A Systematic Literature Review on Multi-Label Classification based on Machine Learning Algorithms

Nurshahira Endut, W. M. Amir Fazamin W. Hamzah, Ismahafezi Ismail, Mohd Kamir Yusof, Yousef Abu Baker, Hafiz Yusoff

Faculty of Informatics and Computing, Universiti Sultan Zainal Abidin, Terengganu, Malaysia

Abstract **– Multi-label classification is a technique used for mapping data from single labels to multiple labels. These multiple labels stand part of the same label set comprising inconsistent labels. The objective of multi-label classification is to create a classification model for previously unidentified samples. The accuracy of multi-label classification based on machine learning algorithms has been a particular study and discussion topic for researchers. This research aims to present a systematic literature review on multi-label classification based on machine learning algorithms. This study also discusses machine learning algorithm techniques and methods for multi-label classification. The findings would help researchers to explore and find the best accuracy of multi-label classification. The review result considered the Support Vector Machine (SVM) as the most accurate and appropriate machine learning algorithm in multi-label classification.**

Keywords **– multi-label, classification, machine learning.**

1. Introduction

Traditional single-label classification in the machine learning and pattern classification domains involves learning from a collection of samples, whereas multi-label classification is connected with finding a single label from a label set. In a collection of disjoint labels L, |L| > 1, the emphasis of single-label classification is on learning from several examples connected to a single label l. Binary classification problem (or, in this case, web and textual filtering) may be defined when |L| = 2, whereas |L| > 2, the challenge of multi-class classification is recognized. The examples in multi-label categorization are linked to a set of labels Y ⊆ L. Previously, text categorization tasks were the primary motivators for multi-label classification.

There are numerous situations in real life where people must classify multi-label data. Text document content can be linked-to several subjects in some real-world applications (labels or categories). Problems with the classification of these types of documents are known as multi-labels that include some complex features. This study aims to systematically review the literature on multi-label classification based on machine learning algorithms. This study investigates and determines the most accurate and appropriate method for multi-label classification. Additionally, this study discusses machine learning algorithm techniques and frequently used methods for multi-label classification. On top of that, it identifies the best machine learning algorithm used for multi-label classification at the end of this study.

2. Multi-label Classification

In the real world, multi-label classification may be used to automatically categorize a variety of materials, including texts, photos, audio, and video. Classifier ensembles, data transformation, and technique adaptation may all be utilized to gain insight from multi-label data. Since its wide range of application domains made multi-label classification so vital over the past few years. Each data instance is assigned several labels simultaneously in multi-label

DOI: 10.18421/TEM112-20
https://doi.org/10.18421/TEM112-20

Corresponding author: W. M. Amir Fazamin W. Hamzah, *Faculty of Informatics and Computing, Universiti Sultan Zainal Abidin, Terengganu, Malaysia.*
Email: amirfazamin@unisza.edu.my

Received: *16 January 2022.*
Revised: *16 April 2022.*
Accepted: *21 April 2022.*
Published: *27 May 2022.*

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classification, which is an extension of standard single-label classification. In recent years, multi-label classification has gained a lot of importance and has attracted a lot of research attention in areas including medical diagnosis, music categorization, emotion recognition, image/video annotation, and many others [1]. Multiple label classification may be described as an issue in finding a model that assigns zero or one for each label in the binary vector Y for given inputs X [2]. Multi-label classification involves associating examples with labels Y and L. From the previous research, many methods have been proposed for applying to multi-label classification problems [3]. To get around the drawbacks of single-label classification, researchers are turning to machine learning algorithms and the multi-label classification method.

The multi-label learning methods are classified into two categories: algorithm adaptation methods and issue transformation methods. Algorithm adaptation approaches primarily focus on expanding certain single class learning algorithms to directly address multi label classification issues [4]. Multi-label classification is a kind of supervised machine learning in which an instance may be linked with more than one label. Among these machine learning methods, the support vector machine (SVM) is well-known as one of the most popular classification systems [5]. Multi-label classification models have shown tremendous promise in text categorization, image classification, automatic annotation for multimedia content, bioinformatics, web mining, rule mining, information retrieval, tag recommendation, and other domains. Multi-label learning makes it easier to find correlations between different labels by modelling multiple labels at the same time [6].

Multi-label classification and the closely related topic of multi-output classification are classification variations in which numerous labels may be applied to each occurrence. As the name suggests, the emphasis of multi-label classification is on learning from a collection of instances that are each linked with a different set of labels [7]. When considering multi-label classification, it should be noted that it is a generalization of multi-class classification, which is a single-label issue that involves properly classifying examples into one of more than two classes. There is no limit to the number of classes to which the instance can be assigned in the multi-label problem.

3. Machine Learning Algorithms

In the field of artificial intelligence (AI), machine learning is a technique that allows frameworks to learn on their own, without the need for a human expert. Programmable computers that can learn from their own experiences have been a major focus of artificial intelligence (AI) [8]. Meanwhile, algorithms that enable computers to learn from their own data are the focus of machine learning. To uncover statistical equations or other patterns in the data, learning does not always need awareness. As a result, many machine learning algorithms will be far apart from how humans can learn. Machine learning algorithms are structured into taxonomies based on desired algorithm results. Algorithms of various types are commonly used including supervised, unsupervised, semi-supervised, reinforcement and transduction.

Supervised learning is the capacity of an algorithm to synthesize knowledge from pre-existing (labelled) data to anticipate future (unlabeled) cases. Unsupervised learning is the process of clustering data on unclassified or uncategorized data using automated methods or algorithms. Classification and regression are two forms of supervised learning algorithms [9]. When input and output variables (x and y) are taught with the mapping function by an algorithm from input to output y = f (x), it is known as supervised learning. When new input data (x) is available, the mapping function may be approached such that predictions for output variables (y) can be generated. Logistic Regression, K-Nearest Neighbors, Decision Trees, Random Forest Classifier, Naïve Bayes, and Support Vector Machine are all examples of supervised learning algorithms.

There are benefits and drawbacks to each machine learning algorithm. The Decision Tree is the most often used classification and prediction system. Since it makes no assumptions about the linearity of the data, the decision tree may be employed even when the parameters are not linearly connected. In situations where categorical input variables converge quickly, Naïve Bayes performs better than alternative discriminative models like logistic regression, which need more training data. With the highest classification performance on the training data, Support Vector Machines (SVMs) are more efficient for accurate classification of future data. SVM's core strength is its ability to deal with a wide range of classification issues, including high-dimensional and non-linearly separable problems [10].

However, machine learning algorithms must be tested to determine the best algorithms for multi-label classification based on accuracy, precision and recall value to evaluate the effectiveness of the classifiers [36]. These tests must be done to ensure their performance before making the final decision.

4. Methodology

The methodology focused on summarizing the methods used in each previous paper and the best features or techniques that have been used in the study from experience without being explicitly programmed to obtain accurate and appropriate results of multi-label classification successfully. This segment discusses the process of the review done, which followed the Kitchenham guidelines for conducting a systematic review [11]. This section describes the methodology used to find the best techniques or methods for multi-label classification. There are three stages to the methodology presented. Its primary methods are as follows:

- Organizing the review
- Conducting the review
- Reporting the review

The paper is constructed as follows. The following section offers activities that build on the planning process linked to multi-label classification. The subsequent sections show the discussed process in conducting the review, whereas the last section briefly updates the result of this systematic review. After that, a clear discussion of several approaches to multi-label classification follows.

4.1. Organizing the Review

To synthesize the most recent years of research in multi-label classification using machine learning algorithms, a systematic review is required. It is also critical that the review's planning stage is used to determine the measures that need to be done more cautiously. The objectives of this study were supported by the results of this systematic review, which were as follows:

- To summarize the existing methodologies and features used in multi-label classification.
- To identify the features used multi-label classification.
- To evaluate the algorithm used for multi-label classification.

As soon as the research goal is known, the most critical component of the protocol for a systematic review is the formulation of the research questions. According to Kitchenham's [11] guidelines, the instruction of research questions needs to consider three main points of the study criteria: population, intervention, and the outcomes of the study. The following sections contain details about each study criterion. Population: high school, high educational institute, and industrial sector; intervention: methods, algorithm and classification techniques; outcome: the best features for multi-label classification and successful classification techniques or approaches.

4.2. Conducting the Review

This section exposes the search strategy, study selection criteria and design of the extraction criteria. There are some detailed explanations for each category discussed as follows.

1) Search Strategy:

This study used a search strategy to identify the most related papers to study and review. The best and relevant papers were collected through five database sources: SAGE Publication, ScienceDirect, Springer Link, IEEEXplore and International Journal on Advanced Science, Engineering and Information Technology (IJASEIT). All database sources are shown in Table 1. The search terms of the paper were constructed by identifying the accuracy techniques that categorize the label classification and the methods for classifying multi-label using machine learning algorithms.

Table 1. Database Name for Findings Papers

No	Database Name	No. of Papers review
1	SAGE Publication	8
2	ScienceDirect	8
3	Springer Link	9
4	IEEEXplore	8
5	IJASEIT	3

2) Selection Criteria:

The following sections outline the study selection criteria used to identify the best studies for this review:

- Researchers who modelled classification using machine learning or data mining techniques.
- Review articles published in peer-reviewed publications in English.
- Studies that investigated the methods used in machine learning of multi-label classification.

This study examined and evaluated the performance based on the previous journals published from the year 2017 to the year 2021. The selection of criteria is very important to help find articles that are similar to the study conducted.

3) Extraction Criteria:

This phase aims to find articles or journals published from 2017 to 2021 that are related to the research topic. The Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) guidelines [12] were also utilized. First, the selection of published articles that matched the multi-label classification using machine learning was carried out. Second, articles were chosen based on their titles, abstracts, and keywords of the papers that satisfied the required standards. The last step is to choose by reviewing the general content of the papers that have been selected. Therefore, 36 articles were identified in this study as options to conduct this survey process perfectly. The collection of the initial group of articles for this study included a review comprising the following criteria:

- Elements needed to be extracted according to the methods or techniques section.
- Studies that investigated the methods used in machine learning of multi-label classification.

Any report that meets one of the following criteria were excluded:

- Methods that were not used in the data extraction stage of a systematic review.
- Articles that were either an editorial, a commentary or other non-original research reports.
- Articles with no associated evaluation element.

The original collection of articles was extracted from the search results after incorporating research reports. As a result, the reports that had been examined were cited in the original documents. The data were collected with the extraction of numerous aspects from the perspective of information originating research comprising references of techniques, the outcomes of the best approach employed, the findings, and publications as shown in Figure 1.

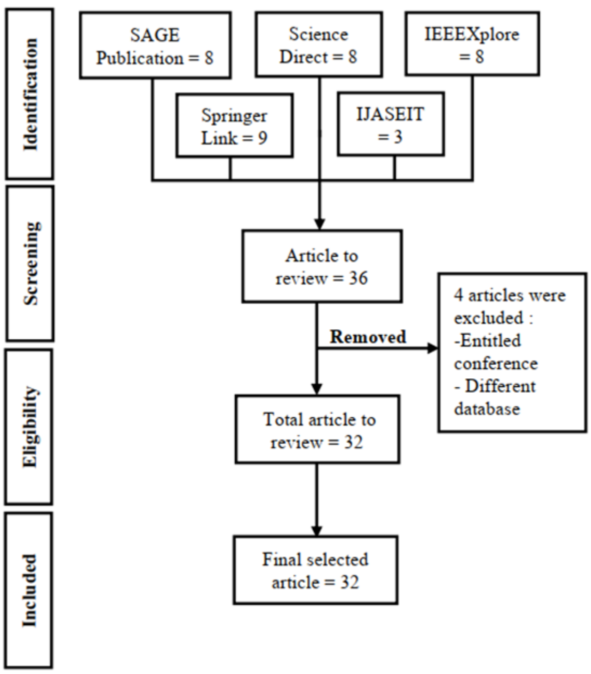

Figure 1. PRISMA flowchart for extraction and direction of research

Figure 1. shows the PRISMA flowchart during the selection process of the articles. As discussed before, five database sources were used for the paper searching and systematic review: SAGE Publication, ScienceDirect, Springer Link, IEEEXplore and IJASEIT. Based on the study conducted, the number of papers found was 36 papers. The use of extraction flow assistance is very helpful in the selection of related studies and research in this review [38]. The research papers were screened and filtered according to the relevant research, only as many as 32 papers. The final selected articles were 32, whereas four articles were excluded due to the entitled conference article, different databases and articles published before 2017. The total was divided into eight articles retrieved from the Sage Publication and Science Direct, nine articles retrieved from SpringerLink, six from the IEEEXplore and five from IJASEIT.

4.3. Reporting the Review

This section lists all the reviews conducted to assist researchers in determining the most effective methods or techniques for multi-label classification. The effort of conducting a systematic review is squandered if the review authors do not report what they conducted and what they discovered. Clear reporting allows others to imitate the methods used in the review, which can aid efforts to verify or reproduce the results. In Table 2., all of the articles analyzed were tabulated according to their Paper Code, Author Name & Year, and References.

Table 2. Selected articles for review

Paper Code	Author Name & Year	References
A1	M. Jethanandani, A. Sharma, T. Perumal, and J.-R. Chang. 2020.	[2]
A2	Ganda, D., & Buch, R. 2018.	[3]
A3	M. M. Bittencourt, R. M. Silva, and T. A. Almeida. 2020.	[33]
A4	Özdemir, O., Batar, M., & Işık, A. H. 2020.	[8]
A5	Sujaini, H., 2020.	[24]
A6	Tarekegn, A., Giacobini, M., & Michalak, K. 2021.	[1]
A7	E. A. Abdel Maksoud, S. Barakat, and M. Elmogy. 2019.	[26]
A8	A. M. K. Izzaty, M. S. Mubarok, N. S. Huda, and Adiwijaya, 2018.	[32]
A9	L. Sun, T. Yin, W. Ding, Y. Qian, and J. Xu. 2020.	[39]
A10	G. Tsoumakas and I. Katakis. 2007.	[37]
A11	R. A. Pane, M. S. Mubarok, N. S. Huda, 2018.	[15]
A12	Y. Zhang, D. Miao, Z. Zhang, J. Xu, and S. Luo. 2018.	[13]
A13	Zheng, X., Li, P., Chu, Z., & Hu, X. 2019.	[42]

A14	D. Urgun and C. Singh, 2019.	[4]
A15	Z. Cai and W. Zhu. 2018.	[35]
A16	Nareshpalsingh, J. M., & Modi, H. N. 2017.	[41]
A17	J. Huang, G. Li, Q. Huang and X. Wu, 2016.	[43]
A18	Wang, Z. W., Wang, S. K., Wan, B. T., & Song, W. W. 2020.	[28]
A19	Kongsorot, Y., Horata, P., Musikawan, P., & Sunat, K. 2017.	[20]
A20	A. Dagliati, S. Marini, L. Sacchi, G. Cogni, M. Teliti, V. Tibollo, P. De Cata, L. Chiovato, and R. Bellazzi. 2018.	[21]
A21	Thangaraj, M., & Sivakami, M. 2018.	[22]
A22	F. Thabtah and D. Peebles. 2020.	[23]
A23	Kadhim, A. I. 2019.	[40]
A24	Singla, K., & Biswas, S. 2021.	[25]
A25	Siblini, W., Kuntz, P., & Meyer, F. 2019.	[18]
A26	Zhang, Z., & Sun, C. 2020.	[30]
A27	R. Alazaidah, F. Thabtah, and Q. Al-Radaideh. 2015.	[44]
A28	Ceylan, Z. 2018.	[29]
A29	J. Levatić, D. Kocev, and S. Džeroski. 2015.	[27]
A31	Zhou, L., Zheng, X., Yang, D., Wang, Y., Bai, X., & Ye, X. 2021.	[6]
A32	Zhou, Y., Cui, S., & Wang, Y. 2021.	[17]

5. Result

5.1. Classification of Data sources and Techniques

Described below are the methods and features that were used in the writing of this review. The basis classifiers employed in this study's investigations were selected based on the literature. The objective is to compare several classifiers for multi-label classification from the current study and how they worked in numerous areas. This research seeks to address the following studies based on the following questions:

- Can machine learning algorithms reliably be used for multi-label classification?
- How do neural networks perform compared to other supervised learning algorithms?
- Which classifier has the best performance in multi-output labels?
- Do the algorithms perform better when using multiple text inputs?

These are some of the questions researched to find and provide relevant answers to this study. The presence of these research questions allows a study to be conducted more easily and clearly. Table 3. illustrates the specifics of the algorithm category based on the article review that was completed. There were 32 primary studies in this review relating to the accuracy and appropriate algorithms used for multi-label classification research.

Table 3. The type of algorithm category

Category Code	Algorithm Category
B1	Decision Tree
B2	Logistic Regression
B3	K-Nearest Neighbors
B4	Random Forest
B5	Naive Bayes
B6	Support Vector Machine

Table 4. illustrates the frequency of algorithms used in the study throughout this research. The features were divided based on the six categories discussed above. The evaluation of the experimental classification model resulted in the selection of the best relevant and accurate algorithms for multi-label classification using machine learning.

Table 4. The frequency of algorithms used in the study

Paper No	Category Code					
	B1	B2	B3	B4	B5	B6
A1	√		√		√	√
A2	√			√		√
A3	√				√	√
A4	√	√	√	√	√	√
A5				√		√
A6	√				√	
A7	√	√	√		√	√
A8		√	√		√	√
A9			√			
A10	√	√	√		√	√
A11	√	√	√	√	√	√
A12			√	√		√
A13		√			√	√
A14	√		√			√
A15				√		
A16	√		√		√	√
A17		√	√		√	√
A18			√			√
A19			√			√
A20	√	√		√	√	√
A21	√	√			√	
A22	√	√	√	√		
A23		√	√			
A24	√		√		√	√
A25			√	√		√
A26			√			√
A27	√					
A28	√			√	√	

A29	√			√		√
A30			√		√	√
A31	√	√	√	√	√	√
A32				√		√

5.2. The Type of Algorithm used for Multi-label Classification

Regression is used to find the association between the dependent and independent variables, whereas classification is used to properly forecast each instance in the data [13]. Nevertheless, a systematic review is carried out with an emphasis on the many obstacles confronted by authors when adopting different classification approaches in their study [14]. Classification and regression are contrasted in this article; clustering is an unsupervised classification algorithm that organizes input data based on their similarities. Meanwhile, text mining is one of the data mining domains available for labelling, processing and identifying multi-label data, which will be created with machine learning as it has most libraries for text processing to be predefined. The Decision Tree (DT), Logistic Regression (LR), K-Nearest Neighbor (KNN), Random Forest (RF), and Support Vector Machine (SVM) are among the examples of labels used as training targets.

Table 5. shows the total number of algorithms used in the review study. Based on the survey conducted by an effective randomized sampling algorithm collected from an article study, the best of the algorithm can be demonstrated through the final results of the data percentage accuracy of the multi-label classification frequently used by the researchers to classify the multi-label.

Table 5. Number of algorithms used in the review study

Type of Algorithm	Number of Study Used
DT	18
LR	12
KNN	21
RF	12
NB	17
SVM	24
Total Study Used	**104**

1) Decision Tree

The Decision Tree classification method is divided into two parts: 1) tree building and 2) tree pruning. The tree building stage follows the top-down way, whereas the tree pruning stage is done in a bottom-up manner. The algorithm selects the attributes that will be utilized to form the internal nodes throughout the learning process, while the leaves represent the class labels [15]. The internal nodes of the tree represent conditions, whereas the external nodes or leaves of the tree represent class labels. The interior branches of nodes indicate test or condition findings. The decision tree results in the leaf that contains opportunities of every class and attributes to be predicted. Decision Tree (DT) is a dominantly algorithm used for predictive modelling in educational data since the classifier outperformed other classification techniques by having higher classification accuracy and lesser misclassification rates. Based on the study conducted, 18 from 104 articles have utilized the Decision Tree algorithm.

2) Logistic Regression (LR)

A continuous number from a linear combination of attributes is predicted by linear regression, whereas the probability of two or more alternative outcomes is predicted by logistic regression, making it feasible to generate categorical predictions [16]. Logistic Regression normalization was applied to the data as a pre-processing step. This approach is used to explore a data set having one or more independent variables to obtain a result. Logistic Regression succeeded to record 12 papers that used this algorithm among 32 papers studied.

3) K-Nearest Neighbor (KNN)

Often, it is better to look at more than one neighbor. The method is called k-Nearest Neighbor (k-NN) classification, which uses k-Nearest Neighbors to figure out and classify the class. It is also called k-NN classification. This technique is a simple algorithm that is easy to understand and implement. The k-Nearest Neighbor is inherently non-linear, and it can detect linear and non-linear spread information. It tends to perform admirably when confronted with a large number of data points [17]. For classification, the k-Nearest Neighbor (kNN) technique employs particular training cases rather than building a model from training data since it is an instance-based learning (IBL) approach [14]. On really tough classification jobs, k-NN is probably superior to more exotic algorithms like Support Vector Machines or Neural Networks. Based on the 32 papers reviewed, the k-Nearest Neighbor technique was employed 21 times.

4) Random Forest (RF)

Classification of the input vector is accomplished using the Random Forest classifier, which consists of several classifier trees, each of which is constructed from a random vector taken from the input data, and each tree casts a unit vote for the most popular class. Increasing an ensemble of trees and letting them choose the most popular class more precisely has considerably increased classification accuracy [18]. This study identified 12 instances that the Random Forest algorithm was used in the test to their dataset for classification.

5) Naïve Bayes (NB)

The Naïve Bayes classifier makes learning simpler by assuming that characteristics are independent of class and assigning probabilistic classification interpretations to those features [14]. Even though independence is a weak assumption in general, Naïve Bayes is routinely pitted against more advanced classifiers in practice. In the presence of feature dependencies, the success of Naïve Bayes may be defined as follows. The quality of the fit to a probability distribution is not necessarily connected to the optimization in terms of zero-one loss (classification error). This research recognized 17 times the use of the Naïve Bayes algorithm.

6) Support Vector Machine (SVM)

The Support Vector Machine (SVM) is a supervised learning method for generating input-output mapping functions from a set of labelled training data. The SVM draws margins as the boundaries between the classes in the provided dataset. The Support Vector Classifier considers the implementation of the Support Vector Machine (SVM) for solving multi-class classification problems [19]. The mapping function can be either a classification function where the input data group is the classification function or a simple regression function. The Support Vector Machine has the most accurate classification performance on the training data, rendering more efficiency for correct classification of the time ahead of data [15]. Came in with the highest accuracy achieved in this study, there were 24 over 104 total number of studies used in 32 articles that used SVM to classify multi-label.

6. Discussion

Exploring the new multi-label classification approach based on the machine learning algorithm, the most common characteristics utilised in multi-label classification are recurrence usage percentages of performance. The efficacy and efficiency of a machine learning method are determined by the characteristics, qualities of the data and the learning algorithms' competence [31]. These findings revealed that while analysing label classification performance, the combination features category chosen has an impact on the accuracy attained. The Support Vector Machine (SVM) was the most often employed method in this research, followed by Decision Tree, Logistic Regression, K-Nearest Neighbours, Random Forest, and Naïve Bayes. According to this research, the Support Vector Machine had the greatest number of repetitions used to find the optimum accuracy for multi-label classification with 23 times. The SVM is a prominent machine learning method or classification that was first presented in the 1990s and is very effective at solving regression and classification issues. In multi-label learning classification, support vector machines (SVMs) are commonly utilized and strongly recommended [20]. Image recognition, speech recognition, text categorisation, face detection, and faulty card detection are among issues that the SVM is often employed to tackle.

In this study, a review on multi-label classification based on the machine learning algorithms articles has been done. An artificial intelligence clustering algorithm was used to extract multiple feature dimensions, such as vocabulary information intended to be used, related feature parameters and context from a wide number of different users. The researchers will be obtaining training data with a relatively limited amount. However, the amount of data in each class is not the same; thus, errors may occur when predicting class data with less training data. The training data is used to generate a classifier then used to determine the classifier's accuracy [41]. This helps to find the most relevant and potential label classifications more effectively, efficiently and accurately.

7. Conclusion

Multiple methodologies were used in this study to conduct a comprehensive literature review of multi-label classification using machine learning algorithms. When using a big dataset for problem generalisation, the SVM's performance was considerably better. For multi-label classification, the Support Vector Machine (SVM) has been seen as the best approach and technique. Multi-label classification issues may be solved using the SVM method. The fundamental benefit of SVM is that training data is straightforward. A classification methods performance is intimately tied to the inherent quality of the training data [34]. Furthermore, this study included a prior presentation on the approaches accessible in the literature as well as the outcomes of comparative research that was utilised to create the model. This review can be used in various fields with more massive experiments to seek new data sets and methods. In future, more machine learning algorithms can be investigated using the ensemble strategy to improve overall multi-label classification accuracy.

Acknowledgements

The Ministry of Higher Education Malaysia (MOHE) funded this research through the Fundamental Research Grant Scheme (FRGS), with the project reference code: FRGS/1/2020/ICT06/UNISZA/02/3. A special thanks to the Centre for Research Excellence and Incubation Management (CREIM) at Universiti Sultan Zainal Abidin (UniSZA) for their assistance in carrying out this research.

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