



Advancing Text Classification: A Systematic Review of Few-Shot Learning Approaches

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Abstract: Few-shot learning, a specialized branch of machine learning, tackles the challenge of constructing accurate models with minimal labeled data. This is particularly pertinent in text classification, where annotated samples are often scarce, especially in niche domains or certain languages. Our survey offers an updated synthesis of the latest developments in few-shot learning for text classification, delving into core techniques such as metric-based, model-based, and optimization-based approaches, and their suitability for textual data. We pay special attention to transfer learning and pre-trained language models, which have demonstrated exceptional capabilities in comprehending and categorizing text with few examples. Additionally, our review extends to the exploration of few-shot learning in Arabic text classification, including both datasets and existing research efforts. We evaluated 32 studies that met our inclusion criteria, summarizing benchmarks and datasets, discussing few-shot learning's real-world impacts, and suggesting future research avenues. Our survey aims to provide a thorough groundwork for those at the nexus of few-shot learning and text classification, with an added focus on Arabic text, emphasizing the creation of versatile models that can effectively learn from limited data and sustain high performance, while also identifying key challenges in applying Few-Shot Learning (FSL), including data sparsity, domain specificity, and language constraints, necessitating innovative solutions for robust model adaptation and generalization across diverse textual domains.

Keywords: Few-shot learning, Text classification, Transfer learning, Machine Learning, Pre-trained Language Models

1. INTRODUCTION

Text classification is a crucial task in natural language processing (NLP), which assigns predefined labels to textual content, facilitating the organization and retrieval of information. The process is integral to a variety of linguistic analyses, including syntactic categorization and semantic analysis, where the methods range from simple Bayesian classifiers to complex deep learning models [1] [2]. The evolution of these classification methodologies, from Bayesian approaches to sophisticated neural networks, mirrors the rapid advancement in the field of NLP, which addresses increasingly complex and nuanced language data [3]. This progress exemplifies how text classification has adapted to the ever-growing demands of processing and understanding large volumes of text in diverse applications. The utility of these techniques extends beyond mere data categorization; they are essential in extracting meaningful patterns from unstructured text, a common form of data in the digital age [4]. Recent advances have seen the integration of context-aware algorithms, which significantly improve the accuracy and granularity of classification tasks [5].

As the volume of digital documents grows across various domains, text classification becomes increasingly crucial, leveraging NLP to efficiently manage, sift, and extract value from an expanding repository of textual content over time. These methodologies underpin a multitude of applications that are central to the current information-driven society. For instance, this technology automates document sorting in digital libraries [6], improves targeted advertising by classifying user interests [7], and improves customer service with automated response systems [8]. Furthermore, it ensures the delivery of relevant content on social networks and sentiment analyses [9] [10] [11] [12], helps in the processing of clinical documents in healthcare [13] [14] [15], filters spam emails for cybersecurity [16] [17] [18] [19], and analyzes customer feedback in business intelligence [20] [21] [22]. These varied applications highlight the indispensable role of text classification across multiple domains, demonstrating its impact from digital media to healthcare and business.

A. Problem Statement

Traditional text classification systems have been dependent on large volumes of annotated data to achieve high

accuracy [23]. There is a scarcity of annotated data which poses several challenges such as reduced model accuracy, increased risk of overfitting, limited generalization, and bias due to unrepresentative samples. It also hampers handling rare events, incurs high annotation costs, and slows adaptation to new terms and usage patterns [24]. These issues hinder effective model training and performance in various text classification tasks.

To mitigate these challenges, few-shot learning presents a promising avenue for training models effectively with a limited amount of labeled data [25] [26]. This is particularly advantageous for applications dealing with rare events or emerging topics where sufficient training data may not be available [27]. Moreover, few-shot learning models have the flexibility to adapt quickly to new tasks, which is essential in the rapidly changing landscape of digital communication [28].

B. Aims and Objectives

The primary objective of this study is to conduct a systematic and comprehensive literature review of the few-shot learning approach in text classification. This involves rigorously defining the scope and objectives, with a focus on examining the application and effectiveness of few-shot learning techniques specifically in the context of text classification tasks. Moreover, this entails a detailed examination of various methodologies and comparative analyses of few-shot learning against traditional models. Additionally, the review seeks to identify pivotal research questions that explore the efficacy, adaptability, and future prospects of few-shot learning approaches in text classification. The purpose is to provide a comprehensive understanding of the current landscape and potential growth areas in this field, providing a clear and structured narrative for both academic and practical applications.

2. LITERATURE REVIEWS AND BACKGROUND

This section explores various studies on few-shot learning and text classification. It begins with an analysis of related works and surveys. Then, it reviews approaches to few-shot learning, primarily in English, with some attention to multilingual models. The section also covers contributions to text classification, including research on Arabic text, offering a comprehensive research overview. Figure 1 shows application of Few-Shot learning in various domains.

A. Surveys

In the field of text classification, encompassing both few-shot learning and general methodologies, a wealth of literature reviews have provided in-depth insight. For instance, the systematic review by Ge et al. [29] specifically focuses on few-shot learning in the context of medical text, providing an in-depth exploration of this niche area. Similarly, Le Glaz et al. [30] present a systematic review on the use of machine learning and natural language processing in mental health, highlighting the advancements and challenges in this research area. Yang's et al. [31]

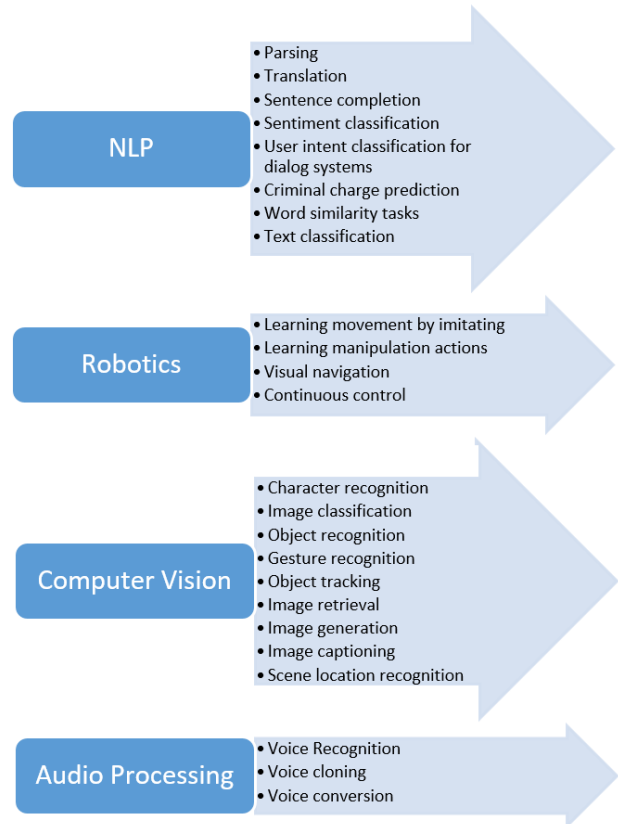


Figure 1. Multiple use cases of Few-Shot learning across diverse domains

provides a comprehensive overview of the advancements in few-shot learning within the realm of natural language processing. Ignaczak et al.'s paper (2021) provides a systematic literature review on text mining in cybersecurity, offering a comprehensive overview of the state of the field. Complementing this, Minaee et al. [32] present a broad overview of deep learning-based text classification methods, covering a wide range of deep learning architectures and their applications in text classification. Similarly, Li et al. in 2020 [33] and two years later (2022) [34] provide extensive surveys that trace the evolution of text classification methods from shallow learning techniques to the latest deep learning approaches. Additionally, Wu et al. [35] review various deep learning methods specifically in the context of text classification, evaluating their effectiveness and comparing different approaches. Brauwert et al. [36] as well as Mabrouk et al. [37] propose a surveys on aspect-based sentiment classification. These collective works offer a comprehensive view of the current trends, methodologies, and challenges in the field of text classification.

B. Few-Shot Learning in NLP 2.3. English Language

Globally, the predominant language, both in speaker numbers and as the main conduit for scholarly inquiry, is English. Such prevalence has cultivated a rich tapestry

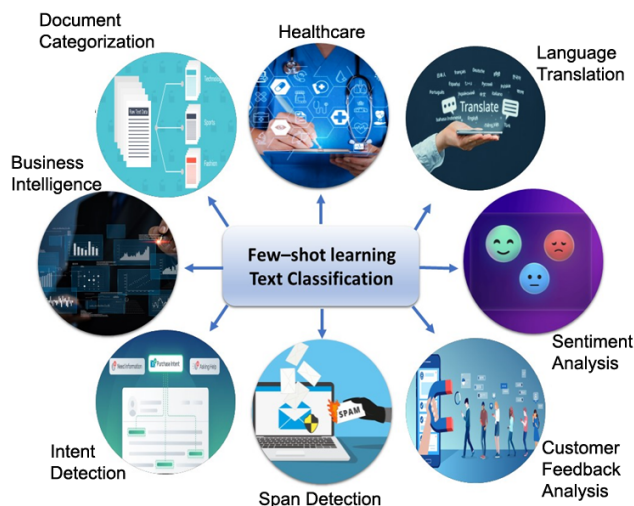


Figure 2. Explored use cases of Few-Shot Learning in the context of text classification domain

of literature, aspects of which we will delve into and illuminate in the following sections of our document. Ye et al. (2021) [38] introduce a challenge for assessing cross-task generalization capabilities in NLP. Bragg et al. (2021) [39] contribute to unifying the evaluation framework for few-shot NLP. Hou et al. (2020) [40] present "FewJoint," a benchmark for few-shot learning in joint language understanding. Lastly, Perez et al. (2021) [41] delve into the true potential of few-shot learning with language models in their study. Liu et al. (2023) [9] and Alqahtani et al. (2022) [10] have demonstrated the effectiveness of few-shot learning models in sentiment classification. Figure 2 shows explored use cases of Few-Shot Learning in the context of text classification domain.

C. Multi-Language

Researchers in few-shot learning with multilingual language models focus on creating systems that can process and comprehend several languages simultaneously [42] [43]. In the context of few-shot learning for Arabic language tasks, research is sparse; however, one notable contribution is the introduction of JASMINE [44], a suite of Arabic autoregressive Transformer language models, which demonstrates significant advancements in few-shot learning across a broad spectrum of NLP tasks.

D. Text Classifications

In the expansive landscape of literature, numerous works have delved into text classification. Sentiment analysis is a notable example, with a wealth of studies dedicated to exploring its intricacies [45] [46] [47]. In the realm of healthcare, several studies have made significant contributions to the analysis of clinical notes using machine learning and deep learning techniques [48] [49] [50] [51]. In the field of cybersecurity, the importance of email filtering in protecting against spam and phishing threats cannot be

overstated, leading numerous studies to explore the efficacy of deep learning approaches [16] [17] [18] [19] [52] [53]. In the sphere of business intelligence, scrutinizing customer feedback is paramount for grasping market dynamics and guiding strategic decisions, prompting a multitude of studies to delve into this area [20] [21] [22] [54] [55].

E. Arabic Text Classifications

Text classification in Arabic has seen significant advancements with the application of machine learning and deep learning models. Recent studies have explored various aspects, from systematic reviews of methodologies and challenges specific to the Arabic language [56] to the implementation of deep learning models [57]. The complexity of Arabic text, with its rich morphology and syntax, poses unique challenges, addressed through semantic ontology-based approaches [58] and the adaptation of BERT models [59]. Moreover, the effectiveness of different machine learning algorithms in handling Arabic text classification tasks has been systematically reviewed, highlighting the need for more tailored approaches to better cater to the linguistic characteristics of Arabic [60].

Prior work provides valuable insights into few-shot learning and text classification, often focusing on specific domains or languages. However, these studies lack a unified framework or comprehensive coverage across diverse contexts. Our approach builds on these strengths by employing a systematic, PRISMA-guided literature review, ensuring thoroughness and reproducibility. By incorporating multilingual and diverse domain perspectives, our study provides a broader understanding, identifying key trends and gaps for future research.

3. CONCEPTS AND PRELIMINAIRES

This section serves as a glossary, equipping readers with the terminologies that are crucial for comprehending the nuanced aspects of few-shot learning methodologies.

A. Few-Shot Learning in Text Classification

Few-shot learning, especially in NLP, addresses learning from limited data. Wang et al. (2020) [25] provided a foundational survey of this concept in text classification, where labeled data scarcity is common. Definition: Few-shot learning involves a program learning from a small set of experiences (E), tasks (T), and a performance metric (P), with its performance improving progressively on tasks T after exposure to experiences E. E is notably minimal in size [25].

B. Types of Few-Shot Learning Approaches

1) Prototypical Networks:

These networks simplify few-shot classification by creating a metric space based on distances to prototype representations of each class [27].

2) *Matching Networks:*

Designed to mimic human-like knowledge generalization, they adapt quickly to new tasks with minimal examples, utilizing memory-augmented neural networks [61] [28].

3) *Relation Networks:*

Operate on learning to compare small sets of images, discerning and generalizing from sparse data [62].

4) *Meta Learning:*

Known as "learning to learn," models are trained to acquire foundational knowledge from various tasks and adapt rapidly with a limited set of labeled examples [63]. Model-Agnostic Meta-Learning (MAML) framework [64].

5) *Metric-Based Learning:*

Learns a function to measure similarity or distance between data points, useful in semisupervised and unsupervised cross-domain FSL contexts. Notably, Vinyals et al. [28] introduce adaptive weighting for support set examples during one-shot query set classification, showcasing the effectiveness of metric-based techniques in Few-Shot Learning.

6) *Transfer Learning:*

Involves leveraging prior knowledge from related tasks to enhance performance in new, data-scarce tasks, effective when features are applicable to both tasks [65]. This approach is effective when features are applicable to both tasks, as noted by Yosinski et al. [66].

4. METHODOLOGY

In the next section, we will outline our methodology, focusing on the structured approach adopted for this research. We begin with an overview of our search strategy, highlighting the comprehensive and systematic methods used to identify relevant literature. This is followed by a discussion of the inclusion and exclusion criteria, explaining the principles guiding our selection of studies for detailed analysis. Lastly, we describe the study selection process, emphasizing the systematic steps and measures undertaken to ensure the reliability and validity of our approach. Figure 3 presents the framework of our study, showcasing the key concepts and their interconnections that are crucial for grasping our approach

1) *Methodological Framework*

In our experimental design, we have adopted a structured literature review approach utilizing the PRISMA guidelines to ensure a comprehensive and reproducible methodology [67]. Our PRISMA-based review commenced with an initial broad search, followed by screenings at various levels—title, abstract, and full text—to ascertain each study's relevance to our research question as shown in Figure 4. This meticulous process allowed us to filter the literature systematically, ensuring that the selected studies meet our inclusion criteria while maintaining a high standard of

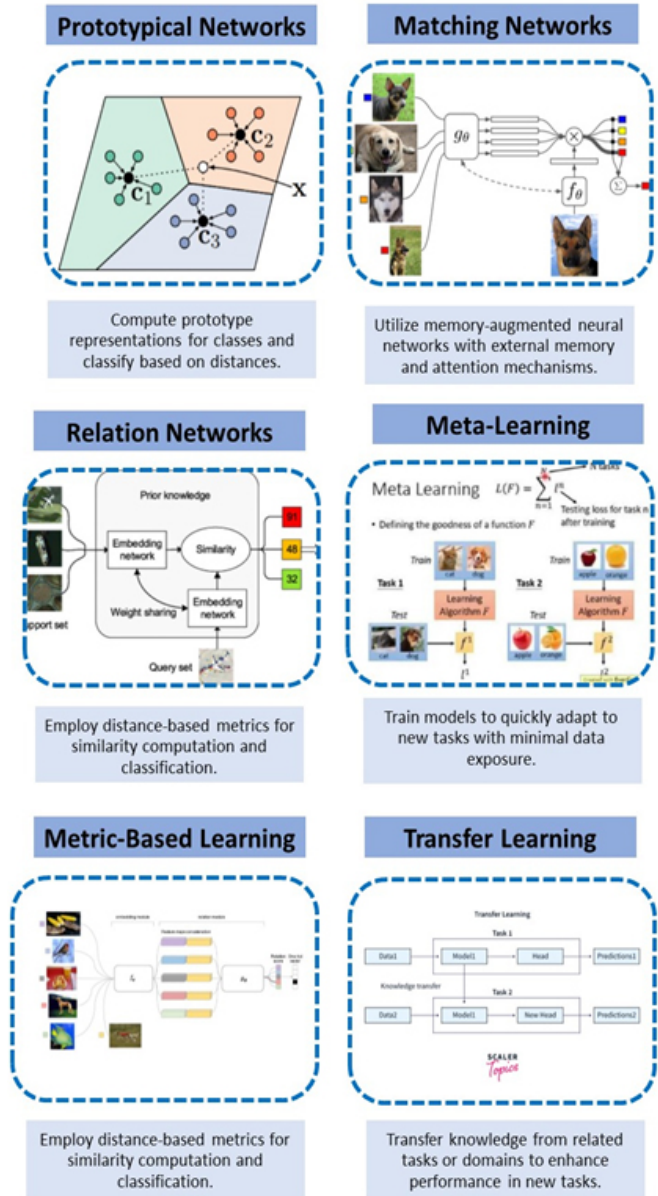


Figure 3. Types of few-shot learning approaches.

research integrity. The use of the PRISMA flow diagram will provide a visual representation of the search and selection process, detailing the number of records identified, included, and excluded, along with the reasons for exclusions. This robust experimental design will contribute significantly to the reliability and validity of our study findings. By focusing on recent literature, we aim to capture the latest advancements and trends and identify gaps for future research. This framework ensures a systematic, transparent, and reproducible review process, enhancing research integrity by meticulously filtering studies and visually documenting the search and selection process for reliability and validity.

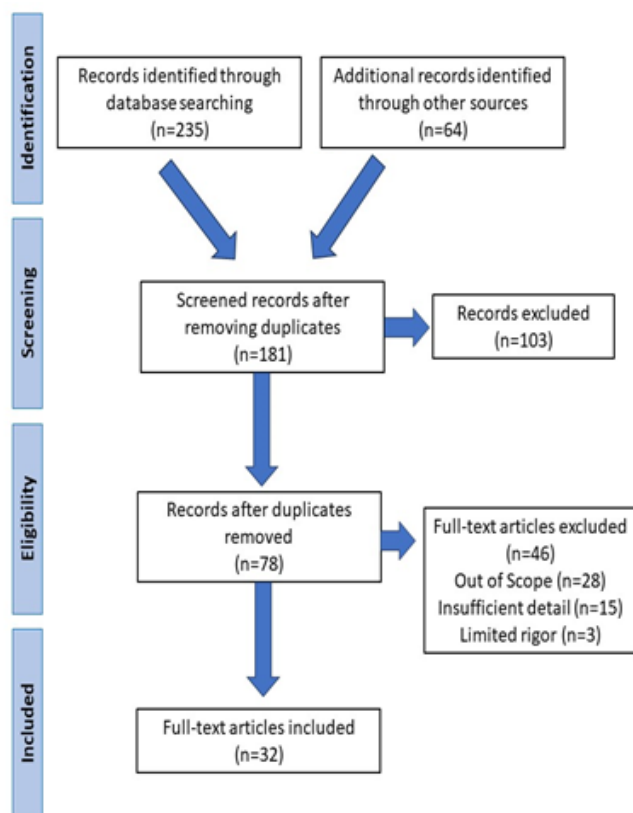


Figure 4. PRISMA Flow Diagram of the literature review process.

2) Databases Used for Literature Search

Our research leveraged a diverse array of academic databases to conduct a thorough and comprehensive search for relevant papers. We selected platforms renowned for their vast collections of scholarly articles, spanning diverse disciplines with a focus on AI and ML. These platforms are esteemed for rigorously curating and indexing peer-reviewed journals, conferences, and academic publications. By utilizing these databases, we ensured access to high-quality research for our literature review. Several electronic databases and search engines, including Google Scholar, IEEE Xplore, arXiv, ACM Digital Library, SpringerLink, ScienceDirect, PubMed, and Web of Science, were systematically queried for scholarly literature across various domains.

3) Search Strategy

This subsection details the systematic approach employed to identify relevant literature pertaining to Few-Shot Learning (FSL) in the realm of text classification. Our search protocol aimed to identify relevant and recent research, focusing on studies from the past six years to align with the latest developments. We targeted esteemed publishers' databases, prioritizing materials from respected conferences, journals, and workshops known for their contributions to AI and machine learning. To refine our literature search strategy and ensure the identification of

TABLE I. Overview of Query Categories and Corresponding Keywords

Category	Queries
Technical Field	Natural language processing, text mining, text classification, named entity recognition, concept extraction
Learning Strategy	Zero-shot, one-shot, fewshot
Type of Learning	Meta-Learning, Transfer Learning, Metric-Based Learning, Matching networks, Prototypical network
Applications	Opinion mining, Emotion Classification, Sentiment detection, Mood analysis
Health	Medical care, Health services, Patient care, Health systems
Business Intelligence	Decision support systems, Enterprise reporting, Business performance management, Data-driven decision-making
Spam Detection	Email spam filtering, Message classification, Unsolicited message blocking, Spam mail identification
Intent Detection	User intent identification, Query intention understanding, Purpose extraction, Intent-based response generation
Customer Feedback	Review analysis, Customer satisfaction measurement, Feedback sentiment assessment, Service improvement insights
Language Translation	Cross-lingual translation, Machine translation accuracy, Bilingual text alignment, Translation model optimization

pertinent studies, we meticulously developed a keyword matrix based on a structured framework outlined in Table I. This framework delineates key dimensions within the realm of natural language processing research, encompassing a range of application domains. For each of these domains, we compiled a targeted list of specific keywords, which were then thoughtfully combined with terms from the 'Technical Field', 'Learning Strategy', and 'Type of Learning' categories to enhance the specificity of our queries. For example, a search for papers in the health sector might leverage combinations such as "Patient care" with "text mining" and "Transfer Learning". This methodical approach to our search process allowed us to conduct a thorough and focused exploration of the relevant literature.

4) Inclusion and Exclusion Criteria

Our research methodology was based on a precise set of inclusion criteria to ensure the selection of highly relevant

studies. We reviewed peer-reviewed papers published in the last seven years, focusing on machine learning applications in areas like sentiment analysis, healthcare, business intelligence, and spam detection. We prioritized papers with empirical results for validation and included theoretical ones if they made significant contributions to the field. These criteria ensured the relevance and scholarly quality of our review.

On the contrary, our exclusion criteria were meticulously crafted to sift through studies that did not align with our stringent standards for relevance and scientific robustness. Specifically, articles lacking peer review, such as pre-prints or editorial pieces, were disregarded. Furthermore, studies falling outside the purview of our defined technical domains or those published more than six years ago were omitted. Additionally, papers devoid of at least one citation were not excluded from consideration. Moreover, we excluded papers solely focused on text classification but not few-shot learning, as well as those addressing few-shot learning but not in the context of text classification. Lastly, articles unavailable in full-text format or inaccessible due to legal constraints were omitted from our review.

Figure 5 presents the framework of our study, showcasing the key concepts and their interconnections that are crucial for grasping our approach.

5. APPLICATIONS AND USE CASES

Few-shot learning addresses the challenge of limited labeled data in text classification, enabling classifiers to generalize effectively with minimal instances. It enhances sentiment analysis, conversational AI, and document categorization, improving customer experience, user interaction, and information management. Moreover, it provides robust solutions for spam detection, ensuring digital security and user trust.

Table II elucidates the diverse applications of fewshot learning in text classification, encompassing a broad spectrum of industries. Complementing this, Figure 2 graphically represents the extensive reach and impact of few-shot learning across these varied applications, showcasing its transformative potential in enhancing text classification methodologies where labeled data is a luxury.

A. Benchmark Datasets

In the field of text classification, the development of deep learning algorithms has highlighted the necessity for varied datasets for effective model training. The surge in natural language processing (NLP) research has led to the creation of numerous datasets, both in English and Arabic, catering to the diverse needs of these advanced algorithms. These datasets are crucial to understanding the linguistic intricacies and training models for interpreting human language accurately. As researchers continue to compile and refine these collections, the aim is not only to advance text analysis techniques but also to ensure that models are versatile across different languages and cultural

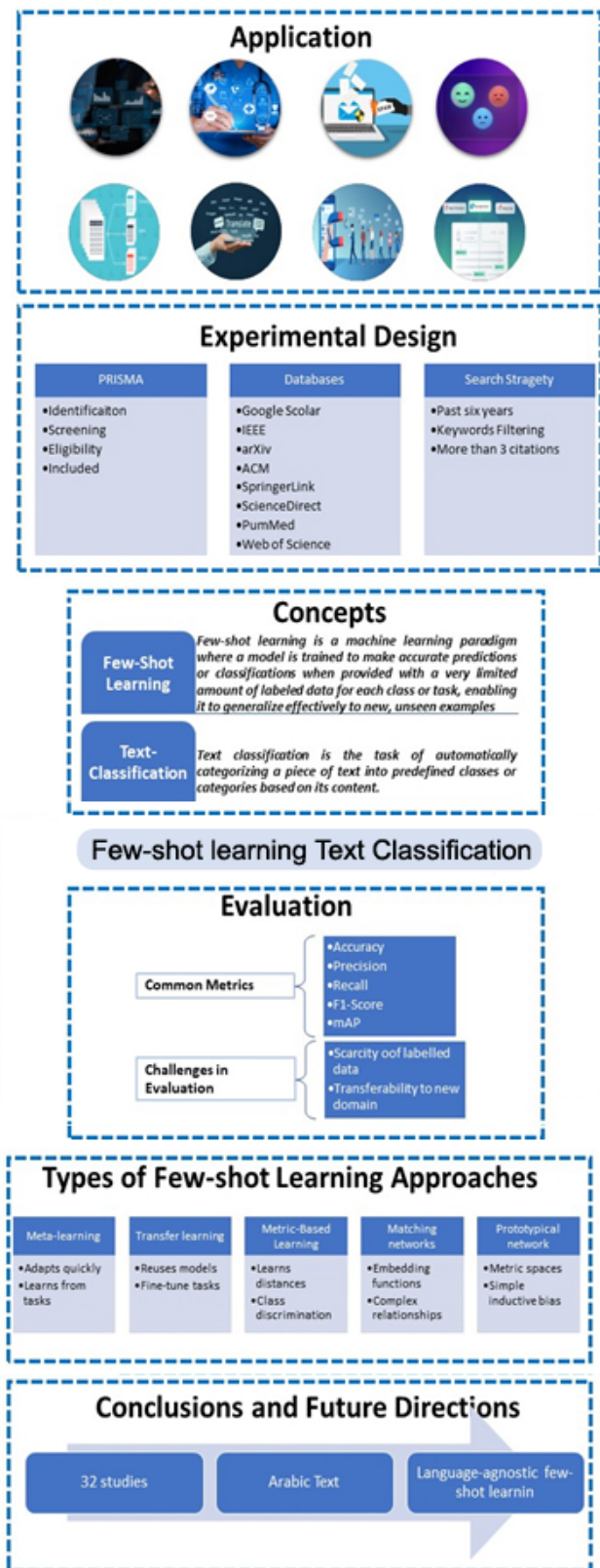


Figure 5. Framework of the study.

TABLE II. Applications of Few-Shot Learning (FSL) in Text Classification

Application	Industry	Challenges
Sentiment Analysis	Marketing and Customer Service	Limited labeled sentiment datasets, domain adaptation
Topic Classification	News Aggregation Platforms	Generalizing across varied topics, adapting to trends
Spam Detection	Email Service Providers	Adapting to evolving spam tactics, limited labeled data
Intent Recognition	Chatbots and Virtual Assistants	Generalizing to diverse user intents, query variations
Named Entity Recognition	Information Extraction Systems	Generalizing to new entity types, handling ambiguity
Text Summarization	News Aggregation and Document Management	Capturing key information, coherent summaries
Document Classification	Legal and Regulatory Compliance	Adapting to legal jargon, generalizing across types
Fake News Detection	Social Media Platforms	Adapting to evolving misinformation tactics, multilingual

contexts, thereby enhancing the global applicability of NLP technologies.

Arabic Sentiment Analysis is an active research field, emphasizing the need for Arabic datasets. The motivation behind this endeavor stems from the realization that dominance of English datasets, have hindered the applicability of advanced ML and NLP models in Arabic contexts. Researchers are actively curating Arabic datasets, vital for training and evaluating models. Ongoing endeavors to expand Arabic datasets reflect a commitment to enhancing text classification and NLP in Arabic, addressing its linguistic and cultural intricacies. A summary of these datasets are presented in Table III.

B. Evaluation Metrics

Evaluation serves as a crucial aspect in assessing the performance of text classification models, encompassing both traditional text classification methods and emerging few-shot learning approaches. Common metrics such as

precision (P), recall (R), F1-score, and accuracy play a pivotal role in quantifying the effectiveness of these models.

Precision (P): Measures the proportion of correctly predicted positive instances among all instances predicted as positive. It is calculated as

$$P = \frac{TP}{TP + FP} \quad (1)$$

Recall (R): Measures the proportion of correctly predicted positive instances among all actual positive instances. It is calculated as

$$P = \frac{TP}{TP + FN} \quad (2)$$

F1-score: Provides a balanced measure of a classifier's performance, calculated as

$$F1 = \frac{2 \times \text{precision} \times \text{recall}}{\text{precision} + \text{recall}} \quad (3)$$

Accuracy: Measures the overall correctness of predictions made by the model across all classes. It is calculated as

$$\text{Accuracy} = \frac{TP + TN}{TP + FN + TN + FP} \quad (4)$$

Top-k Accuracy: Considers a prediction correct if the true class label is within the top-k predicted classes.

Mean Average Precision (mAP): Computes the average precision across all classes in multi-class classification tasks.

Harmonic Mean of Top-k Accuracy (HMTA): Combines the advantages of top-k accuracy and F1 score by computing the harmonic mean of the top-k accuracy and F1-score across all classes.

These metrics offer insights into the performance of text classification models, including few-shot learning approaches, enabling researchers to make informed decisions about their applicability in real-world scenarios. They aid in gauging effectiveness and robustness across domains. However, domain-specific metrics are vital for accurately capturing the intricacies of the task at hand.

6. RESULT

In this section, we present a comprehensive survey of our search and review papers pertaining to few-shot learning in text classification, as outlined in Table IV. Additionally, we conduct an analysis of the obtained results, comparing data collection outcomes and presenting relevant statistics.

A. Data Collection Results

In our study, we gathered a total of 75 research papers published after 2018, focusing on the domain of few-shot learning. However, upon applying our exclusion criteria, we narrowed down the selection to 32 papers. Notably, the majority of these exclusions, amounting to 30 papers, were related to studies conducted in English text contexts, while



TABLE III. Overview of publicly available dataset for Text Classification.

Name	Year	Description	Size
Reuters-21578 [68]	1987	Categorized news articles	21,578 articles
Amazon Reviews [69]	2007	Product reviews and metadata from Amazon	34,686,770 reviews 6,643,669 users 2,441,053 products
PubMed dataset [70]	—	Biomedical literature	33 million records
IMDb Movie Reviews [71]	2011	Reviews for sentiment analysis	50,000 reviews
SpamAssassin Public Corpus [72]	2004	Labeled email messages	6,000 messages
Sentiment140 [73]	2009	Tweets with sentiment annotations	1.6 million tweets
DBpedia Ontology Dataset [74]	2014	Wikipedia articles categorized	4.58 million articles
Yelp Reviews [75]	2015	Reviews for businesses and users	4.7 million reviews
TREC Question Classification [76]	2002	Classified questions	6,000 questions
Stanford Sentiment Treebank [77]	2013	Sentences annotated with sentiment	11,855 sentences
WikiQA [78]	2015	QandA dataset for question answering systems	3,000 QA pairs
Quora Question Pairs [79]	2017	Pairs of questions with annotations	400,000 pairs
BBC News Dataset [80]	2006	Articles from BBC news website	2,225 articles
Jigsaw Toxic Comment Classification [81]	2018	Wikipedia comments with toxicity annotations	160,000 comments
Multi-Domain Sentiment Dataset [69]	2007	Product reviews across types	142,000 reviews
GameWikiSum [82]	2020	Dataset from online games for behavior analysis	282,992 words
AG's News [83]	2015	Collection of news articles	1 million
DBpedia [84]	2007	Structured content from Wikipedia	6.0M entities
MIMIC II [85]	2016	Clinical data from ICU patients	12,000 clinical reports
Multigames dataset [86]	2017	Twitter data on game topics	12,780 tweets
Health Care Reform (HCR) [87]	2011	Tweets with sentiment labels	2,394 tweets
Sentiment Strength Twitter Dataset (SS-Tweet) [88]	2013	Tweets with sentiment strengths	4,242 tweets
SemEval Dataset	2013	Twitter sentiment analysis task	7,967 tweets
20News [89]	1995	News discussion forum discourse	18,000 posts
FewRel dataset [90]	2018	Relation classification dataset for FSL	100 relations, 70,000 instances
HuffPost [91]	2022	News headlines	210,000 headlines
EU legislation - EU-RLEX57K [92]	2019	EU legislative documents	57k documents
IMDB review [71]	2011	Movie reviews	50,000 reviews
Elec [93]	2013	Movie and product reviews	25,000 reviews
Yahoo! Answers [94]	2008	QandA topic dataset	1.4 million
HUFF [91]	2022	News headlines	200,000 headlines
Banking77 [95]	2020	Intent classification dataset for banking domain	13,083 user utterances, 77 intents
HWU64 [96]	2019	Intent classification dataset across domains	25,478 sentences
Clinic150 [97]	2019	Intent classification dataset with out-of-scope queries	23,700 queries, including 22,500 in-scope
SST-2 [77]	2005	Sentiment labeled phrases in parse trees	215,154 phrases
GNAD [98]	2019	German news articles	10,000 articles
Head QA [99]	2019	Spanish health domain questions	not mentioned
Liu57 [96]	2019	User utterances from Amazon Mechanical Turk	25,478 utterances
Snippets [100]	2008	Web search snippets	Size not mentioned
Symptoms [42]	2019	Audio data of medical symptoms	8.5 hours of audio

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Name	Year	Description	Size
NICTA PIBOSO [101]	2012	Benchmark for biomedical abstracts	11,616 sentences
NLPCC [102]	2017	Chinese news headlines dataset	Size not mentioned
THUCNews [102]	2011	News content and labels from Tsinghua University	Size not mentioned
AISstudio [91]	2022	News headline dataset for AISstudio competition	Over 240,000 news text
ArSarcasm-v2 [103]	2021	Arabic sarcasm detection and sentiment analysis	15,548 tweets
ArSAS [104]	2018	Arabic sentences with sentiment labels	21,000 sentences
ArTwitter [105]	2013	Arabic tweets with sentiment labels	1,975 tweets
Ans [106]	2020	Consists of contradicted news titles collected from different news resources in the middle east	3786 news Arabic Sentiment
Twitter Dataset [107]	2015	Tweets in Arabic annotated for sentiment analysis	10,000 tweets
40K Tweets Dataset [108]	2019	A dataset of 40,000 tweets	40,000 tweets
AJGT [109]	2017	Jordanian tweets annotated for sentiment analysis	1,800
LABR [110]	2019	Arabic book reviews with sentiment labels	63,000 review
OSIAN [111]	2018	Arabic news articles categorized into various topics	28,000 articles
ANERCorp [112]	2007	Arabic Named Entity Recognition Corpus	approximately 150,000 tokens
ACE 2003 (BNews) [113]	2003	Subset of the ACE 2003 dataset focusing on broadcast news (BN2003)	15,000 tokens
ASND [114]	2020	Twitter-based benchmark dataset for Arabic Sentiment Analysis	95K tweets
ASND [115]	2020	Arabic Influencer Twitter Dataset AITD	115692 labels

only two papers addressed issues in Arabic text. Out of the 30 studies conducted in English, one was conducted in German and Spanish, while an additional study was conducted in Chinese.

This observation underscores the predominant focus on English language studies within the few-shot learning literature, highlighting a potential gap in research attention towards other linguistic contexts, particularly Arabic. The frequency distribution of the number of papers over time from our study is depicted in Figure 6.

1) Summary of datasets

We undertook a comprehensive analysis of the datasets employed across the spectrum of research papers addressing text classification and few-shot learning. The figure selectively highlights datasets that were referenced more than once in the surveyed literature, deliberately excluding those with only a single mention to focus on the most recurrently used resources in the field.

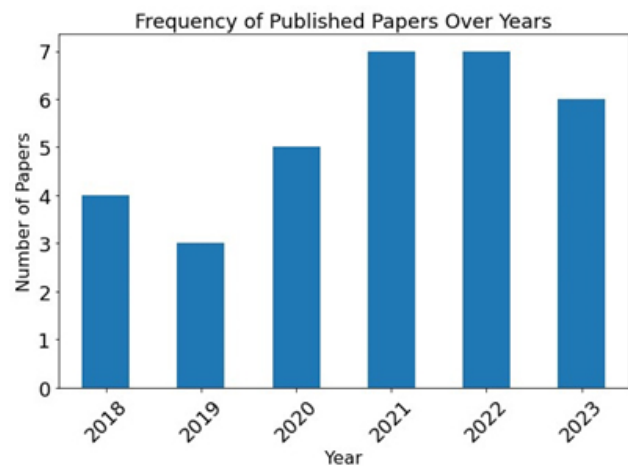


Figure 6. Number of papers related to few-shot learning in text classification from 2018 to 2023

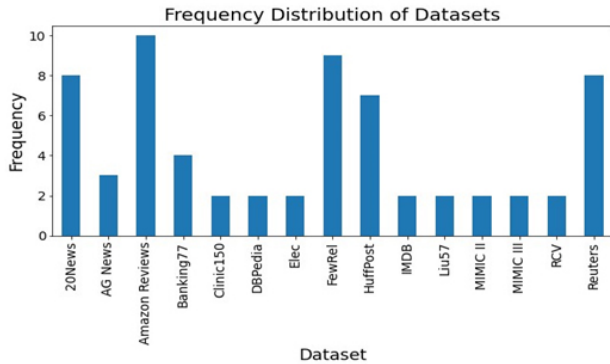


Figure 7. The frequency distribution of publicly available datasets for text classification and few-shot learning utilized in our surveyed papers

Exploring through the datasets, the 'Amazon Reviews' dataset stands out with ten citations, owing to its diverse user-generated content, making it invaluable for text classification studies. '20News' and 'FewRel' datasets are prominent with eight mentions each, indicating their importance in both text and relation classification tasks, especially in few-shot learning scenarios. 'HuffPost' and 'Reuters' datasets follow in frequency, with seven and five mentions respectively (Figure 7).

B. Summary of methodologies and applications

Surveyed methodologies converge on tackling labeled data scarcity in NLP, leveraging deep learning. Many studies opt for neural network architectures tailored for few-shot learning. Meta-learning is prominent, stressing adaptable models with minimal training data. Innovations include metric learning to optimize similarity measures and enhance few-shot system performance. Others explore dynamic routing within meta-learning frameworks to craft class-agnostic representations, bolstering few-shot classification efficacy.

Graph neural networks are employed to capture the relational structure inherent in text data, which is particularly beneficial in tasks like relation extraction and document classification. Selftraining and semi-supervised learning methods are also prominent, leveraging the abundance of unlabeled data to enhance model performance. Additionally, contrastive learning has been utilized to refine text representations, enabling models to distinguish between classes more effectively in a few-shot setting.

C. Innovation and Advancements in Few-Shot Learning and Text classifications

Innovation in methodology is a standout feature of the surveyed literature. Several studies have proposed adaptive models that tailor their approach based on the specifics of the task at hand, whether through the use of hierarchical methods that account for label dependencies or through models that incorporate attention mechanisms to focus on the most salient features of the text. The use of pre-trained embeddings is a common strategy to bootstrap the learning

process, leveraging the rich representations captured by models like BERT, which have been pre-trained on vast corpora of text.

Methods like prototypical networks and meta-learning demonstrate efforts to develop models learning abstract representations from few examples and applying them to new tasks or classes, indicating a commitment to versatile learning paradigms.

D. Arabic Text Classification

The exploration of Arabic text classification within the surveyed papers, although less prevalent, signifies an emergent interest in applying few-shot learning principles to less-resourced languages. The studies that do focus on Arabic tackle the unique challenges of dialectal variation and the lack of extensive labeled datasets by deploying Transformer-based models and self-training methods. While the research on Arabic represents only a very small fraction of the overall body of work, it is a critical step toward achieving linguistic diversity in NLP and addressing the research gap in non-English languages.

Challenges in Arabic text include scarcity of annotated data, dialectal variations, and nuances. Opportunities lie in leveraging pre-trained models like AraBERT [144] for enhanced feature extraction. Studies using ArSarcasm-v2, ArSAS, ArTwitter, Ans, SAtour for sentiment and sarcasm analysis, and MSA resources for NER and POS tagging show few-shot learning's efficacy in improving performance across diverse Arabic text applications.

The findings highlight few-shot learning's potential to revolutionize text classification in low-resource settings by enabling effective model training with minimal annotated data. It improves adaptability to emerging topics, reduces dependency on large datasets, and mitigates overfitting and bias, thus facilitating accurate and generalizable text classification in diverse and evolving language contexts.

7. CONCLUSIONS

Our comprehensive review of the literature in few-shot learning within the realm of text classification has identified a total of 32 studies that meet our stringent criteria, all conducted post-2018 and mostly from 2021 onwards. Few-shot learning methodologies demonstrate significant potential in leveraging minimal labeled data for effective model training. They mitigate constraints of extensive annotated datasets, enhancing adaptability and efficiency in text classification across diverse domains. By enabling models to learn from fewer examples, they reduce reliance on large-scale data and associated acquisition costs. These findings highlight few-shot learning's capability to diminish dependency on voluminous annotated datasets, traditionally essential for training robust text classification models, thus showcasing its transformative impact on model development and resource utilization. Few-shot learning also fosters rapid deployment and adaptation to new tasks, supports multilingual capabilities, and enhances real-time text classification

TABLE IV. Papers pertaining to Few-Shot Learning in text classification.

Study	Year	Methodology	Dataset	Domain
Rios et al. [116]	2018	Detailed analysis of state-of-the-art methods on infrequent labels in multi-label text classification, introduction of novel few- and zero-shot approaches using label space structure.	MIMIC II, MIMIC III	Medical discharge summaries
Yan et al.[117]	2018	Proposal of a Siamese CNNs and few-shot learning-based framework for short text classification to address the challenges posed by limited length and varied sentence structures, with the approach leading to improved accuracy in Twitter classifications and outperforming traditional and some deep learning methods.	Multigames, HCR, SS-Tweet, SemEval-2013	Tweets about sentiment, games, and health care reform
Muhammad, Bailey and Chopra [118]	2018	Prototyping-based few-shot learning for classifying largely unlabeled document corpora, leveraging pre-trained embeddings and minimal manual labeling.	20News	Web content from news
Yu et al. [119]	2018	An adaptive metric learning method for few-shot learning in natural language tasks, which automatically selects the most effective combination of metrics from meta-training tasks to address the challenges posed by task diversity, resulting in improved predictive accuracy on sentiment analysis and dialog intent classification datasets compared to existing algorithms.	Amazon Reviews, User Intent Classification	Product reviews intent
Gao et al.[90]	2019	Introduction of the Few-Shot Relation Classification Dataset (FewRel) with 70,000 sentences across 100 Wikipedia-derived relations, refined through distant supervision and crowdworker verification. Evaluation of state-of-the-art few-shot learning methods reveals challenges in model performance compared to human benchmarks, highlighting the necessity of diverse reasoning skills for the task and suggesting multiple future research avenues.	FewRel	Wikipedia corpus and Wikidata knowledge bases
Ruiying Geng et al.[120]	2019	Introduction of an Induction Network for few-shot text classification, leveraging dynamic routing in meta-learning to learn generalized class-wise representations, improving performance on sentiment and dialogue intent classification datasets compared to existing approaches, demonstrating the efficacy of class-wise generalization.	Amazon Reviews	Product reviews, Open Domain Intent Classification
Bao et al. [121]	2019	Meta-learning for few-shot text classification, addressing the challenge of applying this approach to text by incorporating distributional signatures in addition to lexical features, resulting in a model that consistently outperforms prototypical networks across six benchmark datasets in both fewshot text classification and relation classification tasks by a significant margin.	20News, RCV, Reuters-2157, Amazon Reviews, HuffPost, FewRel	News, Reuters articles, customer reviews, headlines



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Study	Year	Methodology	Dataset	Domain
Lu et al. [122]	2020	multi-graph aggregation model for multi-label zero/few-shot document classification, utilizing pre-trained word embeddings, label descriptions, and predefined label relations. Experiments on MIMIC-II, MIMIC-III, and EU legislation datasets show considerable performance improvements across multiple metrics for few/zero-shot labels.	MIMIC II, MIMIC III, EU legislation dataset	Medical
Chalkidis et al. [123]	2020	Exploration of LMTC challenges such as skewed label distributions and evolving hierarchies, evaluating LWANs, hierarchical methods, and Transformer-based approaches on diverse datasets. Results indicate the effectiveness of Probabilistic Label Trees and Transformer models, introduce a BERT-LWANs fusion as a new state-of-the-art, and propose models leveraging label hierarchies to improve few and zero-shot learning, incorporating a novel graph-aware annotation proximity measure.	EURLEX57K, MIMIC III, Amazon Reviews	English legislative documents, discharge summaries hospitals
Lwowski et al. [124]	2020	Utilization of few-shot learning to refine a semisupervised model, integrating unlabeled COVID19 and labeled influenza data, for public health surveillance via social media, demonstrating the model's effectiveness with an 86 percent accuracy in identifying COVID-19 discussions in recent tweets, despite the challenge of non-spherical data and the lack of labeled COVID-19 datasets.	COVID-19	Tweets about COVID-19
Mukherjee and Awadallah [125]	2020	Enhanced self-training approach for semisupervised learning in text classification tasks, leveraging uncertainty estimates from Bayesian deep learning to select informative instances from unlabeled data, achieving competitive performance with only a fraction of the labeled data typically required for fine-tuning pre-trained language models.	IMDB, Dbpedia, AG News, Elec	Sentiment classification, product reviews, topic of news classification
Lyu et al.[126]	2020	A new few-shot text classification approach combines pre-trained language models with an edgelabeling graph neural network to capture document similarities, extracting features for use in a prototypical network. Validated on sentiment analysis and relation classification datasets, achieves state-of-the-art performance while requiring minimal labeled data.	Amazon Reviews, FewRel	Product reviews, relation
Lee et al.[127]	2021	Introducing a semi-supervised bootstrap learning framework to improve few-shot text classification by enlarging training data using attention weights from an LSTM-based classifier and class-specific lexicons. This method outperforms existing approaches on four benchmark datasets, demonstrating the effectiveness of the constructed lexicons in enhancing classifier accuracy.	IMDB review, AG News, Yahoo, DBpedia	Sentiment analysis

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Study	Year	Methodology	Dataset	Domain
Wei et al. [128]	2021	Data augmentation's efficacy for few-shot text classification, demonstrating enhancement of triplet networks by 3 percent, introducing a robust novel curriculum data augmentation strategy and accelerating training.	HUFF, FerWel, COV-C, Amazon Reviews	COVID-related headlines, relationship between specified head and tail tokens
Xia et al. [129]	2021	Incremental few-shot text classification, proposing two entailment approaches (ENTAILMENT and HYBRID) and releasing two benchmark datasets (intent classification and relation classification) to address the challenges of incrementally learning new classes without re-training on previous examples while maintaining performance across multiple rounds.	IFS-INTENT, IFS-RELATION	Intent detection, relation classification
Han et al. [130]	2021	A meta-learning framework combined with an adversarial domain adaptation network enhances adaptability and generates high-quality text embeddings for new classes in few-shot text classification. Extensive experiments on four benchmark datasets demonstrate superior performance over state-of-the-art models, achieving significant accuracy improvements in both 1-shot and 5-shot classification tasks	Amazon Reviews, Reuters-21578	News, customer reviews, headlines
Wang et al. [131]	2021	TransPrompt, a transferable prompting framework for few-shot learning across similar NLP tasks, which outperforms single-task and crosstask baselines across multiple datasets, showcasing its effectiveness in improving performance on previously unseen tasks and outperforming strong fine-tuning baselines.	7 datasets	News, customer reviews, headlines
Min et al. [132]	2021	A noisy channel approach for language model prompting in few-shot text classification employs channel models to compute conditional probabilities, enhancing stability and performance compared to direct models. Experiments highlight the superiority of channel models in both in-context demonstration and prompt tuning methods with limited training data, imbalanced labels, or the need for generalization to unseen labels.	11 datasets	Various scopes
Zhao et al. [133]	2022	Development of MetaSLRCL, a novel meta-learning framework for few-shot text classification, introducing dynamic, task-and-layer-specific learning rates and a task-oriented curriculum learning mechanism for enhanced learner adaptation and meta-learner generalization, validated by extensive experiments on three benchmark datasets.	FewRel, 20 News, DB Pedia Ontology	Relations, news articles, products
Chen et al. [134]	2022	Introduction of ContrastNet, a contrastive learning framework addressing discriminative representation and overfitting in few-shot text classification by enhancing class-specific text representations and applying unsupervised contrastive regularization, with proven superiority over state-of-the-art models across 8 datasets.	Banking77, HWU64, Clinic150, Liu57, HuffPost, Amazon Reviews, Reuters, 20News	News and reviews



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Study	Year	Methodology	Dataset	Domain
Kim et al. [135]	2022	Proposed ALP method that improves few-shot learning for text classification by generating augmented samples with diverse syntactic structures using Lexicalized Probabilistic context-free grammars. It also introduces novel train-validation splitting strategies to optimize training efficacy by expanding the training split without extra labeled data, providing a robust approach to enhance model performance in few-shot learning scenarios.	SST-2, IMDB, Elec, AG News, DBpedia	Sentiment classification, topic classification
Zhang et al. [136]	2022	The PBML model integrates meta-learning and prompt-tuning to tackle challenges in few-shot text classification, achieving state-of-the-art performance on four datasets. It reduces data requirements for meta-training and provides visualization aids for interpreting its effectiveness, with reproducible code available.	FewRel, HuffPost, Reuters, Amazon Reviews	Relations, news articles, products
Liu et al. [137]	2022	Meta-FCS, a few-shot short-text classification method, integrates text semantic vector representation, meta-learning, fine-tuning, and vector similarity measurement. It efficiently transfers common features across diverse fields while emphasizing task-specific features. Experimental results on sentiment, entity-relationship, and news topic datasets demonstrate substantial improvements over existing methods, showcasing the potential of deep language representation and similarity measurement in few-shot learning for NLP.	Amazon Reviews, FewRel	Product reviews, relation
Muller et al. [138]	2022	FASL, a platform designed to accelerate the training of text classification models by integrating few-shot learning and active learning techniques. The study explores various active learning methods tailored for few-shot setups and develops a predictive model to determine the optimal stopping point for annotation, mitigating the challenge posed by limited access to large validation sets in few-shot learning scenarios.	AG News, GNAD, Head QA, Amazon Reviews	News in English and German, Spanish catalogue product reviews
Kim [139]	2022	LST a self-training method for text classification that leverages a lexicon to guide the pseudolabeling process and improve generalization. By refining the lexicon based on confidence predictions, LST achieves superior performance compared to existing state-of-the-art approaches on several benchmark datasets with limited labeled data.	SST-2, IMDB, Elec, AG News, Dbpedia	Sentiment classification
Yu et al. [140]	2023	Enhancement of retrieval-augmented methods for few-shot learning by developing task-specific retrieval metrics and introducing EM-L and R-L training objectives to tackle weak supervision and gradient vanishing, validated across 10 datasets.	10 diverse datasets	Sentiment classification, Natural Language Inference, aspect-based sentiment analysis

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Study	Year	Methodology	Dataset	Domain
Li [141]	2023	Introduction of a novel approach to few-shot text classification that incorporates knowledge distillation and graph aggregation to leverage unlabeled samples, enhancing meta-learning representation and interaction between query and support sets, with experiments on three public datasets demonstrating improved performance in 5-way 1-shot and 5-way 5-shot setups.	HuffPost, 20News, Reuters	News
Liu et al.[142]	2023	Proposal of novel strategies for few-shot text classification distribution estimation using unlabeled query samples to avoid negative transfer from category differences, involving Gaussian assumption for class/sample distributions and augmentation via sampling, resulting in significant performance improvements on eight datasets.	HuffPost, Amazon Reviews, Reuter, 20News, Banking77, Liu57, Clinic150	News, product reviews, medical
Liao [143]	2023	Mask-BERT enhances few-shot learning (FSL) capabilities of BERT-based models by selectively applying masks on text inputs to filter out irrelevant information, guiding attention towards discriminative tokens. It introduces a contrastive learning loss function to improve text representation separability across categories. Experimental evaluations on benchmark datasets demonstrate Mask-BERT's efficacy in addressing FSL challenges, yielding significant improvements in model performance.	AG News, Dbpedia14, Snippets, Symptoms, PubMed20k, NICTA-PIBOSO	Various domains
Wang [102]	2023	A knowledge-guided prompt learning approach for few-shot text classification. Through the design of a knowledge prompting template and two multi-task frameworks, the method showcases improved performance in experimental evaluation.	NLPCC, THUCNews	English and Chinese news
Seham Basabain et. al [144]	2023	The enhancement of feature extraction from Arabic text in few/zero-shot learning settings by leveraging the semantic information inherent in class label names, using a Transformer-based model like AraBERT, particularly for tasks with limited data and short texts like tweets, across domains such as sarcasm detection and sentiment analysis, demonstrating improved performance over baseline methods.	ArSarcasm-v2, ArSAS, ArTwitter, Ans, SATour	Arabic news, tweets, and sarcasm context
Muhammad Khalifa et al [145]	2021	Self-training approach utilizes pre-trained language models in zero- and few-shot scenarios to improve performance on data-scarce language varieties. It significantly enhances Arabic sequence labeling tasks, including named entity recognition (NER) and part-of-speech (POS) tagging for dialectal Arabic varieties, by leveraging Modern Standard Arabic (MSA) resources. Moreover, it demonstrates the effectiveness of self-training in utilizing unlabeled data to enhance model accuracy.	Arabic named entity recognition (NER) and part-of-speech (POS) tagging	



applications, further underscoring its transformative impact on the NLP field.

Despite the evident progress and achievements, our review delineates notable gaps within the extant research on few-shot learning for text classification. A conspicuous emphasis on English-centric studies emerges, with a stark underrepresentation of other languages, particularly those with intricate linguistic frameworks such as Arabic. This skewed focus inadvertently sidelines the unique challenges and opportunities inherent in non-English languages, which could otherwise contribute valuable perspectives to the adaptability and efficacy of few-shot learning paradigms. Moreover, the proliferation of datasets and benchmarks catering to text classification and broader NLP tasks has not been paralleled by the development of resources specifically designed for few-shot learning contexts, especially within multilingual settings. This discrepancy highlights an urgent need for creation of datasets and the establishment of evaluation benchmarks, aimed at fostering a deeper and more nuanced understanding of few-shot learning's capabilities and limitations across varied linguistic landscapes.

8. FUTURE WORK

In light of the identified gaps, we propose several avenues for future research aimed at advancing the field of few-shot learning in text classification. A critical imperative is the diversification of few-shot learning research to encompass a broader spectrum of languages, with a special focus on languages such as Arabic that have been historically marginalized in NLP research. This endeavor could involve the formulation of novel datasets and benchmarks that are specifically tailored to accommodate the linguistic diversity and complexity of various languages. Further exploration into the realm of cross-lingual and language-agnostic few-shot learning models holds the promise of developing universally applicable and scalable solutions for text classification. Additionally, the convergence of fewshot learning with cutting-edge technologies, including transformer-based architectures and meta-learning strategies, presents fertile ground for enhancing the generalizability, efficiency, and overall performance of text classification models.

The ramifications of our literature survey stretches beyond academia, shaping future research and NLP deployment. Few-shot learning's growth in text classification can democratize access to advanced NLP, benefiting resource-limited environments and languages. This inclusivity promotes balanced technological innovation across cultures. Sustained research efforts are vital for addressing current limitations and exploring new possibilities in text classification and NLP's future landscape.

Emerging trends in few-shot learning for text classification include advancements in meta-learning algorithms such as MAML (Model-Agnostic Meta-Learning), which optimize models to learn quickly from few examples. Integration of large-scale pre-trained models like GPT (Generative Pre-trained Transformer) and BERT (Bidirectional Encoder

Representations from Transformers) enhances performance across diverse tasks and languages, promising more robust and adaptable NLP solutions.

The limitations of our review study include its focus on literature post-2018, which may overlook earlier foundational work, and limited coverage of languages beyond English and their distinct challenges. Additionally, the lack of specific datasets and benchmarks for few-shot learning limits comprehensive analysis and applicability.

Few-shot learning may raise ethical concerns regarding data privacy, as models may access sensitive information with minimal training data. Mitigating biases is crucial, ensuring fair treatment across demographics. Accurate and responsible deployment is vital to prevent misinformation and uphold transparency in decision-making processes. Ethical guidelines must prioritize user consent, protect privacy rights, and promote fairness in algorithmic outputs, fostering trust and accountability in text classification applications.

In essence, the exploration of few-shot learning within text classification has led to important discoveries and greatly benefited the wider field of natural language processing (NLP). Tackling the current shortcomings and exploring new areas could lead to significant breakthroughs, making NLP tools more available, effective, and inclusive for a diverse range of languages.

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