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A Systematic Literature Review of Text Classification: Datasets and Methods

Gusti Muhammad Riduan
Department of Electrical Engineering and Information Technology
Universitas Gadjah Mada
Yogyakarta, Indonesia
gusti.riduan@mail.ugm.ac.id

Indah Soesanti
Department of Electrical Engineering and Information Technology
Universitas Gadjah Mada
Yogyakarta, Indonesia
indahsoesanti@ugm.ac.id

Teguh Bharata Adji
Department of Electrical Engineering and Information Technology
Universitas Gadjah Mada
Yogyakarta, Indonesia
adji@ugm.ac.id

***Abstract*— We study the literature in major journals and conferences on the usage of shallow learning and deep learning methods for text classification. Shallow learning techniques such as Naive Bayes, Support Vector Machine, Random Forests were initially widely used to solve problems in text classification. however, these techniques generally require the presence of a precise feature extraction model, which is often very complex to produce precise accuracy. For this reason, researchers continue to try to find other learning techniques that are more efficient and provide a significant increase in accuracy. So currently deep learning methods such as Convolutional Neural Network (CNN) and Long Short-Term Memory (LSTM) are more widely used to solve text classification cases. From 2016 up to the present, this literature study aimed to recognize and assess research methods and datasets utilized in text classification studies. Seventy-three text classification research articles posted from January 2016 until July 2021 were retained and chosen to be explored further based on the established inclusion and exclusion criteria. This literature review was conducted in a methodical manner. A systematic literature review is defined as a method for recognizing, evaluating, and interpreting all available study materials for the purpose of answer certain research questions. The following diagram depicts the overall distribution of text classification methods. Furthermore, public datasets were used in 85 percent of the research projects, whereas private datasets were used in 15 percent of the research studies. Twenty different strategies have been used. Eight of the most commonly used approaches in text classification were identified from the twenty methods. Researchers recommended integrating various machine learning methods, employing an increased algorithm, appending feature selection, and applying parameter optimization for some classifiers to improve the accuracy of machine learning classifiers for text classification. The findings of this study also revealed that are frequently mentioned and thus significant in the field of text classification.**

Keywords—: system literature review, text mining, text classification, datasets, methods.

1. Introduction

Text mining is a new and fascinating area of computer science study that combines techniques from data mining, machine learning, natural language processing (NLP), information retrieval (IR), and knowledge management to try to tackle the dilemma of information overload. The method of obtaining implicit knowledge from textual material is known as text mining [1].

Text mining emerged from approaches such as text classification, text clustering, and automatic text summarization as a study subject spanning numerous technologies. Text categorization and clustering emerged as a pattern recognition application in the 1950s [2]. The term "text" refers to a collection of phrases or paragraphs written in natural language. Classification is described as the process of assigning a category or a set of categories to each data item from a list of predefined categories [3].

Text classification is a machine learning technique for categorizing open-ended text into a collection of predetermined categories. Text classification is closely related to text clustering [4]. Many text classification datasets and methods are released in different and complex ways, making it difficult to get a full view of the present status of text classification research. Since 2016 up to present, this literature study aimed to recognize and assess research methods and datasets utilized in text classification research. Text classification is a major study issue in natural language processing, it has a wide range of applications [5] and text classification is a crucial task [6].

The following is a breakdown of the paper's structure. The research technique is discussed in section 2. Section 3 presents the findings and answers to the research questions. Finally, in the last section of this paper, we summarize our study.

2. Methodology

2.1 Method of Review

It is decided to take a systematic method to review the literature on text classification mining. In text mining, systematic literature reviews (SLR) have become a well-established review process. An SLR is defined as a method for recognizing, evaluating, and interpreting all available study materials for the purpose of answer certain research questions [7]. Based on the basic guidelines established by Kitchenham and Charters, this literature review was conducted as a systematic literature review also influenced the review technique, style, and some of the figures in this part by Wahono [8].

SLR is carried out in three phases, as shown in Figure 1: planning, conducting, and reporting the literature review. The requirements for a systematic review are identified in the first phase (Step 1). The objectives for conducting the literature review were stated in the chapter's introduction. The existing systematic reviews on text classification are then identified and evaluated. The review process was created to guide the review's execution and decrease the risk of researcher bias (Step 2). The research questions, search strategy, article selection method with inclusion and exclusion criteria. Sections 2.2 until 2.5 the review protocol.

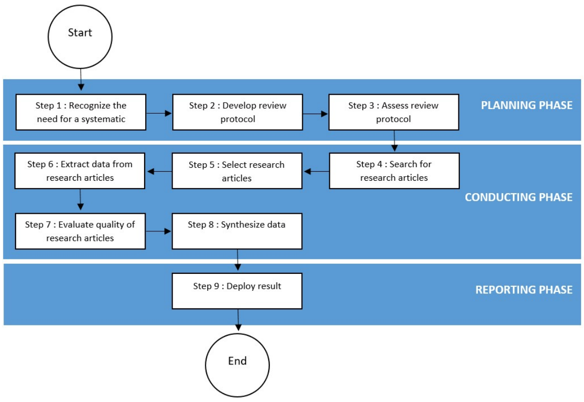

Figure 1 Systematic Literature Review Phase

2.2 Research Questions (RQ)

To keep the review focused, the research questions (RQ) were specified. The PICOC (Population, Intervention, Comparison, Outcomes, and Context) criteria were used to create them [9] . The (PICOC) structure of the research questions is shown in Table 1.

Table 1 Summary of PICOC

Population	Text mining
Intervention	Text classification, methods, dataset
Comparison	n/a
Outcomes	Prediction accuracy of text classification
Context	Datasets public and private

Table 2 lists the research questions and reasons addressed by this literature evaluation. This is very important for researchers to be able to find out which journals are eligible to publish research articles text classification.

Table 2 Research Questions on Literature Review

ID	Research Question	Reason
RQ1	What is the most important journal for text classification?	recognize the most important journals in text mining
RQ2	Who are the most active and influential researchers in text classification	recognize the most active and influential researchers who have made significant contributions to the field of text classification research.
RQ3	What kind the most often used datasets for text classification?	recognize the most widely used datasets for text categorization
RQ4	What kind of text classification methods are used?	recognize text classification opportunities and trends

The text classification methods and datasets were then assessed to see which were significant methods and datasets in text classification. The core research questions are RQ3 and RQ4, whereas the remaining questions (RQ1 to RQ2) assist us assess the background of the research articles. RQ1 to RQ2 provide a summary and outline of a specific topic of text classification research.

2.3 Searching Techniques

Selecting digital libraries, defining the search string, running a pilot search, refining the search string, and retrieving an initial list of main articles from digital libraries matching the search string are all part of the search process (Step 4). To maximize the chances of finding highly relevant articles, a suitable combination of databases must be picked before beginning the search. To have the most comprehensive group of studies feasible, a lot popular literature databases in the subject are searched. For a thorough and broad study of the literature, a broad perspective is required.

The following is a list of the digital databases that were searched:

- IEEE eXplore (https://ieeexplore.ieee.org)
- ScienceDirect (https://www.sciencedirect.com)
- Springer (https://www.springer.com)

The following steps were used to create the search string:

1. Identifying search phrases from PICOC, particularly from the Population and Intervention sections.
2. Finding search phrases based on research questions.
3. Searching terms in relevant titles, abstracts, and keywords are identified.
4. Using selected search phrases, Boolean AND, create a comprehensive search string.

In the end, the following search string was used: text mining AND text classification.

The search string was adjusted, After then, the search string was tweaked to fit each database's unique criteria. Title, keyword, and abstract were used to search the databases. The year of publication was used to narrow the search: 2016-2021. There were two types of publications included: journal papers and conference proceedings. Only items published in English were included in the search.

2.4 Research Articles Selection

The research papers were chosen using inclusion and exclusion criteria. Table 3 lists these requirements.

Table 3 Criteria for Inclusion and Exclusion

Inclusion Criteria	Research articles in university and industry using datasets public or private
	Research articles comparing and discussing model performance in text classification
	Research articles only the journal version
Exclusion Criteria	A research article lacking a strong validation or experiment result of text classification
	No datasets or methods are included in the research article.
	Research article not written in English

The search results were stored and managed using the Mendeley software. Figure 2 depicts the detailed search method and the number of articles found at each phase. The article selection procedure (Step 5) as indicated in Figure 2, with research articles being excluded based on the title and abstract and research articles being excluded based on the complete text. Excluded from the reseach are literature reviews and other research that do not incorporate experimental results. The inclusion of article adds to the article similarity to text classification.

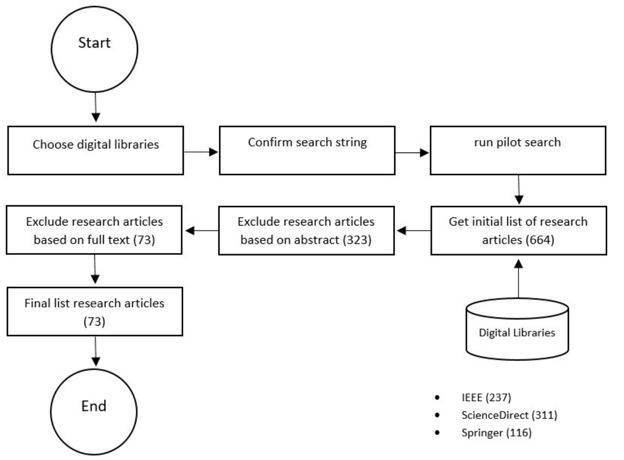

Figure 2 Search and Selection of Research Articles

There were 73 research articles in the final list of research articles for the first phase. The whole texts of 73 research articles were then scrutinized. The quality of the original articles, their relevancy to the research topics, and article likeness were all taken into account in addition to the inclusion and exclusion criteria. Similar papers published in different publications by the same authors were deleted. Following the elimination of articles based on full text selection, 73 research articles remained.

2.5 Extraction of Data

The data from the selected research articles are collected in order to answer the research issues addressed in this review. The data extraction form was completed for each of the 73 research articles that were chosen (Step 6). The data extraction form was created to gather information from the research articles that were required to answer the research questions. The properties were discovered as a result of the research questions and analysis we wanted to present. Table 4 shows the attributes that were used to answer the study questions. The data extraction is carried out in a step-by-step way.

Table 4 Data Extraction Properties Mapped to Research Questions

Property	Research Questions
Researchers and Publications	RQ1, RQ2
Text Classification Dataset	RQ3
Text Classification Methods	RQ4

3. RESEARCH RESULT

3.1 Notable Journal Publications

Seventy-three main articles analyzing the performance of text classification are included in this literature review. The distribution article is shown in text classification between 2016 and 2021. Figure 3 depicts a brief outline of the allocation studies conducted in recent years. Since 2016, additional papers have been published, indicating that more recent and relevant investigations have been incorporated. Figure 3 also demonstrates that the topic of text classification research is still relevant today. The most relevant text classification publications are shown in Figure 3 based on the selected research articles. Note that this graph does not include the conference proceedings.

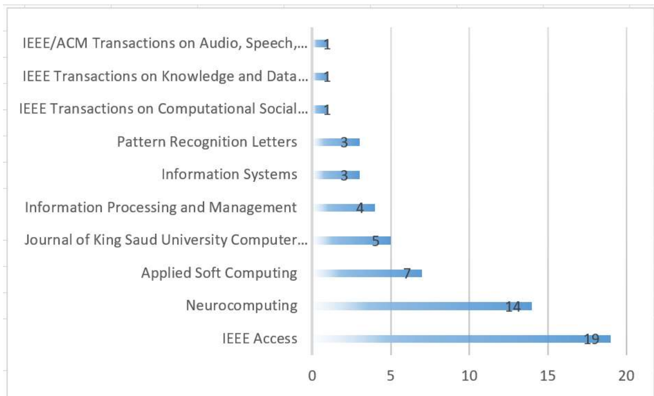

Figure 3 Journal Publications and Allocation of Articles

The most significant text classification journals citescore and impact factor are shown in Table 5. IEEE Access and Neurocomputing journals are the journals with the most researchers publishing their research articles text classification, that have a high Scimago Journal Rank indicator (SJR) and Quartile 1 (Q1). It is a value of journal's impact, impress and dignity. The following is a list of the top ten journals for the topic of Text Classification

Table 5 of Selected Journals

No	Journal Publications	CiteScore	Impact Factor
1	IEEE Access	4.8	3.367
2	Neurocomputing	9.8	5.719
3	Applied Soft Computing	11.2	6.725
4	Journal of King Saud University – Computer and Information Sciences	10.1	13.473
5	Information Processing and Management	8.6	6.222
6	Information Systems	7.3	2.309
7	Pattern Recognition Letters	6.7	3.756
8	IEEE Transactions on Computational Social Systems	6.1	5.365
9	IEEE Transactions on Knowledge and Data Engineering	13.3	6.977
10	IEEE/ACM Transactions on Audio, Speech, and Language Processing	9.1	3.919

3.2 Most Contributing Researcher

Researchers that contributed significantly are very active in the field of text classification research were studied and recognized from the selected primary articles. According to the number of studies included in the research articles, the researchers were mentioned. Leonardo Rocha, Thiago Salles, Felipe Viegas, Dia Abu Zeina, Fawaz S. Al-Anzi, Qingfeng Du, and Jincheng Xu are all active text classification researchers.

3.3 Text Classification Datasets

A dataset is a collection of data that is utilized in machine learning for a specific purpose [10]. A training set is a set of data that is fed into a learning system, which analyzes it and builds a model from it. A test set, also known as an evaluation set, is a data set that contains data that is used to evaluate a learning system's model. The training set and the test set that contain disjoint sets of data are known as the training set and the test set, respectively.

The use of non-public datasets is one of the most serious issues in text classification. Some researchers collect personal datasets using Twitter and newspapers for personal or industrial purposes [11][12]. Several companies used confidential data to construct text classification models, which they then presented at conferences. However, because their datasets cannot be assessed, it is not possible to compare the outcome of such investigations to the outcome of the proposed models. In the 1990s, machine learning researchers had similar challenges, so they created the University of California Irvine Machine Learning Repository (UCI). Kaggle has begun in 2010 with machine learning competitions and now expanded to include a public data platform, a cloud-based data science workbench, and Artificial Intelligence education which contains various public datasets.

The experiment employed ten popular benchmark datasets to test the proposed model in text classification :

- Reuters: There are ten categories in the Reuters-21578 corpora version.
- MR: Each review will be one phrase long. The process of classification entails identifying good and negative reviews.
- 20 Newsgroups : The 20Newsgroup corpus is a collection of almost 20,000 papers divided into 20 categories nearly evenly.
- IMDB: Documentary-style film reviews. The classification entails determining whether or not a review is positive or negative. Positive and unfavorable reviews from the Internet Movie Database have been labeled.
- TREC: This is a group of questions. The exercise entails categorizing a question into one of six types.
- AG's News: A dataset for categorizing news topics. The goal is to categorize each piece of news into one of four different topic kinds.
- UCI Repository : The UCI Machine Learning Repository is a collection of databases, domain theories, and data generators used by the machine learning community to test machine learning algorithms empirically.
- WebKb : The WebKb corpus used in these research is made up of 4199 documents divided into four categories. Web pages were originally collected by the World Wide Knowledge Base (Web- > Kb) project and are now part of the WebKb corpus.
- SST2 is a dataset from the Stanford Sentiment Treebank. The goal, like with the MR dataset, is to categorize each review as positive or negative.
- Yahoo: The Yahoo News Feed dataset is a collection of anonymized user interactions from numerous Yahoo properties' news feeds.

In addition to the datasets above, some researchers also use datasets in languages other than English, such as Single label Arabic News Articles Dataset (SANAD), Saudi Press Agency (SPA), Open Source Arabic Corpora (OSAC), Aljazeera News, News Articles Dataset in Arabic (NADiA) Chinese radiology medical text dataset (CIRTEXT), Alqabas, Turkish datasets, Sina Weibo, Sogou News, THCNews, Toutiao, and Occupational Injury (OI).

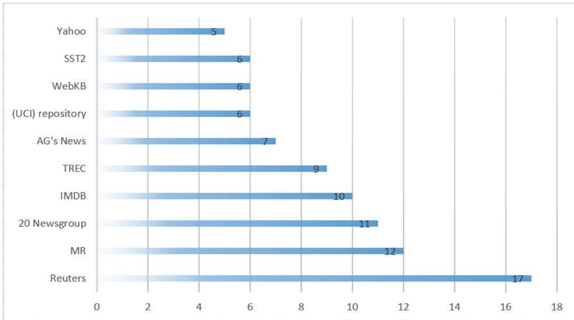

Figure 4. Top Allocation of Datasets

Seventy three main articles analyzing the performance of text classification are included in this literature review. From 2016 to 2021, Figure 5 depicts the result allocation of dataset kinds. Public datasets were used in 85 percent of the research papers, whereas private datasets were used in 15 percent. The majority of public datasets may be found in the UCI Machine Learning Repository and KAGGLE repositories and are openly available. Private datasets belong to private businesses and are not accessible to the general public.

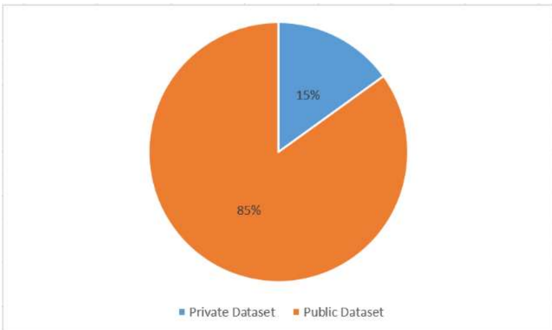

Figure 5 Result Allocation of Datasets

3.4 Text Classification Methods

Since 2016, twenty strategies have been applied and proposed as the best method for text classification problems, as shown in Figure 6.

Twenty different strategies have been used. Eight of the most commonly used approaches in text classification were identified from the twenty methods. Convolutional Neural Network (CNN), Naive Bayes (NB), Support Vector Machine (SVM), Long short-term memory (LSTM), KNearest Neighbor (k-NN), Recurrent Neural Network (RNN), Fuzzy and Bidirectional GRU (Bi-GRU), vector space model (VSM), Sandwich Neural Network (SNN), Random Forests (RF), Linear discriminant analysis (LDA), Deep Belief Network (DBN), LFNN: Lion Fuzzy Neural Network, Hierarchical Label Set Expansion (HLSE), Multi-Domain Adversarial Neural Network, Seed-guided Multi-label Topic Model, Deformable Self-Attention (DSA), Logistic Regression, Hierarchical Comprehensive Context Modeling Network (HCCMN).

3.5 Most Common Methods for Text Classification

Eight of the most commonly used classification methods in text classification have been found from the twenty methods listed in Figure 6 in Section 3.5. They are as follows:

1. Convolutional Neural Network (CNN)
2. Naive Bayes (NB)
3. Support Vector Machine (SVM)
4. Long Short-Term Memory (LSTM)
5. K-Nearest Neighbor (k-NN)
6. Recurrent Neural Network (RNN)
7. Fuzzy
8. Bidirectional GRU (Bi-GRU)

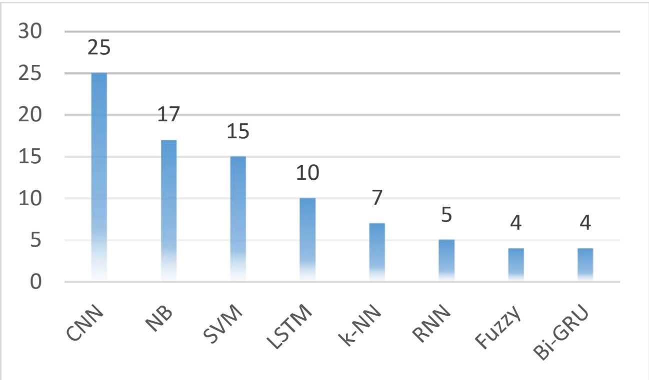

Figure 6 Most Common Methods

The method that we have written here is the main architecture as the parent of many of the latest models that are used and have been modified, for example, Capsule Network, Hybrid Fuzzy Classifier, Multinomial Naive Bayes, and others.

Based on the articles we have collected, we can get shallow learning methods that were widely used until 2018, then from the next method used until the present, deep learning such as Convolutional Neural Network (CNN), Recurrent Neural Network (RNN), and Long Short-Term Memory (LSTM).

Deep learning methods are usually machine learning models capable of providing very high performance in handling various datasets, especially very large datasets. So, deep learning can be said as moderation of machine learning to handle big data.

4. CONCLUSION

Shallow learning techniques such as Naive Bayes, Support Vector Machine, Random Forests were initially widely used to solve problems in Text Classification. however, these techniques generally require the presence of a precise feature extraction model, which is often very complex to produce precise accuracy. For this reason, researchers continue to try to find other learning techniques that are more efficient and provide a significant increase in accuracy. So currently deep learning methods such as Convolutional Neural Network (CNN) and Long Short-Term Memory (LSTM) are more widely used to solve Text Classification cases.

From 2016 and 2021, this literature study aimed to identify, assess methods and datasets utilized in text classification research. Finally, 73 text classification articles published between January 2016 and July 2021 were retained and evaluated based on the established inclusion and exclusion criteria. This literature review was conducted in a methodical manner.

Current text classification research focuses on two subjects, according to a review of the selected research articles : datasets and methods analysis. The following diagram depicts the overall distribution of text classification methods. Furthermore, public datasets were used in 85 percent of the research projects, whereas private datasets were used in 15 percent of the research studies.

Researchers recommended integrating various machine learning methods, employing an increased algorithm, appending feature selection, and applying parameter optimization for some classifiers to improve the accuracy of machine learning classifiers for text classification.

Distribution is shown to demonstrate how interest in different dataset types. Unfortunately, private datasets were used in 15 percent of the articles. Because their datasets are not publicly available, it is impossible to compare the results of such articles with the results of the proposed models. Figure 5 depicts the distribution of primary research across the years and by source. Since 2016, more studies have been posted, and more publicly available datasets have been used in text classification research. as previously stated. Furthermore, researchers are becoming more aware of the benefits of using public databases.

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