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TOPICAL REVIEW

The Impact of Artificial Intelligence on Language Translation: A Review

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ABSTRACT In the context of a more linked and globalized society, the significance of proficient cross-cultural communication has been increasing to a position of utmost importance. Language functions as a crucial medium that establishes connections among people, corporations, and countries, demanding the implementation of precise and effective translation systems. This comprehensive review paper aims to contribute to the evolving landscape of AI-driven language translation by critically examining the existing literature, identifying key debates, and uncovering areas of innovation and limitations. The primary objective is to provide a nuanced understanding of the current state of AI-driven language translation, emphasizing the advancements, challenges, and ethical considerations. In this review, ongoing debates surrounding AI-driven language translations were actively involved. By evaluating different viewpoints and methodologies, insights into unresolved questions that contribute to a broader discourse in the field were provided. The future trajectory of this study involves the incorporation of cross-lingual dialect adaptability and the advancement of Artificial Intelligence translation systems, with a focus on prioritizing inclusion and cultural understanding.

INDEX TERMS Artificial intelligence, language translation, machine translation.

I. INTRODUCTION

In today's age of burgeoning global interconnectedness, the necessity for seamless and efficient communication across diverse languages and cultures has become more imperative than previously. The emergence of Artificial Intelligence (AI) in linguistic translation has revealed novel possibilities portending to span communication chasms and enable more fruitful cross-cultural connections. This article examines the profound influence of AI on language translation through investigating how AI technologies are reconfiguring the translation industry. From examining refinements in machine learning algorithms to illuminating the ethical ramifications of automated translation, this article strives to tender an exhaustive survey of AI's capacity to transcend language obstacles in our progressively interlinked world. Accordingly, a comprehensive understanding of language and its culture associated with the source text, as well as the proficient grasp, should be reflected in the translation process as essential factors [1].

On the other hand, technical advancements have been evolving significantly to enhance efficiency and standards in the field of language translation, facilitating worldwide contact and highlighting the escalating need for inventive technical remedies that could address the longstanding challenge posed by language barriers or restrictions. Additionally, these technologies pose substantial hurdles and uncertainty for the translation profession and its related business [2]. Translating from one language into another is a challenging undertaking where translators must possess a comprehensive understanding of the linguistic intricacies involved in deciphering the overt and covert aspects of language. Moreover, the translation process involves the transfer and transformation of distinctive features from one language into another. Owing to their distinct and remote beginnings, the translation process between any two languages presents several challenges, including vocabulary, syntax, phonetics, style, and other linguistic-related aspects [3].

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Recently, remarkable advancements have been made in the domain of machine translation (MT), and the prominence of MT has increased due to the need to comprehend the vast array of information accessible on the Internet in several languages as well as the heightened level of international commerce. The effectiveness of MT has been significantly aided by computer speed resulting from developments in hardware components as well as the widespread availability of monolingual and bilingual data [4]. AI and MT were discussed for the first time in the context of the translation business by the authors of [5]. This raises the issue of whether MT powered by AI is better than human translation for a wide range of document formats. The purpose of the research is to show how the evolution of AI has affected translation by contrasting the pros and cons of machine and human translation.

In this age of rapid AI development, the abstract highlights the promise of forming a cooperative relationship between humans and AI to produce flawless translation. Their study considers the subtle complexities that arise when applying AI to the task of translating, with a focus on the Chinese language. Improvements in areas such as logical expressions and faithfulness to the source language have been highlighted. The authors pointed out that AI translation may be superior in terms of speed and content understanding, providing a more conventional and succinct linguistic style. Their findings imply that, although AI can help with basic grammatical analysis, human translators may compensate for the shortcomings of AI by recognizing connotations and logical frameworks. They promoted a balanced strategy that makes use of AI's effectiveness while still valuing human translators' contributions to the final product.

Regarding the field of translation education, namely at universities, the authors of the research cited in [6] stress the confluence of AI and MT. The major focus is on how AI and MT may be used in translation training programs for better preparation for future professionals. Although the use of computer-aided technology has increased in structured classroom settings, the authors stress that learners still face a serious dearth of intrinsic motivation in AI-driven self-learning environments. Their major objective was to investigate the potential effects of AI on translation education. It stresses the significance of creating principled ways, thinking critically about the issues that occur, and aligning with academic viewpoints to successfully include AI at higher education. Their study focused on the adaptable nature of MT and its potential to revolutionize the translation industry. Even though AI and MT have great potential for advancement, the authors concurred that it will be a long time before human translation can be fully automated. This demonstrates the ever-growing value of formal education and training in aspiring translators. Their article has raised important questions concerning the role of technology in education and its ability to replace teachers or empower students.

With an emphasis on neural machine translation (NMT), mostly based on deep learning techniques, this research offers thorough details on AI-based machine translation techniques. It looks into their achievements and shortcomings. The following is a summary of the article's contribution:

- Examining the cutting-edge methods for MT, with an emphasis on those powered by AI.
- Investigating the current statistical machine translation (SMT) techniques and highlighting their achievements and limitations in relation to rule-based translation (RT) and NMT techniques.
- Providing a comprehensive overview of NMT techniques, emphasizing the rapid advancement in this era and how these approaches significantly enrich MT.
- Examining and summarizing the current challenges of MT methods.
- Investigating several methods for fuzzy logic and natural language processing (NLP).
- Addressing how NLP and Fuzzy logic techniques can improve the performance of MT when integrating them with NMT.
- Investigating the significant influence of feature extraction techniques in improving the translation accuracy and performance of MT. It analyzes different feature extraction methods, demonstrating their significance in translation and pointing out areas for potential improvements.
- Discussing the assessment metrics that are frequently used to evaluate MT and how, when applied appropriately, these measures are significant in reflecting a model's performance.

This section gives a brief introduction to MT and the emergence of AI in this field. It sheds light on the significant enhancement of language translation owing to the advancement in technology. In addition, the section lists the contributions of this article. The rest of the article is organized as follows: Section II introduces the fundamentals of AI in language translation. Section III, which is considered the core of this work, has addressed several MT methods with a focus on SMT and NMT techniques. It gives a thorough review of these techniques and addresses their pros and cons. In addition, it provides a comparative analysis of NMT techniques, highlighting their strengths and areas of improvement. NLP and fuzzy logic are also discussed in this section, addressing their significant contribution to enhancing MT methods. Subsequently, Section IV highlights the importance of features extraction and selection, illustrating their significant role in improving MT accuracy and performance, whereas the evaluation metrics that are frequently used to assess MT models are addressed in Section V.

Section VI provides a thorough discussion of the article's outcomes, and finally, the article concludes in Section VII. This comprehensive investigation aims to contribute to the evolving landscape of AI-driven language translation by critically examining the current state, challenges, and innovations in the field. The exploration encompasses the intricate interplay between language, technology, and culture, acknowledging both the potential and limitations of AI in reshaping communication across diverse linguistic contexts.

Through this exploration, the authors endeavor to shed light on the transformative influence of AI on language translation, emphasizing the need for a nuanced understanding of the evolving dynamics in this field. The integration of AI and MT, coupled with advancements in deep learning techniques, presents a promising trajectory for the future of translation technology. As the global community becomes increasingly interconnected, the role of AI in breaking down language barriers and fostering cross-cultural communication gains prominence.

In conclusion, the introduction sets the stage for a comprehensive exploration of AI-driven language translation, emphasizing its significance in today's interconnected world. The authors navigate through the complex landscape of language translation, addressing challenges, advancements, and the evolving role of AI in reshaping communication dynamics. The subsequent sections delve deeper into specific aspects, providing a holistic understanding of the intricate relationship between AI and language translation.

II. FUNDAMENTALS OF AI IN LANGUAGE TRANSLATION

(AI), particularly NLP, has been increasingly revolutionizing the translation industry. NLP bridges the gap between humans and computers by improving communication through a better comprehension, processing, and generation for language produced. Modern settings rely heavily on AI-driven translation and other language-centric technologies [7]. Tokenization, part-of-speech (POS) tagging, Named Entity Recognition (NER), syntax analysis, and sentiment analysis are examples of many methods that fall under the umbrella term "natural language processing". NLP has been improved with the help of deep learning, particularly the use of neural networks with attention mechanisms. The important first steps include preprocessing operations, such as tokenization and stemming. NLP provides the backbone for language translation in the ever-evolving field of AI [8].

III. AI-BASED TRANSLATION APPROACHES

This section explores several language translation systems rooted in AI, including statistical and NMT. These breakthroughs signify noteworthy accomplishments in the domains of human creativity and technical growth. In this section, the unique attributes, practical implementations, and pioneering approaches linked to the topic were examined. AI systems use a variety of components, including data, neural networks, and linguistic expertise to effectively comprehend the intricacies inherent in many languages. Furthermore, this section investigates hybrid methodologies that combine rule-based and data-centric artificial intelligence systems to enhance translation precision. These technical advancements enable overcoming language obstacles, understanding idiomatic expressions, interpreting contextual cues, and identifying emotional states. Consequently, these platforms of translation facilitate the improvement of cross-cultural dialogue and enable knowledge acquisition. Fig. 1 showcases AI-approaches that are commonly used in translation.

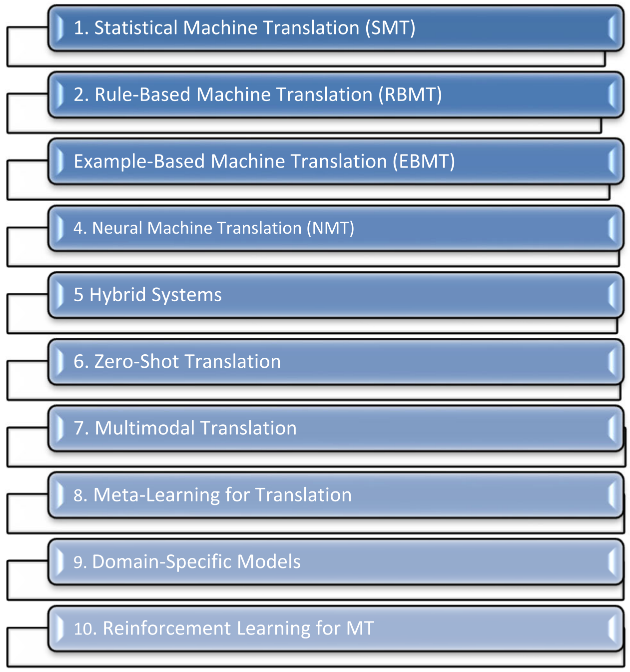

FIGURE 1. AI-based translation approaches.

This section is organized as follows: Subsection A gives a brief introduction to the impact of machine learning (ML) and deep learning (DL) in MT, with more focus on DL approaches. Subsequently, Subsection B discusses SMT with highlighting their achievements and shortcomings, whereas a thorough investigation of NMT is presented in Section C. Finally, Subsections D and E shed light on the improvement of MT when considering fuzzy logic and NLP, respectively.

A. MACHINE LEARNING (ML) AND DEEP LEARNING (DL) IN TRANSLATION

ML and DL are closely connected concepts in the realm of artificial intelligence (AI), which includes the process of instructing computer systems to execute tasks without explicit programming. Transformative technologies have played a pivotal role in driving notable progress across several domains, such as language translation [9].

The two subsections below introduce both ML and DL and cover some translation approaches based on these techniques.

1) MACHINE LEARNING

The process of training computer systems to identify patterns and draw conclusions by analyzing data is referred to as computational learning. The technique involves providing a computer with a dataset and allowing it to learn knowledge from data, thereby gradually boosting its performance. Machine learning algorithms are designed with the

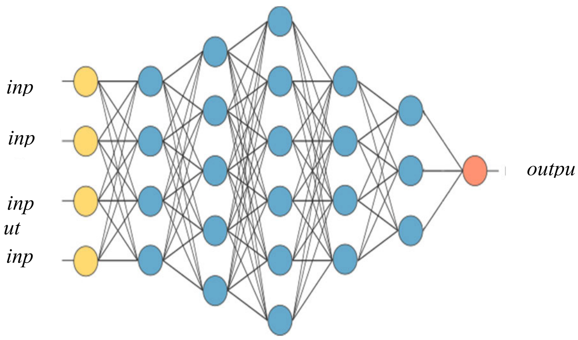

FIGURE 2. DL architecture.

explicit purpose of extracting patterns that can be applied to a wide range of datasets, allowing them to make predictions or assess new unseen data [10]. The core focus on the use of machines is to facilitate the process of identifying patterns, linkages, and trends within data without the need for explicit programming. ML can be categorized into several types, including supervised learning. In supervised learning, an algorithm is used to analyze a dataset consisting of labeled instances. Each input data point in the dataset is accompanied by its corresponding output label. The algorithm develops the capacity to create a relationship between input and output values, allowing it to provide predictions for previously unseen data. Unsupervised learning refers to the examination of unannotated data to identify intrinsic patterns, clusters, or structures in a dataset. Two commonly used techniques in the field of data analysis are clustering and dimensionality reduction [11].

Using a computer method called reinforcement learning, autonomous agents can be trained to make decisions in a sequential fashion via repeated experiences with their environment. The system provides either reinforcement or punishment in response to the agent's actions. This leads to agent learning and change so that it can maximize the outcomes of its activities and the rewards it receives [12].

2) DEEP LEARNING

DL is a distinct subfield of ML that focuses on the use of neural networks to effectively capture complex patterns and representations in datasets. Neural networks are composed of interconnected layers of nodes, often referred to as neurons, which are responsible for the processing and manipulation of data [13]. DL models, sometimes referred to as deep neural networks, include several concealed layers that facilitate the acquisition of hierarchical data representations [14]. The term "Deep" in the context of DL refers to the inclusion of several hidden layers inside the neural network design, as seen in Fig. 2. DL relies heavily on Artificial Neural Networks (ANNs) [15].

There are three primary layers in a neural network: input, hidden, and output layers. Weighted connections link each neuron at these levels to its neighbors in the adjacent layers. In jobs involving large datasets and intricate patterns, such as picture and audio identification, language processing, and the creation of autonomous vehicles, DL models appear to be superior [16].

ML is a broad concept encompassing several approaches. In contrast, DL focuses only on the use of deep neural networks to perform tasks that require sophisticated feature extraction and representation learning. DL has attracted significant attention because of its ability to automatically learn relevant features from raw data, thus reducing the need for human feature engineering [17].

ML and DL have both been significant contributors to the field of language translation. The domain of translation systems has undergone substantial evolution in terms of precision and coherence, mostly attributed to the progress made in DL methodologies, namely, via the use of models such as transformers. These models can grasp complex linguistic patterns and contextual cues, thereby augmenting their proficiency in generating translations that are more genuine and coherent [18].

An alternative approach to training Recurrent Neural Network (RNN) for Word Alignment is to use a bilingual corpus. This dataset was painstakingly assembled [19] and contained 1,200,000 words paired in English and Hindi, along with feature values for each word. This framework makes it possible to infer the Hindi meaning of a word and to produce attribute vector values from numerous attributes of the word. The heart of vector alignment is the matching of English and Hindi word vectors followed by exact word alignment. The entire process is rooted in a parent term, such as "C-DAC WAS," which is assigned at the outset. The vectors of the individual words are added together and multiplied using a parameter matrix and an activation function, such as (tanh), to obtain the parent entity. This method has numerous levels and can be diagrammed as a binary tree [20].

Because of the complex nature of DL applications, graphics processing units (GPUs) such as the NVIDIA GeoForce GTX TitanX have proven to be invaluable allies. Graphics processing units (GPUs) are superior to central processing units (CPUs) in terms of performance owing to their superiority in parallel processing [21]. MT is a rapidly evolving domain of natural language processing, and deep learning has the potential to create translation systems that are indistinguishable from humans. RAEs models, which are used for text processing, were performed very well in this setting. Sentence reconstruction and other similar tasks benefited greatly from word vectors, which may be generated using the Word2vec method. MT relies heavily on overcoming challenges such as limited vocabularies, sparse data, and loss of vector history [22]. However, accurate MT is a huge obstacle because of the massive size of the corpus required for that purpose. When DL architectures are used, the translation systems become more effective. The training process can be significantly improved using several GPUs. By combining and harmonizing these approaches, we may be able to build the best MT system [23].

In-depth research on the intricate technical aspects of an English-to-Urdu MT system was conducted by Shahnawaz and Mishra [24]. The incorporation of a feed-forward back-propagation artificial neural network into the system architecture was important. The main goal was to expand the range of useful Urdu vocabulary and linguistic features, including essential elements, such as verbs, nouns/pronouns, and linguistic complications. Due to their respective classifications as Subject-Object-Verb (SVO) and Subject-Verb-Object (SOV), English and Urdu are fundamentally different languages, making it imperative that grammatical structures must be preserved throughout the translation. To overcome linguistic barriers, it is essential to emphasize the maintenance of the logical connection between grammatical components. The system's surprising flexibility is its ability to translate statements that include a broad variety of linguistic elements. The use of gerunds, infinitives (up to two), prepositions and their objects (up to three), direct and indirect objects, and other grammatical nuances, was discouraged. A neural network stores a large corpus of data, such as a multilingual dictionary and a set of language rules. The system's multilingual lexicon covers more than just the literal translation of English words into Urdu. It also examined their stylistic and semantic implications. The system generates output in Romanized Urdu, which substantially aids the readability of the end users. Analyzing the technical performance of the system it was revealed that it performs very well across several dimensions. Among these were a METEOR score of 0.8583, an F-score of 0.8650, and an n-gram BLEU score of 0.6954. The system's technical proficiency in translating from English to Urdu and its ability to overcome language problems were both confirmed by the combination of these performance indicators, which demonstrates its efficacy.

The research conducted by [25] highlighted that divergence poses a significant challenge in MT. This study delved into the analysis and categorization of divergence, focusing particularly on topic, category, and structural differences. In response, an ANN-driven architecture, comprising a Thematic Divergence Module, Categorical Divergence Module, and Structural Divergence Module, was developed. The primary objective was to expedite translations from Marathi to English by tokenizing English sentences into components, allowing an ANN to match them with corresponding Marathi words. This approach yielded promising results when applied to meticulously studied phrases and words within a neural network. Accuracy scores for the thematic, categorical, and structural modules were 66.67%, 71.43%, and 51.25%, respectively. Infrequent machine evaluation methods validated the practical utility of translation outcomes. Notably, the Categorical Divergence Module outperformed its counterparts, with the Thematic Divergence module achieving a BLEU of 0.2666, and the Structural Divergence module scoring 0.010417 for n-gram analysis.

Kong [26] delved into the profound impact of the AI revolution, specifically DL, on MT. The discussion recognized the pivotal role of teachers in advancing translation education through innovative instruction methods. The increasing importance of learning English fluently, extending beyond academic success to practical benefits in a complex social environment, was emphasized. The research aimed to examine the effects of artificial intelligence on pedagogical practices in teaching English at higher education. The author advocated for a reevaluation of English translation curricula in light of the rise of AI, proposing a shift in pedagogical approaches supported by empirical data. The essay explored the intersection of AI and English translation teaching in the academic world.

Yang [27], provided an exposition on the design methodologies and implementation protocols of an MT system using machine learning ideas. The study compared ML and DL, introducing neural network components like the convolutional neural network. The article analyzed the translation principles and architecture, including order, language, and translation modules. It presented a comprehensive overview of various modules, such as preprocessing, coding, attention, and decoding modules.

The use of case-based reasoning in MT relies on the premise that analogous phrases in the source language have matching translations in the target language as stated in [28]. The analysis demonstrated that English input phrases with related syntactic features yield similar properties in their corresponding Arabic translations. An artificial neural network methodology was employed to establish correspondence between the syntactic attributes of a novel English phrase and pre-existing examples in the case base. Authors used a feed-forward artificial neural network to facilitate the recognition of Arabic syntactic elements, examining the structural composition and characteristics of English sentences. The dynamic method ensures the generation of coherent and contextually accurate Arabic translations, reflecting the inherent structure of input English sentences.

The widespread use of deep learning models has significantly impacted natural language processing. Otter [29] provided a summary and in-depth analysis of deep learning architectures and techniques, discussing recent studies and their contributions. The article addressed fundamental challenges in language processing and offered critical analysis, along with recommendations for future lines of inquiry.

Nagarhalli [30] noted that researchers have utilized various machine learning and deep learning algorithms in NLP, surpassing traditional processes. While NLP careers are growing, there is room for further development, calling for more research in the field. Constant experimentation with different learning methodologies is expected to enhance the efficacy and precision of natural language processing.

Chen's study [31] aimed to enhance MT quality assessment, focusing on real-time spoken material. Unlike research mostly centered on written text, this study explored assessing MT quality in real-time spoken dialogue. The innovative methodology integrated deep neural networks with language

TABLE 1. Characteristics and limitations of DL techniques in translation.

References	Deep Learning Aspect	Description	Effectiveness	Efficiency	Applicability	Limitations/Gaps
[13]	Deep Learning Models	Utilize neural networks for complex pattern capture.	Highly effective for complex patterns.	Resource-intensive for training.	Broad in AI and NLP applications.	Requires substantial data and computational power.
[14]	Hierarchical Data Representations	Inclusion of multiple hidden layers in neural network design.	Enhances the ability to capture nuanced data representations.	Efficient in pattern recognition.	Applicable in diverse AI tasks.	Complexity increases with more layers.
[16]	Neural Network Layers	Input, hidden, and output layers with weighted connections.	Effective in diverse tasks including language processing.	Superior performance with large datasets.	Versatile across many AI domains.	Managing and tuning layer connections can be complex.
[17]	Feature Extraction and Representation Learning	Automatic learning of relevant features from raw data.	Reduces need for human feature engineering.	Efficiency varies with model and task complexity.	Vital for advanced AI tasks.	Depends on quality and variety of input data.
[18]	Contributions to Language Translation	Use of transformers for translation.	Generates more genuine and coherent translations.	Improved with advancements in DL models.	Significant in the evolution of translation systems.	Challenges in capturing subtle language nuances.
[19]	Training RNN for Word Alignment	Using bilingual corpus for training.	Facilitates understanding of language meanings and attributes.	Performance reliant on corpus quality.	Key in developing effective MT systems.	Requires extensive and high-quality bilingual data.
[20]	Role of GPUs in DL Applications	Utilization of GPUs for enhanced performance.	Allows handling of complex DL tasks efficiently.	Superior to CPUs in parallel processing.	Crucial for demanding computational tasks in AI.	High cost and resource requirements for advanced GPUs.
[21]	Overcoming Challenges in MT	Addressing issues like limited vocabularies and data sparsity.	Enhances overall MT capabilities.	Varied efficiency depending on data availability.	Critical for advancing MT systems.	Requires ongoing innovation and data enhancement.
[23]	Combining Approaches for Optimal MT	Harmonizing different ML and DL techniques.	Aims to build the best MT system.	Efficiency achieved through a combination of methods.	Broadens the scope of effective MT.	Balancing various approaches can be challenging.
[24]	English-to-Urdu MT System	Incorporation of a feed-forward back-propagation ANN.	Expands Urdu vocabulary and linguistic features.	Performs well across several dimensions.	Enhances translation between structurally different languages.	Specific to certain language pairs and structures.

characteristic extraction, using the Double Recurrent Neural Network (double-RNN) structure. Empirical assessments demonstrated its similarity to conventional quality evaluation criteria, offering a fair and accurate assessment of translation quality in both Chinese and English. The study paved the way for further advancements in intelligent MT in real-time spoken language.

Yu's work [32] addressed challenges in conventional English translation models, proposing a novel model leveraging intelligent identification and deep-learning methodologies. The investigation included constructing an English word corpus, enhancing part-of-speech tagging accuracy, and developing a novel approach for extracting relevant characteristics. The proposed NMT system, integrating traditional neural networks into deep learning frameworks with an attention mechanism, demonstrated notable accuracy in identifying phrases, improving translation quality, and reducing translation durations.

Table 1 outlined distinctive features and potential gaps of DL methods in the field of translation.

B. STATISTICAL MACHINE TRANSLATION

Statistical-based approaches exhibit superior performance compared to traditional classical-based approaches and provide viable alternatives. In the field of Machine Translation (MT), two fundamental statistical methodologies are Example-Based Machine Translation (EBMT) and Statistical-Based Machine Translation (SMT). These methodologies leverage statistical models for translation, utilizing parameters derived from bilingual parallel-aligned text corpora as the foundation.

However, challenges arise in the case of languages with limited resources. Transformer Architecture represents a significant advancement in MT, processing words in parallel to overcome sequential constraints. It introduces multi-head attention and positional encodings to capture both local and global contexts.

Several techniques contribute to the efficiency of MT [33]:

- Sub-word and Byte-Pair Encoding (BPE): Breaking words into smaller units aids in handling out-of-vocabulary words, facilitating rare or unseen word translations.

- Transfer learning and pre-trained models: Models pre-trained on extensive text data, such as BERT, adapt linguistic features, enhancing translation quality and addressing language nuances.

- Multilingual and Zero-Shot Translation: Multilingual models share encoders and decoders for multiple language pairs, leveraging language similarities. Zero-shot translation enables models to translate untrained language pairs.

- Reinforcement Learning for Evaluation: This technique aids in model evaluation, rewarding accurate translations based on metrics like BLEU and fostering improved translation quality.

In the era of neural networks, language translation benefits significantly from these concepts, resulting in accurate, culturally sensitive, and efficient cross-lingual communication tools that continue to evolve with ongoing research and development.

Khalilov et al. [34] emphasizes that the performance of a translation system decreases when the training data is reduced, aligning with the design of Statistical Machine Translation (SMT) systems. This underscores the need for creative approaches to maximize the use of limited information. The paper proposes a method to enhance the performance of an SMT system with a small training dataset by incorporating a Neural Network Language Model (NN LM).

The study highlights the crucial relationship between objective machine measurements (such as fluency and accuracy) and subjective human criteria in MT assessment. Previous research indicates that, for shorter translation tasks, fluency aligns well with BLEU, while adequacy aligns well with METEOR. The integration of NN LMs into SMT is shown to enhance translation fluency without compromising precision. Although the study does not showcase the benefits of n-gram ordering with larger n, it establishes the reliability of NN LMs, even when working with sparse datasets. The increased generalization of the target language by the in-domain NN LM significantly impacts the smoothness of SMT outputs and the quality of automatically scored translations.

The decoder part of the model proposed in [35] demonstrates robust and efficient attention techniques. The authors conduct an in-depth investigation into how these methods effectively utilize both inter- and intra-clause circumstances to enhance translation quality. The study's distinctiveness lies in its thoughtful approach to addressing challenges posed by hierarchical organizations and its emphasis on meticulously researching attentional processes. The empirical results presented provide strong evidence of the efficacy of the approach, lending credibility to the superior performance claimed by the authors over alternative baseline systems. The findings underscore the relevance of the proposed technique, and the suggested research paths in the report offer substantial directions for future exploration. The authors' interest in exploring the optimal clause sequence, given the complexity of segmenting input phrases, presents a possible extension to their work. The deliberate choice to analyze the model's performance in document-level Neural Machine Translation (NMT) reflects the authors' proactive stance in addressing broader translation challenges. While quantitative data present a compelling argument, incorporating more qualitative research could enhance the understanding of the model's benefits and potential limitations.

The technique proposed in [36] adopts the modular architecture of Statistical Machine Translation (SMT). Initially, a phrase table is generated from monolingual corpora using cross-lingual embedding mappings. Subsequently, this phrase table is combined with an n-gram language model. Fine-tuning of hyperparameters is achieved through an unsupervised version of the Minimum Error Rate Training (MERT) technique, with iterative back-translation contributing to improved results. Experimental results demonstrate substantial improvements over previous unsupervised systems. For the WMT 2014 English-German translation issue, the technique achieves a BLEU score of 14.08, and for the English-French translation test, it attains a BLEU score of 26.22. This represents a noteworthy improvement of 7-10 BLEU points compared to previous techniques. Furthermore, when compared to Moses trained on Europarl, this method effectively narrows the performance gap between supervised SMT, achieving a minimum difference of 2-5 BLEU points. The relevance of this research extends beyond the proposed approach, as the authors provide an open-source implementation, contributing to advancements in unsupervised machine translation. The study effectively bridges the gap between unsupervised and supervised systems, suggesting a viable avenue for enhancing machine translation efficiency and availability in environments with restricted resources.

Traditionally, machine translation (MT) training has favored the use of large parallel corpora. However, recent research has demonstrated promise in training both Neural Machine Translation (NMT) and Statistical Machine Translation (SMT) systems using only monolingual corpora.

Mikel Artetxe's research [37] explores this shifting landscape, critiquing the limitations of traditional unsupervised SMT approaches and highlighting their role in expanding the field of MT. The creators of unsupervised SMT identified and addressed serious flaws in existing methods by utilizing sub-word data, introducing a theoretically based unsupervised tuning strategy, and incorporating a joint refinement procedure. A refined version of SMT was used to seed a second NMT-based model, and a dynamic back-translation technique further refined the model. The proposed technique outperformed the known benchmark in unsupervised machine translation, achieving a remarkable performance of 22.5 BLEU points on the English to German WMT 2014 assignment. This result is 5.5 points better than the previous unsupervised system and 0.5 points higher than the supervised system that won the joint task in 2014. This study significantly contributes to the expanding field of unsupervised machine translation by pushing its boundaries and producing notable results. The authors enhanced unsupervised machine translation capabilities using sub-word information, resilient tuning techniques, and joint refinement, potentially leading to more accurate and easily accessible language translation systems.

In a detailed comparison of two prominent MT systems, NMT and SMT, presented in [38], the authors delve into their inner workings, potential uses, and the evolving nature of MT. The paper effectively explains both NMT and SMT systems, drawing attention to key differences and emphasizing the growing importance of NMT over traditional SMT. Real-world experiments and results add credibility to the claims, showcasing how NMT may be superior to SMT for various language pairs. The inclusion of real-world examples helps readers grasp the tangible benefits of NMT, highlighting the relevance of the study to real-world problems. The study acknowledges NMT limitations and stresses that, despite its potential, SMT outperforms NMT in several fields. The authors' recognition of current technology limitations reflects their unbiased approach and deep understanding of the issue. An area for improvement in this research could involve expanding the limits of NMT technology by providing additional instances or specific examples where NMT demonstrates worse performance compared to SMT, enhancing the understanding of these limitations.

Tan et al. [39] offer a comprehensive assessment of the present condition of NMT, incorporating scholarly investigations and real-world implementations. The study analyzes various aspects of NMT, including modeling techniques, decoding tactics, data augmentation methods, interpretation approaches, and evaluation methodology. Despite the noteworthy accomplishments of NMT, the research underscores substantial challenges requiring further attention and resolution. Emphasizing the need for a deeper understanding of NMT, the study highlights a notable dearth of research into the fundamental processes and rationale influencing the translation results of NMT. Acquiring a thorough understanding of the mechanics and underlying principles of NMT is deemed essential for identifying potential weaknesses and limitations within NMT models.

Improving Neural Machine Translation (NMT) architecture stands as a significant challenge, and the study in [40] emphasizes the pivotal role of transformer design in NMT progress. However, it stresses the need to nurture innovative structures beyond the transformer capacity to achieve a balance between translation quality and computation efficiency. The study also highlights the use of monolingual data as a major issue in NMT, suggesting untapped potential in effectively utilizing sufficient monolingual data to enhance translation accuracy. Further research is necessary to fully realize the benefits of incorporating monolingual data into the context of NMT.

Yang Dong's essay [41] explores the field of Chinese-Korean translation, offering a thorough examination of its present conditions, challenges, and potential solutions. The significance of Chinese-Korean translation in facilitating cultural and scholarly interactions between China and Korea is emphasized. The study delves into the current corpus of literature on Chinese-Korean translation, presenting the theoretical foundation of the translation-based information transformation model. The essay highlights the neural network translation model, providing a detailed overview of its diagram and computational procedure. While experimental results show promise, the report acknowledges significant limitations in the experiment's design, indicating the need for further research. The essay advocates for testing across various corpora and further model improvement to enhance translation quality, making it a valuable resource for the advancement of Chinese-Korean translation procedures.

In [42], the authors conduct an extensive analysis of machine translation systems, focusing on linguistically driven approaches. Evaluating neural machine translation, rule-based, and phrase-based systems in the English-German IT area, the authors combine syntax-aware phrase extraction with Linked Open Data for named entity translation. The work offers a thorough and exhaustive approach to analyzing and improving machine translation systems. The methodical evaluation provides significant insights into the capabilities and limits of each system, particularly concerning complicated language issues. While the in-depth analysis is helpful, a more succinct summary of the article's conclusions could enhance accessibility. Additionally, the applicability of findings outside the English-German IT domain is a consideration, and applying these strategies to other language pairings and areas might be a topic for future study. Table 2 recapitulates the main features and limitations of Statistical Machine Translation (SMT) approaches, offering insights into their efficiency and areas for improvement.

C. NEURAL MACHINE TRANSLATION (NMT)

Neural Machine Translation (NMT) has revolutionized the translation industry by employing artificial neural networks

TABLE 2. Key features and gaps in statistical machine translation techniques.

Ref No.	Approach	Description	Effectiveness	Efficiency	Applicability	Limitations/Gaps
[33]	Statistical Approaches in MT	Discusses the use of statistical models in MT, with parameters derived from bilingual parallel-aligned text corpora.	Offers a solid foundation for translation by statistically analyzing bilingual text corpora, though may face challenges with languages having sparse resources.	Efficient for languages with ample data	Fundamental in early MT systems, particularly SMT and EBMT	Struggles with low-resource languages due to dependency on extensive parallel corpora.
[34]	Neural Network Language Model (NN LM) in SMT	Incorporates NN LM into SMT to improve translation fluency with sparse datasets.	Improves fluency significantly in contexts with limited training data, though larger n-gram benefits are not evident.	High in specific contexts	Enhances SMT systems, especially with limited data	May not show benefits of n-gram ordering with larger n due to shorter sentence lengths.
[35]	Attention Techniques in Decoders	Focuses on the use of advanced attention techniques to utilize inter- and intra-clause relations.	Empirically shown to enhance translation quality by effectively utilizing contextual relations within sentences.	Varies with implementation	Applicable in hierarchical and complex sentence structures	Requires further qualitative analysis to understand model benefits and limitations fully.
[36]	Modular Architecture of SMT	Utilizes cross-lingual embedding mappings to generate phrase tables from monolingual corpora for SMT.	Demonstrates considerable improvements in translation accuracy over earlier unsupervised systems in tests.	Efficient with iterative back-translation	Bridges the gap between unsupervised and supervised MT systems	Focuses on English-German and English-French pairs; applicability to other languages may vary.
[37]	Unsupervised SMT and NMT	Enhances unsupervised SMT and NMT using sub-word data and joint refinement procedures.	Marks a significant performance milestone, outperforming previous unsupervised methods in benchmarks.	Performance improvement notable in benchmarks	Expands the field of unsupervised MT	Limited comparative analysis with supervised systems in diverse linguistic contexts.
[40]	Use of Monolingual Data in NMT	Discusses the potential of using monolingual data to improve NMT accuracy.	Suggests significant untapped potential for accuracy improvements, especially in low-resource language contexts.	Efficiency gains potential with effective utilization	Could significantly benefit low-resource languages	Further research required to maximize the use of monolingual data in NMT.

and deep learning. In contrast to traditional approaches, NMT systems do not rely on human translators for instruction; instead, they utilize massive amounts of parallel text data to autonomously learn translation patterns [43]. The encoder-decoder design is at the heart of NMT, where the encoder analyzes the source phrase to create a compact context vector, subsequently used by the decoder to generate the translated output [44]. NMT improves precision, fluency, and contextual appropriateness, facilitating effortless cross-lingual communication and comprehension [45].

In the realm of NMT, advanced approaches have significantly enhanced the translation process. Seq2Seq architectures, employing an encoder-decoder structure, serve as the foundation. The encoder analyzes the original text, condensing it into a context vector, and the decoder generates the target sequence. Recurrent Neural Networks (RNNs), specifically Long Short-Term Memory (LSTM) units, address sequential input challenges, overcoming the vanishing gradient problem and capturing long-range relationships. The inclusion of attention mechanisms enhances the Seq2Seq model's competency, allowing it to focus on key regions of the source text during translation. These methods collectively underpin the achievements and ongoing advancements in NMT, providing a glimpse into the future of machine-aided translation [46].

Marzouk and Hansen-Schirra [47] conducted a study examining how enforcing Controlled Language (CL) criteria improved the quality of various Machine Translation (MT) systems. While rule-based, statistical, and hybrid MT systems benefited significantly from CL rules, the same did not hold true for NMT. Contrary to expectations, CL criteria led to a decline in the quality of NMT output. The study contributes to understanding how different MT systems interact with controlled languages, offering insights to enhance the efficacy of neural MT in this context.

Training NMT systems without large parallel corpora is challenging [48]. This study proposes an unsupervised method for training NMT systems, leveraging recent advances in unsupervised embedding mapping. The model, featuring an attentional encoder-decoder architecture, can be trained on monolingual corpora. A hybrid training strategy, incorporating denoising and back-translation approaches, enhances learning from monolingual input. Impressively, the proposed approach achieves high BLEU scores on translation tasks, even when trained solely on single-language corpora. This research sets a benchmark for training translation models without parallel data, presenting a novel and practical solution to unsupervised NMT, supported by open-source implementations.

In addressing the challenges of Neural Machine Translation (NMT), researchers have explored various methodologies to enhance robustness, utilize monolingual data, and improve model efficacy.

Cheng et al. [49] highlighted the susceptibility of NMT models to disruptions caused by minor input deviations. To enhance robustness, the study proposed adversarial stability training. This approach aimed to develop resilience in both the encoder and decoder elements of NMT models, ensuring consistency in behavior between the original and disturbed input. Empirical evaluations on translation challenges, including Chinese-English, English-German, and English-French, demonstrated significant gains in translation quality compared to less resilient NMT models.

A novel NMT model incorporating gate mechanisms to optimize monolingual data utilization during training was introduced in [43]. The model separates monolingual and parallel data using a gate, allowing it to distinguish between the two types of input sequences. Experimental results on Chinese-English and English-German language pairs showed substantial improvements compared to robust baseline models. The proposed gated mechanism enhances the model's ability to work with diverse inputs, leading to more accurate and efficient translation.

Gulcehre et al. [50] investigated the incorporation of large amounts of monolingual data to improve NMT. Two methods were explored: supplementing the primary NMT model with scores from a neural language model trained on monolingual data and combining hidden states of the two models. The study demonstrated significant performance improvements, particularly for low-resource language pairs like Turkish and English, compared to baseline models. Integrating language models effectively contributes to enhancing translation accuracy for various language pairs.

Cheng et al. [51] proposed a methodology, AdvAug, to enhance the efficacy of NMT models by mitigating immediate risks using virtual terms obtained from adjacent distributions. The approach disperses hostile words within a specified area, employing embeddings of virtual phrases to train NMT models. Experimental evaluations on Chinese-English, English-French, and English-German language pairs showed substantial gains, surpassing other data augmentation techniques without requiring additional corpora.

Ding et al. [52] introduced a method using layer-wise relevance propagation (LRP) to improve the visualization and comprehension of NMT models. LRP allows the assessment of the specific influence of contextual words on hidden states, enhancing the understanding of NMT mechanics and error analysis. The proposed method outperformed traditional attention mechanisms in understanding NMT. Future plans include extending the methodology to other NMT techniques and language combinations.

Baniata et al. [53] focused on translating Arabic dialects into Modern Standard Arabic (MSA) using a multi-task learning (MTL) model with a recurrent neural network (RNN)-based encoder-decoder architecture. The study introduced a comprehensive approach for NMT, employing a common decoder for all language combinations and separate encoders for each source language. The MTL model addressed challenges associated with Arabic dialects, showing outstanding performance even with limited parallel data. The study suggested further improvements by refining model components, incorporating attention processes, and evaluating its effectiveness in a broader range of real-world situations.

The field of artificial language processing has devoted significant attention to standard Arabic, leading to the development of various resources and tools. However, Arabic dialects, including the Moroccan dialect, have not received adequate attention and lack accessible materials and methodologies. Tachicart and Bouzoubaa [54] aims to rectify this imbalance by proposing a hybrid translation approach that bridges the gap between the Moroccan dialect and standard Arabic. Leveraging the linguistic resemblance between the two, an integrated methodology combining rule-based and statistical techniques is suggested. The proposed technique utilizes pre-existing tools designed for standard Arabic, adapting them to incorporate the specific subtleties of the Moroccan dialect. This article outlines the architectural foundation for implementing the previously described translation procedure. This work introduces a novel translation method for converting the Moroccan dialect into MSA, employing dedicated processing tools tailored for MSA. This initiative marks the first dedicated effort to translating the Moroccan accent. The results of this study are significant, demonstrating the superior effectiveness of the proposed approach in unsupervised machine translation compared to the existing standard.

Al-Gaphari developed a method for successfully and realistically converting the Sana'ani dialect into MSA [55]. This technique is based on morphological concepts applicable to both the Sana'ani dialect and MSA, allowing for a seamless transition between these linguistic varieties. The procedure involves tokenization of the input dialect text, followed by an examination of each token's parts, particularly stems and affixes. Affixes are categorized into dialect-specific and MSA-associated types. Similarly, stems may be traced back to either dialect or MSA. To navigate these scenarios, the system employs a basic morphological stemming algorithm (MSA). Following the completion of the preceding step, the dialect stemmer is used to remove affixes unique to the dialect being examined. This procedure is guided by the morphological parameters defining when affix extraction should take place. The results of the experimental phase show that the Sana'ani dialect exhibits three major forms of distortion: prefixes, suffixes, and stem changes. Using morphological criteria, the approach efficiently overcomes these aberrations. This method was used to evaluate the feasibility of implementing each rule. When the rule conditions are met, the dialect prefix is substituted with its MSA equivalent. If not subject to additional limitations, twisted stem laws essentially establish a parallel corpus of dialect and MSA. The MSA distortion ratio in the Sana'ani dialect was empirically determined in this study, with 16.29% of the 9386 Sana'ani dialect words tested having distorted suffixes, 0.70% having distorted prefixes, and 2.17% having distorted stems. It is critical to understand that these percentages are applied only to the processed words.

To assess the performance of Google Translate's free MT service in the field of law, Killman [56] conducted research using Spanish legal vocabulary items taken from decision summaries compiled by the Supreme Court of Spain. The English machine translations generated by Google Translate were then analyzed by the researcher.

According to the data, MT was used to produce 223 of the total results (36%). Additionally, MT using a different but accurate approach yielded 177 results (28.5%). In addition, 221 outcomes (35.5%) were incorrectly translated using this algorithm.

The results showed that 64.7% of the machine-generated translations were correct, proving the main hypothesis that MT can successfully provide accurate translations of the 621 items tested.

Authors in [57] presented a novel approach to NMT that integrates a hierarchical framework for encoding input texts. The proposed model has a hierarchical structure at the word, phrase, and sentence levels, setting it apart from conventional NMT models. The encoding technique of this structure involves the use of two layers of RNNs. The model's decoder incorporates distinct attention mechanisms to efficiently use both inter- and intra-clause circumstances during the translation of segmented clauses. The study's experimental evaluation primarily focused on the translation process involving Chinese and English, as well as English and German. The assessment findings demonstrated significant improvements in the performance attained by the model compared to comparable baseline systems. This study contributes significantly by introducing a hierarchical encoding structure inside the architecture of NMT. The use of a hierarchical structure consisting of words, phrases, and sentences in the arrangement of the input sentences presents a new aspect of the translation process. The authors provided a comprehensive description of how the incorporation of a hierarchical structure enhances the model's ability to comprehend the sentence context, thereby augmenting the significance of the study findings. Although RNNs are extensively used in the field of NLP, their application for text feature extraction is seldom due to their major emphasis on sequential input.

Su et al. [58] focused on extracting event features from Chinese literature. They suggested a multistep technique to successfully achieve this goal. In the first step, an MT model based on neural networks was employed to prepare the text. This stage covered the handling of event descriptions and the segmentation of Chinese words. Using named entity recognition, a monostacked-bi-LSTM-CRF model was created to extract text event characteristics. The presented algorithm model underwent a comprehensive refining procedure consisting of 21 iterations on the corpus data, yielding notable results. The system achieved a 98.70% accuracy rate in the extraction of tags from all text labels, demonstrating an outstanding degree of precision. The model's performance was supported by a recall rate of 89.31% on the development set, backed by a maximum F-value of 93.88. Furthermore, the model achieved a high level of accuracy (97.81%) in the test sets. It also had an 83.94% recall rate and a maximum F-value of 90.35. By improving the present BI-LSTM-CRF model, this study provides an important contribution to the field. It presents a revolutionary deep-learning-based sequence annotation model with better performance than its predecessor. The model was evaluated using the corpus-based dataset provided by CONLL-2003, demonstrating its improved performance over the prior BI-LSTM-CRF model. The highest value of the F-score increased significantly from 90.1, indicating considerable progress. Nonetheless, this study identified potential areas of development. Two potential paths were proposed for improving the performance of the model. Other factors that may include vocabulary spelling, pronunciation, or Chinese radical information should be added to the semantic word vectors to broaden the system's capabilities. Furthermore, this study investigated the possibility of replacing the Conditional Random Field (CRF) model with a Convolutional Neural Network (CNN) for label categorization evaluation. The idea is that due to its global analysis of the output at each

TABLE 3. Comparative analysis of features and gaps in NMT.

Ref No.	NMT Aspect	Description	Effectiveness	Efficiency	Applicability	Limitations/Gaps
[43]	Parallel Text Data Usage	NMT systems use massive parallel text data for learning translation	Highly effective in understanding nuanced linguistic patterns	Resource-intensive due to large data processing	Broad in translation and linguistic applications	Requires massive amounts of data
[44]	Encoder-Decoder Design	Analyzes source phrase to form a context vector for translation output	Produces natural and consistent translations	Efficient in processing linguistic data	Essential in modern NMT systems	Dependent on the quality of context vector
[45]	Improvement in Translation Industry	NMT advances translation precision, fluency, and contextual appropriateness	Facilitates effortless cross-lingual communication	Efficient in producing accurate translations	Wide applicability in various linguistic fields	Constant evolution and improvement required
[47]	Interaction with Controlled Languages	Examines the effect of CL rules on NMT systems	Superior quality output in NMT systems	Varies depending on the implementation	Applicable in rule-based, statistical, and hybrid MTs	Incompatibility with certain MT frameworks
	Seq2Seq Models	Utilizing encoder-decoder architectures for input-output sequence processing.	Well-suited for translation tasks.	Efficient in handling sequence-based tasks.	Widely applicable in translation and other sequential tasks.	May struggle with very long input sequences.
[48]	Unsupervised Training Methods	Focuses on training NMT systems with monolingual corpora	Effective in situations with limited parallel corpora	Efficiency varies with training methods	Applicable in languages with scarce resources	Limited by unavailability of large parallel corpora
[49]	Adversarial Stability Training	Improves NMT model robustness against input perturbations	Increases translation quality	Enhances model robustness	Relevant in improving NMT system stability	Susceptibility to minor input deviations
[50]	Large Monolingual Data Incorporation	Enhances NMT by integrating large amounts of monolingual data	Significant improvements in translation quality	Efficient with both low and high-resource langs.	Beneficial for a range of language pairs	Integration complexity with different language models
[51]	Immediate Risk Mitigation	Uses virtual terms from adjacent distributions for risk reduction	Leads to enhancements in translation accuracy	Superior to conventional augmentation methods	Applicable in various language pairings	Reliance on advanced embedding techniques
[52]	Visualization and Comprehension Improvement	Employs LRP to understand the influence of contextual words on hidden states	Enhances comprehension of NMT mechanics	Efficient in error analysis	Useful in analyzing and improving NMT models	Limited to specific neural network architectures
[53]	Multi-task Learning for Arabic Dialects	Focuses on translating Arabic dialects into Modern Standard Arabic	Effective in producing high-quality translations	Speedy convergence for limited resource langs.	Applicable in translating diverse Arabic dialects	Challenges due to the variety and complexity of dialects
[54]	Moroccan Dialect Translation	Combines rule-based and statistical techniques for the Moroccan dialect	Demonstrates superior effectiveness in translation	Efficient with dedicated processing tools	Specific to Moroccan and standard Arabic translations	Lack of dedicated resources for Moroccan dialect
[55]	Sana'ani Dialect Morphological Conversion	Applies morphological concepts for translating Sana'ani dialect into MSA	Efficient in overcoming linguistic aberrations	Effective with morphological stemming algorithms	Specific to Sana'ani and MSA language varieties	Limited to the processed words and specific distortions
[56]	Google Translate in Legal Field	Analyzes the performance of Google Translate in translating Spanish legal vocabulary	High accuracy in translating legal terms	Fast and accessible	Specific to Spanish-English legal translations	Limited to legal vocabulary and specific language pair
[57]	Hierarchical Framework Encoding	Integrates a hierarchical structure in encoding input texts for translation	Significantly improves model performance	Efficient in processing segmented clauses	Suitable for Chinese-English and English-German pairs	Requires advanced RNN and attention mechanisms
[58]	Extracting Event Features from Chinese Literature	Focuses on a multistep technique for extracting text event characteristics using a monostacked-bi-LSTM-CRF model and named entity recognition.	Enhances precision in tagging and recall rates for Chinese literature.	High accuracy and recall rate demonstrated.	Useful for Chinese literature and event-focused MT.	Explores integrating additional semantic vectors and potentially using CNNs.

point, the (CNN) approach may yield more effective sequence annotation results than the (CRF) technique. Table 3 provides a comparative analysis of NMT techniques, highlighting their strengths and areas of improvements.

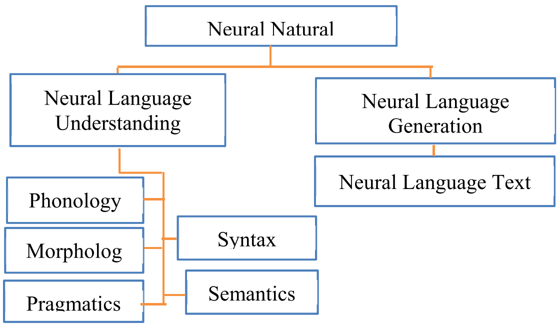

FIGURE 3. Broad classification of NLP.

D. NATURAL LANGUAGE PROCESSING (NLP)

NLP involves various approaches allowing computers to comprehend, process and produce human language, with key applications in translation. Main NLP techniques are [59]:

- Tokenization: Involves breaking text into smaller units, like words or sub-words, facilitating machine processing. This step underlies various NLP tasks.
- Part-of-speech tagging: Assigns grammatical tags to words in a sentence, aiding computers in understanding syntactic structures.
- Named Entity Recognition (NER): Identifies and categorizes named entities in a text, such as people, places, organizations, and dates.
- Parsing and Syntax Analysis: Parsing analyzes sentence structure, extracts word relationships, and builds parse trees mapping linguistic bonds.
- Sentiment analysis: Examines a text's sentiment (positive, negative, or neutral), often used for better understanding consumer feedback.
- Language modeling: Predicts the probability of words or phrases appearing within a context, crucial for various NLP applications, including MT.
- Word embedding: Represents words as dense vectors in a continuous space, effectively capturing semantic links between words.
- Transformer Architecture: Revolutionizing NLP with parallel processing and attention mechanisms, transformers enable more accurate and contextually rich translations.
- Transfer Learning: Pretraining models on large language datasets (e.g., BERT) allows learning contextual language features, fine-tuned for specific NLP tasks, including translation.
- Rule-based Approaches: Traditional rule-based methods remain relevant, involving sets of linguistic rules guiding translation based on grammar and language structure.

These techniques are vital for AI-powered language translation, allowing computers to understand, process, and generate human languages effectively. A broad NLP classification is shown in Fig. 3 [60].

Table 4 highlights the decisive aspects and potential limitations of various NLP techniques, emphasizing their impact on translation accuracy and scope

E. FUZZY ALGORITHMS

MT stands as a powerful tool with profound practical implications in language conversion. The efficacy of MT techniques has significantly advanced due to the progress in deep learning technology. The discipline has undergone a substantial revolution, transitioning from rule-based techniques to statistics-based methodologies, and eventually to neural network-based approaches. Traditional rule-based techniques have given way to SMT, utilizing data-driven models to overcome challenges posed by knowledge acquisition bottlenecks. Fig. 4 visually demonstrates how fuzzy algorithms operate in the context of translation, offering an educational representation [61].

The emergence of end-to-end models, specifically NMT, has streamlined the translation process by simplifying feature creation and incorporating nonlocal contextual information. Li [62] explored existing challenges in English MT and proposed a semantic ordering model based on fuzzy theory. The goal of this study is to enhance translation precision by integrating fuzzy theory into the NMT framework.

The proposed model utilizes neural networks for both the encoder and decoder components, creating a holistic architecture that spans the entire translation process. The inclusion of the semantic ordering functionality contributes to improved translation accuracy. Practical investigations, comparing the performance of machine learning neural networks with typical semantic ordering models, reveal that the fuzzy algorithm-based model achieves higher accuracy and requires less time, highlighting its distinct advantages. However, the field of fuzzy translation lacks a comprehensive and systematic research framework, leading to a fragmented academic environment. While initial results show potential, more research is needed to address practical challenges, technological intricacies, and broader factors such as cost and time.

Li et al. [63] delved into current challenges in English MT and proposed a novel technique using fuzzy theory to enhance semantic layout in English MT within the NMT framework. Neural networks are employed to construct the decoder and encoder components, allowing true end-to-end MT. The study introduces a unique strategy to improve translation output accuracy by incorporating a semantic ordering function into the NMT system. Comparative investigations using machine learning neural networks show that the proposed English metaphysical ordering model, based on fuzzy theory, outperforms typical English semantic ordering models in accuracy and time consumption. While the advantages of adopting a fuzzy algorithm-based semantic ordering strategy within the NMT framework are evident, the field of fuzzy translation still lacks a comprehensive and systematic research framework.

TABLE 4. Essential characteristics and limitations of NLP techniques in translation [59].

NLP Technique	Description	Effectiveness in Translation Tasks	Efficiency in Processing	Applicability in NLP	Limitations/Gaps
Tokenization	Breaking text into smaller units like words or sub-words.	Forms the basis for NLP and translation tasks.	Highly efficient in initial text processing.	Fundamental in various NLP tasks.	May struggle with complex linguistic structures.
Part-of-speech Tagging	Assigning grammatical tags to each word in a sentence.	Assists in understanding the syntactic structure for translation.	Efficient for syntactic analysis.	Crucial for syntactic understanding in NLP.	Accuracy depends on the complexity of the language.
Named Entity Recognition	Identifying and categorizing named entities in text.	Important for preserving meaning in translation.	Varies based on entity complexity and context.	Used in numerous NLP applications beyond translation.	May misinterpret entities with ambiguous contexts.
Parsing and Syntax Analysis	Analyzing sentence structure and relationships between words.	Essential for understanding grammatical relationships.	Resource-intensive for complex sentences.	Integral in advanced NLP tasks like MT.	Parsing complexity increases with sentence complexity.
Sentiment Analysis	Analyzing a text's sentiment as positive, negative, or neutral.	Not directly used in translation but helpful in related areas.	Efficient for consumer feedback analysis.	Applied broadly in customer experience and market research.	May not accurately capture nuanced sentiments.
Language Modeling	Predicting the probability of word or phrase occurrences.	Crucial for generating contextually appropriate translations.	Efficiency varies with model complexity.	Core component in many NLP applications including MT.	Requires large datasets for accurate predictions.
Word Embedding	Representing words as vectors in a continuous space to capture semantics.	Enhances semantic understanding in translation.	Effective in capturing semantic relationships.	Used in various NLP tasks, especially in understanding context.	Struggles with out-of-vocabulary words.
Attention Mechanisms	Improving model focus on relevant parts of input text.	Significantly enhances translation quality.	Increases model accuracy and relevance.	Applied in advanced NLP models for better output generation.	Complexity in implementation and understanding model focus.
Transformer Architecture	Employs parallel processing and attention mechanisms for translations.	Powers state-of-the-art translation models with high accuracy.	Highly efficient in parallel processing of data.	Central in modern NLP applications, especially in MT.	Requires substantial computational resources.
Transfer Learning	Pretraining models on large datasets for fine-tuning in specific tasks.	Enhances contextual language understanding in translation.	Efficient in adapting to specific NLP tasks.	Broadly applicable in various NLP tasks including translation.	Depends on the quality and size of pretraining datasets.
Rule-based Approaches	Creating sets of linguistic rules for translation based on grammar and structure.	Provides structured approach to translation.	Less efficient compared to AI-driven methods.	Relevant in certain contexts where rules are clear and well-defined.	Limited flexibility and adaptability to new linguistic nuances.

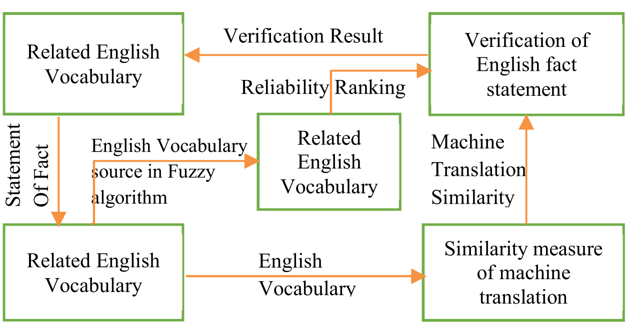

FIGURE 4. Illustration of fuzzy algorithm operations in translation context.

Rana and Atique [64] investigated the field of English to Hindi Example-Based Machine Translation (EBMT), focusing on significant differences in the subject-object-verb (SOV) alignments between the two languages. To enhance outcomes in EBMT, the research introduces a system that utilizes NLP, specifically Fuzzy Logic. The proposed approach leverages Fuzzy Logic's strengths in handling ambiguity and imprecision, efficiently resolving complications arising from linguistic differences. The study outlines three essential phases: matching, alignment, and recombination. The use of Fuzzy Logic in EBMT is a novel strategy with the potential to improve translation accuracy, particularly for language pairs with unique structural traits. The adaptability of Fuzzy Logic enhances translation precision, offering hope for future developments in multilingual communication by demonstrating the compatibility of MT concepts with advanced computational tools.

Yuan et al. [65] conducted an extensive language study employing fuzzy algorithms to enhance an English translation system. The study encompasses language analysis, corpus analysis, vocabulary research, syntax analysis, and translational features. The primary objective is to improve translation accuracy by reducing semantic ambiguity through a deeper understanding of language features. The study presents an image-input and image-recognition-based English translation system, incorporating Gaussian blurring for effective image processing. The Gaussian fuzzy technique, integrated into the translation system, significantly aids in picture noise reduction. The research demonstrates the commitment to enhancing translation accuracy, minimizing ambiguity, and excelling in visual identification. The study's multidimensional approach combines linguistic analysis and computational image processing through the utilization of fuzzy algorithms, resulting in a more accurate translation system. The research addresses the growing need for accurate and natural cross-cultural communication in the evolving landscape of language and technology.

Researchers in [66] employed professional fuzzy semantic theory to enhance translation precision and aid in understanding nuanced emotional undercurrents. The study contributes to the fields of translation and literary communication by leveraging AI-based recognition systems. The improved Generalized Likelihood Ratio (GLR) method provides a robust strategy for interpreting equivocal concepts. The study explores the integration of computer-assisted translation in the classroom to help students comprehend the nuances of English, especially in interpreting music lyrics with metaphors and allusions. The research aims to contribute to language learning and appreciation, offering a framework for improved accuracy and effective communication in the dynamic technological environment.

Zhang and Liu's [67] research focused on reducing data complexity and proposing new approaches for identifying ambiguous information. The study introduces a formal background using fuzzy linguistic aspects for coarse-grained objects, integrating coarse-grained object similarity with formal concept analysis. This method simplifies theoretical foundations and provides a systematic grounding for enhanced data analysis. The study highlights the role of digital elevation models (DEM) in forming the language threshold notion, aiding in constructing models of object-derived and attribute-derived ideas in three-branch fuzzy language concept lattices. The integration of grain computing, formal concept analysis, and the digital elevation model has the potential to revolutionize the identification of fuzzy information in English interpretation, offering refined strategies for data retrieval and eliminating unnecessary repetition.

Zhang and Liu [68] presented a model for English translation to address inconsistencies in results produced by neural networks in English translation systems. The proposed model incorporates an external English data table for fuzzy semantic optimum control retrieval. The study employs a two-stage training process to enhance data retrieval precision, involving standard pretraining on traditional English translation data followed by fuzzy semantic information-enhanced fine-tuning. The model consists of a sequence-generating network for word probability distributions and an evaluation network predicting sentence outcomes. The evaluation network plays a crucial role in assessing the impact of newly generated words on whole sentences by considering optimal solutions in current and future contexts. Empirical results indicate improved semantic information representation using bidirectional neural networks and masked language models for training phrase vectors. The combination of semantic features with fuzzy semantic similarity features enhances score accuracy and generalization capacity in English translation applications. While the proposed method is intriguing for enhancing translation models, a deeper exploration of practical challenges and a broader range of real-world applications could strengthen its applicability to practitioners in the field. The research contributes significantly to addressing reliability and precision issues in neural network-powered translation systems, with a focus on scoring precision and applicability. Providing a detailed explanation of assessment metrics and their significance would enhance the reader's understanding of the model's performance. Table 5 highlights the use of fuzzy algorithms in translation, emphasizing key characteristics and identifying areas that lack comprehensive research.

IV. FEATURE EXTRACTION

Feature extraction in translation is a crucial process, involving the distillation of essential linguistic information from source texts. This step forms the foundation for subsequent stages of machine translation (MT), facilitating more accurate and contextually aware language conversion. Fig. 5 provides an illustration of the general feature extraction model [69].

The study conducted by Cui et al. [70] focused on the significant obstacles often encountered in conventional English translation systems. These concerns include the lack of a clear semantic context, inadequate selection of semantic features, and decreased translation accuracy. In this regard, an intelligent recognition of the English translation model is presented, utilizing sophisticated feature extraction techniques to address these concerns. This research comprises a search model that plays a crucial function in performing thorough searches for the underlying meanings and content inside the language that necessitates proofreading. This model accelerates the translation process by efficiently comprehending and analyzing the semantic complexities inherent in English texts. Furthermore, the model leverages the analysis of behavior log data to obtain valuable insights into user behavior and preferences, thereby enabling system optimization to enhance user experience. The central focus of the proposed model is the application of the maximum-entropy principle. This principle serves as a fundamental notion that partitions the work of phrase recognition into three separate components: identification of the sentence head, identification of the sentence tail, and identification of the whole

TABLE 5. Summary of fuzzy algorithm features and gaps in translation.

Ref No.	Study Focus	Description	Contribution to MT	Efficiency in Translation Process	Applicability in MT	Limitations/Gaps
[62]	Semantic Ordering in NMT Using Fuzzy Theory	Examines challenges in English MT, suggesting semantic ordering models based on fuzzy theory to improve translation precision.	Integrates fuzzy theory into NMT for enhanced precision.	Requires less time and achieves higher accuracy.	Useful for NMT frameworks.	Lacks comprehensive research; more development needed.
[63]	Semantic Layout in English MT	Proposes a novel technique using fuzzy theory to enhance semantic layout in English MT.	Improves output accuracy and reduces semantic ambiguity.	Outperforms typical semantic ordering models.	Suitable for English MT systems.	Early stage; needs more research and practical implementation.
[64]	EBMT for English to Hindi Translation	Introduces a system using NLP and Fuzzy Logic for EBMT, focusing on SOV alignments in English to Hindi translation.	Uses Fuzzy Logic for efficient resolution of linguistic differences.	Enhances translation accuracy.	Applicable in EBMT, especially for complex language pairs.	More exploration needed in the application of Fuzzy Logic in MT.
[65]	Language Study Using Fuzzy Algorithms	Conducts a language study to improve an English translation system using fuzzy algorithms.	Enhances translation accuracy and minimizes semantic ambiguity.	Includes Gaussian blurring for effective image processing.	Applicable in computational image processing for MT.	Requires integration of linguistic analysis with computational techniques.
[66]	Fuzzy Semantic Theory in Translation	Uses professional fuzzy semantic theory to enhance translation precision and emotional understanding.	Improves accuracy and emotional interpretation in translations.	Utilizes AI recognition for processing fuzzy information.	Relevant in the field of language interpretation.	Needs further exploration in AI-based recognition systems.
[67]	Ambiguous Information Identification	Proposes a new formal background using fuzzy linguistic aspects for coarse-grained objects.	Simplifies data analysis and reduces complexity.	Enhances computer speed and efficiency.	Useful for identifying fuzzy information in English interpretation.	Requires exploration in the integration of grain computing and formal concept analysis.
[68]	Fuzzy Semantic Optimum Control in English Translation	Provides a model for English translation addressing inconsistencies using fuzzy semantic optimum control retrieval.	Improves precision in data retrieval for English translation.	Utilizes bidirectional neural networks for training.	Suitable for enhancing reliability in neural network-powered translation systems.	Requires further exploration in practical applications and assessment criteria.

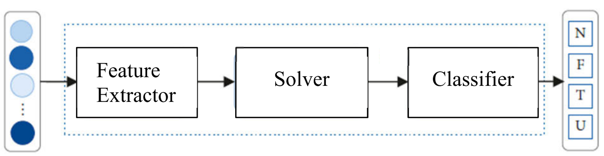

FIGURE 5. General feature extraction model.

clause. This methodology enables a more sophisticated and precise examination of English language text, thereby assisting in the identification of the most suitable feature semantics for translation purposes. The experimental results provide evidence of the efficacy of the algorithm developed in the course of this study. The model consistently demonstrates a much superior recognition rate in comparison to conventional approaches, thereby suggesting its proficiency in capturing and comprehending the intricate semantic context inherent in English texts. This advancement represents a noteworthy step in addressing the persistent challenges encountered in traditional English translation systems.

Li [71] highlighted the crucial role of translation in assessing students' proficiency in English. As stated, translation serves as a complete measure of students' mastery of their English vocabulary, sentence structure, grammar, and associated abilities. However, the process of manually evaluating translations may be laborious, subjective, and difficult to standardize, owing to the inherent flexibility of the criteria used for assessment. This paper proposes the design and implementation of an automatic rating system for translation, taking into account advancements in feature extraction algorithms. These algorithms have shown effectiveness in learning and identifying patterns from different types of information, such as text. This system aims to make contextually relevant judgments. The primary objective of this method is to improve the levels of impartiality, correctness, and efficiency of the evaluation of translations. Nevertheless, the lack of specific guidelines in translation assignments, along with the subjective nature of human evaluators who might be affected by their emotions and perspectives, may result in discrepancies in the criteria used for grading. The study presented an automated rating system that provides a prompt and effective alternative to human grading, resulting in a notable reduction in the amount of time instructors dedicated to this activity. Consequently, this facilitates educators in allocating a greater amount of time to direct instructional activities while simultaneously affording language learners the opportunity to systematically enhance their translation ability. Furthermore, this study emphasizes the capacity of an automated system to accommodate large-scale assessments. Automation of the grading process at educational institutions has the potential to decrease dependence on human resources and materials, resulting in enhanced efficiency. This approach also ensures the preservation of fairness and uniformity of assessment standards.

Liang et al. [72] underscored the pivotal role of text feature selection in text mining and information retrieval. Feature extraction, a fundamental process, employs specific metrics to identify relevant subsets of features, aiming to reduce dimensionality within test data. This step eliminates irrelevant or redundant features, serving as a preprocessing step for learning algorithms, enhancing accuracy, and reducing processing time. Deep learning, especially notable for uncovering intricate feature interactions and learning lower-level features directly from raw data, has limitations. Both supervised and reinforcement learning methods require substantial data support, presenting challenges in scalability and performance for more advanced tasks. Concerns about volatile data quality raise reliability, accuracy, and fairness issues that require future attention. Due to the intrinsic nature of text feature extraction, each method has distinct advantages and limitations. It is recommended to employ multiple extraction methods to extract the same features whenever feasible, ensuring a robust and comprehensive approach.

Dong et al. [73] addresses constraints in conventional interactive English translation systems, focusing on the clarity of the English semantic context, efficacy of feature selection procedures, and overall correctness of translation. The study introduces an interactive English-Chinese translation system using advanced feature extraction methods. This system, supported by feature extraction algorithms, produces better translation results and offers a potential resolution to challenges in the semantic context and translation precision in interactive systems. Further investigation and verification of this methodology could make a substantial contribution to translation technology.

In the context of text mining and information retrieval, Gite et al. [74] highlights the crucial significance of text feature selection, particularly using Ant Colony Optimization (ACO), to enhance classification accuracy and efficiency. The study acknowledges the challenges in feature selection for text data, emphasizing the importance of resolving unpredictable data-quality challenges to improve the reliability, precision, and equity of forthcoming applications. Text feature extraction encompasses various methodologies with unique strengths and limitations. The research suggests investigating multiple extraction strategies to capture the same features, providing robust and efficient text feature extraction solutions.

Dandapat and Way [75] introduced an innovative methodology to enhance named entity recognition (NER) in low-resource languages like Hindi by leveraging cross-lingual information. The approach involves using an online machine translation (MT) system alongside a unique word alignment procedure to project Hindi words onto their corresponding English translations. Cross-lingual features are estimated using an English NER model in conjunction with alignment data, and these features are integrated into a support vector machines-based classifier.

The study demonstrates a significant improvement in NER efficacy, with a notable absolute increase of 2.1 points (equivalent to a relative improvement of 2.9%) compared to a baseline model that already performed well. This research showcases the capability of MT systems to transfer information from languages with abundant resources to those with limited resources, particularly beneficial for low-resource languages like Hindi. While the primary focus is on NER, the authors express intentions to extend the technique to address additional classification issues in natural language processing (NLP), such as part-of-speech (POS) labeling and noun phrase (NP) chunking. Future research will involve assessing the proposed methodology using diverse classification algorithms and integrating cutting-edge features for a comprehensive investigation of its overall efficacy. The study also examines various word alignment tools to evaluate their impact on the strategy's effectiveness, promising substantial contributions to addressing natural language processing challenges in languages with limited resources.

Table 6 provides an analysis of different feature extraction methods, emphasizing their significance in translation and highlighting areas for potential improvements.

V. EVALUATION METRICS

The assessment of machine translation (MT) quality holds significant importance, employing either automated methodologies or human translators based on specific information requirements. Human-based approaches are essential to evaluate the adequacy of machine-translated materials, while automated techniques are advisable for assessing an entire MT system.

Munkova et al. [76] emphasizes the importance of using error ratio and accuracy metrics for individual phrases or segments when assessing MT output quality. The f-measure, capturing both accuracy and recall through a harmonic average, is identified as a suitable choice for assessing MT output quality. This finding holds true for the analysis of individual words, and the visualization of various measures using an icon graph demonstrates that the f-measure reflects average values of precision and recall.

In [77], the authors provide a comprehensive examination of breakthroughs in MT over seven decades, focusing on recent success in neural machine translation (NMT) techniques. The study traces the evolution of MT from

TABLE 6. Analysis of feature extraction techniques and their impact on translation.

Ref No.	Study Focus	Description	Contribution to Feature Extraction in MT	Efficiency in Feature Extraction Process	Applicability in MT	Limitations/Gaps
[70]	Intelligent Recognition in English Translation	Addresses obstacles in conventional English translation systems using sophisticated feature extraction techniques.	Improves semantic context understanding and feature selection in English translation.	Speeds up the translation process.	Applicable for enhancing semantic understanding in English MT.	Focuses on addressing challenges in traditional English translation systems.
[71]	Automatic Rating System for Translation	Proposes an automatic rating system for translation that utilizes advancements in feature extraction algorithms.	Aims to offer impartial, correct, and efficient translation evaluation.	Enhances evaluation efficiency and fairness.	Suitable for large-scale educational translation assessments.	Requires further development for consistent and objective grading.
[72]	Text Feature Selection in Information Retrieval	Emphasizes the importance of text feature selection to enhance accuracy and reduce processing time in text mining and information retrieval.	Reduces dimensionality of feature vector spaces in text mining and information retrieval.	Contributes to improved accuracy and reduced processing time.	Beneficial for learning algorithms and deep learning models.	Challenges in scalability and volatile data quality in deep learning models.
[73]	Interactive English-Chinese Translation System	Discusses constraints in interactive English translation systems and proposes an advanced feature extraction method.	Enhances English-Chinese translation quality with sophisticated feature extraction methods.	Produces better translation results than conventional methods.	Useful for interactive English-Chinese translation systems.	Focuses on semantic context clarity and translation correctness.
[74]	Text Feature Selection with Ant Colony Optimization	Discusses the significance of feature extraction using Ant Colony Optimization (ACO) to improve classification accuracy and efficiency.	Enhances classification tasks and learning performance in text categorization.	Improves efficiency in handling datasets with a large number of values.	Useful for optimization algorithms in text categorization.	Encounters challenges with complex planning problems and pattern recognition.
[75]	Enhancing NER in Low-Resource Languages	Provides a methodology to augment NER in Hindi using cross-lingual information and MT systems.	Significantly enhances the efficacy of NER for Hindi language.	Shows a relative improvement in NER performance.	Effective for NER in languages with limited resources.	Intends to expand to other classification issues in NLP.

rule-based and example-based methodologies to statistical machine translation (SMT) and delves into the significance of the transformer model. Addressing data scarcity, the study explores multilingual translation models and contemporary simultaneous translation techniques. The article also discusses the extensive applicability of MT, summarizing ongoing issues and suggesting prospective avenues for future study.

Liu [78] introduces a new framework for assessing machine-generated translation efficacy based on deep learning methodologies. The proposed model combines unsupervised and supervised learning, extracting language information to enhance language vector feature extraction. The methodology involves unsupervised learning, noise reduction for reconstructing automated translation samples, and improved language vector feature extraction using language vector functions and machine automatic translation data.

The integration of the language vector function into the deep-learning-based translation quality evaluation model enables the automated assessment of machine translation (MT) quality. Experimental findings demonstrate the model's effectiveness in assessing the quality of machine-generated translations, exhibiting consistency across various phrase patterns and independence from the quantity of sentences being assessed. The model maintains notable accuracy and precision throughout the assessment process, as evidenced by low disparities between machine-generated translations and real translations.

However, it's essential to note that the assessment outcomes may vary with modifications to the language or sentence structure of the translated text. The model's BLEU score gradually increases with the number of phrases, reaching a peak value of 98, indicating high efficacy in assessing MT quality. This comprehensive model has significant potential for influencing machine translation and language processing, particularly in language acquisition and translation endeavors.

In [79], an error analysis approach is employed to evaluate three popular neural network machine translation systems: Google, Baidu, and iFLYTEK. The analysis uses President Xi Jinping's keynote address at the 2018 Boao Forum for

Asia to assess translation accuracy across ontology, text, and discourse levels. The research categorizes translation faults, offering both quantitative and qualitative insights into each category. The study highlights progress in Chinese recognition at the ontology level but underscores challenges in idiomatic phrases and proper nouns. Syntactic and grammatical errors in sentence formation are identified, along with issues in contextually informed word selection. The study also addresses challenges in maintaining logical coherence, handling culture-specific content, and balancing fluency and fidelity to the source text at the text level. Solutions are proposed to improve machine translation and ensure effective communication of the speaker's intended meaning.

A research on Machine Translation Evaluation (MTE) [80] acknowledges its dual purpose: evaluating machine translation quality and providing feedback to enhance translation systems. The study explores MTE's evolution over time, categorizing research approaches into human evaluation, machine evaluation, and meta-evaluation. It emphasizes the importance of MTE in scenarios lacking reference translations and compares reference-translation-based and reference-translation-independent procedures for evaluating translation quality. Various automated evaluation strategies, from simple string matching to complex models considering grammar, semantics, and deep learning, are discussed. The study investigates the credibility of test datasets and the validity of human and machine evaluation standards, stressing the need for regular introspection to maintain the efficacy and legitimacy of MTE techniques.

In the research presented in [81], a novel English translation correction system is introduced to address constraints faced by machine translation. The system comprises essential elements such as a semantic translation model, translation memory, fuzzy input utterance function, decision function for selecting appropriate translations, and an output calibration mechanism. These components work together within a structured framework consisting of five modules. The system improves translation precision by identifying and rectifying translation faults, exhibiting enhanced precision compared to conventional machine translation algorithms. The efficacy of the system lies in its ability to enhance the efficiency and accuracy of English translation corrections, reducing the need for human proofreading and meeting the accuracy requirements of consumers. However, the study acknowledges challenges in maintaining the quality of machine translation, particularly the need for frequent updates to translation memory to incorporate new terms and their implications. The suggestion of creating sub-banks within the translation memory system is proposed as a solution to efficiently organize phrases and improve search operations.

In the study outlined in reference [82], the accuracy of Google Translate (GT) in translating culinary literature is assessed using a semiotic approach. The goal of this research is to build a library of Internet-based works on French cuisine. While GT demonstrates accuracy at the word, phrase, and sentence levels in translating culinary-related texts, it struggles to convey cultural nuances between languages. The semiotic perspective involves changing the linguistic form from the source language to the matching form in the target language while maintaining the underlying meaning. The study concludes that GT exhibits high accuracy in translating linguistic details of culinary texts but needs improvement in capturing cultural nuances. The research suggests that human-robot hybrids, exemplified by GT, might eventually replace human translators in certain contexts, highlighting the evolving role of IT in language translation.

In the study conducted by Liu and Zhu [83], a detailed comparison of six popular Neural Machine Translation (NMT) programs was performed to assess their performance in translating government writing from Chinese to English. The investigation utilized both objective technological metrics and subjective human assessments. The research identified flaws in machine-generated translations through a comprehensive analysis and comparison of translations produced by different NMT systems. To address the identified issues, a novel approach called the "NMT+ Lexicon Intelligent Translation Assistant" was proposed. This method significantly reduced errors in NMT-generated English translations of specific phrases, leading to improved translation quality across various assessment criteria. The study results suggest that adopting the proposed method has the potential to enhance the overall quality of machine translation. Among the NMT systems examined, IFLYTEK demonstrated the best performance in practical communication scenarios. The findings provide valuable insights for individuals seeking suitable machine translation systems for dealing with political issues and contribute to laying the groundwork for enhancing the efficiency of NMT systems. Additionally, a web-based corpus platform providing access to political document corpora and cue lexicons was proposed.

In Sun Yiqun's work [84], a mathematical framework for quantitatively assessing machine translation is established, utilizing the Analytic Hierarchy Process (AHP) and fuzzy mathematics theory. This method eliminates the need for subjective assessment of weight values by employing pairwise comparisons of judgment matrices. The research collected data through questionnaire surveys to evaluate translation quality and applied fuzzy mathematics to construct a fuzzy matrix, forming the basis for a comprehensive assessment of machine translation quality. By accumulating a comprehensive assessment vector, the study objectively measures the quality of translated content. Disparities in various quality indicators of translation software were investigated using a fuzzy comprehensive evaluation method. The research facilitates the identification of translation-quality software and provides valuable insights for software developers to enhance the design and quality of their programs.

In Ramun's study [85], it was found that when there are mistakes in machine-translated texts, understanding them requires more mental effort than when there are no mistakes.

Lexical errors, in particular, pose the greatest challenge to mental processing. The study aims to provide groundwork for understanding how readers' minds work while consuming mechanically translated material. However, future studies are recommended to increase sample sizes, explore a wider range of text lengths, and include participants from diverse demographic backgrounds to enhance the validity and reliability of the results.

Hasyim's research [86] focuses on the translation of recipes from French to Indonesian, specifically evaluating the accuracy of machine translation in this culinary setting. The study demonstrates that Google Translate (GT) utilizes a semiotic translation framework, successfully conveying the essence of French-Indonesian culinary texts through words, phrases, and sentences. However, the challenge lies in cultural equivalence, where GT struggles to grasp cultural subtleties, resulting in translations that are too literal. The research suggests that improving GT's accuracy in translating cultural equivalents can effectively enhance the overall quality of translation in culinary literature.

Acikgoz and Sert's work [87] emphasizes the crucial role of machine translation in advancing globalization, making complex subjects more accessible to non-specialists. Lin and Chien [88] echoes this sentiment, stating that reliable machine translation of technical material is no longer science fiction, contributing to increased accessibility of professional information. The authors argue that the use of digital tools and automated translation services is essential for the acquisition and dissemination of scholarly work, avoiding the cost and time constraints associated with human translation.

The study detailed in [89] examines how machine translation affects the translation workflow of the Directorate-General for Translation (DGT), focusing on English-French (statistical MT) and English-Finnish (neural MT) translation paradigms. The research, based on data collected from 20 professional translators at the DGT, reveals that on average, machine translation improves productivity, with varying effects among translators. The study also explores the weak links between technical difficulty and post-editing time, emphasizing the psychological benefit of not having to start translations from scratch as one of the reasons for choosing machine translation.

In Adiel et al.'s study [90]; the comparative accuracy of machine-based and human-based translations was examined, with a specific focus on Arabic-to-English translation. This research encompassed two distinct translation contexts: medical language, specifically health awareness messages, and literary language, particularly ancient Arabic poetry stanzas. The data collection involved obtaining medical texts from King Fahad Hospital of Imam Abdulrahman Bin Faisal University and literary texts from an unpublished translation collection. The study utilized the word error rate equation (WER) and included the analysis of proficient translators as part of its research approach. The findings suggest that machine-based translation offers some advantages but still requires substantial human involvement through intensive editing. In essence, while machines play a supplementary role, active human involvement remains crucial in the Arabic-to-English translation process.

For a comprehensive overview of important research covering various areas of machine translation (MT) quality evaluation, refer to Table 7 in the respective document.

VI. MACHINE TRANSLATION AND ETHICS

In this section, the authors briefly touch upon different viewpoints and various aspects related to translation ethics in the era of AI. While the document only provides a glimpse of these perspectives, a more in-depth exploration reveals that many scholars have extensively discussed the ethics of machine translation (MT) evaluation.

For instance, Rossi and Carré [91], as cited by Kenny [92], raised concerns about the ethics resulting from the methods employed in MT evaluation. They argue that the automatic evaluation of MT systems, driven by considerations of speed, cost, and ease of measurement, is unethical. They contend that publicizing machine output as reaching human parity based on automatic evaluation results equivalent to those of a reference human translator is unethical. This perspective is closely tied to the ethical considerations within the translation process itself.

Another viewpoint, presented by Canfora and Ottmann [93], suggests that the translation of legal contracts may be subject to data ownership rights. They argue that when using any MT, the confidentiality and liability of the contract content might be exposed to disclosure, posing an ethical problem. This opinion revolves around the relationship between stakeholders in the translation process.

Zasiekin and Vakuliuk [94] posit that Neural Machine Translation (NMT), being unsupervised, is a responsible party for ethical problems. They consider poor quality of translated content produced by NMT, as well as other MT systems, as a violation of the moral rights of the content authors. This perspective advocates for the rights of the party involved in content creation.

Renowned scholars in translation have also raised ethical concerns about the use of translations made by human translators for training machine models by developers. Questions have been raised about data ownership, and ethical considerations are brought into play when developers automate a translation without informing the original translator. To address these concerns, obtaining consent for reusing translations must align with legal agreements between translators and developers to prevent ethical violations. This view emphasizes the ethical rights of various parties involved in the training of machine translation models.

Concerning various aspects, ethical considerations are linked to the use of MT by translators in providing services to clients. To address this, agreements between human translators and clients should explicitly stipulate whether the use of machine translation is allowed or not. Both

TABLE 7. Machine translation evaluation methodologies, contributions, and future directions.

Ref No.	Study Focus	Description	Contribution to MT Quality Assessment	Methodology Used for Assessment	Limitations/Challenges	Recommendations/Future Directions
[76]	Error Ratio and Accuracy in MT Output Assessment	Emphasizes using all metrics of error ratio and accuracy for each phrase or segment in MT output assessment.	Uses the f-measure to capture both accuracy and recall.	Human-based approach with automated methodologies.	Not specified in the summary.	Further analysis at the word level.
[77]	Evolution and Breakthroughs in MT	Reviews the progression of MT from rule-based to NMT, emphasizing the transformer model and data scarcity solutions.	Highlights the advancement of NMT and its contemporary techniques.	In-depth analysis of MT techniques.	Focuses on NMT's recent success, overlooking earlier MT forms.	Investigating ongoing issues and future research directions.
[78]	Framework for Assessing Machine-Generated Translations	Presents a new deep learning-based framework to evaluate MT quality.	Utilizes unsupervised and supervised learning for quality assessment.	Deep learning methodologies for automated evaluation.	Variability in assessment outcomes with language or sentence structure changes.	Continuous model improvement and adaptation.
[79]	Error Analysis of Neural Network MT Systems	Examines popular neural network MT systems using error analysis.	Identifies translation errors at different levels and suggests improvements.	Error analysis approach.	Issues in sentence formation and handling culture-specific content.	Enhanced language understanding for idiomatic phrases and proper nouns.
[80]	Historical and Methodological Perspectives on MTE	Discusses the history and approaches of Machine Translation Evaluation (MTE).	Categorizes MTE methods and evaluates translation quality.	Human, machine, and meta-evaluation.	Not specified in the summary.	Regular introspection to maintain MTE efficacy and legitimacy.
[81]	English Translation Correction System	Proposes an English translation correction system with multiple modules for improved precision.	Aims to improve translation precision and address MT constraints.	Semantic translation model, translation memory, and fuzzy input function.	Challenges with evolving language and managing translation memory.	Organizing phrases in sub-banks for efficiency.
[82]	Semiotic Approach to Assessing Google Translate	Evaluates the accuracy of Google Translate in translating culinary literature.	Highlights GT's linguistic accuracy but notes challenges in cultural translation.	Semiotic approach for translation assessment.	Difficulty in translating cultural nuances.	Improvement in translating cultural equivalents.
[83]	Comparison of NMT Programs in Political Context	Compares six NMT programs for translating government documents from Chinese to English.	Suggests an intelligent translation assistant to improve NMT accuracy.	Objective and subjective assessments.	Flaws in existing NMT systems for specific phrases.	Use of NMT+ Lexicon Intelligent Translation Assistant for better quality.
[84]	Quantitative Assessment of MT	Introduces a mathematical framework for quantitatively assessing MT.	Utilizes Analytic Hierarchy Process (AHP) and fuzzy mathematics for assessment.	Fuzzy comprehensive evaluation method.	Not specified in the summary.	Focus on pinpointing software deficiencies for improvement.
[85]	Mental Effort in Understanding Machine-Translated Texts	Studies the mental effort required to understand texts with errors in machine translation.	Highlights lexical errors as a significant challenge in MT.	Not specified in the summary.	Limited to understanding mental effort, requires broader studies.	Expand research scope for comprehensive understanding.
[86]	MT Accuracy in Culinary Text Translation	Examines the accuracy of machine translation in translating recipes from French to Indonesian.	Shows GT's effectiveness in linguistic details but not in cultural translation.	Semiotic translation framework.	Struggles with cultural nuances.	Enhancing translation of cultural equivalents in culinary texts.
[87]	Role of MT in Advancing Globalization	Discusses the impact of MT in facilitating understanding of complex subjects.	Highlights the increasing accessibility of professional information through MT.	Not specified.	Not specified y.	Encourages the use of digital tools for scholarly work dissemination.

TABLE 7. ***(Continued.)*** **Machine translation evaluation methodologies, contributions, and future directions.**

Ref No.	Study Focus	Description	Contribution to MT Quality Assessment	Methodology Used for Assessment	Limitations/Challenges	Recommendations/Future Directions
[88]	Professional Information Accessibility via MT	Supports the use of MT in making professional information more accessible.	Asserts that MT can enable non-specialists to grasp complex topics.	Not specified.	Not specified.	Advocates for the use of MT in the dissemination of professional knowledge.
[89]	MT Impact on Translation Workflow at DGT	Investigates the impact of MT on the translation workflow of the Directorate-General for Translation (DGT).	Assesses productivity increase with MT use in professional translation.	Monitoring of professional translators using MT.	Varies widely from translator to translator.	Focus on the psychological benefit of MT in professional translation.
[90]	Comparative Accuracy of MT: Arabic to English	Compares machine-based and human-based translations from Arabic to English.	Suggests the need for human involvement despite MT's supplementary function.	Word error rate equation (WER) and expert analysis.	Requires intensive human editing for accuracy.	Emphasizes the active role of humans in Arabic-to-English translation.

translators and clients need to be aware of their rights when machine translation is employed in the translation process.

The ethical considerations related to the use of machines in translation production involve multiple parties, including the translator, the machine, the developers, and potentially the computers acting as agents. Sakamoto [95] emphasizes the importance of clients being aware of the use of machine translation in the translation process. Chesterman [96] delves into the ethics and trust of clients in translation, proposing guidelines to safeguard the rights of clients with a focus on quality, source authorship, and target readers. The ethical issues surrounding artificial intelligence (AI) and machine translation (MT) have complex social and non-social dimensions that are challenging to encompass fully in this study. However, the study attempts to provide an overview of these issues.

In summary, all stakeholders involved in machine translation should have a comprehensive understanding of the ethical considerations and issues related to their rights when using MT. Concerns such as data related to translation and translators, data ownership, permissions for data reuse, copyrights, and payment must be thoroughly considered to ensure ethical practices in the field of machine translation.

VII. DISCUSSION

The domains of (AI), particularly (MT) and (NLP), have been greatly enhanced by (DL) techniques, which use neural networks and hierarchical data processing. Due to these developments, language translation has become much more effective, enabling the analysis of complex patterns. The resource-intensive nature of these models necessitates substantial processing capacity and large datasets, which are obstacles to the implementation of DL in MT. This sophisticated approach recognizes both the revolutionary impact of DL on MT capabilities and the critical resource challenges that arise from its implementation. These models have also shown great effectiveness in complicated pattern recognition. Language processing and other jobs requiring delicate data interpretation are areas where these models shine, but they struggle when it comes to handling sparse data, maintaining large systems, and capturing linguistic nuances. To overcome inherent limits and fully exploit DL's potential in AI applications, continual innovation and expansion of computing and data resources are crucial. The combination of multiple ML and DL approaches holds the possibility of further optimizing MT systems. Moreover, these models excel at catching complicated patterns and subtleties, increasing the efficacy of language translation and widening AI applications. Nevertheless, the efficacy of these methods is constrained by the substantial resource demands for training and the challenge of managing intricate network structures. The use of RNNs, transformers, and bilingual corpora in machine translation has improved translation accuracy and coherence, but dealing with language complexities and data restrictions remains a difficulty. Although GPUs have resolved many computing issues, their high cost and technical requirements limit their availability. Future breakthroughs rely on merging multiple ML/DL techniques to overcome present constraints and fully realize DL's promise in developing complex, accurate MT systems across a wide range of language pairings and structures. NMT has transformed the translation industry by utilizing sophisticated techniques such as the utilization of parallel text data, encoder-decoder designs, and unsupervised training methods to improve translation accuracy, fluency, and contextual suitability. When it comes to producing reliable translations for various language uses, these systems are very effective, but at the cost of requiring significant resources and extensive data for optimum performance. Translation quality and system resilience have been enhanced by the use of techniques such as adversarial stability training and the integration of extensive monolingual data sets.

NMT faces challenges such as the need for abundant parallel corpora, complexities in integration, and the ongoing need for system progress and improvement. Notwithstanding these obstacles, NMT continues to broaden its scope, including the translation of several Arabic dialects and comprehension of legal terminology. This showcases the adaptability and promise of NMT in overcoming language barriers. The area is characterized by a persistent drive towards more advanced models and training techniques to overcome current constraints and fully use the promise of NMT in worldwide communication. The review of recent advances in machine translation shows a wide range of novel approaches and ideas that considerably improve translation accuracy and efficiency. Statistical models based on bilingual texts are the basic technique for early MT systems, demonstrating successful in resource-rich languages but having limits in low-resource settings. Incorporating Neural Network Language Models (NN LM) into Statistical Machine Translation (SMT) systems improves fluency, especially in scenarios with sparse data. Attention mechanisms in decoders significantly improve translation quality by maintaining contextual relevance, but their full potential requires deeper qualitative investigation. Modular architectures in SMT using phrase tables produced from monolingual corpora outperform earlier approaches, particularly in unsupervised circumstances. The comparison of Neural Machine Translation (NMT) with SMT demonstrates NMT's developing advantage in certain language pairings, despite the need for a better understanding of NMT's limits. Comprehensive NMT evaluations stress the need of new topologies beyond transformers, as well as a greater understanding of NMT physics. The use of monolingual data in NMT offers improved accuracy in low-resource languages, while linguistically driven techniques give a deep examination of MT systems, providing valuable insights into dealing with complicated linguistic challenges. Collectively, these advancements highlight a dynamic evolution in machine translation, driven by a combination of statistical, neural, and linguistically informed methodologies, all of which contribute to the larger goal of developing accurate, efficient, and contextually aware cross-lingual communication tools. In the field of NLP, several strategies ranging from tokenization to rule-based approaches are essential for improving translation processes and strengthening linguistic understanding. Tokenization and part-of-speech tagging are fundamental techniques that establish the basis for effective text processing and syntactic analysis. Although Named Entity Identification and Parsing have their limits when it comes to handling linguistic ambiguity and complexity, they do improve semantic correctness and understanding of grammatical links even more. Advanced techniques like language modelling and word embedding enhance semantic understanding, depending on large training datasets. Attention mechanisms and Seq2Seq models enhance translation accuracy by prioritizing pertinent textual components and effectively handling sequential data, notwithstanding difficulties associated with lengthy sequences and implementation complexities. In modern NLP, the transformer architecture provides remarkable accuracy by using parallel processing, but at the expense of significant computational resources. Transfer learning enhances the flexibility of NLP applications by customizing pre-trained models for particular tasks, with the efficacy depending on the quality of the underlying datasets. On the other hand, rule-based approaches provide a systematic but less flexible approach to translation. Collectively, these many NLP strategies form the foundation of translation technology, with each one playing a role in the complex framework of language processing while addressing their own distinct difficulties. The use of fuzzy algorithms and theories into MT has represented a substantial advancement in improving translation precision and effectiveness. The findings demonstrate that integrating fuzzy logic into translation processes, ranging from semantic ordering to layout optimization in NMT frameworks, enhances both accuracy and efficiency by reducing the time and resources needed for translation jobs. These techniques are widely applicable to other languages and machine translation systems, including translations from English to Hindi and improvements in the semantic aspects of English machine translation. This showcases their adaptability in dealing with linguistic difficulties and ambiguities. Furthermore, the integration of fuzzy semantic theories with AI recognition in translation highlights an enhanced comprehension of emotional subtleties, hence enhancing the quality of translation. However, the area recognizes the need for more systematic and thorough research to address current constraints. These include the incorporation of computational approaches with language analysis and the practical use of fuzzy logic-based models. As these approaches progress, they have the potential to greatly enhance the translation process, resulting in increased accuracy, efficiency, and contextual relevance. While a comprehensive review for various AI techniques in translation has been provided, there is still a chance to integrate comparative analysis of different methodologies like deep learning, neural networks, fuzzy logic, and feature extraction in particular contexts or language pairs. Discovering potential novel algorithms, revolutionary advancements in computational linguistics, and emerging technologies have the potential to reshape the landscape of machine translation to provide insights into the future of this dynamic field. Addressing difficulties such as managing idiomatic expressions, cultural subtleties, and emotional tones would provide a nuanced comprehension of the present state of machine translation technology. Extending the discussion to cover how AI tools can improve human translation in achieving greater accuracy and efficiency can gain new insights into the collaboration between human cognitive talents and AI technology, resulting in improved accuracy and efficiency. Incorporating specific case studies or real-world applications of AI in translation across different domains would offer practical insights into the effectiveness, challenges, and context-specific nuances of applying AI in translation. Exploring the intersection of MT and NLP with other disciplines like cognitive science and linguistics could provide a holistic view of AI's role in translation.

VIII. CONCLUSION

In this comprehensive investigation, a thorough exploration into the realm of AI-driven translation was conducted, aiming to analyze the intricate effects of Artificial Intelligence on the field of language translation. The study delves into various methodologies, challenges, trends, and potential future developments in this domain. Key concepts such as Machine Learning, Deep Learning, Statistical Machine Translation, Natural Language Processing, Neural Machine Translation, Fuzzy Algorithms, Feature Extraction, and Evaluation Metrics were examined, revealing their integration has not only facilitated communication across linguistic barriers but has also fundamentally transformed the nature of the translation process.

The investigation highlights that Artificial Intelligence, particularly Neural Machine Translation, stands at the forefront of this transformative movement. Translation accuracy has achieved new heights due to improved capabilities in understanding context, subtleties, and idiomatic expressions. The study emphasizes the significant enhancement of machine translation efficacy through the collaborative integration of human knowledge. Looking ahead, promising opportunities lie in the emergence of multimodal translation, incorporating picture and voice recognition, offering potential for more inclusive communication. The study recognizes the growing importance of addressing linguistic diversity through adaptive translation systems sensitive to contextual nuances.

In conclusion, the exploration of AI-driven translation reveals a trajectory filled with possibilities and prospects. The fusion of human creativity with AI accuracy opens up a limitless realm of communication possibilities, contributing to the development of a global society capable of overcoming linguistic barriers. The authors collectively contribute to the ongoing narrative of artificial intelligence in the translation field. Future research directions are envisioned to focus on developing innovative structures for Neural Machine Translation, overcoming its limitations, and maintaining high translation accuracy with acceptable timeframes to meet real-time translation needs.

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