similarity [Jaccard 1912] and the concept of rank labels were used. The concept of Jaccard's Similarity [Jaccard 1912] consists of calculating the similarity between two labels l_a and l_b, we use the formula presented in Equation (2).

$$J(l_a, l_b) = \frac{|\{i \mid l_a \in Y_i \wedge l_b \in Y_i\}|}{|\{i \mid l_a \in Y_i\} \cup \{i \mid l_b \in Y_i\}|} \tag{2}$$

Thus, Jaccard's Similarity helps to determine the proximity between the original labels, enabling the creation of meta-labels only for the most correlated ones. To select the best labels that will be used to generate meta-labels, a multiplicative factor (k) which represents a float value that multiplies the original number of labels in the dataset was used, and the result indicates the number of meta-labels that will be generated and inserted into the data set. Once the number of meta-labels to be generated is obtained, a simple search for the most correlated labels considering the Jaccard similarity results is done to determine the labels to be used in the creation of meta-labels.

Finally, a model can be created with the original labels plus the generated meta-labels, and the ECC model is created. After obtaining the prediction on the test dataset, the predictions made for the meta-labels are removed from the results. This step is important because, to compare the proposed method with the original approach used in ECC, meta-labels must be deleted and the performance is evaluated using only the original labels.

4. EXPERIMENTS AND RESULTS

For the experiments, 19 well-known multi-label datasets were selected. Table (I) shows the datasets and their metadata: the m, d, and $|\mathcal{L}|$, which respectively denote instances, features, and labels, as well as cardinality and density abbreviated as Card and Dens. The last column is MeanIR: the mean imbalance ratio [Charte et al. 2013]. The datasets were chosen to consider a minimum of 10 labels to avoid the issue of having too few label candidates to generate meta-labels.

Table I: Datasets used in experiments (Obtained from: https://cometa.ujaen.es)

Name	Domain	m	d	$\lvert\mathcal{L}\rvert$	Card	Dens	MeanIR	Name	Domain	m	d	$\lvert\mathcal{L}\rvert$	Card	Dens	MeanIR
birds	Audio	645	279	19	1.01	0.05	5.40	ng20	Text	19300	1026	20	10.29	0.05	1.00
cal500	Audio	502	242	174	260.44	0.15	20.57	ohsumed	Text	13929	1025	23	16.63	0.07	7.86
enron	Text	1702	1054	53	33.78	0.06	73.95	PlantGO	Biology	978	3103	12	10.79	0.09	6.69
EukPAAC	Biology	7766	462	22	11.46	0.05	45.01	PlanPAAC	Biology	978	452	12	10.79	0.09	6.69
foodtruck	Other	407	33	12	22.90	0.19	7.09	reutersk500	Text	6000	603	103	14.62	0.01	51.98
genbase	Biology	662	1213	27	12.52	0.05	37.31	slashdot	Text	3782	1101	22	11.81	0.05	17.69
HumanGO	Biology	3106	9858	14	11.85	0.08	15.28	stackex_chess	Text	1675	812	227	24.11	0.01	85.78
HumPAAC	Biology	3106	454	14	11.85	0.08	15.28	tmc2007_500	Text	28596	522	22	22.20	0.10	15.15
langlog	Text	1460	1079	75	11.80	0.02	39.26	yeast	Biology	2417	117	14	42.37	0.30	7.19
medical	Text	978	1494	45	12.45	0.03	89.50								

The ECC algorithm was executed using the R utiml package (https://github.com/rivolli/utiml) with $seed = 1$, $m = 10$ (number of CC models), $subsample = 0.75$ (fraction of samples in the models), $attr.space = 0.5$ (fraction of features used in the models) and $replacement = TRUE$ (to ramdoly choose the instances with replacement). The experiments used two base algorithms: decision trees (C5.0) and support vector machines (SVM). The proposed method was evaluated using four different k values (that determine the number of meta-labels): 0.3 (i.e. number of meta-labels equal to 30% of the number of labels), 0.5, 0.8 and 1.0 named respectively as $A03$, $A05$, $A08$, and $A10$ models. To evaluate the models, 12 different multilabel measures were chosen: Macro-Precision, Macro-Recall, Macro-F1, Micro-Precision, Micro-Recall, Micro-F1, Precision, Recall, F1, Hamming-Loss, Accuracy and Subset-Accuracy [Bogatinovski et al. 2022].

All experiments used 5-fold cross-validation and the results were aggregated using averages. The running environment was composed of a cluster environment with several nodes, each one containing 28-core Intel(R) Xeon(R) CPU E5−2660 2.00 GHz with 128 GB of RAM. The time consumed by the algorithms was not taken into account.

To verify whether the overall differences in performance across the different approaches on each specific measure are statistically significant, the corrected Friedman test was used, followed by the Nemenyi post-hoc test, as recommended by [Demsar 2006]. The results from the Nemenyi post-hoc test are presented with average rank diagrams, also known as critical diagrams.

Table (II) and Table (III) present the obtained results when using C5.0 and SVM respectively. Firstly, the results obtained are approximately similar. However, note that the SVM algorithm consistently outperforms C5.0's results, even if by a small margin when comparing the averages. Secondly, and more importantly for this study, is the performance of the proposed method. When viewing and analyzing the tables, it is noticeable that the proposed methods show improvements over traditional ECC in measures such as Micro-Precision, Precision, Hamming-Loss, and Subset-Accuracy. That finding can be observed in the critical diagrams presented in Figures 2d and 2p for Micro-Precision, Figures 2g, 2s for the Precision, Figures 2j, 2v for the Hamming-Loss, and Figures 2l and 2x for the Subset-Accuracy. In all the aforementioned critical diagrams, at least one augmented chain result ($A03$, $A05$, $A08$, and $A10$) is not connected to ECC by the critical distance lines (horizontal lines) in the plots. However, when analyzing the rest of the measures, the proposed method does not outperform ECC in terms of the recall and accuracy measures, and also the F1 ones (which are computed through the precision and recall ones.

Table II: Results with C5.0 as base algorithm.

	Macro-Precision					Macro-Recall					Macro-F1				
	ECC	**A03**	**A05**	**A08**	**A10**	**ECC**	**A03**	**A05**	**A08**	**A10**	**ECC**	**A03**	**A05**	**A08**	**A10**
birds	0.215	0.260	0.251	**0.270**	0.268	**0.239**	0.232	0.236	0.214	0.199	0.210	**0.226**	0.225	0.213	0.199
cal500	**0.151**	0.133	0.145	0.131	0.142	**0.143**	0.090	0.091	0.089	0.090	**0.133**	0.095	0.097	0.094	0.096
enron	**0.203**	0.202	0.200	0.199	**0.203**	**0.142**	0.111	0.106	0.102	0.099	**0.147**	0.126	0.121	0.116	0.113
EukPAAC	0.128	0.133	0.137	**0.152**	0.149	**0.113**	0.101	0.099	0.102	0.100	**0.109**	0.106	0.102	0.106	0.103
foodtruck	**0.221**	0.188	0.207	0.203	0.196	**0.228**	0.143	0.130	0.121	0.126	**0.203**	0.149	0.138	0.125	0.130
genbase	**0.649**	0.630	0.563	0.605	0.639	**0.644**	0.609	0.537	0.550	0.589	**0.644**	0.614	0.543	0.567	0.602
HumanGO	0.683	**0.700**	0.684	0.681	0.694	**0.618**	0.611	0.590	0.571	0.597	**0.630**	0.627	0.610	0.598	0.619
HumPAAC	0.157	**0.205**	0.172	0.193	0.184	**0.147**	0.134	0.126	0.128	0.133	0.140	**0.142**	0.132	0.135	0.140
langlog	0.055	**0.061**	0.050	0.055	0.052	**0.065**	0.050	0.047	0.054	0.048	**0.052**	0.047	0.042	0.049	0.043
medical	0.255	0.231	0.258	0.268	**0.286**	0.247	0.203	0.229	0.238	**0.248**	0.241	0.205	0.229	0.238	**0.254**
ng20	0.615	0.710	0.702	**0.726**	0.705	**0.681**	0.626	0.622	0.590	0.621	0.631	**0.642**	0.638	0.616	**0.642**
ohsumed	0.505	0.508	0.513	**0.543**	0.519	**0.371**	0.265	0.269	0.253	0.255	**0.388**	0.318	0.329	0.311	0.313
PlantGO	0.703	**0.790**	0.752	0.726	0.699	**0.665**	0.636	0.638	0.606	0.591	0.656	**0.666**	0.658	0.626	0.606
PlanPAAC	0.160	0.165	0.134	0.163	**0.186**	**0.147**	0.125	0.126	0.129	0.138	0.134	0.122	0.118	0.124	**0.137**
reutersk500	0.243	0.239	**0.247**	0.246	0.246	**0.195**	0.143	0.143	0.153	0.143	**0.195**	0.161	0.161	0.169	0.160
slashdot	0.297	0.299	**0.337**	0.268	0.257	**0.200**	0.182	0.188	0.180	0.171	0.186	0.175	**0.187**	0.176	0.163
stackex_chess	**0.056**	0.038	0.032	0.031	0.032	**0.057**	0.019	0.017	0.016	0.019	**0.049**	0.021	0.018	0.018	0.021
tmc2007_500	0.717	0.758	0.768	**0.784**	0.782	**0.508**	0.414	0.411	0.404	0.398	**0.555**	0.488	0.490	0.482	0.472
yeast	0.468	0.451	0.474	**0.484**	0.455	0.364	**0.368**	0.361	**0.368**	0.365	0.370	0.378	0.371	**0.382**	0.375
Average	0.341	0.353	0.349	**0.354**	0.352	**0.304**	0.266	0.261	0.256	0.259	**0.299**	0.279	0.274	0.271	0.273
RankSum	65	57	60	52	**51**	**23**	53	68	71	70	**35**	49	65	69	67

	Micro-Precision					Micro-Recall					Micro-F1				
	ECC	**A03**	**A05**	**A08**	**A10**	**ECC**	**A03**	**A05**	**A08**	**A10**	**ECC**	**A03**	**A05**	**A08**	**A10**
birds	0.337	**0.343**	0.342	0.338	0.308	**0.413**	0.370	0.370	0.370	0.326	**0.370**	0.356	0.355	0.353	0.317
cal500	0.451	0.516	0.520	0.505	**0.526**	**0.398**	0.288	0.289	0.286	0.287	**0.423**	0.369	0.371	0.365	0.371
enron	0.611	0.676	**0.682**	0.657	0.656	**0.565**	0.469	0.467	0.441	0.431	**0.587**	0.553	0.554	0.527	0.520
EukPAAC	0.385	0.390	0.390	**0.393**	0.391	**0.409**	0.355	0.356	0.359	0.355	**0.396**	0.371	0.372	0.375	0.372
foodtruck	0.558	0.668	0.678	**0.698**	0.672	**0.538**	0.411	0.384	0.377	0.385	**0.547**	0.509	0.489	0.489	0.488
genbase	0.952	0.947	0.918	**0.971**	0.917	**0.950**	0.930	0.865	0.901	0.900	**0.950**	0.938	0.890	0.935	0.908
HumanGO	0.784	0.781	0.781	**0.790**	0.781	**0.779**	0.762	0.755	0.726	0.745	**0.781**	0.771	0.768	0.757	0.762
HumPAAC	0.358	**0.377**	0.363	0.367	0.375	**0.378**	0.334	0.321	0.326	0.333	**0.367**	0.354	0.341	0.345	0.353
langlog	0.204	0.214	0.209	**0.223**	0.216	**0.237**	0.184	0.180	0.193	0.186	**0.219**	0.198	0.193	0.207	0.200
medical	0.733	0.744	0.752	0.763	**0.766**	**0.713**	0.652	0.664	0.672	0.681	**0.722**	0.695	0.705	0.714	0.721
ng20	0.555	**0.625**	0.622	0.591	0.621	**0.681**	0.626	0.622	0.589	0.621	0.612	**0.625**	0.622	0.590	0.621
ohsumed	0.532	0.595	**0.608**	0.600	0.599	**0.561**	0.422	0.421	0.407	0.412	**0.545**	0.494	0.497	0.485	0.488
PlantGO	0.759	**0.794**	0.790	0.774	0.774	**0.814**	0.796	0.792	0.778	0.773	0.785	**0.795**	0.791	0.776	0.773
PlanPAAC	0.304	0.306	0.313	**0.325**	0.317	**0.328**	0.284	0.294	0.304	0.298	**0.315**	0.294	0.303	0.314	0.307
reutersk500	0.449	0.501	0.509	**0.511**	0.505	**0.441**	0.355	0.362	0.362	0.358	**0.445**	0.416	0.423	0.424	0.419
slashdot	0.336	0.408	**0.419**	0.386	0.399	**0.375**	0.345	0.355	0.326	0.339	0.352	0.374	**0.384**	0.353	0.367
stackex_chess	0.309	**0.402**	0.393	0.382	0.388	**0.309**	0.172	0.166	0.162	0.163	**0.309**	0.241	0.234	0.227	0.230
tmc2007_500	0.700	0.753	**0.757**	0.754	0.755	**0.722**	0.633	0.621	0.617	0.618	**0.711**	0.688	0.682	0.678	0.679
yeast	0.655	0.661	**0.664**	0.661	0.662	**0.600**	0.598	0.595	0.595	0.597	0.626	**0.628**	**0.628**	0.626	**0.628**
Average	0.525	0.563	**0.564**	0.563	0.559	**0.537**	0.473	0.467	0.463	0.464	**0.530**	0.509	0.505	0.502	0.501
RankSum	88	54	**43**	45	55	**19**	54	66	74	72	**32**	54	60	72	67

	Precision					Recall					F1				
	ECC	**A03**	**A05**	**A08**	**A10**	**ECC**	**A03**	**A05**	**A08**	**A10**	**ECC**	**A03**	**A05**	**A08**	**A10**
birds	0.274	**0.303**	**0.303**	0.297	0.280	**0.224**	0.215	0.215	0.209	0.185	0.232	0.238	**0.239**	0.232	0.210
cal500	0.461	0.525	0.532	0.522	**0.543**	**0.405**	0.293	0.294	0.292	0.293	**0.420**	0.366	0.368	0.363	0.367
enron	0.624	0.671	**0.675**	0.640	0.641	**0.594**	0.500	0.494	0.475	0.463	**0.585**	0.545	0.542	0.516	0.509
EukPAAC	0.383	0.390	0.388	**0.391**	0.389	**0.406**	0.355	0.357	0.360	0.356	**0.379**	0.363	0.363	0.366	0.363
foodtruck	0.581	0.687	0.685	**0.707**	0.689	**0.631**	0.509	0.497	0.491	0.493	**0.543**	0.532	0.525	0.530	0.521
genbase	0.960	0.954	0.906	**0.966**	0.919	**0.961**	0.948	0.881	0.931	0.914	**0.956**	0.944	0.889	0.942	0.910
HumanGO	**0.812**	0.805	0.806	0.804	0.803	**0.817**	0.801	0.800	0.771	0.784	**0.797**	0.786	0.785	0.772	0.777
HumPAAC	0.359	**0.375**	0.360	0.367	0.373	**0.386**	0.341	0.327	0.336	0.341	**0.356**	0.348	0.333	0.341	0.347
langlog	0.209	0.216	0.208	**0.224**	0.217	**0.227**	0.175	0.167	0.184	0.176	**0.202**	0.187	0.179	0.195	0.187
medical	0.750	0.751	0.758	0.769	**0.776**	**0.739**	0.686	0.696	0.709	0.721	0.727	0.702	0.711	0.723	**0.732**
ng20	0.590	**0.626**	0.623	0.592	0.622	**0.684**	0.630	0.627	0.593	0.626	0.619	**0.625**	0.622	0.590	0.621
ohsumed	0.547	0.591	**0.602**	0.594	0.593	**0.593**	0.459	0.461	0.445	0.452	**0.530**	0.488	0.494	0.482	0.485
PlantGO	0.795	**0.807**	0.803	0.786	0.787	**0.829**	0.810	0.804	0.791	0.789	0.800	**0.801**	0.797	0.780	0.780
PlanPAAC	0.299	0.306	0.312	**0.326**	0.316	**0.335**	0.295	0.306	0.315	0.310	0.307	0.298	0.307	**0.318**	0.310
reutersk500	0.466	0.495	0.502	**0.504**	0.499	**0.510**	0.429	0.437	0.437	0.435	**0.463**	0.446	0.453	0.455	0.452
slashdot	0.357	0.407	**0.419**	0.385	0.398	**0.401**	0.369	0.382	0.350	0.365	0.364	0.381	**0.394**	0.361	0.376
stackex_chess	0.336	**0.397**	0.393	0.380	0.388	**0.323**	0.183	0.177	0.174	0.175	**0.298**	0.236	0.232	0.226	0.229
tmc2007_500	0.719	0.759	**0.762**	0.758	0.758	**0.763**	0.682	0.670	0.666	0.667	**0.702**	0.678	0.672	0.668	0.669
yeast	0.662	0.666	**0.668**	0.667	0.666	**0.607**	0.603	0.601	0.599	0.602	**0.605**	0.604	0.604	0.602	0.603
Average	0.536	**0.565**	0.563	0.562	0.561	**0.549**	0.489	0.484	0.480	0.481	**0.520**	0.504	0.501	0.498	0.497
RankSum	85	48	**47**	51	54	**19**	56	63	75	72	**32**	54	59	71	69

	Hamming-Loss					Accuracy					Subset-Accuracy				
	ECC	**A03**	**A05**	**A08**	**A10**	**ECC**	**A03**	**A05**	**A08**	**A10**	**ECC**	**A03**	**A05**	**A08**	**A10**
birds	0.075	0.072	**0.071**	0.072	0.075	0.196	**0.206**	**0.206**	0.199	0.178	0.096	**0.117**	0.116	0.106	0.099
cal500	0.161	0.146	**0.145**	0.147	0.146	**0.272**	0.230	0.231	0.227	0.231	0.000	0.000	0.000	0.000	0.000
enron	0.051	**0.048**	**0.048**	0.050	0.051	**0.470**	0.438	0.436	0.414	0.408	0.135	**0.140**	0.133	0.128	0.131
EukPAAC	0.065	0.063	0.063	**0.062**	**0.062**	**0.348**	0.343	0.344	0.347	0.344	0.255	0.287	0.288	**0.290**	0.288
foodtruck	0.170	0.152	0.153	**0.151**	0.155	0.432	0.451	0.449	**0.456**	0.437	0.135	0.243	0.263	**0.281**	0.229
genbase	**0.005**	0.006	0.010	0.006	0.008	**0.945**	0.930	0.880	0.931	0.895	**0.908**	0.882	0.849	0.894	0.847
HumanGO	**0.037**	0.038	0.039	0.040	0.039	**0.763**	0.752	0.749	0.740	0.745	**0.661**	0.653	0.644	0.649	0.652
HumPAAC	0.110	**0.103**	0.105	0.105	**0.103**	0.321	**0.328**	0.314	0.322	**0.328**	0.221	**0.272**	0.257	0.267	**0.272**
langlog	0.026	**0.023**	**0.023**	**0.023**	**0.023**	0.173	0.175	0.166	**0.182**	0.173	0.099	0.141	0.131	**0.147**	0.136
medical	0.015	0.016	0.015	0.015	**0.014**	0.690	0.670	0.680	0.691	**0.699**	0.579	0.574	0.586	0.598	**0.601**
ng20	0.044	**0.039**	**0.039**	0.042	**0.039**	0.586	**0.620**	0.617	0.585	0.616	0.492	**0.604**	0.602	0.570	0.600
ohsumed	0.068	0.063	**0.062**	**0.062**	**0.062**	**0.441**	0.426	0.433	0.421	0.424	0.195	0.256	**0.265**	0.257	0.260
PlantGO	0.040	**0.037**	0.038	0.040	0.041	0.775	**0.786**	0.782	0.764	0.763	0.703	**0.743**	0.740	0.716	0.715
PlanPAAC	0.128	0.123	0.122	**0.119**	0.121	0.286	0.294	0.302	**0.313**	0.305	0.224	0.281	0.289	**0.298**	0.289
reutersk500	0.016	**0.014**	**0.014**	**0.014**	**0.014**	0.413	0.423	0.430	**0.432**	0.429	0.274	0.359	0.369	**0.371**	0.370
slashdot	0.074	0.062	**0.061**	0.064	0.063	0.330	0.368	**0.381**	0.349	0.364	0.235	0.330	**0.344**	0.315	0.331
stackex_chess	0.015	**0.012**	**0.012**	**0.012**	**0.012**	**0.214**	0.179	0.176	0.172	0.174	0.029	0.045	0.046	0.046	**0.049**
tmc2007_500	0.059	**0.058**	**0.058**	0.059	0.059	**0.606**	0.588	0.583	0.579	0.580	0.297	**0.313**	0.310	0.308	0.311
yeast	0.217	0.215	**0.214**	0.215	**0.214**	0.493	**0.495**	**0.495**	0.493	0.494	0.145	**0.152**	0.151	0.147	**0.152**
Average	0.072	**0.068**	**0.068**	**0.068**	0.069	**0.461**	0.458	0.456	0.454	0.452	**0.520**	0.504	0.501	0.498	0.497
RankSum	82	**45**	46	55	57	55	**49**	54	62	65	79	**47**	51	49	49

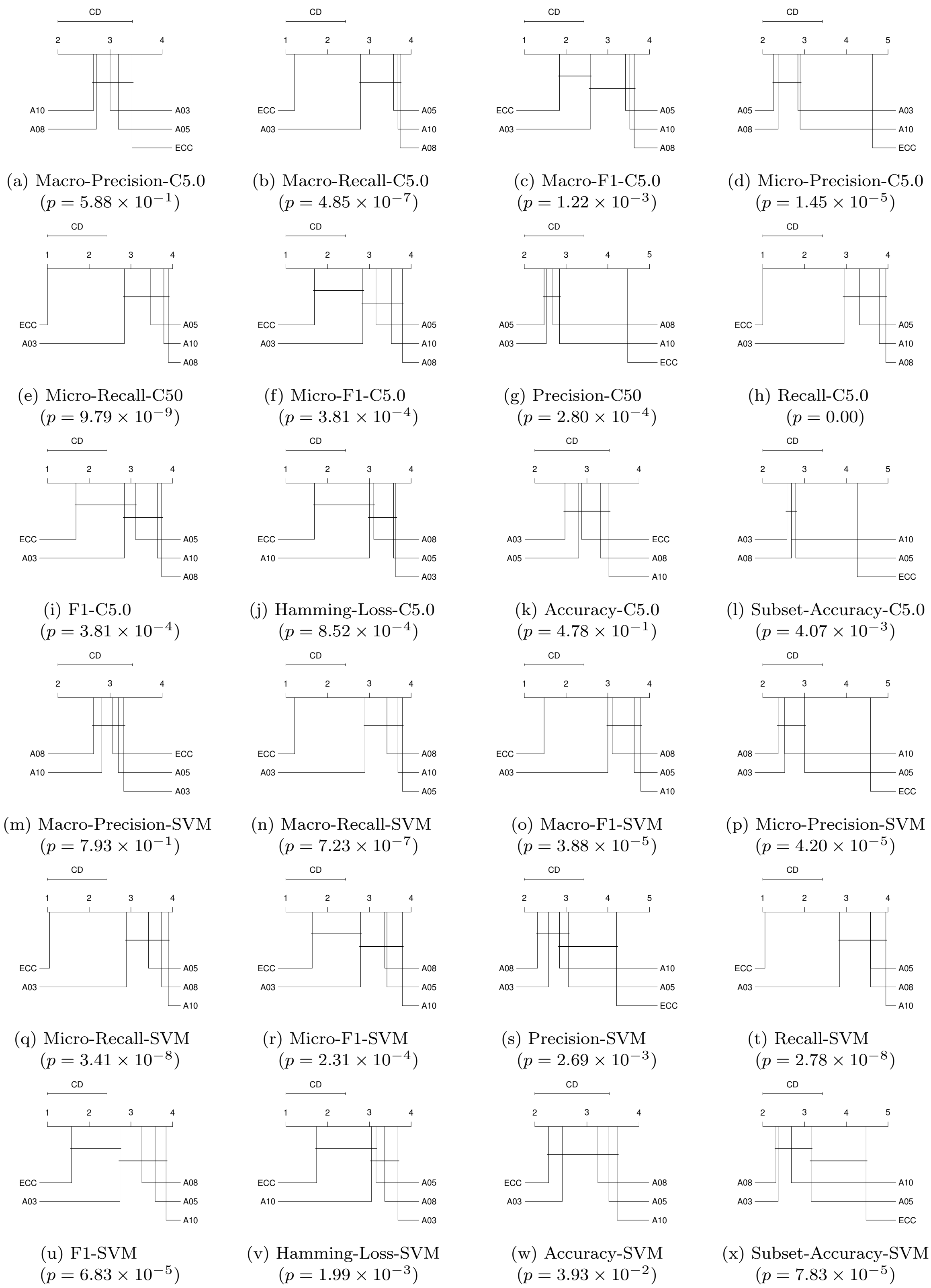
Table III: Results with SVM as base algorithm.

	Macro-Precision					Macro-Recall					Macro-F1				
	ECC	**A03**	**A05**	**A08**	**A10**	**ECC**	**A03**	**A05**	**A08**	**A10**	**ECC**	**A03**	**A05**	**A08**	**A10**
birds	**0.100**	0.096	0.073	0.096	0.084	**0.100**	0.092	0.080	0.082	0.085	**0.068**	0.065	0.052	0.058	0.061
cal500	**0.168**	0.148	0.147	0.156	0.152	**0.178**	0.082	0.080	0.072	0.071	**0.161**	0.090	0.089	0.083	0.082
enron	**0.249**	0.232	**0.249**	0.234	0.234	**0.196**	0.119	0.121	0.114	0.112	**0.200**	0.141	0.144	0.136	0.133
EukPAAC	0.176	**0.189**	0.180	0.186	0.187	**0.140**	0.128	0.129	0.130	0.131	0.136	0.134	0.135	**0.137**	0.134
foodtruck	**0.284**	0.188	0.218	0.175	0.157	**0.248**	0.107	0.106	0.095	0.093	**0.237**	0.108	0.107	0.091	0.087
genbase	0.667	0.658	0.652	0.643	**0.669**	**0.677**	0.622	0.605	0.611	0.631	**0.669**	0.631	0.616	0.619	0.638
HumanGO	0.698	0.707	**0.714**	0.701	0.691	0.642	**0.658**	0.655	0.645	0.640	0.649	**0.666**	**0.666**	0.654	0.648
HumPAAC	0.234	0.229	**0.243**	**0.243**	0.238	**0.193**	0.171	0.177	0.169	0.180	**0.190**	0.177	0.187	0.178	0.187
langlog	0.083	0.069	0.074	0.074	**0.075**	**0.076**	0.061	0.059	0.061	0.062	**0.068**	0.057	0.056	0.057	0.060
medical	0.305	0.307	0.294	**0.316**	0.312	**0.304**	0.283	0.281	0.292	0.289	0.297	**0.281**	0.278	0.293	0.289
ng20	0.707	**0.739**	0.734	0.729	0.721	**0.778**	0.754	0.752	0.742	0.737	0.738	**0.743**	0.739	0.731	0.724
ohsumed	0.530	0.572	**0.607**	0.580	**0.607**	**0.406**	0.319	0.317	0.319	0.320	**0.432**	0.380	0.381	0.384	0.385
PlantGO	0.677	0.695	0.656	0.697	**0.702**	0.650	0.650	0.626	**0.656**	0.639	0.647	0.645	0.616	**0.658**	0.644
PlanPAAC	0.174	0.187	0.195	0.245	**0.250**	**0.185**	0.171	0.163	0.184	0.171	0.165	0.162	0.157	**0.184**	0.172
reutersk500	0.253	**0.257**	0.242	0.249	0.243	**0.176**	0.147	0.137	0.137	0.136	**0.181**	0.160	0.148	0.147	0.143
slashdot	**0.430**	0.402	0.422	0.416	0.404	**0.352**	0.298	0.305	0.302	0.292	**0.356**	0.319	0.328	0.327	0.314
stackex_chess	**0.120**	0.092	0.086	0.097	0.092	**0.108**	0.042	0.042	0.046	0.047	**0.103**	0.053	0.051	0.057	0.056
tmc2007_500	0.736	0.796	0.800	0.804	**0.811**	**0.570**	0.470	0.457	0.455	0.450	**0.627**	0.566	0.557	0.555	0.550
yeast	0.513	0.568	**0.573**	0.551	0.544	**0.455**	0.412	0.394	0.397	0.388	**0.448**	0.427	0.414	0.424	0.415
Average	0.374	0.375	0.377	**0.379**	0.378	**0.339**	0.294	0.289	0.290	0.288	**0.336**	0.305	0.301	0.304	0.301
RankSum	58	62	60	**51**	54	**23**	55	72	65	70	**28**	57	69	59	72

	Micro-Precision					Micro-Recall					Micro-F1				
	ECC	**A03**	**A05**	**A08**	**A10**	**ECC**	**A03**	**A05**	**A08**	**A10**	**ECC**	**A03**	**A05**	**A08**	**A10**
birds	0.219	**0.228**	0.205	0.199	0.209	**0.242**	0.231	0.206	0.202	0.210	**0.230**	**0.230**	0.206	0.201	0.209
cal500	0.457	0.559	0.573	0.583	**0.585**	**0.448**	0.259	0.253	0.231	0.223	**0.452**	0.352	0.350	0.330	0.322
enron	0.594	**0.689**	0.684	0.680	0.673	**0.613**	0.461	0.462	0.441	0.448	**0.603**	0.552	0.550	0.534	0.538
EukPAAC	0.435	0.448	0.448	**0.450**	0.442	**0.466**	0.408	0.412	0.409	0.400	**0.450**	0.427	0.430	0.429	0.420
foodtruck	0.553	0.707	0.712	**0.716**	0.700	**0.544**	0.358	0.352	0.335	0.334	**0.547**	0.474	0.470	0.456	0.451
genbase	0.956	0.953	0.924	**0.975**	0.950	**0.961**	0.919	0.894	0.925	0.928	**0.959**	0.936	0.909	0.949	0.939
HumanGO	0.755	0.759	0.758	0.759	**0.760**	0.801	0.801	**0.805**	0.799	0.791	0.777	0.779	**0.781**	0.778	0.775
HumPAAC	0.432	0.444	0.447	0.439	**0.454**	**0.444**	0.395	0.396	0.388	0.399	**0.438**	0.418	0.420	0.412	0.424
langlog	0.237	0.254	0.245	**0.265**	0.254	**0.264**	0.217	0.209	0.226	0.217	**0.250**	0.234	0.226	0.244	0.234
medical	0.743	0.771	0.766	0.764	**0.778**	**0.746**	0.696	0.706	0.704	0.716	0.745	0.732	0.735	0.732	**0.746**
ng20	0.701	**0.732**	0.728	0.721	0.711	**0.778**	0.754	0.752	0.742	0.737	0.737	**0.743**	0.740	0.732	0.723
ohsumed	0.568	0.642	0.642	0.647	**0.648**	**0.577**	0.460	0.459	0.457	0.457	**0.572**	0.536	0.535	0.536	0.536
PlantGO	0.757	0.759	0.749	**0.769**	0.759	**0.807**	0.800	0.795	0.806	0.797	0.781	0.779	0.771	**0.787**	0.778
PlanPAAC	0.364	0.383	0.366	**0.393**	0.363	**0.396**	0.363	0.347	0.375	0.349	0.379	0.373	0.356	**0.384**	0.356
reutersk500	0.398	**0.452**	0.433	0.424	0.432	**0.383**	0.315	0.303	0.296	0.302	**0.386**	0.371	0.357	0.349	0.355
slashdot	0.507	0.577	0.585	**0.588**	0.574	**0.571**	0.508	0.515	0.517	0.507	0.536	0.540	0.547	**0.550**	0.538
stackex_chess	0.344	0.491	0.483	0.484	**0.498**	**0.356**	0.230	0.223	0.227	0.233	**0.350**	0.313	0.305	0.309	0.317
tmc2007_500	0.733	0.777	0.780	0.782	**0.785**	**0.730**	0.645	0.626	0.624	0.626	**0.731**	0.705	0.695	0.694	0.697
yeast	0.664	0.697	0.702	0.701	**0.707**	**0.685**	0.641	0.622	0.613	0.609	**0.675**	0.668	0.659	0.654	0.654
Average	0.374	0.375	0.377	**0.379**	0.378	**0.569**	0.498	0.491	0.490	0.488	**0.558**	0.535	0.528	0.529	0.527
RankSum	87	48	57	**45**	48	**20**	55	65	71	74	**31**	53	65	64	72

	Precision					Recall					F1				
	ECC	**A03**	**A05**	**A08**	**A10**	**ECC**	**A03**	**A05**	**A08**	**A10**	**ECC**	**A03**	**A05**	**A08**	**A10**
birds	0.197	**0.218**	0.200	0.188	0.203	**0.134**	0.125	0.115	0.106	0.109	0.146	**0.148**	0.138	0.127	0.133
cal500	0.464	0.574	0.588	0.600	**0.606**	**0.453**	0.265	0.260	0.236	0.229	**0.448**	0.351	0.349	0.327	0.319
enron	0.620	**0.685**	0.673	0.669	0.661	**0.640**	0.496	0.496	0.480	0.486	**0.604**	0.544	0.539	0.526	0.530
EukPAAC	0.442	0.448	0.449	**0.451**	0.442	**0.470**	0.415	0.418	0.416	0.408	**0.439**	0.421	0.423	0.423	0.415
foodtruck	0.596	0.716	0.719	**0.723**	0.711	**0.645**	0.468	0.462	0.451	0.447	**0.551**	0.518	0.516	0.510	0.503
genbase	0.967	0.952	0.918	**0.972**	0.950	**0.970**	0.934	0.903	0.944	0.940	**0.964**	0.938	0.905	0.953	0.941
HumanGO	0.795	0.797	0.797	**0.799**	**0.799**	**0.836**	0.834	0.840	0.835	0.827	0.794	0.795	**0.797**	0.796	0.793
HumPAAC	0.439	0.446	0.448	0.440	**0.455**	**0.461**	0.412	0.412	0.405	0.416	**0.432**	0.418	0.419	0.411	0.424
langlog	0.254	0.253	0.243	**0.264**	0.253	**0.248**	0.205	0.197	0.212	0.203	**0.237**	0.219	0.211	0.227	0.218
medical	0.773	0.790	0.782	0.781	**0.793**	**0.775**	0.740	0.740	0.741	0.752	0.753	0.745	0.742	0.742	**0.755**
ng20	0.730	**0.742**	0.739	0.731	0.721	**0.782**	0.760	0.757	0.748	0.742	**0.746**	**0.746**	0.743	0.735	0.726
ohsumed	0.593	0.638	0.640	**0.644**	**0.644**	**0.618**	0.509	0.509	0.508	0.507	**0.567**	0.536	0.536	0.538	0.538
PlantGO	0.789	0.786	0.778	**0.796**	0.785	**0.819**	0.812	0.805	0.817	0.808	0.792	0.788	0.781	**0.796**	0.786
PlanPAAC	0.376	0.383	0.367	**0.394**	0.364	**0.406**	0.371	0.358	0.385	0.361	0.381	0.372	0.359	**0.385**	0.358
reutersk500	0.418	**0.445**	0.424	0.414	0.423	**0.454**	0.392	0.373	0.369	0.376	**0.415**	0.407	0.387	0.382	0.389
slashdot	0.540	0.578	0.586	**0.590**	0.575	**0.598**	0.540	0.546	0.548	0.537	0.548	0.548	0.555	**0.558**	0.545
stackex_chess	0.393	0.484	0.479	0.480	**0.492**	**0.377**	0.245	0.240	0.241	0.250	**0.343**	0.305	0.299	0.300	0.310
tmc2007_500	0.748	0.777	0.777	0.778	**0.782**	**0.770**	0.691	0.672	0.671	0.674	**0.721**	0.692	0.680	0.680	0.684
yeast	0.671	0.695	0.699	0.693	**0.700**	**0.692**	0.646	0.629	0.618	0.613	**0.658**	0.644	0.636	0.625	0.625
Average	0.374	0.375	0.377	**0.379**	0.378	**0.587**	0.519	0.512	0.512	0.510	**0.555**	0.533	0.527	0.528	0.526
RankSum	80	49	58	**44**	54	**20**	54	68	68	75	**30**	52	68	62	73

	Hamming-Loss					Accuracy					Subset-Accuracy				
	ECC	**A03**	**A05**	**A08**	**A10**	**ECC**	**A03**	**A05**	**A08**	**A10**	**ECC**	**A03**	**A05**	**A08**	**A10**
birds	0.086	**0.083**	0.085	0.086	0.085	0.116	**0.120**	0.112	0.103	0.105	0.043	0.049	**0.053**	0.044	0.039
cal500	0.163	0.142	**0.140**	**0.140**	**0.140**	**0.298**	0.220	0.218	0.203	0.197	0.000	0.000	0.000	0.000	0.000
enron	0.051	**0.048**	**0.048**	0.049	0.049	**0.485**	0.436	0.435	0.422	0.426	0.126	0.138	**0.140**	0.132	0.134
EukPAAC	0.059	**0.057**	**0.057**	**0.057**	0.058	**0.404**	0.401	0.401	0.403	0.396	0.299	0.341	0.338	**0.344**	0.338
foodtruck	0.173	**0.151**	**0.151**	0.153	0.155	0.440	**0.444**	0.442	0.437	0.431	0.141	0.269	0.270	**0.274**	0.272
genbase	**0.004**	0.006	0.008	0.005	0.006	**0.955**	0.927	0.894	0.943	0.931	**0.920**	0.887	0.857	0.911	0.894
HumanGO	0.039	**0.038**	**0.038**	0.039	0.039	0.751	0.754	**0.755**	0.754	0.752	0.626	**0.633**	0.631	0.632	**0.633**
HumPAAC	0.096	0.093	0.093	0.094	**0.092**	0.395	0.397	0.398	0.390	**0.403**	0.287	0.334	0.335	0.327	**0.339**
langlog	0.025	**0.022**	0.023	**0.022**	**0.022**	0.209	0.204	0.196	**0.211**	0.202	0.134	0.164	0.158	**0.167**	0.162
medical	0.014	0.014	0.014	0.014	**0.013**	0.709	0.704	0.703	0.704	**0.718**	0.580	0.585	0.590	0.591	**0.611**
ng20	0.028	**0.027**	**0.027**	0.028	0.029	0.724	**0.736**	0.733	0.725	0.715	0.662	**0.706**	0.702	0.695	0.683
ohsumed	0.062	0.058	0.058	**0.057**	**0.057**	**0.480**	0.472	0.472	0.475	0.475	0.235	0.297	0.296	0.300	**0.303**
PlantGO	0.041	0.041	0.042	**0.039**	0.041	0.769	0.765	0.758	**0.775**	0.764	0.701	0.697	0.690	**0.712**	0.700
PlanPAAC	0.117	0.110	0.113	**0.108**	0.114	0.359	0.363	0.351	**0.375**	0.349	0.297	0.335	0.328	**0.347**	0.322
reutersk500	0.017	**0.015**	0.016	0.016	0.016	0.373	**0.390**	0.370	0.367	0.374	0.260	**0.345**	0.325	0.329	0.333
slashdot	0.053	0.046	0.046	**0.045**	0.047	0.501	0.527	0.534	**0.536**	0.524	0.369	0.464	0.471	**0.474**	0.461
stackex_chess	0.014	**0.011**	**0.011**	**0.011**	**0.011**	**0.251**	0.234	0.229	0.229	0.239	0.041	0.064	0.063	0.064	**0.073**
tmc2007_500	**0.054**	**0.054**	0.056	0.055	0.055	**0.630**	0.608	0.597	0.596	0.600	0.336	**0.347**	0.343	0.342	0.346
yeast	0.200	**0.193**	0.194	0.196	0.195	**0.556**	0.548	0.538	0.529	0.528	0.215	**0.235**	0.229	0.230	0.227
Average	**0.374**	0.375	0.377	0.379	0.378	**0.495**	0.487	0.481	0.483	0.481	0.330	0.363	0.359	**0.364**	0.362
RankSum	81	**44**	54	50	56	**43**	48	65	61	68	83	43	58	**42**	49



(a) Macro-Precision-C5.0 ($p = 5.88 \times 10^{-1}$)

(b) Macro-Recall-C5.0 ($p = 4.85 \times 10^{-7}$)

(c) Macro-F1-C5.0 ($p = 1.22 \times 10^{-3}$)

(d) Micro-Precision-C5.0 ($p = 1.45 \times 10^{-5}$)

(e) Micro-Recall-C50 ($p = 9.79 \times 10^{-9}$)

(f) Micro-F1-C5.0 ($p = 3.81 \times 10^{-4}$)

(g) Precision-C50 ($p = 2.80 \times 10^{-4}$)

(h) Recall-C5.0 ($p = 0.00$)

(i) F1-C5.0 ($p = 3.81 \times 10^{-4}$)

(j) Hamming-Loss-C5.0 ($p = 8.52 \times 10^{-4}$)

(k) Accuracy-C5.0 ($p = 4.78 \times 10^{-1}$)

(l) Subset-Accuracy-C5.0 ($p = 4.07 \times 10^{-3}$)

(m) Macro-Precision-SVM ($p = 7.93 \times 10^{-1}$)

(n) Macro-Recall-SVM ($p = 7.23 \times 10^{-7}$)

(o) Macro-F1-SVM ($p = 3.88 \times 10^{-5}$)

(p) Micro-Precision-SVM ($p = 4.20 \times 10^{-5}$)

(q) Micro-Recall-SVM ($p = 3.41 \times 10^{-8}$)

(r) Micro-F1-SVM ($p = 2.31 \times 10^{-4}$)

(s) Precision-SVM ($p = 2.69 \times 10^{-3}$)

(t) Recall-SVM ($p = 2.78 \times 10^{-8}$)

(u) F1-SVM ($p = 6.83 \times 10^{-5}$)

(v) Hamming-Loss-SVM ($p = 1.99 \times 10^{-3}$)

(w) Accuracy-SVM ($p = 3.93 \times 10^{-2}$)

(x) Subset-Accuracy-SVM ($p = 7.83 \times 10^{-5}$)

Fig. 2: Critical diagrams for individual measures ($\alpha = 0.05$).

5. CONCLUSION

Therefore, it can be concluded that the addition of meta-labels improves metrics such as Micro-Precision, Precision, Hamming-loss, and Subset-Accuracy. On the other hand, the other metrics perform better without meta-labels, regardless of whether the C5.0 or SVM algorithm is used. Metrics such as rank and average are essential for validating which method stands out when considering all datasets together. However, the ranking metric is more significant because a classifier may perform exceptionally well on one dataset while underperforming on others, leading to a high average value that can be misleading.

It is important to note that the number of meta-labels can significantly influence the results. The factor k, as discussed in this article, when multiplied by the number of labels in the dataset, determines the number of meta-labels inserted into the chain. This factor is crucial for applications utilizing the proposed method in conjunction with the ensemble classifier chain (ECC). Additionally, the choice of algorithm, whether C5.0 or SVM, also plays a role, a lower factor k might yield better performance with one algorithm, while a higher k may be necessary for optimal results with another.

Based on this work, there are still many details to be explored, which we are interested in addressing in future work. It is possible to compare results obtained with smaller and larger datasets, and other correction measures can be used. Finally, still on the issue of excluding meta-labels, experiments, and analyses can be carried out regarding the order in which these meta-labels are inserted into the chain. Moreover, to verify the behavior of augmented ECC using other base classifiers like Naive Bayes, Bayes Net, and KNN ones.

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