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SURVEY

Machine Translation Performance for Low-Resource Languages: A Systematic Literature Review

TAOFIK O. TAFA[1,2], SITI ZAITON MOHD HASHIM[1], MOHD SHAHIZAN OTHMAN[1], HITHAM ALHUSSIAN[3], (Senior Member, IEEE), MAGED NASSER[3], SAID JADID ABDULKADIR[3], (Senior Member, IEEE), SHARIN HAZLIN HUSPI[1], SARAFA O. ADEYEMO[1,2], AND YUNUSA ADAMU BENA[1,4], (Member, IEEE)

[1]Faculty of Computing, Universiti Teknologi Malaysia, Johor Bahru 81310, Malaysia
[2]Department of Computer Science, Federal College of Education (Technical) at Gusau, Gusau 632101, Nigeria
[3]Department of Computer and Information Sciences, Universiti Teknologi PETRONAS, Seri Iskandar, Perak 32610, Malaysia
[4]Faculty of Engineering, Kebbi State University of Science and Technology, Aliero, Nigeria

Corresponding authors: Taofik O. Tafa (tafa@graduate.utm.my) and Maged Nasser (maged.nasser@utp.edu.my)

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ABSTRACT Machine translation (MT) for low-resource languages continues to face significant challenges because of limited digital resources and parallel corpora, despite remarkable developments in neural machine translation (NMT). Addressing these challenges requires a thorough review of existing research to identify effective strategies and methods. To achieve this, a systematic literature review (SLR) is conducted following PRISMA guidelines and systematically analysing studies published in various academic databases in the last five years (between 2020 and 2024). A total of 69 relevant articles were examined to evaluate the performance of MT, explore persistent challenges and assess the effectiveness of proposed or used solutions. The analysis shows that while NMT has emerged as the predominant approach, its effectiveness is often reduced by the scarcity of training data and the structural complexity of low-resource languages. Strategies such as active learning, data augmentation, multilingual models and transfer learning are identified as critical for improving translation performance. Additionally, emerging research trends, including data pre-processing, optimization of decoder and rule-based approach demonstrate promising directions for addressing existing limitations. In terms of evaluation, most of the studies used Character n-gram F-score (ChrF), Translation Edit Rate (TER), Metric for Evaluation of Translation with Explicit Ordering (METEOR), Word Error Rate (WER) and Bilingual Evaluation Underscore (BLEU) as techniques' validation metrics. This review provides a detailed evaluation of the current state of MT for low-resource languages and emphasizes the need for further research into underrepresented languages and the development of comprehensive datasets.

INDEX TERMS Low-resource languages, machine translation, machine translation performance, machine translation techniques, systematic literature review.

I. INTRODUCTION

There has been a significant improvement in machine translation (MT) of languages with adequate linguistic resources in recent times. However, MT performance for low-resource languages remains a critical challenge. These languages, according to [1], often lack sufficient digital resources and support, extensive parallel corpora, comprehensive linguistic resources, and robust computational infrastructure, leading to translation quality that are short of standard. Despite the increasing number of research in the area, there is no comprehensive synthesis of the latest cutting-edge techniques, challenges, and effective methodologies specifically tailored for low-resource languages. The performance of MT for

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low-resource languages has been a focus of recent research efforts. Neural machine translation (NMT) emerged as the dominant approach in MT systems, but its effectiveness for low-resource languages is hampered by the lack of parallel corpora [2].

For further advancement in MT performance, especially for low-resource languages, there is a need for a piece of work that goes beyond explanation or implementation of various techniques explored to enhance MT performance in languages with limited or no linguistic resources. A study that carefully examine earlier literature on MT performance in these languages is worthwhile. A systematic literature review (SLR) on the other hand can satisfy all these purposes. This SLR addresses this gap by consolidating and analysing existing research on MT performance for low-resource languages. The study evaluates published articles between 2020 and 2024, identifying temporal trends in MT techniques, challenges and limitations of low-resource MT and strategies and methodologies used or proposed in enhancing MT performance for low-resource languages.

II. RELATED WORKS

Several studies have been conducted on MT performance for low-resource languages and some of these studies looked at improving NMT accuracy using monolingual data and the adaptation of model architectures, highlighting the importance of extensive research in this area. For example, [1] emphasize methods for improving translation accuracy through NMT model architecture adaptations and the use of monolingual data after revealing a significant absence of high-quality and extensive parallel corpora for the Kashmiri language, which remains a barrier to effective MT. A systematic review by [3] investigated the landscape of multilingual sentiment analysis for low-resource languages and used a multilingual automatic speech recognition (ASR) system for initialization in low-resource scenarios and found that deep learning-based methods significantly enhanced sentiment classification performance. In their study, connectionist temporal classification (CTC) was included as an additional target during training and decoding, which significantly improved internal representations and final translation quality. Yazar et al. [4] conducted an SLR of low-resource NMT, which highlighted the importance of incorporating additional data sources such as monolingual data to enhance translation quality when parallel bilingual data is scarce. Among the findings of the study is that bilingual evaluation underscore (BLEU) was found to be most widely used metric among the studies reviewed out of 13 evaluation metrics identified for assessing translation quality. Abdullah and Rusli [5] explore the challenges and advancements in analysing sentiments expressed in multiple languages across various social media platforms, utilising MT preprocessing technique, which is crucial for handling texts in multiple languages, especially when resources for certain languages are limited, and found that hybrid approaches combining MT, tokenization, and deep learning yielded the most effective results across multiple language pairs.

Similarly, [6] focused on strategies to improve low-resource speech-to-text translation by employing an encoder-decoder framework with multilingual ASR for initialization and using CTC during training. These approaches have shown considerable improvements, achieving a BLEU score of 7.3 on Tamasheq French data and identifying effective strategies for low-resource speech-to-text translation. Ranathunga et al. [7] provided a comprehensive survey on NMT for low-resource languages, highlighting the use of supervised, unsupervised, semi-supervised, and transfer learning techniques to improve robustness, interpretability, and alleviate bias in multilingual models. Their study emphasized the challenges posed by limited resources and the problem in collecting labeled data, suggesting that fine-tuning techniques, which transfer knowledge between parent and child models, are highly effective. Additionally, [8] demonstrated that augmenting training data with parser-generated syntactic phrases significantly improves NMT performance in low-resource scenarios, achieving notable improvements in BLEU and Metric for Evaluation of Translation with Explicit Ordering (METEOR) scores.

Recent advancements in MT have increasingly leveraged large language models (LLMs) such as GPT-4, LLaMA, and DeepSeek, which exhibit strong cross-lingual transfer capabilities, especially for low-resource languages [9]. Unlike traditional NMT models that rely heavily on parallel corpora, LLMs are pretrained on vast multilingual data and can perform zero-shot and few-shot translation tasks with impressive fluency and contextual understanding [9], [10]. For instance, GPT-4 has demonstrated proficiency in translating over 50 languages with minimal or no task-specific fine-tuning [11], while Meta's LLaMA and DeepSeek models have shown notable performance improvements in zero-shot MT benchmarks through their decoder-only or encoder-decoder transformer designs [9]. Lankford et al. [12] streamlined the fine-tuning process of a multilingual LLM (adaptMLLM) and significant improvements were observed in translation performance for low-resourced language pairs, such as English to Irish and English to Marathi. These advancements collectively contribute to a nuanced understanding of strategies and methodologies aimed at improving MT performance for low-resource languages. This study aims to systematically review recent developments in MT for low-resource languages, focusing on performance trends, challenges, and strategies used or proposed to improve MT for low-resource languages, thereby offering researchers a consolidated reference point for future innovations in this domain.

A. LOW-RESOURCE LANGUAGES

Low-resourced languages are languages with limited computational and linguistic resources [3], which affects the development and performance of MT systems. There are

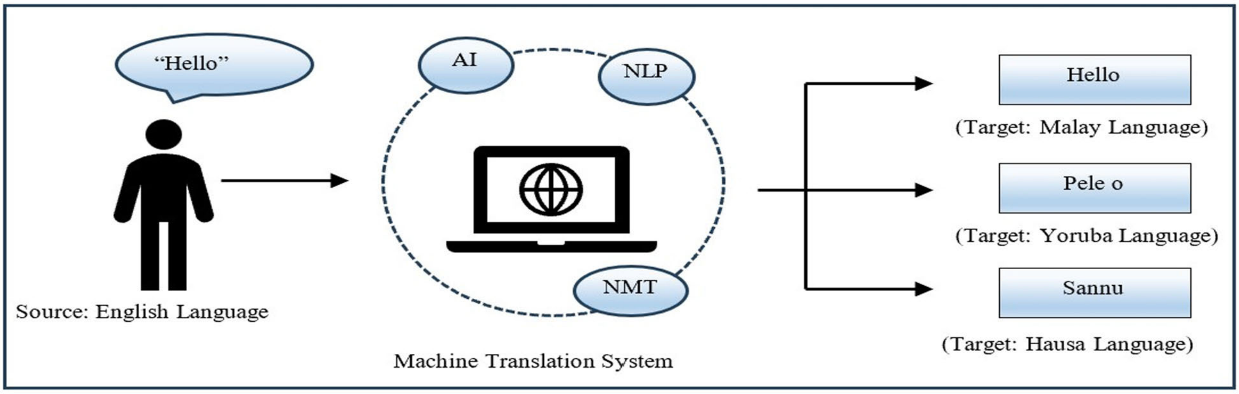

FIGURE 1. MT system translating into low-resource languages (Authors own creation.

often no large corpora and pre-trained models for these languages, making it difficult to train effective MT systems, and often leads to lower accuracy in language understanding, generation and relevance of responses for MT systems [13]. This lack of resources stems from multiple factors, including historical underrepresentation in technological advancements, and limited documentation of these languages [7]. For instance, many African languages face challenges such as complex grammatical structures, noun classification systems, and verb morphology [14], which add further difficulties to natural language processing (NLP) tasks. Furthermore, the challenges of tokenization and inherent linguistic differences compared to resource-rich languages worsen the problem of resource inequality, as low-resource languages are often inefficiently tokenized, resulting in increased costs and lower model performance [15], [16]. Not only are these languages underrepresented in digital platforms, but the existing data is often noisy or domain-specific and usually comes from religious or government sources that may not be representative of general language use [17]. These challenges are not only limited to translating the low-resource languages but also affecting the translation of high-resource languages like English into the low-resource languages. Figure 1 illustrates an MT system (Google Translate) challenge of translating into low-resource languages. Though the English word "Hello" is literally translated as "Pele o" (Yoruba language) and "Sannu" (Hausa language), the two words contextually mean "sorry" in both Yoruba and Hausa low-resource languages respectively. Also, "Hello" in English is returned as "Hello" in Malay.

Low-resource languages are increasingly being integrated into various natural language understanding (NLU) tasks beyond MT, including abstractive summarization using multilingual models like multilingual Bidirectional and Auto-Regressive Transformers (mBART) and Multilingual Text-to-Text Transfer Transformer (mT5), cross-lingual question answering with translated datasets, and Named Entity Recognition (NER) via transfer learning or lexicon-based methods, despite persistent challenges in tokenization, morphology, and data scarcity [18], [19].

The preservation and translation of low-resource languages is crucial for cultural heritage, social diversity and technological inclusivity, as many of them, spoken by marginalized communities, are at risk of extinction due to the lack of written documentation, digital resources and institutional support [7].

B. NOTABLE MT MODELS FOR LOW-RESOURCE LANGUAGES

Several MT models have been developed specifically to address challenges associated with low-resource languages. These models focus on improving data efficiency and leveraging techniques such as transfer learning, data augmentation, backtranslation, multilingual models and unsupervised learning to improve performance on languages with limited data availability, all of which can be utilized to translate between various low-resource language pairs.

Table 1 provides an overview of notable MT models designed to address the challenges of translating low-resource languages. It highlights the models employed, languages targeted and the models' unique features and achievement.

III. METHODOLOGY

For this systematic review work, we adopted a rigorous and comprehensive research methodology. We began by defining clear research questions to guide the study, focusing on the techniques used, challenges and limitation faced in MT for low-resource languages and strategies and techniques used to enhance MT of these languages. We systematically searched multiple academic databases. Inclusion and exclusion criteria were established to select studies published in peer-reviewed journals from 2020 to 2024. Articles that are not directly related to machine translation for low-resource languages were excluded. Data extraction was performed on selected studies, capturing essential information such as the languages addressed, MT models used, datasets, evaluation metrics, and key findings. We employed qualitative analysis to identify common themes, trends, and gaps in the research. While performing, documenting, and reporting our SLR, we adhered to the Preferred Reporting Items for Systematic reviews and

TABLE 1. Overview of notable mt models for low-resource languages.

Model	Architecture type	Methods/Techniques	Low-resource languages	Key features	Result achieved
Character NMT [20]	Recurrent/ Convolutional	Recurrent Neural Network (RNN), Convolutional Neural Network (CNN).	Arabic, Vietnamese	Adapted character neural translation model.	Encouraging results on Arabic datasets.
JoeyNMT [21], [22]	Transformer	Transformer with self-attention.	isiZulu	Language Identification (LID) model, logistic regression, multinomial naive Bayes (MNB).	JoeyNMT performed well on isiZulu; Transformer NMT with self-attention achieved state-of-the-art performance on other languages.
mBART [23]	Transformer (Seq2Seq)	Fine-tuning pre-trained models.	Thai, Myanmar	mBERT is based on the BERT (Bidirectional Encoder Representations from Transformers).	Significantly boosts performance for languages like Thai and Myanmar.
Seq2Seq with mBART-50 [24]	Transformer (Seq2Seq)	Pre-trained seq2seq - knowledge distillation.	Slovenia language	Sequence-to-sequence (seq2seq) architecture.	Effective for generative tasks, they face challenges in classification tasks due to the limited resources available for the Slovenian language.
LGE-Transformer [25]	Transformer	LGE-Transformer method for neural machine translation.	Chinese - Malay	Gated dynamic encoding module, linguistically enhanced pre-training and hybrid cross-attention module.	Improve the performance of NMT for low-resource language pairs, such as Chinese-Malay.
FairSeq [26]	Transformer	Transformer-based multilingual training.	isiZulu, Xhosa, Hausa	Data augmentation, transfer learning.	Enhanced translation quality for African languages.
MASS [27]	Transformer (Seq2Seq)	Masked sequence-to-sequence pre-training.	Vietnamese, Urdu, Kazakh	Bidirectional pre-training for LRLs.	Improved BLEU scores in low-resource settings.
MarianMT [28]	Transformer	Transfer learning, multilingual modeling.	Somali, Sinhala, Pashto	Efficient training on limited data.	State-of-the-art accuracy for LRLs.
mT5 [29]	Transformer (Text-to-Text)	Pre-trained multilingual transformer model.	Amharic, Swahili, Tagalog	Fine-tuning for translation tasks.	High BLEU scores across diverse languages.
mBERT[30]	Transformer (Encoder-only)	Multilingual BERT fine-tuning.	Arabic, Hindi, Swahili	Token-level representation for LRLs.	Enhanced downstream translation tasks.
NLLB (No Language Left Behind) [31]	Transformer (Multilingual NMT)	Multilingual NMT, dense and sparse modeling.	200+ languages, including Igbo, Tigrinya	Focus on inclusivity for under-represented languages.	Significantly improved translation quality globally.
FLORES [32]	Transformer (Benchmarking setup)	Fine-tuning on specific language pairs.	Bengali, Sinhala, Khmer	Linguistically diverse benchmarking.	Improved performance on low-resource benchmarks
ByT5 [33]	Transformer (Character-level Seq2Seq)	Character-based sequence-to-sequence learning.	Bhojpuri, Maithili, Sinhala	Token-free approach for better linguistic coverage.	Promising BLEU scores on unseen languages.
IndicTrans [34]	Transformer	Transliteration, multilingual fine-tuning.	Indic languages (e.g., Kannada, Marathi)	Optimized for Indian languages.	Higher accuracy compared to bilingual baselines.

Meta-Analyses (PRISMA) guidelines, as shown in Figure 2. PRISMA ensures transparency and comprehensiveness in review process [35].

In conducting the SLR, recent research and literature review tools were used. A bibliometric analysis was conducted to examine the key items co-occurrence using R-studio. Harzing's Publish or Perish was used to retrieved and analysed articles obtained from various academic databases. Microsoft Excel was employed for listing articles, facilitating the SLR procedures and generation of visual representations and charts. SciSpace, an amazing AI tool developed to assist researchers in navigating and understanding scientific literature easily [36], was also used in analysing and extracting relevant information from the studied articles, while Zotero was utilised in managing the articles' citations. The comprehensive approach ensured a thorough and unbiased review, providing valuable insights into the current state and future directions of MT for low-resource languages.

The final selection of 69 studies was determined through a structured review process based on PRISMA, which involved initial retrieval of 1534 articles and subsequently removal of duplicates, refining to related years, language and abstract screening, and full-text eligibility checks based on clearly defined inclusion and exclusion criteria. This methodological rigour ensures that the selected studies are highly relevant, current, and peer-reviewed, focusing specifically on MT for low-resource languages.

A. RESEARCH QUESTIONS AND RATIONALE

In pursuit of fulfilling the primary aim of the study, three research questions (RQ) were formulated with each of them having sub-questions. These research questions and the rationale behind each of them are outlined in Table 2.

B. DATA SOURCE AND SEARCH STRATEGY

The research strategy for this study involved a meticulously designed database search protocol using the following five databases that are highly relevant to our field:

- Science Direct: https://www.sciencedirect.com/
- Web of Science: https://www.webofscience.com/
- Scopus: https://www.scopus.com/
- SpringerLink: https://link.springer.com/
- IEEE Xplore: https://ieeexplore.ieee.org/

Search terms were formulated, and the following search strings were eventually used: "machine translation" AND ("low resource" OR "under resource") AND languages. The keywords "low resource" or "under resource" were used as parts of the search strings because the two terms are usually used in articles synonymously. Table 3 gives the initial search results. The papers were then screened based on their title, keywords, and abstract. The outcomes of the database searched were documented as lists on the respective database platforms, imported into Excel spreadsheets, and consolidated on the primary worksheet. During the screening, non-relevant articles and those that are not open access were excluded.

C. INCLUSION/EXCLUSION CRITERIA

In an SLR, inclusion and exclusion criteria are defined to ensure that only relevant and high-quality studies are selected for review [37]. These criteria help in directing the study toward the scope of the research questions.

Inclusion criteria:

- Articles published in journals which are focused and related to MT of low-resource languages.
- Articles within the period from 2020 to 2024.

Exclusion criteria:

- Non-English publications
- Articles that cannot be accessed
- Informal studies (articles from unknown sources)
- Articles that were irrelevant to the research questions

D. QUALITY ASSESSMENT

The quality assessment was conducted to refine the scope of data collection and analysis of this study. The focus of the quality assessment was to evaluate how well each of the studies answered the research questions [37] posed in this study. To ensure objectivity, two independent reviewers conducted quality assessments using predefined quality assessment questions linked to research questions. Inter-rater agreement was computed using Cohen's Kappa to ensure quality [37] and a Cohen's Kappa coefficient (κ) of 0.73 was obtained, indicating substantial agreement. This assessment helped in the precise extraction of relevant studies and elimination of irrelevant ones. Table 4 lists the three quality assessment questions used to determine the quality assessment criteria, while Table 5 served as the scoring matrix for assigning points to each paper. The three quality assessment questions were carefully selected for their alignment with study's research questions and their ability to filter for relevance. The maximum obtainable score is 3 and papers scoring 2 or higher were included because they either provided a generally comprehensive identification and analysis with some detail or addressed the topic thoroughly with solid data and clear analysis. Table 6 presents the list of the studied articles and the results of the quality assessment score of each article.

IV. RESULTS

In this study, we analysed 69 articles published between 2020 and 2024 to determine the state of MT for low-resource languages. A brief data analysis was conducted on the key terms and abstract fields of the 69 studied articles using R-Studio. Figure 3 highlights key themes and relationships in the fields. *Neural machine translation* emerges as the central concept, closely linked to *machine translation* and *low-resource languages*. The visualisation shows that *transfer learning* and *data augmentation* play a major role as methods for improving translation for low-resourced languages. Other notable keywords are *attention mechanism, transformer*and *BERT*, which reflect the technical approaches used. The figure also shows the interaction with broader terms such as *artificial intelligence* and *machine learning*, highlighting their importance for the advancement of translation

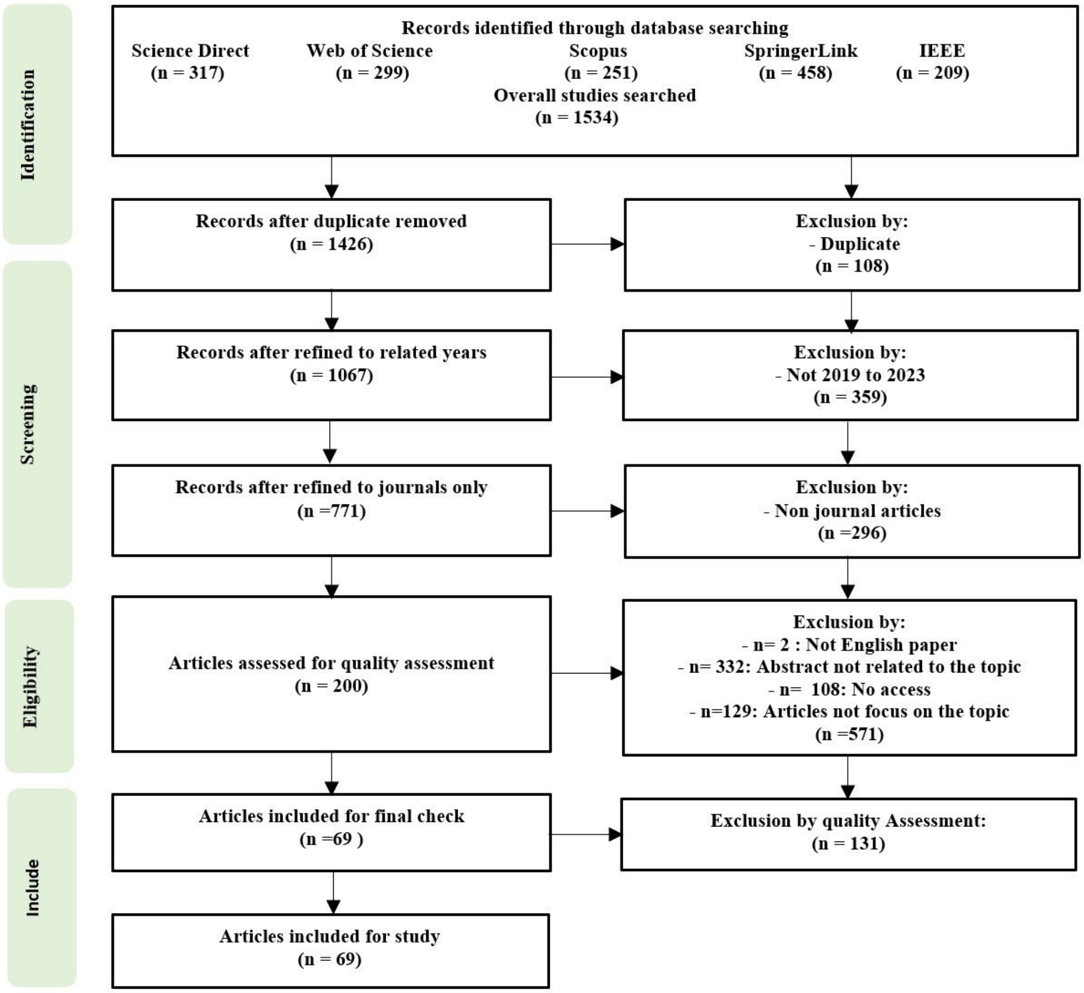

FIGURE 2. Studies selection process using PRISMA (Authors own creation).

technologies. The following subsections present the analysis and results for each of the research questions.

A. CURRENT TRENDS, TECHNIQUES AND PERFORMANCE IN MT FOR LOW-RESOURCE LANGUAGES (RQ1)

Recent advances in MT have led to the development of innovative techniques tailored to low-resource languages. This section reviews the trends in publications on MT for low-resource languages, the current MT techniques used for such languages, and the differences in the accuracy and effectiveness of these techniques for low-resource languages.

1) TREND OF STUDIES IN MT OF LOW-RESOURCE LANGUAGES IN RECENT YEARS (RQ1.1)

Figure 4 represents the publication trend in the study area from 2020 to 2024. There is an increase related to the study between 2020 to 2022, followed by a slight decline after the peak in 2022. Lowest rates were observed in 2020 and 2021. This could be because of the global effect of the COVID-19 pandemic, which disrupted virtually every activity including research. The sharp rise in 2022 suggests a strong recovery and possibly an influx of new techniques, models, and tools that improved translation performance, leading to increased research outputs. The slight decrease in 2023 and 2024 might indicate stability in the field, with continued but slightly lower levels of publication activity as the initial surge of innovation settled into more sustained research efforts.

2) DISTRIBUTIONS OF THE STUDIES ACCORDING TO DATABASE AND PUBLISHER (RQ1,2)

The distribution of articles obtained from various databases for the study is provided in Figure 5. Web of Science contributed the highest proportion of articles at 35%, indicating its extensive coverage and relevance in this research area. SpringerLink follows with 27%, showcasing its significant contribution. Scopus provided 19%, illustrating its substantial yet slightly lesser role. IEEE Xplore and Science Direct contributed the least among the databases but still played crucial roles in the systematic review. This distribution highlights the importance of leveraging multiple databases to

TABLE 2. Research questions and rationale.

No.		Research questions	Rationales
RQ1		What are the current trends, techniques and performance in MT for low-resource languages?	To identify current studies on MT for low-resource languages, addressing the need for effective translation of these languages.
	RQ1.1	What is the trend of studies in MT of low-resource languages in recent years?	
	RQ1.2	What are the distributions of the studies according to databases and publishers?	
	RQ1.3	What specific MT techniques are predominantly used for low-resource languages?	
	RQ1.4	How do the accuracy and effectiveness of these techniques vary across different low-resource languages?	
RQ2		What are the primary challenges and limitations faced by MT systems when dealing with low-resource languages?	To identify and understand the challenges and limitations of MT systems for low-resource languages to improve translation performance.
	RQ2.1	What are the challenges and limitations faced by MT systems when processing low-resource languages?	
	RQ2.2	How do the specific constraints of low-resource languages impact the performance and accuracy of MT systems?	
RQ3		What strategies and methodologies have been proposed or implemented to enhance the performance of MT systems for low-resource languages, and how effective have they been?	To evaluate proposed strategies and methodologies for improving MT performance for low-resource languages, assessing their effectiveness.
	RQ3.1	What specific strategies and methodologies have been proposed or used to improve the performance of MT systems for low-resource languages?	
	RQ3.2	How have these strategies and methodologies been validated in terms of performance?	

TABLE 3. Search results.

Database	Search results
Science Direct	317
Web of Science	299
Scopus	251
SpringerLink	458
IEEE Xplore	209
Total	**1534**

TABLE 4. Quality assessment questions.

Quality assessment (QA) questions	Relevant to the research question (RQ)
QA1: How accurately and comprehensively does the study identify and describe the various MT techniques currently used for low-resource languages, and how rigorously does it evaluate their effectiveness?	RQ1
QA2: To what extent does the research thoroughly identify and analyse the primary challenges and limitations faced by MT systems for low-resource languages, and how well does it support its findings with empirical evidence or theoretical analysis?	RQ2
QA3: How effectively does the study review and validate the proposed or implemented strategies and methodologies for enhancing MT performance for low-resource languages, and to what degree does it provide clear evidence of their effectiveness?	RQ3

gather comprehensive and diverse literature for a thorough review.

There is a diverse range of publishers that have contributed to the study area, with varying levels of publication output, as indicated in Figure 6. The distribution of articles

TABLE 5. Quality assessment scoring matrix.

Quality assessment scoring criteria Score	Score
Comprehensively identify a clear explanation of the answers to the specific RQ.	High = H = 1
Identifies some explanation, but not specific, detailed, or clear enough to the specific RQ.	Medium = M = 0.5
Fails to identify information in response to the specific RQ.	Low = L = 0

across different publishers suggests a broad interest and engagement from the academic community in exploring MT performance for low-resource languages. Some journals have a higher number of publications related to MT for low-resource languages, while others have fewer contributions. This is influenced by factors such as journal scope and focus. IEEE Access and ACM have the highest articles, indicating their high relevance and visibility in the field. Information, Machine Translation and Multimedia Tools and Applications show moderate activity, reflecting their broader scope within computer science and applications. Specialized journals like Computer Speech and Languages, Frontiers in Artificial Intelligence, etc. have fewer publications, likely due to their specific focus and higher competition. Overall, the analysis shows that studies targeted journals with a direct connection to MT and a wider impact within the computational linguistics community.

3) PREDOMINANT MT TECHNIQUES USED FOR LOW-RESOURCE LANGUAGES (RQ1.3)

Analysis of the studied articles shows that there is diversity of techniques explored in MT of low-resource languages,

TABLE 6. List of studied articles and quality assessment scores.

References	Author(s) and year	Database	Quality assessment scoring			
			Q1	Q2	Q3	Score
[12]	Lankford et al. (2023)	Web of Science	1.0	1.0	1.0	3.0
[16]	Harish, B. S., & Rangan, R. K. (2020)	SpringerLink	1.0	1.0	1.0	3.0
[17]	Chakrabarty et al. (2023)	Scopus	1.0	1.0	0.5	2.5
[34]	Bala Das et al. (2024)	Scopus	1.0	1.0	0.5	2.5
[38]	Hujon et al. (2024)	Science Direct	1.0	1.0	1.0	3.0
[39]	Shi and Yu (2022)	Scopus	1.0	1.0	1.0	3.0
[40]	Asefa et al. (2024)	IEEE Xplore	1.0	0.5	1.0	2.5
[41]	Sel and Hanbay (2024)	Scopus	1.0	1.0	1.0	3.0
[42]	Li et al. (2021)	Scopus	1.0	0.5	1.0	2.5
[43]	Shi et al. (2022)	Scopus	1.0	1.0	0.0	2.0
[44]	Baruah et al. (2021)	Scopus	1.0	1.0	1.0	3.0
[45]	Sheshadri et al. (2023)	ScienceDirect	1.0	1.0	1.0	3.0
[46]	Ngo et al. (2022)	Scopus	1.0	1.0	1.0	3.0
[47]	Woldeyohannis and Meshesha (2022)	Scopus	0.5	1.0	0.5	2.0
[48]	Yan et al. (2022)	Web of Science	1.0	1.0	1.0	3.0
[49]	Sel and Hanbay (2022)	Web of Science	1.0	1.0	1.0	3.0
[50]	Tonja et al. (2023)	Web of Science	1.0	1.0	1.0	3.0
[51]	Slim et al. (2022)	SpringerLink	1.0	1.0	1.0	3.0
[52]	Singh et al. (2021)	SpringerLink	1.0	1.0	1.0	3.0
[53]	Tars et al. (2022)	Scopus	1.0	1.0	0.5	2.5
[54]	Gyasi and Schlippe (2023)	Scopus	1.0	1.0	1.0	3.0
[55]	Shi et al. (2022)	Web of Science	1.0	0.5	0.5	2.0
[56]	Pang et al. (2024)	Web of Science	1.0	1.0	0.5	2.5
[57]	Wu et al. (2022)	Web of Science	1.0	1.0	1.0	3.0
[58]	Jiang et al. (2022)	Web of Science	1.0	0.5	1.0	2.5
[59]	Zhang et al. (2024)	Web of Science	1.0	1.0	1.0	3.0
[60]	Ramesh et al. (2021)	Scopus	1.0	1.0	1.0	3.0
[61]	Bhuvaneswari and Varalakshmi (2024)	Web of Science	1.0	1.0	1.0	3.0
[62]	Klimova et al. (2023)	SpringerLink	1.0	1.0	1.0	3.0
[63]	Park et al. (2020)	Web of Science	0.5	0.5	1.0	2.0
[64]	Qin et al. (2022)	SpringerLink	0.5	1.0	1.0	2.5
[65]	Kann et al. (2022)	Web of Science	1.0	1.0	1.0	3.0
[66]	Chen et al. (2024)	Science Direct	1.0	1.0	1.0	3.0
[67]	Zhang et al. (2020)	Web of Science	1.0	1.0	1.0	3.0
[68]	Hlaing et al. (2022)	Web of Science	1.0	0.5	1.0	2.5
[69]	Li et al. (2024)	Science Direct	1.0	0.0	1.0	2.0
[70]	Wang et al. (2024)	Web of Science	1.0	1.0	1.0	3.0
[71]	Yusuf et al. (2024)	IEEE Xplore	0.5	0.5	1.0	2.0
[72]	Li et al. (2020)	Web of Science	1.0	1.0	1.0	3.0
[73]	Zhang et al. (2021)	Web of Science	1.0	1.0	1.0	3.0
[74]	Lankford et al. (2022)	Scopus	1.0	0.5	1.0	2.5
[75]	Liu et al. (2020)	SpringerLink	0.5	1.0	1.0	2.5
[76]	Lalrempuii and Soni (2023)	SpringerLink	1.0	1.0	1.0	3.0
[77]	Zheng and Che (2023)	SpringerLink	1.0	1.0	1.0	3.0
[78]	Rubino et al. (2020)	SpringerLink	1.0	1.0	1.0	3.0
[79]	Sujaini et al. (2023)	Web of Science	1.0	1.0	1.0	3.0
[80]	Liu et al. (2021)	SpringerLink	0.0	1.0	1.0	2.0
[81]	Wijono et al. (2023)	Web of Science	1.0	1.0	1.0	3.0
[82]	Vu and Bui (2023)	Web of Science	1.0	1.0	1.0	3.0
[83]	Jain et al. (2020)	Web of Science	1.0	1.0	1.0	3.0
[84]	Escolano et al. (2021)	Web of Science	1.0	1.0	0.5	2.5
[85]	Fernando et al. (2023)	SpringerLink	1.0	1.0	1.0	3.0
[86]	Sarveswaran et al. (2021)	SpringerLink	1.0	0.5	0.5	2.0
[87]	Gete and Etchegoyhen (2022)	SpringerLink	1.0	1.0	1.0	3.0
[88]	Luo et al. (2020)	Web of Science	1.0	1.0	1.0	3.0
[89]	Dhanjal and Singh (2022)	SpringerLink	1.0	1.0	0.5	2.5
[90]	Lone et al. (2023)	SpringerLink	1.0	0.5	1.0	2.5
[91]	Jha and Patil (2023)	SpringerLink	1.0	1.0	1.0	3.0
[92]	Meetei et al. (2023)	ScienceDirect	1.0	0.5	1.0	2.5
[93]	Yousuf et al. (2024)	IEEE Xplore	1.0	1.0	1.0	3.0
[94]	Chen et al. (2024)	IEEE Xplore	1.0	1.0	1.0	3.0
[95]	Singh and Singh (2022)	SpringerLink	1.0	1.0	1.0	3.0
[96]	Li et al. (2024)	IEEE Xplore	1.0	0.5	1.0	2.5
[97]	Karyukin et al. (2023)	Web of Science	1.0	1.0	0.5	2.5
[98]	Gutherz et al. (2023)	Web of Science	1.0	1.0	1.0	3.0
[99]	Orken et al. (2022)	SpringerLink	1.0	1.0	1.0	3.0
[100]	Bhagwat et al. (2023)	SpringerLink	1.0	1.0	1.0	3.0
[101]	Sanchez-Cartagena et al. (2024)	IEEE Xplore	0.5	0.5	1.0	2.0
[102]	Maimaiti et al. (2021)	IEEE Xplore	1.0	1.0	1.0	3.0

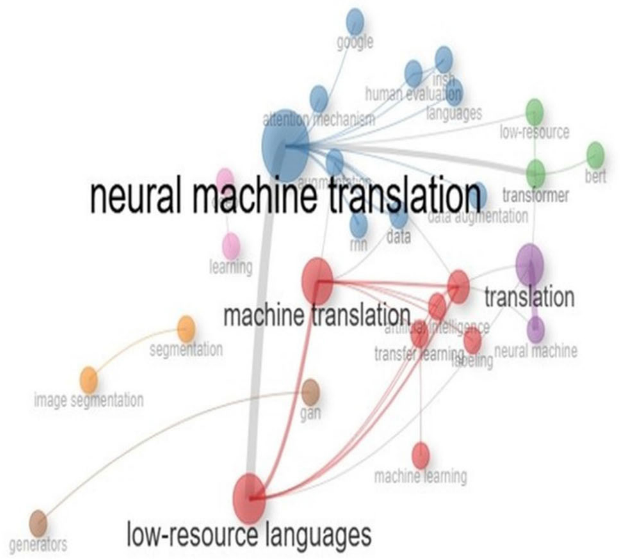

FIGURE 3. Key themes co-occurrence.

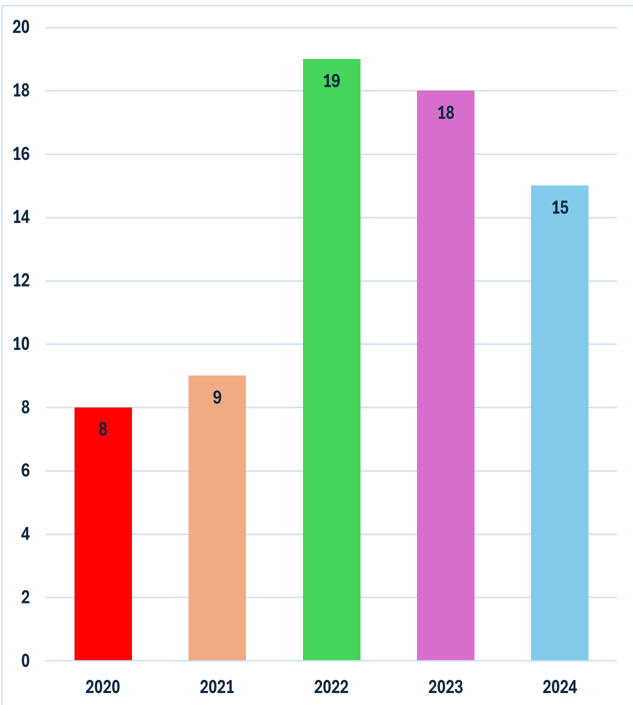

FIGURE 4. Year-wise publication trend of the studied articles.

reflecting the ongoing efforts at addressing the unique challenges posed by these languages in the field of MT. Table 7 provides an analysis of MT techniques used for low-resource languages. It categorizes the studied articles based on specific techniques, with transformer-based MT architecture being the most predominant. Other notable techniques include statistical MT, and transfer learning. Hybrid and unsupervised approaches are among the less used techniques in the studied articles.

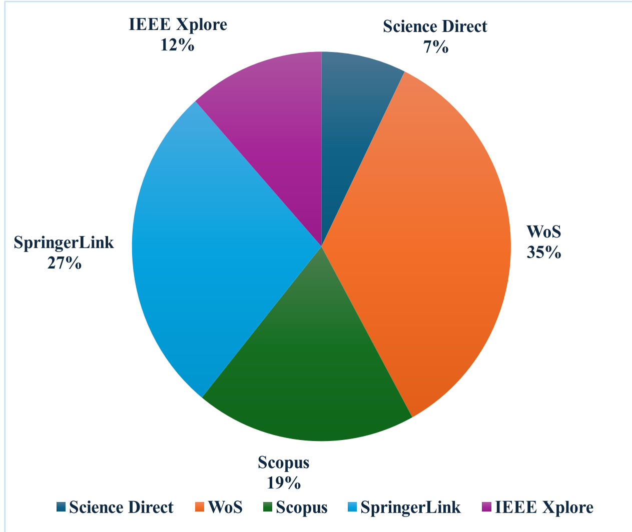

FIGURE 5. Database wise distribution of studied artilces.

4) VARIATION IN ACCURACY AND EFFECTIVENESS OF MT TECHNIQUES ACROSS DIFFERENT LOW-RESOURCE LANGUAGES (RQ1.4)

Accuracy in translation refers to the exactness of the translation in terms of word choice and grammatical structure, that is the degree of similarity between the original text in one language and its equivalent in another language [103]. Effectiveness in translation, on the other hand, refers to the overall ability of a translation method to achieve its intended goal [104]. In the case of MT for low-resource languages, this includes not only accuracy, but also other factors such as adaptability, robustness, and utility resources of the translation systems. Table 8 summarises the accuracy and effectiveness of various MT techniques across different low-resource languages as used in the studied articles. MT Techniques covered include data augmentation, example-based, hybrid, multimodal, multilingual models, pivot-based translation, rule-based, statistical MT, transfer learning, transformer architecture, unsupervised methods, and meta learning. Each technique is assessed for its performance in translating specific languages, highlighting which methods are more successful in terms of accuracy and effectiveness. The comprehensive evaluation indicates that while all techniques show promise, transformer-based models (i.e. NMT models) are particularly effective across a wide range of languages.

B. PRIMARY CHALLENGES AND LIMITATIONS FACED BY MT OF LOW-RESOURCE LANGUAGES (RQ2)

Despite significant advances in MT, low-resource languages continue to pose challenges that hinder the development of

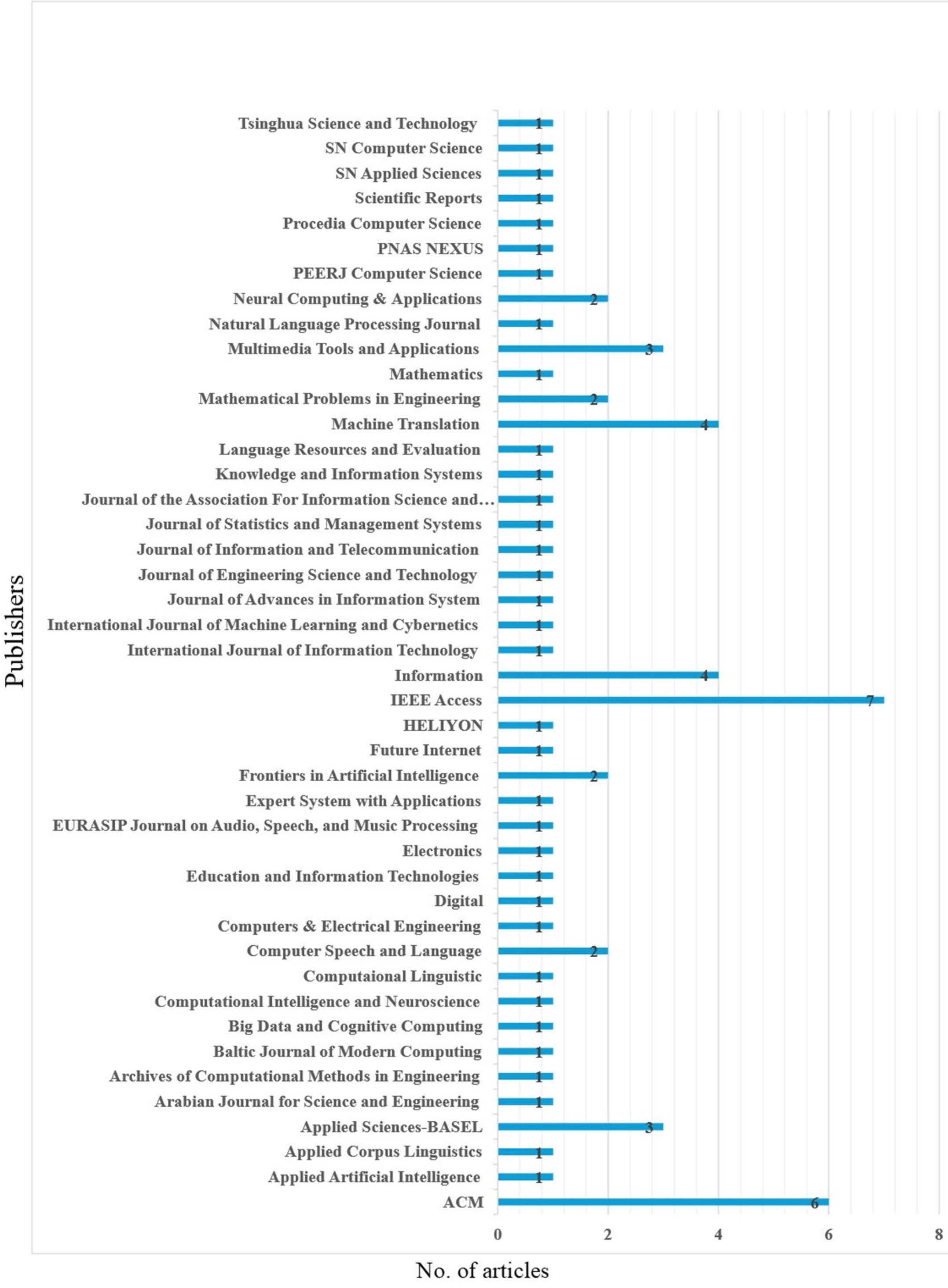

FIGURE 6. Publisher wise distribution of studied artilces.

robust translation systems. This section examines the main challenges and limitations faced by MT systems for these languages and how the specific challenges affect the overall performance of MT systems.

1) CHALLENGES AND LIMITATIONS FACED BY MT SYSTEMS WHEN PROCESSING LOW-RESOURCE LANGUAGES (RQ2.1)

The study shows that while there are many challenges and limitations common to all low-resource languages, the extent

TABLE 7. Studied articles based on MT techniques.

MT techniques	No. of studied articles	Reference(s)
Data augmentation.	3	[77]. [82], [96].
Example-based.	1	[90].
Hybrid.	1	[52].
Multimodal.	2	[39], [92]
Multilingual models.	3	[12], [34], [85].
Rule-based.	3	[16], [52], [100].
Statistical MT.	15	[44], [47], [52], [60], [71], [69], [75], [79], [86], [89], [90], [91], [93], [94], [100].
Transfer learning.	8	[38], [51], [53], [57], [59], [64], [71], [93].
Transformer architecture	47	[16], [34], [38], [40], [41], [42], [43], [44], [45], [46], [48], [49], [50], [52], [54], [54], [56], [59], [60], [61], [62], [63], [65], [67], [68], [69], [70], [72], [72], [74], [75], [76], [78], [80], [81], [83], [84], [87], [88], [90], [91], [95], [97], [98], [99], [101], [102].
Unsupervised learning.	1	[34].
Meta learning	1	[66].

to which they have been investigated varies considerably. Table 9 categorises the challenges and limitations in MT for low-resource languages, as evidenced by various articles studied. A primary issue is the lack of sufficient training data, as many languages, including Hindi, Tamil, and Vietnamese, do not have adequate datasets, which hampers performance. Additionally, structural variability among languages, such as Japanese and Amharic, complicates translation due to differing language structures. Complex morphology in languages like Japanese and Indonesian further complicates accurate translation. During the training process, error propagation and training instability can lead to performance issues, affecting languages such as German and Arabic. Tokenization problems arise when breaking text into smaller units, complicating translation for languages like Bengali and Hindi. Lexical challenges related to vocabulary and structure also hinder translation efforts in languages like Tibetan and Tamil. Moreover, feature integration issues make it difficult to combine various linguistic and contextual features effectively, impacting languages like Bengali and Hindi. Finally, textual challenges, including fragmentary texts and the absence of standardised orthographies, pose additional obstacles for languages such as Akkadian and Uzbek. Collectively, these challenges highlight the multifaceted difficulties MT systems face, significantly affecting their overall effectiveness and accuracy in translating low-resource languages.

2) IMPACT OF SPECIFIC CONSTRAINTS OF LOW-RESOURCE LANGUAGES ON PERFORMANCE AND ACCURACY OF MT SYSTEMS (RQ2.2)

The study shows that the specific constraints of low-resource languages impact significantly on the performance and accuracy of MT systems. As highlighted in Table 10, one of the main challenges is the lack of sufficient training data and the poor quality of pseudo-parallel corpora, which results in insufficient word representation and less accurate translations, making model training difficult and limiting effectiveness. In addition, structural differences and the inherent difficulty of language pairs degrade translation quality, while complex morphological and lexical challenges make it difficult to generate high-quality cross-linguistic embeddings, negatively impacting prediction accuracy. Problems with the generalization of the model further worsen the situation, leading to instability and inconsistent performance in different contexts. The complexity of the language makes it difficult to create standardized datasets and limits the generalizability of MT techniques. In addition, tokenization issues lead to fragmented translations, and textual challenges hinder the alignment of parallel data, which has a negative impact on translation quality. Finally, feature integration issues lead to noise and reduce overall effectiveness. Overall, the limitations outlined present a significant obstacle for MT systems, hindering their ability to generate dependable and precise translations for languages with limited resources and support.

C. STRATEGIES AND METHODOLOGIES PROPOSED OR USED TO ENHANCE THE PERFORMANCE OF MT SYSTEMS FOR LOW-RESOURCE LANGUAGES (RQ3)

To overcome the inherent challenges of translating low-resource languages, researchers have proposed and implemented a variety of innovative strategies and methods. This section analyses these approaches, and the metrics used to validate them.

1) STRATEGIES AND METHODOLOGIES FOR IMPROVING THE PERFORMANCE OF MT SYSTEMS FOR LOW-RESOURCE LANGUAGES (RQ3.1)

The studied articles employed various strategies and methodologies to enhance the performance of MT systems for

TABLE 8. Accuracy and effectiveness of MT techniques across different low-resource languages in the studied articles.

MT techniques	Low-resource languages	Techniques accuracy	Techniques effectiveness
Data augmentation	Estonia, German, Nepali, Romania. Russia, Sinhala, Swahili, Turkish, Urdu, Vietnamese.	√	√
Example-based	Assamese, Bengali, Bodo, Dogri, Gujarati, Hindi, Kannada, Kashmiri, Konkani, Dogri, Santali, Maithili, Malayalam, Manipuri, Marathi, Nepali, Odia, Punjabi, Sanskrit, Santali, Sindhi, Tamil, Telugu and Urdu.	√	√
Hybrid	Assamese, Bengali, Devnagari, Dogri, Gujarati, Kannada, Malayalam, Marathi, Punjabi, Sinhala, Tamil, Telugu and Urdu.	√	√
Multimodal	Hausa and Hindi.	√	√
Multilingual models	Irish, Marathi, Sinhala, Tamil and Turkish.	√	√
Pivot-based translation	Japanese, Indonesian and Malay.	√	√
Rule-based	Assamese, Bengali, Devnagari, Dogri, Gujarati, Hindi, Kannada, Kannada, Malayalam, Marathi, Punjabi, Punjabi, Sinhala, Tamil, Telugu and Urdu.	X	√
Statistical MT	Afrikaans, Amharic, Arabic, Assamese, Bahasa, Bangla, Batak Toba, Belorussian, Bengali, Bodo, Bosnian, Dayak Ahe, Dayak Taman, Devnagari, Dogri, Dogri, Dutch, German, Gujarati, Hindi, Indonesian, Javanese, Kannada, Kashmiri, Kromo, Madura, Pontianak, Malay, Malayalam, Marathi, Melayu Ketapang, Melayu Pontianak, Melayu Sambas, Minang, Mizo, Ngoko, Odia, Persian, Polish, Punjabi, Punjabi, Santali, Serbian, Sinhala, Sinhalese, Sundanese, Tamil, Telugu and Vietnamese.	√	√
Transfer learning	Algerian Arabic, Bengali, Hausa, Kazakh, Khasi, Nepali, Sinhalese and Vietnamese.	√	√
Transformer architecture	Akkadian, Algerian Arabic, Amharic, Arabic, Ashaninka, Assamese, Aymara, Azerbaijani, Bangla, Basque, Bengali, Bodo, Bribri, Catalan, Czech, Devnagari, Dogri, Dravidian, German, Gujarati, Hausa, Hebrew, Hindi, Ibo, Indo-Aryan, Indonesian, Irish, Japanese, Javanese, Kannada, Kashmiri, Kazakh, Khasi, Khmer, Korea, Lao, Maghrebi, Malay, Malayalam, Manipuri, Marathi, Mizo, Myanmar, Nahuatl, Nepali, Odia, Otomí, Pashto, Persian, Polish, Punjabi, Quechua, Raramuri, Romania, Russia, Sanskrit, Santali, Shipibo-Konibo, Sinhala, Sinhalese, Spanish, Swahili, Tamil, Telugu, Tibetan, Turkish, Twi, Urdu, Uyghur, Uzbek, Vietnamese, Walaytta, Wixarika and Yoruba.	√	√
Unsupervised learning	Indonesia and Japanese.	√	√
Meta learning	Afrikaans, Arabic, Breton, Burmese, Catalan, Croatian, Czech, Finnish, French, Galician, Greek, Gujarati, Irish, Kannada, Kazakh, Malayalam, Maltese, Marathi, Odia, Pashto, Portuguese, Romanian, Russian, Sorbian, Spanish, Tamil, Telugu, Ukrainian, Urdu, Welsh and Yoruba.	√	√

low-resource languages as seen in Table 11. These strategies include active learning, data augmentation, embedding alignment, optimization of decoder, and multilingual models, among others. These approaches aim to address the challenges associated with translating languages that have limited digital resources. The review highlights the importance of a multifaceted approach, combining active learning to efficiently utilize data, data augmentation to expand training datasets, embedding alignment to capture semantic similarities across languages, and multilingual models to leverage shared representations. Additionally, the role of transfer learning, optimization of decoder parameters, and rule-based approaches in further refining MT systems were emphasised. This suggests that a combination of these strategies offers a comprehensive solution for improving MT performance in resource-limited contexts.

TABLE 9. Challenges and limitations of MT for low-resource languages.

MT challenges and limitations	Description	Low-resource languages	No. of studied articles	Reference(s)
Lack of sufficient training data and poor quality of pseudo-parallel corpora.	Relates to the availability and quality of data necessary for effective machine translation.	Amharic, Assamese, Bengali, Catalan, Czech, Filipino, German, Hausa, Hindi, Indic, Indonesian, Irish, Japanese, Kannada, Kazakh, Khasi, Khmer, Konkani, Korean, Lao, Livonian, Malagasy, Malay, Malayalam, Marathi, Mizo, Myanmar, Nepali, Oriya, Pashto, Persian, Polish, Punjabi, Romanian, Russian, Sami, Sanskrit, Santali, Sinhala, Swahili, Tamil, Telugu, Tibetan, Turkish, Twi, Urdu, Uyghur, Vietnamese, Voro and Wolaytta.	63	[12]. [16], [38], [39], [40], [41], [42], [43], [44], [45], [46], [47], [48], [49], [50], [52], [53], [54], [55], [56], [57], [58], [59], [60], [61], [62], [63], [64], [65], [66], [68], [69], [70], [71], [72], [73], [74], [75], [76], [77], [78], [79], [80], [82], [83], [84], [85], [86], [87], [88], [89], [90], [91], [92], [93], [94], [95], [96] [97], [99], [100], [101], [102].
Structural variability and language pair difficulty.	These challenges and limitations pertain to the complexities arising from differences in language structures and how they align during translation.	Amharic, Basque, Bengali, German, Gujarati, Hindi, Indonesian, Japanese, Kannada, Khasi, Malay, Malayalam, Marathi, Persian, Punjabi, Sanskrit, Sinhala, Spanish, Tamil, Telugu, Turkish and Vietnamese.	10	[34], [38], [46], [47], [49], [51], [52], [61], [85], [87].
Complex morphology and lexical challenge.	Involves difficulties related to the structure and vocabulary of languages.	Amharic, Arabic, Assamese, Basque, Bengali (Bangla), German, Gujarati, Hindi, Indic Mizo, Indonesian, Irish, Japanese, Kannada, Khasi, Konkani, Malay, Malayalam, Marathi, Nepali, Oriya, Punjabi, Sanskrit, Santali, Sinhala, Spanish, Tamil, Telugu, Tibetan, Twi, Urdu, Vietnamese and Wolaytta.	32	[12], [16], [34], [40], [41], [42], [45], [47], [50], [51], [52], [54], [60], [64], [66], [67], [69], [72], [76], [80], [81], [83], [85], [86], [87], [89], [90], [91], [94], [95], [101], [102].
Model generalization issues and training complexity.	Related to the intricacies of training models and their ability to generalize across different contexts.	Batak Toba, Dayak Ahe, Dayak Taman, German, Javanese Kromo, Javanese Ngoko, Kazakh, Korean, Livonian, Madura, Melayu Ketapang, Melayu Pontianak, Melayu Sambas, Minang, Romanian, Russian, Sami, Santali, Sundanese, Tiociu Pontianak, Uyghur, Vietnamese, Voro and Wolaytta.	7	[48], [50], [53], [58], [62], [79], [90].
Language complexity.	Inherent difficulties that arise from the structural and linguistic characteristics of the languages involved such as language pair difficulty, language dissimilarity and dialect diversity.	Algerian Arabic, Amharic, Assamese, Aymara, Bengali, Bodo, Bribri, Catalan, Czech, Dogri, Guarani, Gujarati, Indonesian, Irish, Kannada, Kashmiri, Kazakh, Khmer, Konkani, Korea, Lao, Maithili, Malayalam, Manipuri, Marathi, Nahuatl, Nepali, Odia, Otomi, Pashto, Polish, Punjabi, Quechua, Raramuri, Sanskrit, Santali, Shipibo-Konibo, Sindhi, Sinhala, Tamil, Telugu, Tibetan, Twi, Urdu, Uyghur, Vietnamese and Wixarika.	15	[16], [43], [44], [51], [54], [57], [64], [65], [74], [79], [80], [82], [91], [100], [102].
Error propagation, training instability and catastrophic forgetting.	Issues that arise during the training process.	Arabic, Catalan, Czech, German, Indonesian, Japanese, Kazakh, Khmer, Korea, Lao, Malay, Nepali, Pashto, Polish, Romania, Russia, Sinhala, Tamil, Tibetan, Turkish, Uyghur and Vietnamese.	5	[43], [56], [57], [78], [84].
Tokenization problems.	Problems that arises when texts are broken down into smaller units, or tokens, which can be words, sub-words or phrases.	Bengali (Bangla), Gujarati, Hindi, Kannada. Malayalam, Punjabi, Tamil, Telugu and Urdu.	1	[94].
Textual challenges.	Difficulties that arise from the nature and quality of the text being translated such as fragmentary texts and absence of standardized orthographies.	Akkadian, Azerbaijani and Uzbek.	2	[98], [102].

TABLE 9. ***(Continued.)*** **Challenges and limitations of MT for low-resource languages.**

Feature integration issues.	Referring to the challenges associated with effectively combining various linguistic and contextual features into a cohesive translation model.	Bengali, Filipino, Hindi, Indonesian, Khmer, Malay, Myanmar and Vietnamese.	1	[17].

TABLE 10. **Constraints'impact on MT of low-resource languages.**

MT challenges and limitations	No. of studied articles	Reference(s)	Impact of the specific constraint on the performance and accuracy of MT systems
Lack of sufficient training data and poor quality of pseudo-parallel corpora.	62	[12], [34], [38], [39], [40], [41], [42], [43], [44], [45], [46], [47], [48], [49], [50], [52], [53], [54], [55], [56], [57], [58], [59], [60], [61], [62], [63], [64], [65], [66], [68], [69], [70], [71], [72], [73], [74], [75], [76], [72], [78], [79], [80], [82], [83]. [84], [85], [86], [87], [88], [89], [90], [91], [92], [93], [94], [97], [98], [99], [100], [101], [102].	Poor representation of words, less accurate translations, difficult models' training, limits the effectiveness of MT systems.
Structural variability and language pair difficulty.	9	[34], [40], [41], [43], [45], [46], [55], [80], [82].	Complication of translation, degrade translation accuracy and quality.
Complex morphology and lexical challenge.	31	[12], [34], [38], [40], [41], [42], [45], [46], [50], [51], [52], [54], [60], [64], [66], [67], [69], [72], [76], [80], [81], [83], [85], [86], [87], [89], [91], [94], [95], [101], [102].	Difficulty in generating high-quality cross lingual embeddings which impacts the prediction quality, hinders performance of MT model and complicates generation of accurate embeddings.
Model generalization issues and training complexity.	7	[48], [50], [53], [62], [73], [79], [90].	Limits the MT model's generalizability to other contexts, instability and inconsistent performance.
Language complexity.	15	[42], [43], [44], [51], [54], [57], [64], [65], [74], [79], [80], [82], [91], [100], [102].	It is difficult to create a standardized dataset, complicating the translation process, limiting MT techniques generalizability.
Error propagation, training instability and catastrophic forgetting.	5	[43], [56], [57], [78], [84].	Limits the accuracy, reliability, and scalability of translation systems.
Tokenization problems.	1	[93].	Fragmented and less accurate translations.
Textual challenges.	2	[98], [102].	Complicates the alignment of parallel data and affects translation quality.
Feature integration issues.	1	[17].	Addition of noise and reduction in effectiveness.

2) METRICS USED TO VALIDATE STRATEGIES AND METHODOLOGIES FOR LOW-RESOURCE MT SYSTEM (RQ3.2)

The strategies and methodologies used in improving MT performance in the studied articles have been validated through a comprehensive analysis of various performance metrics, as highlighted in Table 12. The BLEU score was utilized in 10 articles, while the Translation Edit Rate (TER) was the most frequently applied metric, appearing in 59 articles, indicating its widespread acceptance for assessing translation quality. Other metrics such as METEOR, Recall-Oriented Understudy for Gisting Evaluation (ROUGE), and Character n-gram F-score (ChrF) were also employed, with 41, 5, and 58 articles respectively, showcasing a diverse approach to evaluation. Additionally, the Word Error Rate (WER) was referenced in 32 articles, further emphasizing its relevance in performance assessment. The inclusion of Google's variant of BLEU (Gleu) in 5 articles highlights the exploration of alternative evaluation methods. F1-score has the list references, probably because it is primarily designed for classification tasks [105] and not for sequence generation tasks like translation. This multifaceted validation approach underscores the robustness of the methodologies, as they are assessed through various established metrics, allowing for a comprehensive understanding of their effectiveness in translation tasks.

V. LIMITATION

Although the SLR on MT for low-resource languages is comprehensive, it has several limitations. First, the study focuses only on articles published between 2020 and 2024. This time limitation may result in the exclusion of relevant baseline studies or earlier methods that could provide valuable context or insight into the development of MT techniques. In addition,

TABLE 11. Strategies and methodologies proposed/used to improve the performance of MT systems for low-resource languages.

Strategies/Methodologies	No. of Studied Articles	Reference(s)
Active learning.	58	[12], [39], [40], [41], [42], [43], [44], [45], [46], [47], [48], [49], [50], [52], [53], [54], [55], [56], [57], [58], [59], [60], [61], [62], [63], [64], [65], [66], [68], [69], [72], [73], [74], [75], [76], [77], [78], [79], [80], [82], [83]. [84], [85], [86], [87], [88], [89], [90], [91], [92], [93], [94], [95], [96], [97], [100], [101], [102].
BERT supervision method.	56	[12], [39], [40], [41], [42], [43], [44], [45], [46], [47], [48], [49], [50], [52], [53], [54], [55], [56], [57], [58], [59], [60], [61], [62], [63], [64], [65], [66], [68], [73], [74], [75], [76], [77], [78], [79], [80], [82], [83]. [84], [85], [86], [87], [88], [89], [90], [91], [92], [93], [94], [95], [96], [97], [100], [101], [102].
Data augmentation.	57	[12], [16], [39], [40], [41], [42], [43], [44], [45], [46], [47], [48], [49], [50], [52], [53], [54], [55], [56], [57], [58], [59], [60], [61], [62], [63], [64], [65], [66], [68], [73], [74], [75], [76], [77], [78], [79], [80], [82], [83]. [84], [85], [86], [87], [88], [89], [90], [91], [92], [93], [94], [95], [96], [97], [100], [101], [102].
Data pre-processing.	40	[12], [34], [44], [48], [56], [57], [58], [59], [60], [61], [62], [63], [64], [65], [66], [68], [73], [74], [75], [76], [77], [78], [79], [80], [82], [83], [84], [85], [86], [87], [88], [89], [90], [91], [92], [93], [94], [95], [96], [97].
Document and sentence alignment.	9	[34], [46], [47], [49], [51], [52], [61], [85], [87].
Embedding alignment.	5	[43], [56], [57], [78], [84].
Hybrid approaches.	1	[94].
Lexical constraint mechanism.	8	[48], [53], [58], [60], [62], [73], [79], [90].
Multilevel unit and semantic/linguistic information modelling.	15	[34], [43], [44], [51], [54], [57], [64], [65], [74], [79], [80], [82], [91], [100], [102].
Multilingual models.	56	[12], [39], [40], [41], [42], [43], [44], [45], [46], [47], [48], [49], [50], [52], [53], [54], [55], [56], [57], [58], [59], [60], [61], [62], [63], [64], [65], [66], [68], [73], [74], [75], [76], [77], [78], [79], [80], [82], [83], [84], [85], [86], [87], [88], [89], [90], [91], [92], [93], [94], [95], [96], [97], [100], [101], [102].
Optimization of decoder parameters.	30	[12], [34], [40], [41], [42], [45], [46], [50], [51], [52], [54], [60], [64], [66], [67], [68], [72], [76], [80], [82], [84], [85], [87], [89], [90], [92], [94], [95], [101], [102].
Oversampling approach.	2	[98], [102].
Rule-based approach.	31	[12], [34], [40], [41], [42], [45], [47], [50], [51], [52], [54], [60], [64], [66], [67], [69], [72], [76], [80], [81], [83], [85], [86], [87], [89], [90], [91], [94], [95], [101], [102].
Transfer learning.	60	[12], [16], [34], [38], [39], [40], [41], [42], [43], [44], [45], [46], [47], [48], [49], [50], [52], [53], [54], [55], [56], [57], [58], [59], [60], [61], [62], [63], [64], [65], [66], [68], [71], [73], [74], [75], [76], [77], [78], [79], [80], [82], [83], [84], [85], [86], [87], [88], [89], [90], [91], [92], [93], [94], [95], [96], [97], [100], [101], [102].
Transformer encoder-decoder architecture.	9	[34], [46], [47], [49], [51], [52], [61], [85], [87].

the exclusion of non-English articles may further limit the scope and potentially overlook important research in other languages that could provide a more complete view of the challenges and advances in MT for low-resource languages.

Secondly, the study relies on specific academic databases such as Science Direct, Web of Science, Scopus, SpringerLink and IEEE and this may lead to bias in the selection of studies. These databases may not include all relevant literature, especially from new or less established sources that could offer innovative approaches or insights. In addition, the quality assessment process, though rigorous, is inherently subjective and may vary depending on the assessors' interpretation of the relevance and quality of the studies. This subjectivity could lead to the exclusion of potentially valuable studies that do not meet the predefined quality assessment criteria, thereby limiting the scope of the evidence generated in the review. Overall, these limitations suggest that while the SLR provides a valuable overview, it might not entirely encompass the diversity and complexity of research within the field of MT for low-resource languages.

TABLE 12. Metrics used in validation of strategies and methodologies.

Metric	No. of Studied Articles	Reference(s)
BLEU	11	[16], [34], [38], [46], [47], [49], [51], [52], [61], [85], [87].
TER	59	[12], [34], [38], [39], [40], [41], [42], [43], [44], [45], [46], [47], [48], [49], [50], [52], [53], [54], [55], [56], [57], [58], [59], [60], [61], [62], [63], [64], [65], [66], [69], [73], [74], [75], [76], [77], [78], [79], [80], [82], [83], [84], [85], [86], [87], [88], [89], [90], [91], [92], [93], [94], [95], [96], [97], [99], [100], [101], [102].
METEOR	41	[12], [34], [44], [48], [56], [57], [58], [59], [60], [61], [62], [63], [64], [65], [66], [69], [72], [73], [74], [75], [76], [77], [78], [79], [80], [82], [83], [84], [85], [86], [87], [88], [89], [90], [91], [92], [93], [94], [95], [96], [97].
ROUGE	5	[43], [56], [57], [78], [84].
ChrF	58	[12], [34], [38], [39], [40], [41], [42], [43], [44], [45], [46], [47], [48], [49], [50], [52], [53], [54], [55], [56], [57], [58], [59], [60], [61], [62], [63], [64], [65], [66], [68], [73], [74], [75], [76], [77], [78], [79], [80], [82], [83], [84], [85], [86], [87], [88], [89], [90], [91], [92], [93], [94], [95], [96], [97], [100], [101], [102].
WER	32	[12], [16], [34], [40], [41], [42], [45], [47], [50], [51], [52], [54], [60], [64], [66], [67], [69], [72], [76], [80], [81], [83], [85], [86], [87], [89], [90], [91], [94], [95], [101], [102].
Gleu	5	[48], [58], [74], [81], [94].
F1-score	2	[38], [71].

VI. CONCLUSION

This systematic review provided a comprehensive examination of the current state of MT techniques for low-resource languages. By adhering to PRISMA guidelines, the study has systematically identified and analysed relevant research, highlighting the challenges, limitations, and effective strategies employed in this critical area of study. The findings underscore the pressing need for innovative methodologies, such as LLMs fine-tuning for low-resource languages, prompt-based translation, multimodal translation, and knowledge-enhanced NMT, to improve translation performance and address the constraints faced by these languages.

The findings reveal that transformer-based NMT remains the dominant architecture for low-resource language translation tasks, with TER and ChrF emerging as the most frequently applied evaluation metrics. However, the emergence of LLMs such as GPT-4, is redefining the MT landscape by enabling cross-lingual generalization through zero-shot and few-shot learning, even in the absence of parallel corpora. Despite these advancements, data scarcity remains the most pressing challenge in low-resource MT. This constraint is being addressed through strategies such as multilingual modeling, synthetic data generation, and transfer learning. Based on these insights, future MT research should prioritize scalable data-efficient techniques, the integration of LLMs, and the development of open-access multilingual benchmarks to enhance translation quality and inclusivity for low-resource languages. This study ultimately provides a framework for additional research and advancement in the domain of MT, thus facilitating the development of more efficient and fair translation strategies for languages with limited resources and digital support.

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TAOFIK O. TAFA received the Bachelor of Science degree in computer science from the University of Uyo, Nigeria, in 2002, and the Master of Science degree in computer science from the University of Wolverhampton, U.K., in 2014. He is currently pursuing the Ph.D. degree in computer science with the Faculty of Computing, Universiti Teknologi Malaysia.

SITI ZAITON MOHD HASHIM received the B.Sc. degree in computer science from the University of Hartford, USA, the M.Sc. degree in computing from the University of Bradford, U.K., and the Ph.D. degree in soft computing from The University of Sheffield, U.K. She is currently an Associate Professor and the Deputy Dean (Research, Innovation and Development) of the Faculty of Computing, Universiti Teknologi Malaysia. She has authored more than 140 publications. Her research interests include soft computing and applications, machine learning, and intelligent systems.

MOHD SHAHIZAN OTHMAN received the B.Sc. degree in computer science from UTM, in 1998, and the M.Sc. and Ph.D. degrees in information technology from Universiti Kembangan Malaysia (UKM), in 2001 and 2008, respectively, specializing in web information extraction, information retrieval, and machine learning. He is currently an Associate Professor with the Faculty of Computing, Universiti Teknologi Malaysia (UTM). His expertise includes data analytics, machine learning, optimization, web mining, content management, AI-driven education analytics, e-learning, social learning, business intelligence, and geographic information systems (GIS).

HITHAM ALHUSSIAN (Senior Member, IEEE) received the B.Sc. and M.Sc. degrees in computer science from the School of Mathematical Sciences, Khartoum University, Sudan, and the Ph.D. degree from Universiti Teknologi PETRONAS, Malaysia. He is currently a Senior Lecturer with the Department of Computer and Information Sciences and a Core Research Member with the Centre for Research in Data Science (CERDAS), Universiti Teknologi PETRONAS. His current research interests include real-time parallel distributed systems, cloud computing, big data mining, machine learning, and secure computer-based management systems.

MAGED NASSER received the bachelor's degree in mathematics and computer science from Ibb University, Yemen, in 2013, the Master of Computer Science degree from Banaras Hindu University (BHU), India, in 2017, and the Ph.D. degree majoring in molecular similarity searching based on deep learning from Universiti Teknologi Malaysia, in 2022. From September 2022 to August 2023, he was a Postdoctoral Researcher with Universiti Sains Malaysia. He has been a Lecturer with the Department of Computer and Information Sciences, Universiti Teknologi PETRONAS, since September 2023. His research was on fake and spam news detection based on deep learning. He specializes in in computer science disciplines includes machine learning, deep learning, data mining, cheminformatics, and programming.

SAID JADID ABDULKADIR (Senior Member, IEEE) received the B.Sc. degree in computer science from Moi University, the M.Sc. degree in computer science from Universiti Teknologi Malaysia (UTM), and the Ph.D. degree in information technology from Universiti Teknologi PETRONAS (UTP). He is currently an Associate Professor and a member with the Centre for Research in Data Science (CeRDaS), UTP. He is involved in flagship consultancy projects for PETRONAS under pipeline integrity, materials corrosion, and inspection. His research interests include machine learning, deep learning architectures, optimizations, and applications in predictive analytics. He is serving as the Treasurer for the IEEE Computational Intelligence Society Malaysia Chapter and the Editor-in-Chief for *Platform* journal.

SHARIN HAZLIN HUSPI received the Ph.D. degree in computer science from RMIT University, Australia. She is currently the Director of the Applied Computing and Artificial Intelligence Department, Faculty of Computing, Universiti Teknologi Malaysia. She has more than 35 articles relevant to her research interests. Her research interests include natural language processing (NLP), data analytics, text mining and analytics, and user centered evaluation.

SARAFA O. ADEYEMO received the H.N.D. degree in computer science from The Federal Polytechnic Offa, Nigeria, in 2003, and the M.Sc. degree in computer science from the University of Wolverhampton, U.K., in 2014. He is currently pursuing the Ph.D. degree in computer science with the Universiti Teknologi Malaysia.

YUNUSA ADAMU BENA (Member, IEEE) received the Bachelor of Science degree in information technology (IT) from Kebbi State University of Science and Technology, Aliero, Nigeria, in 2012, and the Master of Science degree in information technology from Universiti Teknologi Malaysia, in 2018, where he is currently pursuing Ph.D. degree in computer science.