**Table 1.7.** Summary of the researched of multi-label classification

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| **Author(s)** | **Methods** | **Approx. accuraccy score** | **Approx. hamming loss** | **Comments** |
| Santos et. al. (2011) | BR, CC, PS, ECC, EPS for the base estimators:  • KNN; • Decision trees (DT); • SVM; • Naïve Bayes (NB);  • multi-layer perceptron(MLP) (NB);  Back-Propagation Multi-Label Learning;  Multi-Label k-Nearest Neighbors (MLKNN); | presented in the paper | presented in the paper | Comparision of prediction results obtained by applying various multi-label classification methods is made for both problem transformation and problem adaptation approaches |
| Statistics Education (2020) | • One vs All; • One vs One; • Label Powerset; • Multi-Label k-Nearest Neighbors (MLKNN); | SCut threshold: • 0.71; • 0.64; • 0.67; • 0.42; MCut threshold: • 0.65; • 0.45; • 0.66; • 0.43; | SCut threshold: • 0.12; • 0.16; • 0.15; • 0.27; MCut threshold: • 0.15; • 0.20; • 0.16; • 0.29; | SCut threshold adjusts the threshold for each label to minimize MSE for the train set; MCut threshold determines a unique threshold for each instance based on the largest difference in ranked probabilities of the labels. |
| Cherman et al. (2011) | Label Power Set (LP ), Binary Relevance (BR), and BR+ with the following base estimators: • J48; • KNN; • SMO; • NB; | Label Power Set (LP ): • 0.91; • 0.83; • 0.93; • 0.88; Binary Relevance (BR): • 0.94; • 0.84; • 0.94; • 0.89; BR+: • 0.95; • 0.93; • 0.95; • 0.90; | Label Power Set (LP ): • 0.04; • 0.09; • 0.03; • 0.05; Binary Relevance (BR): • 0.03; • 0.08; • 0.02; • 0.05; BR+: • 0.02; • 0.03; • 0.02; • 0.05; | Label Power Set (LP), Binary Relevance (BR), and BR+ (BRplus), an extension of BR. |
| Chiang et al. (2012) | • KNN where k=10 (BR-KNN); • logistic regression (BR-LR); • IBLR; • MLKNN; • RAKEL; • Perceptron with Margins (PM); • Passive-Aggressive Perceptron (PA); • Ranking SVM (RS); | presented in the paper | presented in the paper |  |
| Read et al. (2009) | Binary methods: • Classifier chains(CC); •Binary method(BM(BR)); • Subset mapping(SM); • Meta stacking(MS); Ensemble methods: • Ensembles of Classifier Chains(ECC); • Ensembles of Binary Methods(EBM); • Ensembles of Pruned Sets (EPS); • RAKEL RAndom K labEL subsets (RAK); | Binary methods: • 0.40-0.75; • 0.32-0.73; • 0.34-0.73; • 0.32-0.73; Ensemble methods - small datasets: • 0.45-0.78; • 0.36-0.77; • 0.45-0.74; • 0.45-0.76; Ensemble methods - large datasets: • 0.18-0.53;  • 0.01-0.41; • 0.09-0.52; • 0.02-0.53; |  |  |
| Rokach et al. (2014) | • RAKEL; • RAKEL++; • DD-BALANCOR; • BALANCOR; • INLAC; • BALCO; for the base classifiers: • SMO; • J48; | presented in the paper | presented in the paper |  |
| Madjarov et al. (2012) | • Binary Relevance (BR); • Classifier Chain (CC); • Calibrated Label ranking (CLR); • Quick weighted algorithm for multi-label learning (QWML); • Hierarchy of multi-label classifiers (HOMER); • ML-C4.5; • Predictive clustering trees (PCT); • Multi-Label k-Nearest Neighbors (ML-kNN); • Random k-label sets (RAKEL); • Ensamble of classifier chains(ECC); • RFML-C4.5; • RF-PCT; | • 0.03-0.89; • 0.03-0.89; • 0.09-0.89; • 0.09-0.68; • 0.18-0.88; • 0.01-0.73; • 0.00-0.54; • 0.01-0.63; • 0.00-0.73; • 0.00-0.80; • 0.01-0.49; • 0.14-0.91; | • 0.01-0.26; • 0.01-0.26; • 0.01-0.26; • 0.01-0.26; • 0.01-0.36; • 0.01-0.25; • 0.01-0.27; • 0.01-0.23; • 0.01-0.29; • 0.00-0.28; • 0.01-0.20; • 0.14-0.20; |  |
| Chen et al. (2013) | • C4.5; • Binary-SVM; • Bayesian network (BN); | • 0.42; • 0.53; • 0.42; | • 0.23; • 0.20; • 0.430 |  |
| Tsoumakas et al. (2007) | • Sequential minimal optimization (SMO); • K-nearest neighbors (K-NN); | • 0.34; • 0.2-0.99; | • 0.00-0.29; • 0.00-0.24; |  |
| Tahir et al. (2010) | • Multi-Label k-Nearest Neighbors (MLKNN) - adaptation of the kNN lazy learning algorithm for multi-label  data; ML-kNN uses the kNN algorithm  independently for each label; • Calibrated Label ranking (CLR); • Random k-label sets (RAKEL); • Instance Based Logistic Regression (I-BLR) ; | Enron dataset: • 0.35; • 0.40; • 0.43; • 0.34 ; Scene dataset: • 0.63; • 0.58; • 0.57; • 0.65 ; Yeast dataset: • 0.49; • 0.50; • 0.47; • 0.50 ; | Enron dataset: • 0.05; • 0.06; • 0.05; • 0.06; Scene dataset: • 0.10; • 0.12; • 0.11; • 0.09 ; Yeast dataset: • 0.20; • 0.21; • 0.24; • 0.20 ; | Heterogeneous ensemble of multi-label learners is presented to si- multaneously tackle both imbalance and correlation problems. For multi-label classiﬁcation, this idea is especially appealing, as ensembles methods are well-known for overcoming over-ﬁtting problems and improving the performance of individual classiﬁers. |
| Prathibhamol et al. (2016) | • logistic regression based multilabel classiﬁcation (MLC-LR); | Scene dataset: • 0.77; Yeast dataset: • 0.75; | Scene dataset: • 0.09; Yeast dataset: • 0.12; |  |
| Nareshpalsingh et al. (2017),  Aldrees et al. (2016) | • Ensamble of classifier chains (ECC); • Random k-label sets (RAkEL); • Ensamble of pruned sets(EPS); • Multi-Label k-Nearest Neighbors (MLKNN); | • 0.33; • 0.32; • 0.26; • 0.24; | • 0.04; • 0.05; • 0.06; • 0.06; |  |
| Hao et al. (2022) | - | - | - | Proposes a novel multi-label classification method which can deal with missing features and labels simultaneously, and uses the matrix factorization to try to recover the missing values of features and labels simultaneously. In addition, to overcome the problem of tail labels in matrix factorization, an extra classi- fier is built for the sparse tail labels. |
| Endut et al. (2022) | • Support Vector Machine (SVM); • Decision tree(DT); • Logistic Regression; • Random forest (RF); • K-nearest neighbors (K-NN); • Bayesian network (BN); | - | - | - |
| Dery (2021) | - | - | - | Table of sub-cases of multi-label ranking provided. |
| Weng et al. (2021) | - | - | - | - |
| Zhang et al. (2014) | - | - | - | - |
| Alazaidah et al. (2016) | - | - | - | Categorization of MLC algoritms acciording to the degree of correlations among labels. |
| Sorower (2020) | - | - | - | Evaluation measures described. |
| Mahani (2023)  Vaishali et al. (2018) | - | - | - | Taxonomy, performance metrics presented. |
| Tarekegn et al. (2020) | - | - | - | Evaluation measures described. Comparison of specific methods proposed for addressing imbalanced MLC. |

Note. The accuracy scores of the authors' predictions is presented with the values form an interval in cases when several databases were experimented with or when different accuracy scores were obtained according to different learning style dimensions - in such cases, the range between the minimum and maximum values achieved is provided.