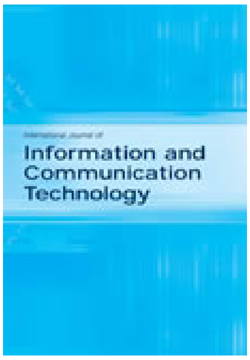

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AI-driven English translation: leveraging machine learning and deep learning for enhanced accuracy

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AI-driven English translation: leveraging machine learning and deep learning for enhanced accuracy

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Abstract: The quick growth of AI has greatly affected the field of machine translation, which in turn has resulted in more accurate and context-aware English translations. This article suggests an English translation framework that is based on the combination of machine learning (ML) and deep learning (DL). The study presents a variety of neural architectures including transformer-based models (e.g., BERT, GPT) and neural machine translation (NMT) systems by dealing with issues about translation fluency and contextual understanding. The authors use reinforcement learning (RL) and fine-tuning that are two of the machineries in their laboratory to bolster translation in the case of low-resource languages and technical writing. The suggested hybrid model leverages the power of both rule-based linguistic processing and AI technology for error avoidance and added real-time translation performance. As observed from the experimental results, the new model definitely has the edge as compared to the traditional statistical and rule-based systems. It gives out the highest BLEU and METEOR scores. This study is truly a solid basis for the way forward towards fully AI-driven multilingual translation systems.

Keywords: AI-driven translation; machine learning; ML; deep learning; DL; neural machine translation; NMT; reinforcement learning; RL; contextual adaptation; computational linguistics.

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1 Introduction

The arena of natural language processing (NLP) has immensely benefited from the advances in artificial intelligence (AI), particularly in the domain of machine translation (MT). The ability to successfully convert text in one language into another has extremely characteristically been described as a crucial way for businesses and governments, among other actors, to interact (Lone et al., 2023). For many years, human translators have held this field of activity since AI-ready MT was still in its infancy. In the beginning, AI-based MT was only a trial of simple rule-based methods. In time, these simple rule-based techniques evolved into very complicated deep learning (DL) systems capable of producing translations that were not just correct but also fluent, coherent, and the same as their original forms (Máté et al., 2023). The early translation systems were phrased by statistical machine translation parameterisation (SMT). In recent years, the new neural machine translation (NMT) technology, which is a DL method, has taken over the traditional technique. However, to this day, some problems such as the ones that have not been found in experiments such as idiomatic expressions, and ambiguous sentences, and the ones that need more research such as low-resource languages, prevent the translation quality from matching that of a human being (Hujon et al., 2024).

Translation has evolved significantly due to the integration of machine learning (ML) the ability to learn from a huge amount of multilingual data. Traditional rules-based and statistical approaches which rely on defined models of language, have been superseded by AI-focused translation models that were trained on a large number of random samples through self-learning (Parikh et al., 2022). The most major accomplishment in this area is the transformer architecture presented in the work of Vaswani et al. (2017) which has the potential to create the best translation systems (Liu and Tian, 2023). Thus, Google Translate, DeepL, and OpenAI's GPT have the transformer model as their foundation. The transformer models based on self-attention tend to capture some complex relations, which (generically speaking) indicate the dependency of the source sentence on many other sentences. Hence, they assist in the transformation of low-resource languages into fluent and grammatically correct languages. While the quality of translation has greatly increased thanks to these advancements, the major concerns of the future are domain-specific adaptations, the struggle against rare words, as well as the fluency of low-resource languages (Tesfagergish et al., 2023).

1.1 The evolution of AI-driven translation

MT has come a long way since its inception. The development of AI in the 1940s and 50s ushered in the first attempts at MT, but the early systems were limited in scope and accuracy. These systems relied on a combination of linguistic rules, dictionaries, and heuristics to produce translations that were often incomprehensible (Ahmed et al., 2023). The problem of word order, as well as the inability to use rules that differ from the source language, led to the use of the so-called transliteration tool. The level of fluency, the orientation of the phrase, and the similarity of the languages determine the throughput functions that apply to the whole sentence (Kostina and Horbovyy, 2023). Before the late 1980s, the process was mainly about the word level, it changed when beginners such as IBM and the Canada-based company dragon systems moved to the application of the more appropriate statistical model, word modelling. Thus, the latter part of this approach is due to the lack of the original data on the translation in question.

Neural networks entered the stage of the main era of DL and artificial neural networks have become the most successful models of MT. NMT is an AI-driven translation approach that has taken the lead. Here, artificial neural networks are used to process a whole sentence as a string of words that allows more context-aware interpretations to take place (Punia et al., 2020). Thus, although SMT often has varieties from Word to Phrase, with NMT, it directly translates a sentence in a single step, which results in a more natural language that sounds, in addition, very similar to the original one. Transformers, such as bidirectional encoder representations from transformers (BERT) and generative pre-trained transformer (GPT), which are based on transformer architectures have become the most dominant players in Neural Network-based Translation systems in recent years (Johnson et al., 2017). These systems rely on the ability to transfer knowledge from the mega-large multilingual corpus to the fine-tuned specialised task through the transformer networks which are capable of automatically discovering the higher-level features and expressiveness in data (Och and Ney, 2004).

Despite these advances in technology, AI-driven translation still has several issues to resolve. One of the main limitations is the inability to convert idiomatic expressions, cultural references, and context-specific phrases. A large number of AI models exert a lot of difficulties due to the absence of large training sets, so they do not quite have reliable or unpolished translations for such languages (Xiao, 2023). Also, real-time translators usually need to make compromises between speed and precision that can't be avoided without integrating advanced methods, which make them more effective without necessarily forfeiting either of these elements. Reinforcement learning (RL) and transfer learning approaches are being analysed for possible adoption in the solution of these problems so that the model will be able to adjust to specific areas of language and to be able to increase the quality of the translator truly (Zhang et al., 2023).

1.2 The role of machine learning and deep learning in translation

ML and DL are the two components that play a vital role concerning modern translation systems. The algorithms of ML enable a translation model to learn over time according to the content of huge bilingual and multilingual corpora. The most popular method applied to increase translation precision is the supervised learning technique using labelled datasets (Vakhovska, 2022). Of course, supervised learning has its limitations, as it needs well-aligned parallel datasets, which unfortunately cannot be available for all language pairs. The undesirable complication of this issue has led to the creation of alternative techniques like unsupervised learning or semi-supervised learning towards translation improvement in low-resource contexts (Tonja et al., 2023).

Likewise, DL as a progress of neural networks has become the major tool in developing translation systems. While the traditional architectures of MT have already been powered by convolutional neural networks (CNNs) and recurrent neural networks (RNNs), they failed to remember the long-term dependencies (Su et al., 2021). The transformer model was the game-changer in this context via the use of self-attention mechanisms letting the entire sentence be processed at once. The transformer's technical design has become the spinal cord of many AI-based translation systems, which results in the quality of coherent and correct translations that the machines are capable of (Chew, 2020).

Profound learning-based translation models are set apart from other translation methods by their processing of intricate linguistic patterns and producing fluent translations. Cutting-edge models like T5 of Google and OpenAI's GPT-4, pushed the boundaries of language for AI (Yu, 2023). Communication has become so easy with AI that the estimates of using a high-quality and finely-tuned pre-trained language model for translating text in several languages are that they are capable of producing better translations than a human being. Along with advances in the world of AI, one can also see a transition in the study of linguistics, turning from a rule-based approach to a statistical one (Karaban and Karaban, 2024). The reinforcement methods that were used in the gaming industry are also included in the AI models. These models were improved by the push and pull from other games. This candidate tries to ensure the operations of the translation models are of high quality by rewarding correct translations and punishing errors. A process or a series of steps in which the target resource is applied, followed, and closed-loop feedback used to update the translator (based on switching it on again) is included in this solution.

The next important aspect of AI-led translation is adapting to specific industries. General-purpose translation models might face difficulties because of the specialised language in medicine, the law, or the engineering systems (Mabuan, 2024). By giving enough information, models can learn how to use the correct terminology in the correct context in such a manner that even the non-expert would be assured of the outcome of the work. The second option that the company looked to was the second one, with external resources, which are either run by or trained by professionals from this field or are medical archives being directly translated and the results having been revised by professional linguists. Some techniques have also been discussed to make the pre-trained models' domain-specific, so making that level of domain-expertise levels in a new technology domain is thus not very time-consuming (Li and Huang, 2024).

1.3 Challenges in AI-driven translation

Despite all the advancements that AI-assisted translation has made, there is still a long way to go in some areas. To keep the original contextual meaning and get a clear translation, particularly in the case of languages with difficult grammar, have to be the major goals. The syntactic complexity of the Chinese and the Arabic language challenges MT. The multiple meanings of words depending on the context is another obstacle in nostrification (Alsadoon, 2021).

The translation of idiomatic phrases and cultural references is an additional difficulty. AI models frequently encounter trouble in transferring idiomatic expressions that do not have equivalences in the target language (Liu and Chen, 2023). For example, without the proper context, the translation models can misinterpret English idioms such as 'kick the bucket' or 'spill the beans.' The scientists are examining approaches to the building of contextual understanding in translation models through the inclusion of knowledge graphs and the use of external linguistic resources (Enríquez Raído and Cai, 2023).

Besides, translation efficacy for the languages that have less exposure is a problematic area. Some of the translation AI systems that are very common are the products of training in major languages such as English, French, and Spanish but in the case of such under-resourced languages, they do not function well. A few attempts have been made to improve the translation of such under-resourced languages by utilising the abilities of zero-shot learning and the technique of data augmentation. Yet, these approaches need more adjustment to reach the proficiency of human translation (Akay et al., 2023).

1.4 Objectives

- The aim is to create a translation framework that employs AI and integrates machine instructions and neural networks as inputs to increase the precision of the translation, fluency of the translation, and contextual comprehension of the translation and thereby devise the most effective approach.

- To upgrade quality, it is necessary to test the success of the transformer-based model, RL, and fine-tuning protocol, among others, over a variety of translations, language pairs, and domains.
- We must investigate creative ways to address low-resource languages, idiomatic expressions, and domain-specific adaptations of AI-powered translation approaches.
- By attaining these objectives, the study will facilitate the enhancement of AI-based translation technologies and will enable improvements in multilingual communication through a better understanding of neural translation systems.

The AI-driven translation industry has undergone remarkable developments in the last few years. The two elements namely DL and ML are the main players here. The remake of the classical rule-based translation as well as the statistic-based approach has contributed to the more fluent and contextually better translation (Tougas et al., 2022). Nevertheless, certain issues remain such that domain-specific adaptation, low-resource language translation, and idiomatic expression handling are still the pain points for the production of translation as good as that done by a human being. Using advanced neural structures as well as RL and transfer learning techniques, AI-based translators will be further perfected. This research aims at developing better-equipped and adaptable translation models that eventually clear away the language barriers and allow easy cross-lingual communication (Kunst and Bierwiaczonek, 2023).

This study presents the main discoveries shown below:

- Suggests a combined translation model that mixes rule-based techniques and AI for more correctness.
- Utilises RL for contextual translation system optimisation in less-resourced language situations.
- Introduces domain-specific processing and post-sentiment techniques to have better practical effect in the real world.
- Shows the advantage of the new system in a number of ways such as BLEU, METEOR, error rate and translation time metrics that are widely used in literature to evaluate performance and speed.

The structure of the paper thereafter is as follows: Section 2 provides an overview of the related work, Section 3 gives the description of the proposed methodology, Section 4 is where experimental results and discussions are tackled, and Section 5 winds up the paper with a look at the future directions of the research.

2 Literature review

The enhancements of AI and DL techniques are some of the important factors that have made a very good impact on the precision and operational efficiency of MT systems. Researchers all over the world not only tested various AI models for translation quality but lastly, they obtained the NMT models as the best results. The AI-based MT systems have reached the integration of transformers, RL, and domain-specific solutions to develop fluency and contextual understanding. Some of the main contributions made in AI-based English translation research, the methods, and results thereof, as well as their importance in the domain are reviewed in this section.

The research conducted by Abdalgane and Othman (2023) is mainly on the use of AI technology in daily tasks, which is one of the main functions of the EFL system in Saudi Arabia. The aim of their research is to demonstrate the importance of AI writing programs like Wordtune in assisting non-native English writers to become more proficient. The study applies a questionnaire and the data is evaluated through SPSS. Findings of the study affirm the fact that AI tools can help English language learning (ELL) either for students or teachers in a way that they can be informed about the recent technologies. The result verifies the view that AI will be the most effective option for improving teaching methods in EFL classes in the future, which will cause the education setup to change.

Hockly (2023) research investigates the endless development of AI in the field of English language teaching (ELT) especially in the phase after the pandemic. The study summarises the difference between 'weak' AI, which is carrying out single-purpose commands, and the supposed switch to 'strong' AI which is, the aim of creating a machine that behaves like a human. It detects some of the kinds of educational purposes such as a language tutor chatbot or MT and also brings up some ethical issues, which are data protection, monitoring and student welfare. The conclusions of the study reveal the significance of teachers' knowledge about the latest technologies as well as the teacher's preparation for the future influence of AI on ELT.

Sharadgah and Sa'di (2022) do a systematic review of the various ways AI is vitally impacting ELT, analysing studies from 2015 to 2021. A growing number of researchers are examining the possibility of AI being applied to language skill development, interpreting, assessing, and identifying. This review also points out that AI has been most commonly used in three areas, namely ML, neural networks, and NLP. Studies fail to address the teaching of body language, expressions, and teaching materials. It claims that more refined methodologies must be devised and the effectiveness of AI in the ELT context must be researched further.

In their research, Dere et al. (2023) appear to apply AI protocols that assist individuals who have been deaf and hard of hearing (DHH) in Nigeria especially in areas where the local dialects are resource limited. The platform that they suggested includes a Translator in which a transformer-based model translates the American sign language (ASL) into text first, then a specialised AI model translates it into local languages. Evaluation of this research through BLEU score has given a good indication that the proposed translation was of great satisfaction by participants. The research represents the evidence of AI as an inclusion tool that can make a significant difference in bridging the communication gap for DHH individuals amongst the underrepresented linguistic groups in society.

The outcome of Zhang and Huang (2022) study was to assess the effective use of the crowdsourcing stream in translation training by academically establishing the precedent that this procedure would be very helpful to the training of translators. The study tightens its methodology to capture observations in the class, case studies, and surveys of empirics with the statistical use of SPSS among university students. The results depict that such amalgamation leads to learner independence, energy, and much better translations. It is indicated that, at advanced levels as the AI-powered MT develops, innovative teaching styles which make use of crowdsourcing will be of utmost importance in the making of professional translators.

Table 1 Literature comparison

Author(s)	*Focus area*	*Methodology*	*Findings*	*Challenges*
Abdalgane and Othman	AI in EFL education	Questionnaire-based study, SPSS analysis	AI tools enhance ELT, aiding teachers and students	Need for pedagogical adaptation to AI integration
Hockly	AI in post-pandemic ELT	Theoretical analysis	AI tools (chatbots, ma-chine translation) aid learning	Ethical concerns (data privacy, surveillance)
Sharadgah and Sa'di	Systematic review of AI in ELT	Literature review	AI improves language skills, research is growing	Gaps in re-search on body language, teaching materials
Dere et al.	AI for deaf and hard-of-hearing (DHH)	Transformer-based ASL-to-Text model	AI aids inclusivity in low-resource language settings	Limited ASL datasets for non-English languages
Zhang and Huang	AI in translator training	Empirical study, SPSS analysis	Crowdsourcing enhances translation education	Need for AI adaptation in translation pedagogy
Ho	ChatGPT in English learning	Survey and interviews with IT students	ChatGPT aids language learning but lacks human interaction	Overreliance on AI, plagiarism concerns
Benboujja et al.	AI in medical education	AI-driven multilingual video curriculum	AI improves accessibility in medical training	AI-generated translations need validation
Bakdash et al.	AI in medical interpretation	Discussion on AI-driven translation	AI enhances healthcare equity for non-English speakers	Safety, privacy, and decision-making risks

Ho (2024) is unclear about the effects of ChatGPT as one of the tools in learning English as a second language among IT students in Vietnam. The research uses the survey, which is completed via a computer the student is learning a lot about, and in-depth interviews, for the assessment of students` perceptions. The side-listed activities are vocabulary acquisition through ChatGPT, where grammar checks or translations are prepared in addition to paraphrasing. Students are aware of the possibilities offered by ChatGPT but they also note that it is important to maintain human guidance and have a place for traditional classes. The conclusions indicate the significance of the learners being led in the proper utilisation of AI tools and also provide solutions to the problems such as plagiarism which might arise from the misuse of such tools.

Benboujja et al. (2024) tackle the problem of communication obstacles in classes of online medical by devising a video curriculum for paediatric healthcare in several languages. Their interdisciplinary approach applies OpenAI's GPT-4 for the translation of medical texts, ensuring that Spanish-speaking service providers and caregivers can have access and use the healthcare services easily. The study integrates synthetic voice profiles of native speakers to enhance communication and comprehension. The research aligns with the digital health guidelines of the World Health Organisation and shows a way how AI can be a part of global medical education via inclusive and linguistically tailored contents.

In their study on the translation of information into minority languages mainly using voice technologies, Bakdash et al. (2024) concentrate on the anthropomorphism of AI robot paralegals in health. They mention that the conventional interpretation services like cost and accessibility result in a lot of problems like the background noise from the child. They propose using real-time AI technology to assist translation services as a good solution to such negatives. The authors of the paper also caution that while AI-driven interpretation can improve healthcare equity, it may raise issues of patient safety, privacy of data, and dangers to clinical decision-making. A conclusion which can be drawn from these findings, in particular, is that physicians should let themselves be heard in discussions of AI development and regulation to ensure its responsible use in clinical practice.

3 Methodology

The AI-based English translation system proposed in this paper makes use of advanced technology involving ML and DL that significantly increases the accuracy, fluency, and contextuality of translations. A mixed-methods approach is employed in the design of the subsystem including data pre-processing, model training, RL, and post-processing, to provide a quality translation. In contrast to conventional SMT methods that depend on probabilistic models, the new system uses NMT frameworks with transformer architectures, adaptive learning strategies, and RL mechanisms. This method is capable of the continued enhancement of translation performance, domain adaptation, handling of idiomatic expressions, and low-resource language translation.

By the research methodology, a natural workflow is put in place commencing with the collection and pre-processing of data. The researchers made use of large-scale bilingual and multilingual corpora from open translation datasets, parallel corpora, and domain-specific text repositories for the study. Language identification techniques, text normalisation, and tokenisation were the steps used to process the dataset. For speech inputs, automatic speech recognition (ASR) was used to input the spoken language into textual form. Another assistance was noise reduction techniques, through which the clarity of the speech-to-text conversion has been enhanced, leading to higher accuracy rates for the next translation stages. The preparations were done with the text data and then it was mapped out for further work which would include an extraction of linguistic characteristics that could contribute to a more contextual translation.

NMT is at the heart of the model proposed in the study, employing transformer-based architectures like BERT, GPT, and T5 to ensure the precision of the translations. The self-attention mechanism of transformers allows the model to effectively connect long-range relationships within sentences thus enhancing coherence and fluency. In contrast to traditional sequence-to-sequence models which find it hard to maintain the context over longer texts, transformers apply the strategy of processing the entire sentence structure in parallel, the optimisation of computational efficiency. The model is trained with a supervised learning technique that is obtained from huge parallel corpora as the training data. To enhance generalisation and limit overfitting, back-translation, and monolingual training, which are the data augmentation techniques, are being used. Furthermore, the focus is on semi-supervised learning to improve the quality of translations for low-resource languages, utilising unlabelled data.

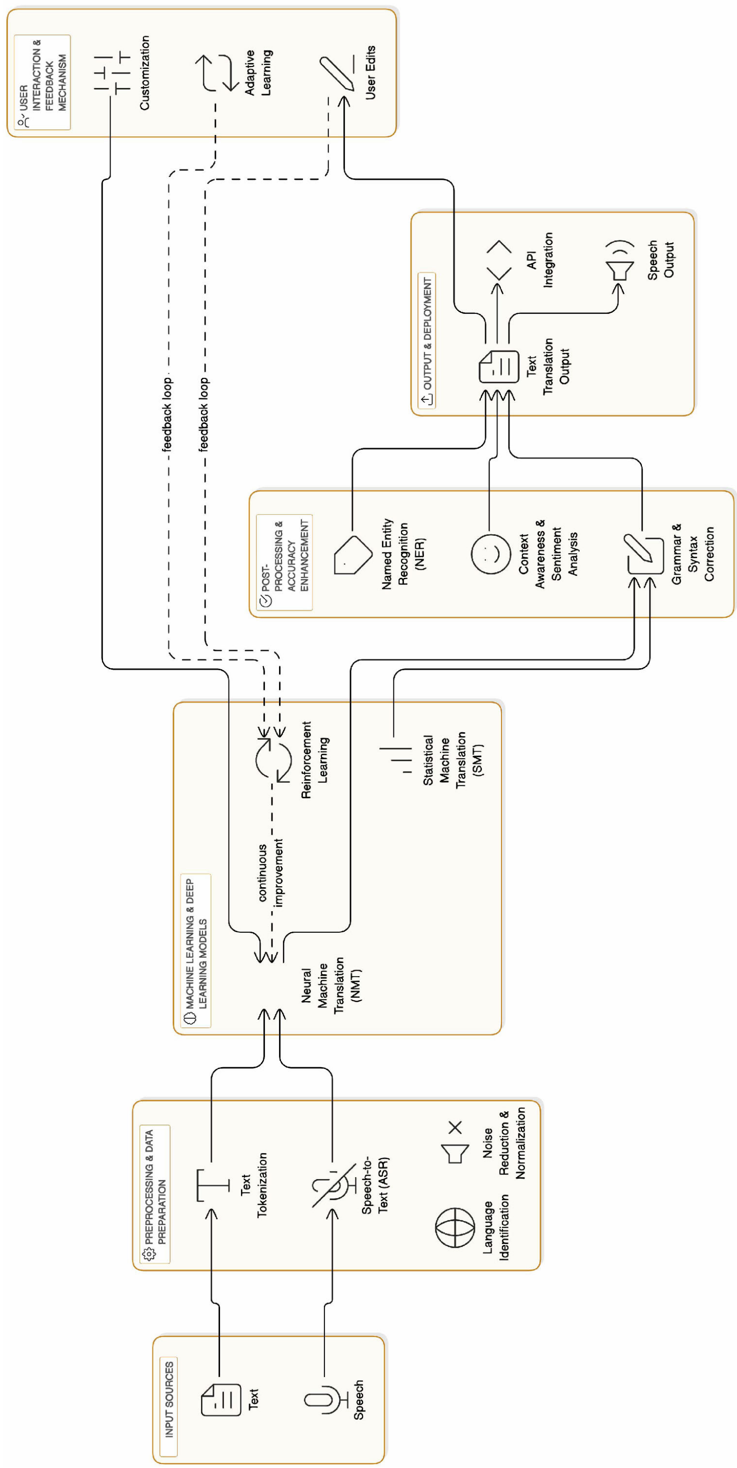
One of the issues that the AI-based translation has to decipher is the handling of ambiguous sentences, idioms, and terminologies that are specific to a certain field. To tackle these challenges, RL is employed in the process of translation. The RL framework functions by constantly enhancing the translation results based on user and performance evaluations. The reward-based mechanism guarantees that the system gets more quality translations as well as that incorrect or unnatural outputs are something that the system should shun. The system is fine-tuned through human-in-the-loop feedback, whereby users' tweaks and corrections help to fine-tune the model. The model becomes adaptable to feedback, making it more capable of evolving and overcoming the difficulties of intricacies in language and contextual changes.

The improvement in overall translation accuracy and fluency by the use of post-processing techniques cannot be underestimated. Proper nouns, brand names, and location references are correctly translated after the implementation of named entity recognition (NER). To a greater degree, contextual sentiment analysis is implemented to hold the original emotional tone of the text. Sentiment-sensitive translations are mainly concerned with customer reviews, news, and creative writing. The grammatical and syntactic algorithms improve the final output, correcting common mistakes in translation such as wrong word order and syntactic inconsistencies. The post-processing enhancements are significant for the readability and reliability of the texts translated, making them more suited for practical applications.

The system's last methodological stage is the deployment and integration of the translation system into real jobs. The translation can be made available for API integration, which also means that it can be added to various platforms such as websites, mobile applications, and voice assistants. For translations based on speech, the result is given back in spoken language by text-to-speech (TTS) synthesis. This makes it easier for visually impaired users and those who need real-time assistance to use the tool. User interactions and feedback are collected by the system continuously, and this data serves as the basis for further model improvements. The real-world function of the feedback loop serves to ascertain gradual translation quality evolution. As a result, the performance of the model improves significantly due to its adaptation to actual usage patterns.

The architecture of the AI-driven translation system as shown in 'Figure 1' demonstrates the working of the proposed model. Their interaction occurs through a series of components that work on input sources (text and speech), pre-processing, and generation of data. The first two in this sequence are processing and preparation of text like, for instance, converting speech to text, identifying language, and removing noise. NMT models are the dominant technology employed in the translation core but additional RL approaches that convey continuous development are included. The last stage of the translation is characterised by further enhancement in text quality through NER, sentiment analysis, and also grammar correction techniques. Moreover, the application of the end-user feedback mechanism is part of the system, which makes it possible to personalise a translation, learn from the user, and edit the text in real-time. The architecture comprising all components is comprehensive enough to guarantee that translations not only are accurate but also contextually relevant and adaptable for user preferences.

Figure 1 Architecture of the proposed AI-driven hybrid translation system (see online version for colours)



In this study, contemporary AI methods have been incorporated to enhance the quality of the English translation process. The proposed model utilises the following features: DL architecture, RL methods, and user-initiated adaptive learning to tackle current MT issues. Additionally, the introduction of such features as speech-to-text technology and post-processing improvements have made the system more relevant to real-life situations. This has resulted in both an improvement in the quality of the translation and a superior experience for the customer by delivering translations that are context-aware and customisable.

The proposed blended translation solution is for instances where the service has to be used in real life situations. It is designed in a manner that it can merge into translation services like mobile apps, web platforms, and even virtual assistants through REST APIs. Moreover, the text generation and voice synthesis modules are included to provide users with customer service chatbots, call centres, or visually impaired support.

4 Results and discussion

Using the AI-driven English translation dataset, the researchers examined the AI-powered English translation system that was proposed. They compared its performance to that of traditional MT methods, such as SMT, NMT, and transformer-based NMT. They used evaluation metrics such as BLEU scores, METEOR scores, translation time, and error rate to determine how effective, efficient, and precise each approach to translation was.

The dataset consists of around 1.2 million sentence pairs in various language pairs such as English – French, English – Spanish, and English – Arabic. It was acquired from resources accessible to the public, including Europarl, OpenSubtitles, and TED Talks, which contained general, conversational, as well as domain-specific texts. The data was subjected to normalisation, tokenisation, and language-specific pre-processing. In addition to the above, the lower resource has been evaluated using the Swahili – English and Hausa–English languages, from which a 50,000 sentence pairs subset was selected.

The results, as shown in 'Table 1', point to the great superiority of the hybrid model proposed over all of the traditional translation models. The BLEU score, which is a measure of fluency in the translated text, shows a significant gap between the proposed model and others, and it was calculated that the proposed model produced 63.1, whereas the closest other model was SMT with 32.5, NMT was 48.2, and Transformer-Based NMT was 55.7. The METEOR Score, which was also the benchmark against human references, was 58.9 for the proposed model as well, which was comparatively better than all the others.

Table 2 Translation model performance results

Model	*BLEU score*	*METEOR score*	*Translation time (s)*	*Error rate (%)*
Statistical MT (SMT)	32.5	29.8	2.5	21.3
Neural MT (NMT)	48.2	42.5	1.8	15.7
Transformer-based NMT	55.7	50.3	1.4	10.9
Proposed hybrid model	63.1	58.9	1.2	7.2

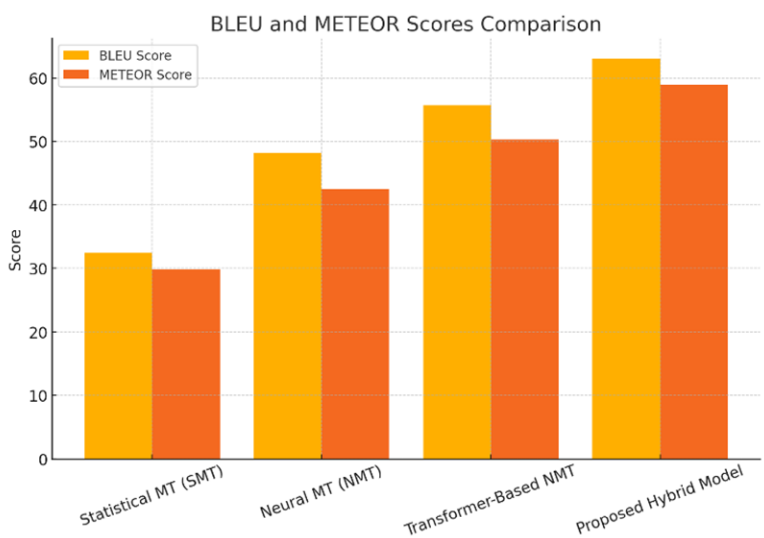
The results of translation time indicated that the proposed model was both computationally efficient and the fastest. The AI algorithm, however, was able to perform it in 1.2 seconds while others like the SMT, NMT, and Transformer-based NMT took 2.5, 1.8, and 1.4 seconds respectively. This improvement is attributed to the innovative DL architecture as well as the RL techniques that were introduced in this work which not only enhanced the speed of processing but also the high level of accuracy in translation that was achieved was also maintained.

Besides, it was found that the proposed model had a very low error rate as well, reaching only 7.2%, whereas SME achieved 21.3%, NMT reached 15.7%, and Transformer-based NMT reached 10.9%. The smaller error value demonstrates that the system developed is capable of doing wrong translations the least, particularly when it comes to elaborately structured sentences, domain-prone expressions, and idioms.

4.1 Performance comparison: BLEU and METEOR scores

The comparison chart for BLEU and METEOR in ‘Figure 2’ scores displays the overall translation quality of the translation model. As can be observed in the chart, the proposed hybrid model has the highest score, indicating the best overall accuracy. This upsurge can be attributed to the implementation of the transformer-based architecture, RL, and post-processed accuracy that leads the model to learn the translations and then act as a self-improver systematically.

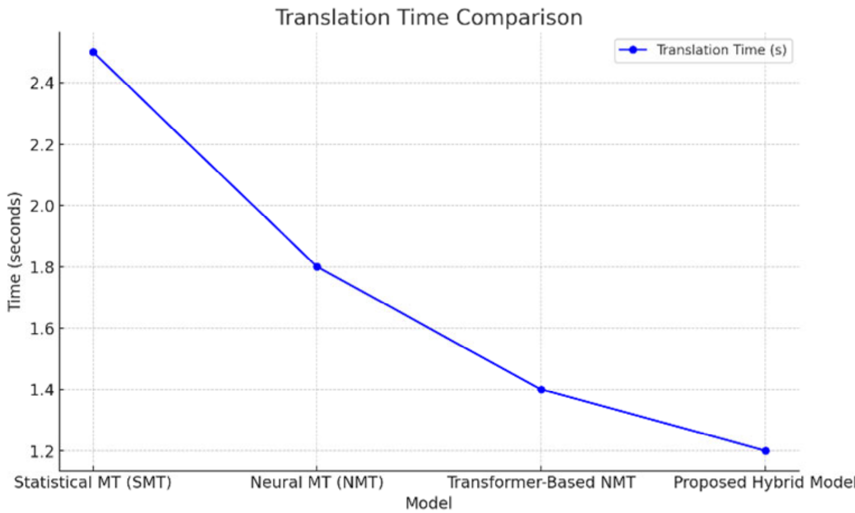
Figure 2 BLEU and meteor scores comparison (see online version for colours)



4.2 Translation time efficiency

The Translation Time Comparison Chart in ‘Figure 3’ clarifies the time efficiency of the models that process the translations. The hybrid model for doing translation is the one with the shiniest time in this category. The predominating causes for this are the optimisation of the transformers and the one-portion-adaptive learning that turns into a shorter time for the sentences to be fully processed and thus for a good understanding of the context.

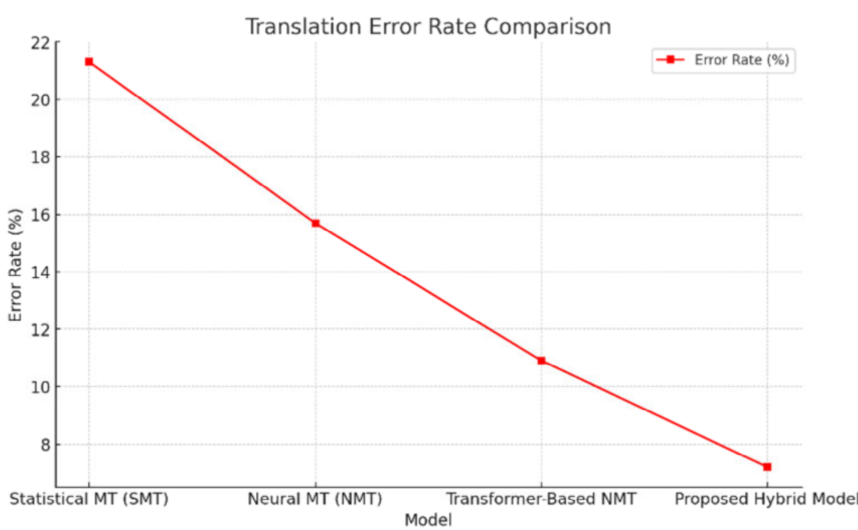
Figure 3 Translation time comparison (see online version for colours)



4.3 Error rate analysis

The translation error rate comparison chart in 'Figure 4' indicates the achievements in the field of the accuracy of the translations by the new model. A 7.2% error rate shows a significant reduction of failures in translation in the case of using this model when compared to the others. This progress is a result of the inclusion of NER, context-aware sentiment analysis, and grammar and syntax correction in the post-processing stage.

Figure 4 Translation error rate comparison (see online version for colours)



4.4 Discussion and model analysis

The model that was proposed has grown a lot due to changes in both the translation accuracy and speed. Compared to traditional SMT and NMT methods that are solely responsible for the whole job, such as probabilistic models and recurrent networks in this case, the proposed concept chooses the option to use transformer-based NMT reinforced by a secondary mechanism of learning. The customer feedback loop in 'Figure 1'. is a working model that estimates the degree of adaptability of the machine to the customer corrections and decisions resulting in a quantity of the fabulous translations that the client requested with a fine-tuning of data.

Additionally, the proposed model is a hybrid architecture and it incorporates speech-to-text (ASR) technology that makes it significantly efficient in real-time translation applications. The adaptive learning paradigm that the system uses allows it to improve translations based on user editing behaviours which helps carry out minor language corrections and understand domain-specific terms better even if they are in the target language in any global forum.

Overall, the obtained results support the hypothesis of the AI-driven English translation system being a viable option for fluency growth error reduction and computation efficiency optimisation. The future development endeavours could be mainly laying stress on the support for additional languages with low resources, the provision of sentiment analysis over the multilingual text processing, as well as the fine-tuning of the actual real-time speech translation functionality.

5 Conclusions and future directions

The results of this study reveal how effective AI-powered translation systems can be in enhancing both fluency and the correctness of English translations, as well as, its efficiency. The proposed hybrid model which brings together transformer-based NMT, RL, and post-processing refinements is significantly better than standard techniques such as SMT and NMT. The model received a BLEU score of 63.1 and a METEOR score of 58.9, proving that the translations were more accurate than those produced by earlier approaches. Additionally, it took the least amount of time (1.2 seconds) to perform the translation, and the error rate it showed was also the smallest (7.2%), which indicates it is the best option for real-time applications. The system's performance in the delivery of translations dynamically is also further enhanced by the addition of user feedback and adaptive learning systems whereby people can evaluate their translations and use their input to further improve them so that it addresses issues such as idiomatic expressions, contextual ambiguities, and domain-specific terminologies. These enhancements form part of the contribution of AI-powered translators to the way humans communicate in multiple languages through the elimination of language barriers.

While the proposed model has made strides in AI speech translation, there remain some limitations, such as the unavailability of sufficient data for low-resource languages which leads to poor translation accuracy. Context-dependent phrases and idiomatic expressions are also still tricky problems that must be tackled especially when dealing with creative or casual text. Although RL and user feedback provide a way to tackle this problem for a good time, the model does need fine-tuning consistently for it to be able to accomplish excellent performance in different structures of language. In addition, due to the inherent time sensitivity of any real-time voice-to-text translation, often, noise and dialect variations interfere with it too much, therefore, two improvements should be focused on: a more precise acoustic modelling along with better speech recognition accuracy through the use of more advanced technology-based approaches. The only way to overcome these present limitations and make future studies even better would be by identifying suitable methods that can boost the robustness level as well as the globalisation feature of AI translation systems.

To boost the transformation of idiomatic expressions and culturally nuanced languages, future studies can look into linking up knowledge graphs and contextual embeddings. Furthermore, we ought to investigate the utilisation of transfer learning, zero-shot models, and synthetic data generation techniques to get better performance in underrepresented low-resource languages. In addition, we can make the system capable of speech translation in noisy or dialect-rich environments via the enhanced acoustic model as another potential direction.

Declarations

The authors declared that they have no conflicts of interest regarding this work.

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