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A REVIEW QUESTIONS CLASSIFICATION BASED ON BLOOM TAXONOMY USING A DATA MINING APPROACH

Sucipto[1], Didik Dwi Prasetya[2], Triyanna Widiyaningtyas[3]

[1,2,3] Department of Electrical Engineering and Informatics,Universitas Negeri Malang, Malang, Indonesia
[1] Department Information System, Universitas Nusantara PGRI Kediri, Kediri, Indonesia

[1] http://orcid.org/0000-0003-3412-002X , [2] http://orcid.org/0000-0002-3540-2961 , [3] http://orcid.org/0000-0001-6104-6692

Email: sucipto.2305349@students.um.ac.id, didikdwi@um.ac.id, triyannaw.ft@um.ac.id

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ABSTRACT

Bloom's taxonomy is used to categorize learning objectives into various cognitive levels. This study discusses the role of ontology in the classification of Bloom's taxonomy-based questions using a computer science approach in text mining. This research aims to review and analyze using a systematic ontology approach in cognitive level question classification techniques using Bloom's taxonomy with a text-mining scientific approach. Based on the prism method, 22 papers were analyzed from 490 articles from databases such as Scopus, ACM, IEEE, Springer, and Elsevier, published in 2016-2023. Meanwhile, qualified experts have not validated the main factors influencing the application of taxonomy-based question classification. Based on the evaluation results of using traditional, deep learning, and hybrid models in single-class question classification, it provides higher accuracy than in multiple classes in the case of bloom taxonomy. In various classification models, there is no significant difference in accuracy in the algorithm; the difference in results occurs due to data imbalance problems in multiple classes in the case of bloom taxonomy. This case provides a considerable opportunity to explore the topic of Bloom's taxonomy in the knowledge discovery database in KDD databases

I. INTRODUCTION

Ontology is a branch of philosophy that studies the nature of reality or existing existence [1]. Ontology deals with what exists, its nature, and how it relates to each other. The role of ontology is very significant in scientific development [2]. Ontology studies the nature of setting the foundation for science, developing scientific theories, and solving problems scientifically [2]. In the scientific approach of computer science, ontology can help develop new information systems and technologies by knowing the fundamental nature of a system or technology [3]. The use of ontology is not only limited to philosophical scientific studies but also includes all studies of scientific aspects, including computer science [4].

Computer science is a science that studies everything related to computing, which includes hardware and software in which it is related to information governance and programming language algorithms [5]. Computer science can support other sciences, such as education [6]. The development of educational science, especially regarding teaching materials, requires a valid strategy for conducting an analysis. Analysis of teaching materials One of them is in the classification of questions made by the teacher. The determination of questions used to maintain student learning outcomes needs to be standardized following the method of determining the classification of questions. One commonly used model is using the bloom taxonomy (BT) approach [7].

Bloom's Taxonomy is a learning classification framework with various levels. Bloom's Taxonomy was first developed by Benjamin Bloom in 1956 and revised several times, the last version published in 2001 [8]. Blomm's taxonomy has three domains: cognitive, affective, and psychomotor [9-11]. Bloom's domain taxonomy is presented in Figure 1.

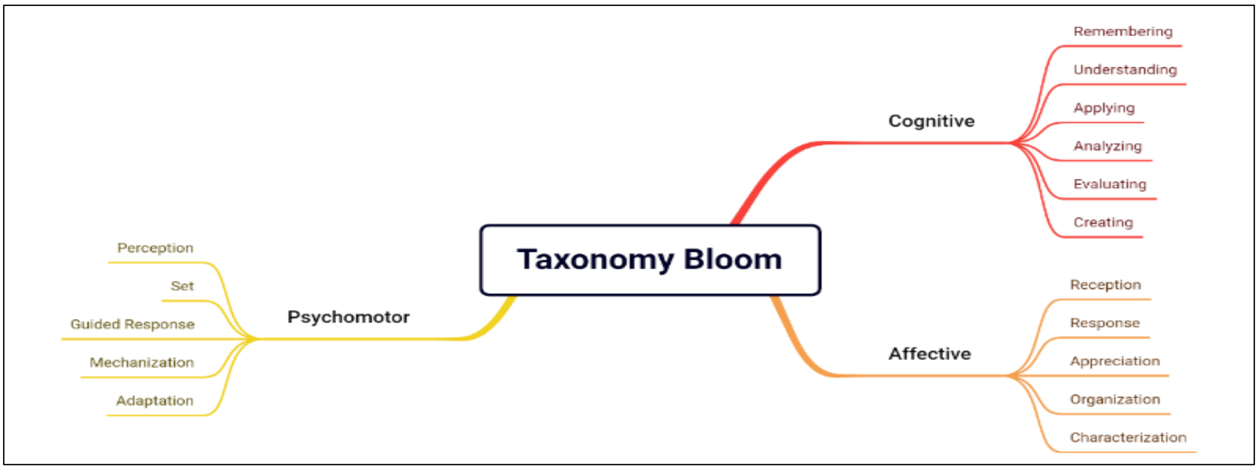

Figura 1: Taxonomy Bloom Domain.
Source: Authors, (2024).

Bloom's taxonomy can be classified using a computer science scientific approach. Processing techniques in computer science are called Data Mining or knowledge discovery in databases (KDD) [12]. Several branches of data mining science are presented in Figure 2.

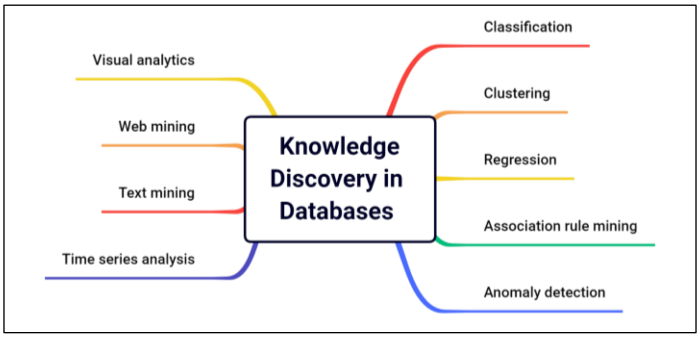

Figura 2: Knowledge Discovery in Databases.
Source: Authors, (2024).

Ontology can provide the development of new understanding by combining two different sciences. In this case, with the classification questions in Bloom's taxonomy, optimization can be done with computer science, especially using knowledge discovery in databases. KDD is a computing-based big data processing. KDD is commonly used in various domains, such as business, finance, health, and education [13]. The KDD approach can efficiently classify questions in the domain of bloom taxonomy [14]. Research on the bloom taxonomy that has been extracted chiefly focuses on the cognitive domain. This cognitive focus is related to the student's thinking level, where six cognitive domains are divided into high-order thinking skills (HOTS) and low-order thinking skills (LOTS).

Learning question classification using Bloom's Taxonomy with the KDD approach in ontologies can be harmonized with the same techniques by adopting a formally structured knowledge model. In this case, an ontology defines important concepts and relationships between the fundamental scientific relationships of Bloom's taxonomy classification and classification in KDD [15]. Integral components for KDD ontologies, particularly classification techniques, include Knowledge Concepts, Classification methods, Data, Evaluation and Validation, Application Context, Relationships, Dependencies, and Technology.

Using ontologies in collaborative learning between Bloom's taxonomy and text classification in KDD is essential in improving our understanding of classification methods, facilitating data integration and analysis, and strengthening the development of intelligent systems capable of automating question classification in various application contexts [16]. The critical role of Ontology is essential to know the basis of classification determination in Bloom's taxonomy and fundamental determination in text classification techniques in KDD. Basic science knowledge can create novelty in classifying text questions in Bloom's taxonomy and understanding the basis of science based on existing research in the field of Bloom's taxonomy in the KDD text classification. Much research still needs to be done to facilitate classification with bloom taxonomy. Ontology was conducted to determine and investigate KDD classification techniques from an alternative perspective with comprehensive methods used with existing literature review analysis. This systematic review and validation ensures an intense exploration of topics within a new framework.

The question classification project on Bloom's taxonomy still needs to be studied in the KDD approach. In the literature review study, KDD analyzes the scientific base of text, such as news texts and social media. In question classification with taxonomy, the bloom has things that need to be explored with the KDD approach. This research was conducted by applying an Ontology-based Systematic Literature Review (SLR) by conducting a comprehensive survey of Scopus, ACM, IEEE, Springer, and Elsevier sources. The aim is to provide an optimal KDD use process and the novelty of KDD techniques to handle question classification with bloom taxonomy more accurately, including identifying areas where further research is needed or has been extensively researched for practitioners and research projects.

II. LITERATURE REVIEW

II.1 TRADITIONAL METHOD

This section discusses some research results on applying KDD to traditional algorithm models. Research conducted by Mohasseb examines the question answering classifying questions with a focus on BoW grammatical structure on the TREC 2007 dataset with DT, NB, SVM, and J48 algorithms. Optimal results were obtained J48 algorithm with 91% accuracy [17]. Another study conducted by Wang discussed the topic of text categorization, classified focusing on term-weighting with optimization of the chi-square test and information gain (entropy-based) on KNN and SVM algorithms with private data. Optimal results were obtained using the KNN algorithm compared to SVM with a difference of less than 1% with an average accuracy of 98% [18]. Gani conducted another study on question classification in the Bloom taxonomy domain on private datasets on Term Weighting Unigram, TF-IDF with SVM, NB, and MLP algorithms. Optimal results on SVM and MLP algorithms [19]. Sangodiah conducted another study in the case of question classification in the domain of bloom taxonomy in the Reuters dataset. This research focuses on improving the TF-IDF1-3 Term Weighting using SVM and NB algorithms. Optimal results on SVM algorithm with 73.3% accuracy [20]. Another study was conducted by Mohammed in the same case as Sangodiah on private data. This research focuses on improving the extracted feature on TFPOS-IDF and word2vec using SVM, KNN, and LR algorithms—optimal results of the SVM algorithm with 89.7% accuracy [21].

II.2 DEEP LEARNING METHOD

This section discusses some research results on the application of KDD in Deep Learning Algorithm models. Khilji's research examines question answering and optimizing the rule-based BERT algorithm on private data. Optimal DL accuracy results of 90% [22] Another study by Liang discussed the question answering with optimization on TF-IDF feature extraction on LSTM-CNN algorithm on private data. The optimal DL accuracy result of 94.2% [23]. Another study by Hung discussed question-answering optimizing word embeddings with the Bi-LSTM algorithm on private data. Optimal DL accuracy result of 94.36% [24]. SHAIKH conducted another study on question classification in the domain of bloom taxonomy on a private dataset. The focus of this research is improving word embedding with the LSTM algorithm. Optimal DL accuracy results of 87% [25]. Gani conducted another study on question classification in the domain taxonomy bloom on a private dataset. Focus on the case of word embedding with the CNN algorithm—optimal DL accuracy results of 86% [26].

II.3 HYBRID METHOD

This section discusses some research results on the application of KDD in the Traditional Hybrid Algorithm model. Razzaghnoori's research examines question answering and optimizing the TF-IDF feature extraction on the RNN algorithm. On UTQD.2016 data. Optimum accuracy results of 85% [27]. Another study conducted by Wu discussed question-answering optimizing hybrid classification using the CNN-SVM algorithm with Word2Vec on private data. Optimum accuracy result of 83.7%[28]. Hasmawati conducted another study on question classification in the bloom taxonomy domain on a private dataset with IndoBERT-SVM-NB optimization. Optimum accuracy results of 82%[29]. Gani conducted another study on question classification in the bloom taxonomy domain on a private dataset with ETFPOS-IDF optimization on ANN. Optimum accuracy result of 83.3% [30].

II.4 RELATED SECONDARY RESEARCH

Research on SLR based on depth Ontology on classification using KDD on text data Most focused on general text [31-33]. Previous SLR research was conducted in the public domain with a target on single-class [34-36]. In the last literature review, it was known that the accuracy results in question classification in models using BT and non-BT had different accuracy. This is because the domain is a single class, and the BT classification uses multi-class cognitive domains. The results of using Traditional, Deep Learning, and Hybrid models are still in the results where there is no significant difference in outcomes [7]. The challenge of using BT in classification questions still has great opportunities for optimization with the application of pre-processing, feature extraction, and hybrid.

III. MATERIALS AND METHODS

This study used the PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) method, including preliminary steps, methods, and results. This comprehensive method ensures a systematic and thorough review process, thereby increasing the reliability of the results. The method plot is presented in Figure 3.

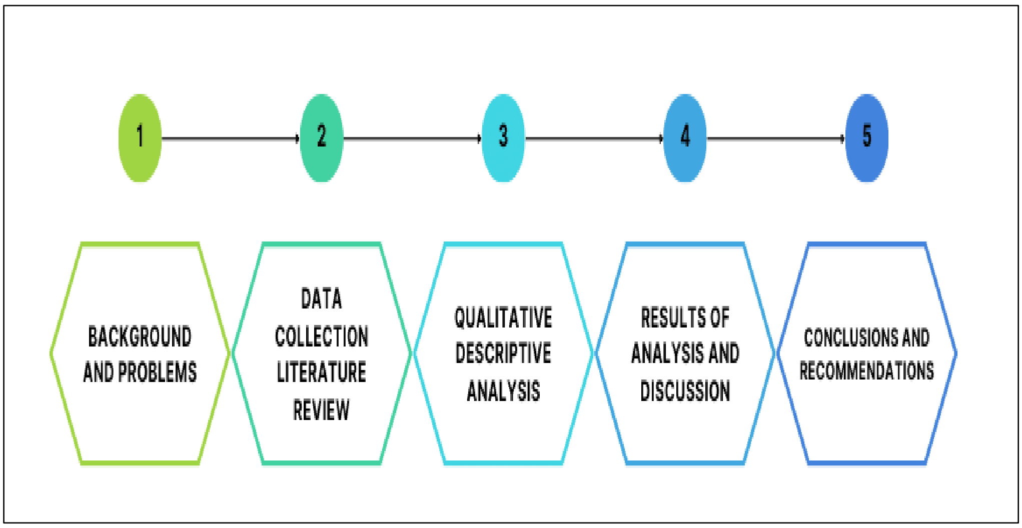

Figura 3: Research Methods.
Source: Authors, (2024).

This research searches metadata-based strings on digital databases such as Scopus, ACM, IEEE, Elsevier, and Springer, processed using Mendeley Desktop and Xmind applications. Scopus is a database index that is a leading index database and is famous for its comprehensive peer-reviewed literature database and is widely used in academic research. ACM, IEEE, Elsevier, and Springer are leading sources in the Scopus and WoS indexes for computer science and technology publications, offering an extensive collection of academic journals in various scientific fields, including Bloom's taxonomy and KDD. The articles collected in the database have undergone quality control and are validated by qualified experts.

This review aims to find answers to the literature review results based on data collected on current challenges in applying KDD learning in classifying questions within the scope of Bloom's taxonomy? Which type of traditional or deep learning algorithm is more effective in classifying question cases within Bloom's taxonomy? Which extract feature model is used for questions within the scope of bloom taxonomy?

IV. RESULTS AND DISCUSSIONS

The ontology of classification question learning in KDD refers to a formally defined knowledge model for understanding, describing, and compiling concepts, relationships, and entities involved in the question classification learning process on Bloom's taxonomy. The results of the literature search are presented in this chapter. The main components of the classification learning ontology are shown in Table 1.

Tabela 1:The Main Components of The Classification Learning Ontology.

Component	Description
Concepts and Terminology	The ontology contains definitions of essential concepts and terminology related to question classification in Bloom's taxonomy, such as sentiment analysis, question labeling, text summary, natural language inference, and so on [31], [36], [37]
Methods and Algorithms	Ontology of various descriptions Data mining algorithms are used to learn the rules of question classification using Bloom's taxonomy. Algortima is divided into two: traditional and deep learning [38], [39]
Data and Preprocessing	The ontology includes concepts related to data used in question classification using bloom taxonomy, such as feature extraction in traditional methods and LSTM in Deep Learning. Ontologies also describe how data is prepared before being applied in a text question classification model[26], [40], [41].
Data Source	Ontology describes various data sources used in the learning process of question classification using taxonomy blomm. Some sources, such as DUC sources, come from private and open data [42], [43], [44].
Evaluation and Validation	Ontologies include definitions of evaluation metrics used to measure the accuracy of text classification models, including K-Fold cross-validation, confusion matrix, BLEU, and ROUGE[19], [45], [46]

Source: Authors, (2024).

Based on the definitions from Table 1, forecasting learning ontologies help understand and present the structured information needed to develop, apply, and understand the calcification process of the question using Bloom's Taxonomy. Trends regarding BT in the last five years, as shown in Figure 4, are still relevant to examine. BT topic data is taken from Google Trends.

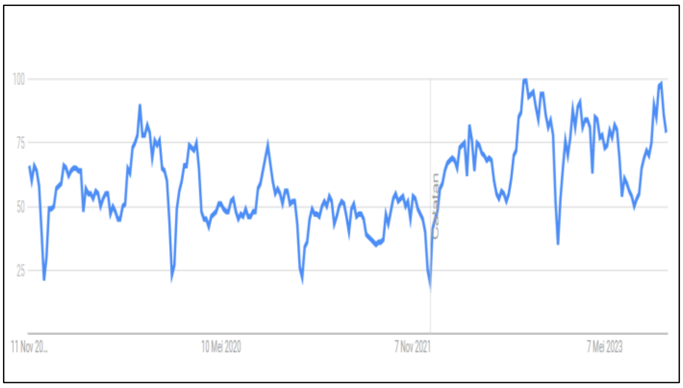

Figura 4: Interest over time "Taxonomy Bloom."
Source: Authors, (2024).

The distribution of data in Figure 5 on the trend topic of bloom taxonomy is spread across 145 areas. Some countries still focus on bloom taxonomy with a multi-scientific approach to export the science. As in the literature review, taxonomy is applied to questions in education and other fields such as news, novels, and general texts[25],[40].

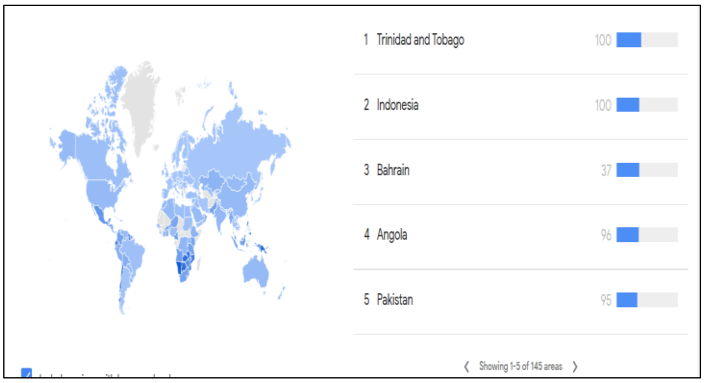

Figura 5: Interests by region "Taxonomy Bloom."
Source: Authors, (2024).

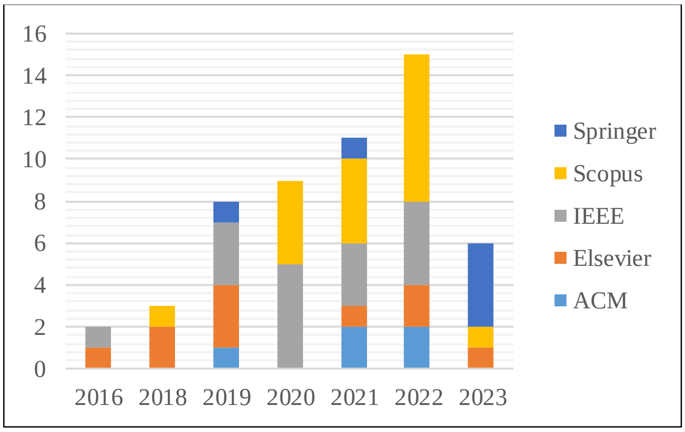

Figura 6: Selected paper database source.
Source: Authors, (2024).

Figure 6 shows that the number of papers on Bloom's classification data mining focus on taxonomy has been collected and become literature in recent years, as reflected by the number of published articles in publishers. This data is collected from various databases included in the Scopus index. Figure 7 is an extract from Figure 6 on KDD classification using the bloom taxonomy domain.

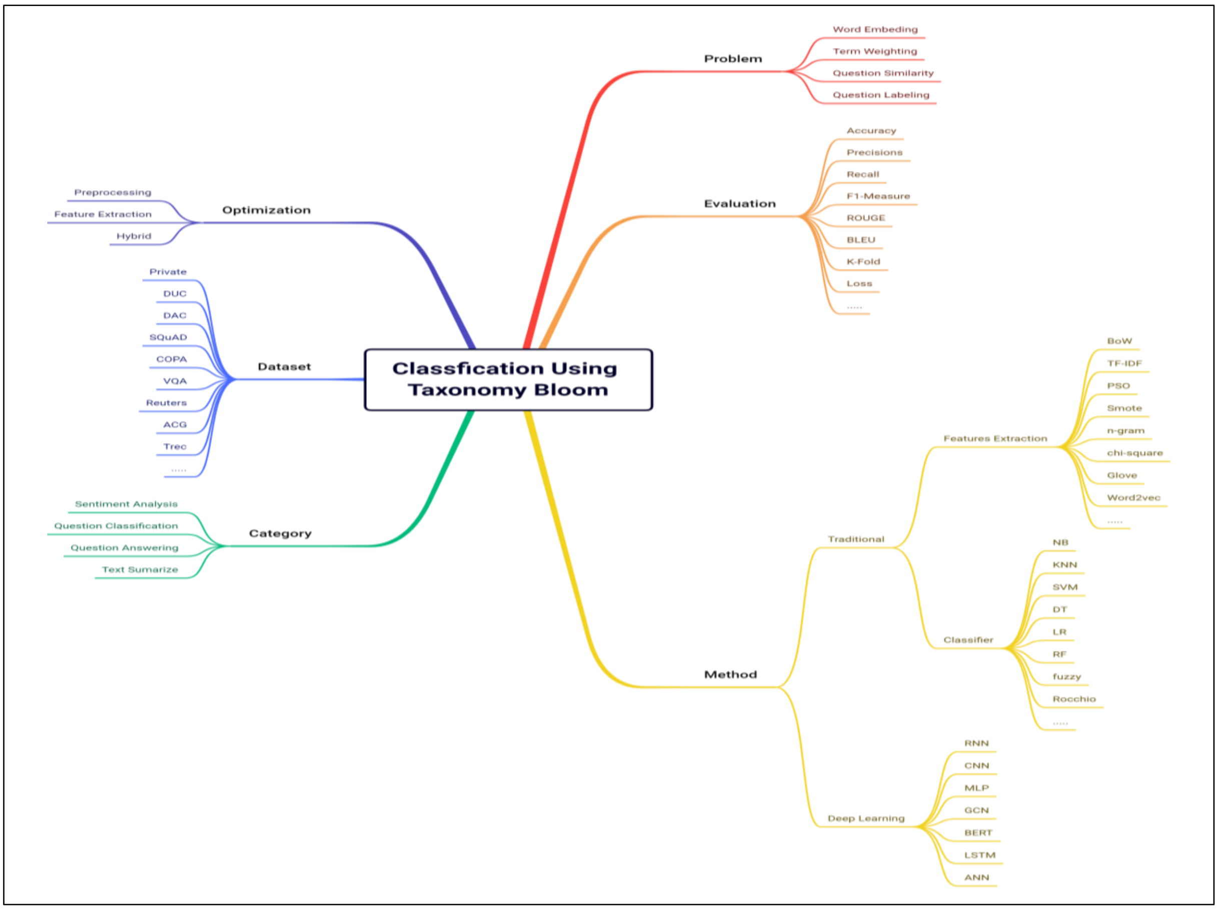

Figura 7: Components of Classification Question on Taxonomy Bloom.
Source: Authors, (2024).

III.1 CATEGORY

In the SLR data depicted in Figure 7, several categories apply question classification using Bloom Taxonomy. There are four discussions as follows:

Sentiment Analysis (SA) is a technique of analyzing points of view based on reviews, comments, or answers to a question textually. In general, SQ becomes divided into binary problems and plural class problems. Binary sentiment analysis classifies text into positive and negative classes, whereas plural class sentiment analysis classifies text into detailed labels or multi-level intensity. In the BT SA domain, it is a study in plural classes, one of which is about personality [47].

Question Answering (QA) is one method that can be used to access information widely to explore knowledge[48]. It can automatically return answers that have good accuracy based on the database collected and find out the essence of a short fact or long passage to a question asked by humans[47],[49]. There are two types of QA categories, namely extractive and generative. Extractive QA is TC's job: In the presence of questions and a series of candidate answers [42]. Generative QA is a text-generating task requiring quickly generating answers[48],[50],[51]. The data mining approach can classify each answer complexly based on candidates processed in a particular dataset as correct or no answers[42],[50],[51]. Bloom Taxonomy's approach in QA can provide knowledge by categorizing skills and understanding [15],[52].

Question Classification (QC) is a process that aims to categorize questions into specific classes or categories based on the nature or purpose of the question. One of the primary purposes of question classification is to find out the user's intention or the purpose of the question so that the system can provide appropriate responses or actions. QC, in this case, uses the BT domain. Some of BT's research in data mining approaches in cognitive medicine [40],[53],[54]. Assessment is essential to achieve course objectives and improve the teaching and learning process. In any exam conducted in any academic or training field, it is necessary to ensure the quality of the question papers used to test various cognitive skills. Bloom's taxonomy with a data mining approach is famous for evaluating student learning ability [55]. Bloom's taxonomy can also help classify educational objectives into levels of specificity and complexity [40].

Text Sumarize (TS) in data mining is the process of summarizing or rearranging information in text to produce a summary that shows the essence or essential points of the text [56]. This technique can cope with large volumes of text data and help users understand important information quickly [57]. TS can be used in question classification cases to make finding the essence of a question easier. Applying TS in question classification in the BT domain makes it easier to find keywords in the Bloom dictionary [41].

III.2 PROBLEM

Several problems are raised in the classification using Bloom Taxonomy in the data mining approach. The following issues are discussed in Figure 7:

Word embedding (WE) is a processing technique representing words in vector form in high-dimensional space. The primary function of word embedding is to reveal semantic and syntactic relationships between words by assigning numerical vectors to each word-disclosure of word relationships to find word similarity. Applying classification models to textual data can be converted into numerical measures to help embed comments. The selection of techniques in determining the proper embedding of the word plays a vital role in the classification [57]. Using WE in question classification improves the quality of questions according to the BT domain [26],[58],[59].

Term weighting (TW) is used in text processing and information retrieval. The term TW gives weight or importance to each word in the document or question. TW in question classification determines how relevant a word is in a question. TW is a technique close to traditional data mining methods [18]. TW is a fundamental problem in text classification of traditional data mining models and directly affects classification accuracy [30],[60],[61]. Researchers discuss the TW problem to improve existing methods into new techniques[30],[60],[62].

Question Labeling (QL) is a method used to mark questions based on a particular approach. QL on a data mining approach, assigning labels or categories to questions on data sets for data learning[8]. Labeling data on questions is used for classification or grouping questions based on data on specific topics; for example, in taxonomy [60, 63]—one of the ascetics QL is used as a method in BT. QL in BT uses a multi-class method [40],[64],[65].

Question Similarity (QS) is an idea that measures how similar questions consist of two or more questions that have a meaning or meaning of a particular purpose. The application of QS on the role of assessment in student learning in determining the leading indicators of student achievement in front of exam questions. QS challenges in categorizing exam questions automatically into learning levels using Bloom's taxonomy. Using a data mining approach, this derivative rule makes it easier to analyze exam questions [41]. The Question Similarity mechanism is proposed to prevent the Question Answer system from asking irrelevant or unanswerable questions. This mechanism effectively finds irrelevant and unanswerable questions by incorporating human ways of thinking [48]. Another application of QS is used in automated essay grading systems, which can be beneficial in evaluating student learning outcomes as it allows them to demonstrate their knowledge [66].

III.3 DATASET

In the application of question classification in data mining, several uses of datasets exist. Data sets are divided into two, namely private data and public data. The use of private datasets raises problems in data cleansing; this data cleansing problem can cause the accuracy of results in data mining to be reduced. Frequently used public datasets such as DUC [42],[56],[61], DAC [67], SQuAD [68],[48], COPA [15], VGA [52], Reuters [20], AQG [55], dan Trec [17],[69]. Some question classification studies use private datasets. Private data sets are used because they directly relate to the object under investigation [26],[40],[44],[50],[70]. Implementing question classification in datasets is associated with public data sets' quality and determining experts' labels. When the dataset pre-processing process is correct, it will get higher accuracy [21],[44],[63],[71].

III.4 METHOD

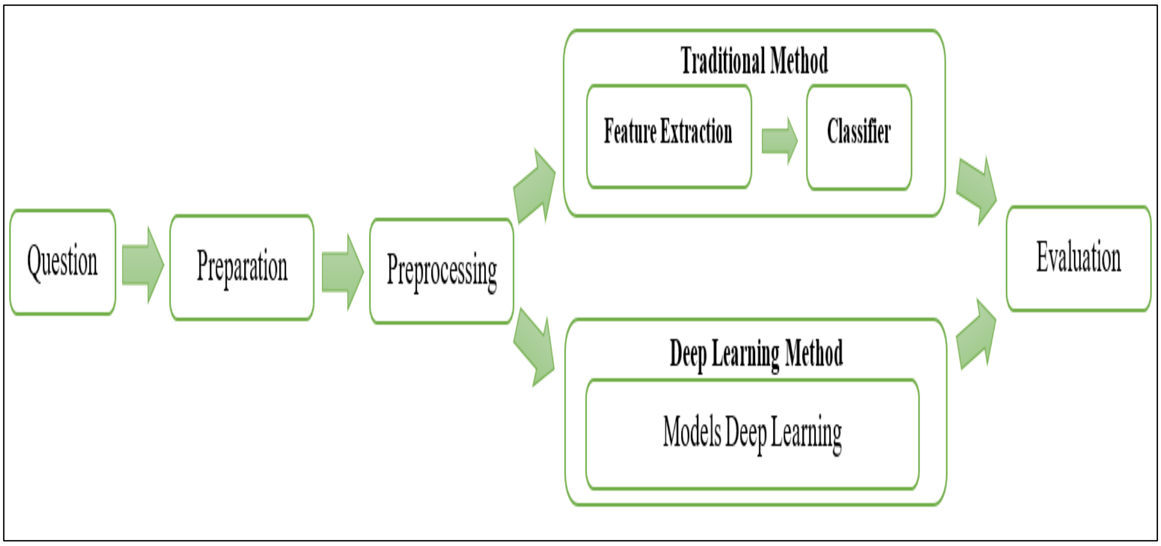

Figura 8: Classification Methods.
Source: Authors, (2024).

The types of methods for calcification are divided into two, as presented in Figure 8. In this case, the classification stage consists of the dataset process in the form of questions, the preprocessing stage, and the classification and evaluation method stage. The discussion of the two is as follows:

III.4.1 TRADITIONAL

Applying the method to the question classification technique is still widely used. The application of this method is still used as it relates to the case methodology. Several classification methods are used, such as NB, KNN, SVM, DT, LR, RF, Fuzzy, Rocchio, etc. The use of a famous traditional method is KNN-SVM. The results of determining the popular method are obtained from research that compares several methods. The best application of traditional methods in accuracy is by comparing several classification methods [18-20],[47],[72]. The KNN-SVM method provides better accuracy results compared to other methods. The application of improvements to traditional methods gets better results—improved classification method by improving pre-processing [17],[54],[60],[73].

III.4.2 Deep Learning

Applying Deep learning methods in question classification is quite a popular method. Deep learning methods were chosen because the process is shorter than traditional methods. The Deep Learning model includes an extraction feature in it. This method is widely preferred because it is more practical [26],[52],[57],[67],[71]. Deep Learning Method research can also be modified in the extraction feature for better accuracy, such as adding n-gram and Word2Vec features[23],[26]. In the deep learning method, the CNN method is a popular algorithm, with some studies having good accuracy [22],[52],[57],[65],[69],[71].

III.4.3 Optimization

Handling question classification in KDD has other options besides Traditional and Deep Learning. Another option is to do a Hybrid method on the Traditional Classification Method or a hybrid method on Deep Learning such as LTSM-CNN [23],[57],[71]. Hybrid methods can be applied to two or more classification or combination method models in both models. Hybrid models in both methods, such as SVM-CNN [28], and SVM-RNN [27]. The selection of this hybrid method aims to increase accuracy in classification.

III.5 EVALUATION

In KDD, classification evaluation is critical because it allows an understanding of the classification model's ability to predict and understand text correctly. This helps determine whether the selected model adequately understands the text. Evaluation will enable inter-models to compare the performance of various classification models to determine which model is best suited for a given text data. It also helps select and use the model that offers the best results. Evaluation helps fine-tune and optimize model parameters; This makes it possible to try different configurations and parameters to improve model performance. In evaluation can understand what types of errors are often caused by the model by doing an evaluation. For example, whether the model tends to misclassify specific text or has problems understanding particular contexts. Evaluation helps in assessing whether the model that has been built can make sound predictions on never-before-seen data, ensuring the model can generalize to new data. With a good evaluation, we can understand more deeply how text in a particular domain or field can be processed and classified. Text classification results are usually used for decision-making. Proper evaluation results ensure that the predictions used in the decision-making process are reliable. With continuous evaluation, the model can be continuously improved as new data is added and changed. Thus, the model's performance can be improved on an ongoing basis.

Classification models are widely used in classification questions using the Confusion Matrix [25],[53],[74], K-Fold Valdation [19],[46],[75], ROUGE [45],[67],[68], BLEU [44],[45],[68], and Loss [50],[65],[71],[73], [76]. Sometimes, the evaluation only focuses on accuracy and F1-Score [20],[30],[47], [59],[77],[78]. The selection of the evaluation model adjusts to the needs of the framework in question classification and is not limited by the use of traditional, Deep Learning, and Hybrid methods.

V. CONCLUSIONS

This paper comprehensively reviews Ontology's approach to understanding Question Classification in Bloom's taxonomy model. The data used in this case can be categorized into private and public data. Most studies use private data. Using private data provides new opportunities for optimization in the data preparation stage. In this case, various models, such as traditional models, deep learning models, and hybrid models, tend to optimize in pre-processing and parameter optimization in algorithms. In the evaluation model, the accuracy model becomes popular, although other models allow giving different results. Based on the evaluation results of using traditional, deep learning, and hybrid models in single class question classification provides higher accuracy than in multiple classes in the case of bloom taxonomy. In various classification models, there is no significant difference in accuracy in the algorithm; the difference in results occurs due to data imbalance problems in multiple classes in the case of bloom taxonomy. This case provides a considerable opportunity to explore the possibility of Bloom's taxonomy using KDD.

VI. AUTHOR’S CONTRIBUTION

Conceptualization: Sucipto, Didik Dwi Prasetya and Triyanna Widiyaningtyas.
Methodology: Sucipto and Didik Dwi Prasetya.
Investigation Sucipto and Didik Dwi Prasetya.
Discussion of results: Author One, Didik Dwi Prasetya and Triyanna Widiyaningtyas.
Writing – Original Draft: Sucipto.
Writing – Review and Editing: Sucipto and Didik Dwi Prasetya.
Resources: Sucipto.
Supervision: Didik Dwi Prasetya and Triyanna Widiyaningtyas.
Approval of the final text: Sucipto, Didik Dwi Prasetya and Triyanna Widiyaningtyas.

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