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Application of ELAN in Human-Machine Mutual Translation of English for the News

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Abstract: - The translation of English news means the process of converting news articles published in English into another language. These articles may also be referred to as English news. This process comprises understanding the substance of the source article and accurately translating its tone and intent into the target language. A human translator or machine translation software can be used to perform the translation manually. In the disciplines of software globalization and technological translation, the Human-Machine Mutual Translation technique has grown significantly with the advancement of civilization and the quickening growth of research and innovation. Because of this practical need, translators have begun to focus more on machine translation and have conducted some productive research in this area. As a result, we suggested the EUDICO Linguistic Annotator (ELAN) in Human-Machine mutual translation of English for the news. EUDICO stands for European Distributed Corpora Project. The Max Planck Institute for Psycholinguistics created the EUDICO Linguistic Annotator as a software program for the linguistic annotation of language data. For this study, the English news dataset was used. The data were pre-processed by using normalization. The results were evaluated using performance metrics such as translation quality, precision, BLEU, recall, and computation time. The findings show that the recommended procedure provides an accurate translation of English news when compared to previously used methods. The results demonstrated that translation quality and computation time of proposed model are 95% and 60s respectively.

Keywords: English news, EUDICO Linguistic Annotator (ELAN), English, Human-Machine Mutual Translation and innovation

Research Highlights

- "English news translation" refers to the act of translating news stories originally published in English into a different language. English news is another name for these pieces. This process requires reading the source material with comprehension and then accurately translating its meaning and style into the target language.
- A human translator or machine translation software can do the actual translation work. With the development of civilization and the acceleration of research and innovation, the Human-Machine Mutual Translation technology has evolved substantially in the fields of software globalization and technological translation.
- Translators have started to put more effort into machine translation and have made good strides in this field as a result of this practical need.
- Therefore, in the context of human-machine mutual translation of English for news, we proposed the EUDICO Linguistic Annotator (ELAN).
- The dataset utilized for this investigation was the English news dataset. Normalization was used to pre-process the data. Translation quality, accuracy, BLEU, recall, and computation time were some of the performance criteria used to assess the outcomes.
- The results demonstrate that, in comparison to other methods, the suggested procedure yields more accurate translations of English news. The findings showed that the suggested model has a translation quality of 95% and a calculation time of 60s.

I. Introduction

The phrase human-machine mutual translation (HMMT) describes the capacity for machines and people to translate languages for one another in real-time. Without the use of a human translator, this technology makes it possible for individuals that speak various languages to interact efficiently. The advancement of HMMT technology can transform communication and link people on a global scale. It may enable individuals from various nations and cultures to collaborate more successfully by removing language problems. The system is still not flawless, and issues including accuracy and cultural sensitivity need to be resolved [1].The process of transferring spoken or written English into another language is referred to as the translation of English. A machine translation system may carry out this task automatically or manually from a translator. Translation of English is essential for communication and knowledge between people that speak many languages. It plays a crucial role in international business, diplomacy, and cultural exchange. It is essential to global commerce, diplomacy, and cultural exchange [2].Human-Machine translation has gained popularity as a tool for professional translators working in the English language as well as for companies and organizations that need to translate big quantities

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of material properly and fast. The human-Machine translation may be helpful for anybody who needs to translate papers, websites, or other resources for their own needs or their studies. Human-Machine translation systems may have trouble with idiomatic phrases, cultural allusions, and other linguistic features that call for a thorough knowledge of the source and destination languages [3].The process of translating a text from one language to another and then back to the original language to compare the two versions and spot any differences or mistakes is known as mutual translation. This technique is often used to examine the correctness of translations and ensure that the source text's subtlety and meaning are maintained in the target language. The mutual translation is a useful technique for both learning languages and determining one's level of ability. Language learners may pinpoint their weaknesses in the grammar, syntax, and vocabulary of the target language by translating a document from their home tongue into another language, then back again. It is challenging to satisfy the demands for the large-scale translation since manual translation is expensive and ineffective. Consequently, the need for automated translation technology is growing among people every day, and machine translation technology development is the general trend [4].The process of translating English news broadcasts, reports, and articles into other languages for readers, listeners, and viewers that speak multiple languages is referred to as the translation of English for the news. Frequently, this is done to increase the audience for news material and to provide precise and timely information to several audiences throughout the globe. A human translator can translate news manually, or a machine translation system may accomplish this automatically. A competent translator analyses and comprehends the English news material before manually translating it into the target language while maintaining the original text's meaning, tone, and subtlety. Since this procedure might take some time, it guarantees the correctness and excellence of the translation [5].News companies may now employ automated translation software to translate news stories more rapidly and affordably due to developments in machine translation technology in recent years. Machine translation, meanwhile, is not always reliable and may make mistakes, especially when it comes to idiomatic phrases, cultural allusions, and linguistic complexity. To assure accuracy and quality, skilled human translators should still evaluate and modify the translations, even though machine translation might be a beneficial tool for news translation. News has long been identified as an important component of everyday living in this digital world [6].ELAN, short for "EUDICO Linguistic Annotator," is a program used for linguistic analysis and language documentation. While not being created to translate English between humans and machines for the news, it may nonetheless be used in some ways to speed up and enhance the translation process. Transcribing and analyzing speech in the source and destination languages to find patterns and enhance machine translation precision is one possible use of ELAN in human-machine mutual translation. Time-aligned transcripts of audio or video recordings may be produced using ELAN, and these transcripts can then be examined to spot recurring mistakes or mistranslations. To train and enhance machine translation algorithms, annotated corpora of bilingual news items or transcripts may also be created using ELAN in human-machine mutual translation. To increase the precision and effectiveness of machine translation, the annotations may include data on word alignment, part of speech, and syntactic structure. The participation of human translators in the process of reciprocal translation may also be facilitated by LAN. Users of the program may comment and exchange media assets and text, which can help organize translation projects and give input on the quality of translations. To verify interpreting theories and possibilities to create to the test, interpreting corpora are important linguistic resources [8].ELAN may nevertheless be a helpful tool for enhancing the accuracy and effectiveness of the translation process even if it is not expressly created for human-machine mutual translation of English for the news. As news companies work to provide their readers with accurate and timely news in several languages, the usage of human-machine reciprocal translation for the news has grown in popularity. This strategy can retain good translation quality while lowering expenses and increasing efficiency. It is essential to stay aware that machine translation is not always accurate and may make mistakes, especially when it comes to idiomatic idioms, cultural allusions, and linguistic complexity. Hence, using human translators in the translation process is still essential for producing translations of high quality [9].Machine translation has proliferated in the translation of news in recent years. Even though machine translation may assist increase productivity and save expenses, it is still not as precise as human translation and may miss some of the finer details of the original text. In the framework of human-machine reciprocal translation of English for the news, ELAN is a tool for corpus construction, transcription, alignment, linguistic analysis, and assessment [10]. Hence, we proposed ELAN for human-machine translation of English for news.

II. Related Works

The research [11] suggests a fuzzy-algorithm-based investigation of the English translation scheme's linguistics. The study intended to provide a deeper understanding of language analysis and comprehension in order to remove semantic understanding uncertainty in the translation process. To achieve this, it thoroughly understands the language's features and analyzes the language using the corpus, vocabulary, grammar, and translation characteristics. Thus, there is an improvement in the quality of comprehension. The study [12] aims to improve the effectiveness of English intelligent translation using neural networks by improving the multi-objective optimization method and creating a model based on the English intelligent translation system. The study also employs parallel corpora and monolingual corpora for the training stage, as well as a semi-supervised neural machine translation approach to thoroughly examine the virtualization route with an emphasis on node pattern and data flow analysis. Deep learning and large data have grown quickly, which has allowed for advances in the study of text and phonetics, the two fundamental components of language [13]. The translation model of a deep learning neural network called SCN-LSTM (Skip Convolutional Network and Long Short Term Memory) is created by learning and training the real dataset and the publically available PTB utilizing prior research findings. More specifically, the accuracy rate of the SCN-LSTM translation model is higher than that of the other model. The study [14] aims to show how to use multi-task learning to train federated learning models and assess the effectiveness of Chinese-English transfer learning utilizing language pairings and copious amounts of parallel corpus data. Moreover, this study suggests a weight-sharing-based moderate neural machine translation technology that enhances the effectiveness of low-resource neural machine translation between Mandarin and English. A control experiment is designed by the research to assess the effectiveness of its methodology. The study [15] suggested that English translation technology using neural networks and an intelligent depth of knowledge make up the research material of this blog. To discover a more advantageous approach for translating lengthy English sentences, this blog mostly draws on the already-existing British algorithms. To increase the number of phrase patterns that the principles can match, part-of-speech tagging and policies must be improved. By experimental virtual environment, the findings of this paper's enhanced hybrid recommendation algorithm reveal that the method's accuracy is not very high. The study [16] encompasses an analysis of graduate English translation education, case studies, machine learning algorithms concepts and approaches, and the difficulty of bandwidth vocabulary classroom design. The findings of the trials demonstrate that conventional annotation training suffers from some problems, some of which are brought on by students also by instructors. The study [17] used an intelligent fuzzy decision tree (DT) technique to construct a phrase-structured syntactic tree. This tree structure is then applied to the MT translation, analyzing the sentence and word-level QE results. This demonstrates that the translation QE route benefits more from the method of fusing interdependent words with reference implementation patterns than from the method of fusing phrase structural characteristics with source language patterns by connecting the training prediction outputs of annotation QE models. This paper [18] intends to analyze the use of computer-assisted proofreading in the translation of English words. Create software for an embedded environment-based automatic translation system by optimizing the translation algorithm, loading it, and employing keyword combinations and semantic feature analysis. Consequently, the translation system is automatically created using a cross-compiler and multi-threaded word etymology. Network translation, customer, System application, translation organization and administration, online translation interaction, and other component structures are primarily included in the building workflow for software modules.

III. Proposed Methodology

The efficient production of high-quality translations is made possible by the use of human-machine mutual translation, which makes use of the advantages of both machine translation systems and human translators. As a result, we investigate the use of ELAN in the human-machine translation of English for news. English news dataset was used in this study. Figure 1 depicts the methodological design.

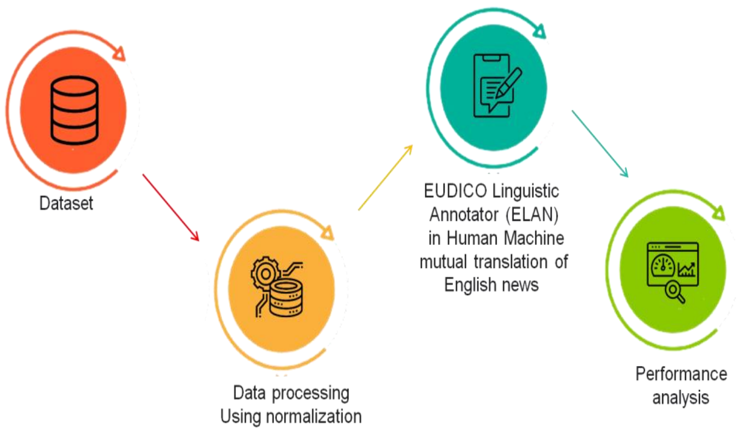

Figure 1: Methodological Design

A. Dataset

Primarily English news stories are utilized in this work for training and testing objectives since the goal is to employ fact-checking information from an improved capacity language to confirm the authenticity of news in a limited resource language. All English COVID-19 news from the three databases ReCOVery, FakeCovid, and CoAID comprise the training database [19].

B. Data preprocessing

As part of the data gathering and data evaluation, preprocessing converts unstructured data into a format that computers can understand and analyze. The text, images, videos, and some other real material are improperly organized. It typically contains errors and contradictions, is hard to comprehend, and lacks a cogent design. Normalization is a pre-processing step, a scaling strategy, or a mapping method. Using ideas like mean and standard deviation, the normalization process transforms unstructured data into normalized values or ranges of data. As a consequence, utilizing the normalization variable, the data information may be normalized, as illustrated in equations 1, 2, and 3 below.

$$u_i' = \frac{u_i - A}{std\ (A)} \tag{1}$$

$$std\ (A) = \sqrt{\frac{1}{(m-1)} \sum_{i=1}^{m} (u_i - \bar{A})^2} \tag{2}$$

$$\bar{A} = \frac{1}{m} \sum_{i=1}^{m} u_i \tag{3}$$

The normalized values in each of the rows above may thus be determined using the normalizing method. The standard deviation of a row is zero if all of the values are identical and all of the variables are set to 0. The range of values between 0 and 1 is shown by the normalizing technique. Scaling is a method that provides a range of numbers between -1 and 1.

C. EUDICO Linguistic Annotator (ELAN) in Human-Machine mutual translation of English news

The Max Planck Institute for Psycholinguistics created ELAN, a software program for linguistic interpretation of language input. It enables users to make, modify, and evaluate linguistic annotations for a range of language data, such as transcripts, written texts, audio and video recordings, and more. ELAN may be used to annotate and analyze linguistic data to enhance machine translation algorithms in the setting of human-machine mutual translation. linguistic annotations such as part-of-speech tags, syntactic structures, and semantic roles may be used to train machine translation prediction algorithms. ELAN can be used to evaluate the output's dependability by comparing machine translation output with human translations and analyzing the differences between the two. This may assist machine translation systems to become better by pointing out typical faults and problem regions. The initial stage is to gather linguistic data that can be utilized for annotation, such as audio or video footage, summaries, or written discourse. Selecting an annotation system, or set of rules and standards for annotating the linguistic data, is the next stage. The unique research issue and the desired language properties influence the choice of the annotation method.

Choosing the right sample to depict the English language attributes of the specialist field by the features of English for specific reasons of translation is essential when defining the corpus's origin. It's also important to charge interest to the reasoning of the dispersion of the various corpora kinds. The expert teaching resources with reasonably high recognition in the linked professional area, as well as the genuine English discussion language, must cover the different scenarios of the study subject as thoroughly as possible, and a relevant corpus must be chosen. The corpus must be capable of most accurately portraying the linguistic traits of pertinent disciplines and representing the validity of their discussions throughout the selection procedure. In this specialized discipline, the corpus consists of genuine English-language news and other resources. They are distributed differently. To increase the usefulness of the English corpus for the goal of translation, the choosing proportion of the corpus must be as compatible as feasible with the real condition of the specialty. The guidelines for the construction of corporate English syntax may be sorted out, for instance, by analyzing high-frequency terms with expert qualities, sentence structures in conversation, theatrical aspects, etc. ELAN's usability varies; customers may struggle with the original formation of files since doing so necessitates learning a few possibly perplexing principles as soon as a fresh file is generated. But if the file is set up correctly, the ELAN display is quite user-friendly and provides a variety of methods to change the information and the way it is displayed. A maximum of five media files must be imported in the initial phase. While dealing with video, one should remove the audio track in .wav format and upload it into ELAN together with the customer's video stream. When a.wav is accessible, ELAN shows the spectrum, enabling it simpler for a user to see and "take" a section of audio for annotations. ELAN makes it simple for customers to synchronize several video files that could be accidentally slightly out of sync (depicted in ELAN Pseudocode).

Pseudocode 1: ELAN

```
function alignAnnotations(annotations, mediaFile):
  for each annotation in annotations:
        start_time = annotation.start_time
    end_time = annotation.end_time
    media_segment = mediaFile.extractSegment(start_time, end_time)
    annotation.associateWith(media_segment)
```

$return\ mediaFile\ with\ annotations$
$annotations\ =\ loadAnnotationsFromELANFile("annotations.eaf")$
$mediaFile\ =\ loadMediaFile("recording.mp4")$
$alignedMediaFile\ =\ alignAnnotations(annotations, mediaFile)$
$saveAlignedMediaFile(alignedMediaFile, "aligned\_recording.mp4")$

In any case, ELAN will connect annotations to the initial of many uploaded video clips when creating a report. In ELAN, there are two types of annotation levels: independent tiers and referencing tiers. Just the former can be connected to the calendar, and modifications performed on a primary level will also impact its children's levels but not the other way around due to the parent-child connection. One should first set up the linguistic kinds for the project prior one can create tiers. The characteristics of the levels that will subsequently give to those categories are determined by these preconceptions. A primary level, for instance, could be broken into smaller time-based sections; as a result, the language type time partition is given to the tier that contains these shorter sections. Schematic partition and conceptual connection are other forms that are offered. The second step is to generate the levels when all necessary linguistic categories for a certain annotated file have been created. The great flexibility with which customers may create levels is one of ELAN's finest characteristics. As long as the language categories and parent-child connections between tiers are properly understood, an infinite number of tiers are permissible. ELAN provides the convenience of allowing type/tier settings to be stored as patterns to make it easier to create files in the following with the same component structure and to import specific level settings from other ELAN documents. The selection of linguistic kinds and layers for a given project can be intimidating to novice consumers because it necessitates (a) comprehending the distinctions between the kinds that are available and (b) having sufficient familiarity with their media to know in advance which kinds and layers users require. Recognizing kinds and levels requires reading the handbook, and the information given there is far more detailed than in earlier editions of the text. Regulated vocabularies may be built up using ELAN as well, which is helpful if you often employ a small number of descriptor values. With every single file, restricted languages may be developed, or they can be saved in a pattern and exported later.

To improve classifying outcomes, special attention must be given to the uniformity and regularization of the corpus's classifying set. This will help to avoid biases and one-sidedness during the translation process and ensure that the translation of the corpus reflects the real face of the language as much as conceivable. ELAN may be used to establish comprehensive annotation data by the corpus's recovery criteria for creating a Human-Machine mutual translation of English news.

IV. Result And Discussion

The results were evaluated and discussed in this part using performance indicators such as translation quality, precision, BLEU, recall, and computation time. Low-resource neural machine translation (LRNMT) method [20], recurrent Neural Network (RNN) [21], and naive Bayesian Algorithm (NBA) [22] are the existing approaches used for comparison.

Translation quality is the degree to which a translation successfully conveys the meaning and intent of the source material in the target language. The quality of the translation might differ based on several variables, including the translator's language competency, translation abilities, subject-matter expertise, and cultural peculiarities of the source and destination languages. It is essential to have a procedure in place for modifying and evaluating translations before their completion and publication. Figure 2 shows the translation quality of the suggested techniques. Table 1 shows the outcome of translation quality. When compared to existing techniques, the proposed method provides a high degree of translation quality.

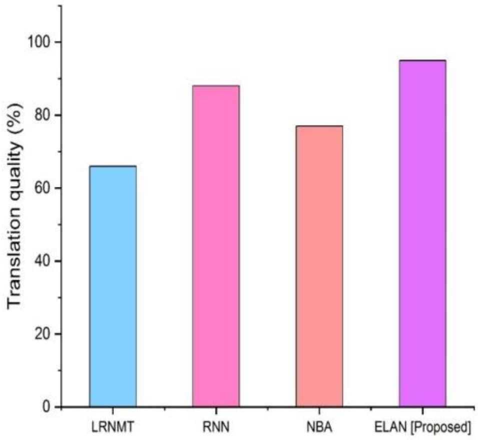

Figure 2: Comparison of Translation quality

Table 1: Outcomes of Translation quality

Methods	Translation quality (%)
LRNMT	66
RNN	88
NBA	77
ELAN [Proposed]	95

Precision is the most essential criterion for accuracy; it is specified to be the proportion of correctly classified cases among all occurrences of predictively positive data. It is determined by dividing the number of true positives (positive outcomes that were properly detected) by the total of true positives and false positives (the number of incorrectly identified positive results).In other words; precision may be defined as the percentage of identifications that are accurate. Precision in the context of the human-machine mutual translation of English for the news refers to the correctness of the machine translation system in creating translations that are true to the original English text. The equivalent values for the precision metrics are displayed in Figure 3. Table 2 presents a comparison between the precision of the proposed approach and the existing methods. The proposed method provides more precision than the existing ones. Equation (4) is used to compute the precision.

$$\text{Precision} = \frac{\text{TP}}{\text{TP+FP}} \tag{4}$$

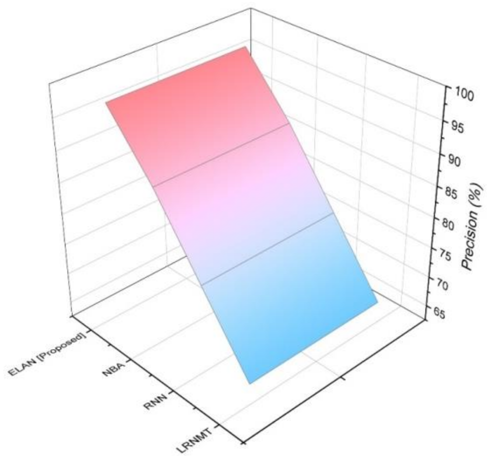

Figure 3: Precision of the suggested methodologies

Table 2: Outcomes of Precision

Methods	Precision (%)
LRNMT	66
RNN	77
NBA	88
ELAN [Proposed]	97

A metric called BLEU (Bilingual Evaluation Understudy) is used to evaluate how well machine translation output performs. The BLEU score evaluates how similar two machine-generated translations are to one another in order to calculate the n-gram gap between those translations and one or more reference translations. Higher scores indicate greater translation quality. The BLEU score is determined by how well the machine-generated translation and the reference translations match n-grams. Mutual translation of English for news purposes between humans and machines, BLEU can be used to evaluate the quality of translations produced by machines versus those produced by humans. Figure 4 shows the BLEU of the suggested techniques. Table 3 shows the outcome of BLEU. In comparison to existing methods, the suggested approach offers a high level of BLEU. Equation (5) is used to compute the BLEU.

$$\text{BLEU}=\text{BP}\times\exp\left(\sum_{n=1}^{N}\frac{1}{N}\log p_n\right) \quad (5)$$

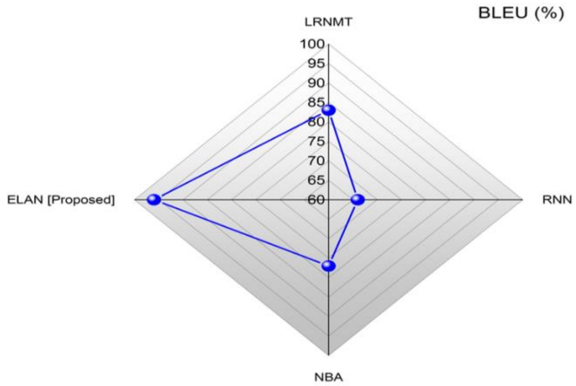

Figure 4: BLEU of the suggested methodologies

Table 3: Outcomes of BLEU

Methods	BLEU (%)
LRNMT	83
RNN	66
NBA	77
ELAN [Proposed]	96

Recall is the ability of a model to recognize each significant sample in a set of data. A statistical definition of it is the proportion of True Positives divided by the sum of True Positives and False Negatives. Equation (6) is utilized to compute the recall. The percentage of relevant items that are returned by a search or classification algorithm is measured by a recall. The number of relevant things that were properly classified as such is known as a true positive, while the number of relevant items that were mistakenly classified as irrelevant is known as a false negative. The comparative statistics for the recall measures are displayed in Figure 5. Table 4 displays the proposed method's recall in comparison to the current approaches. Compared to current techniques, the proposed method provides higher recall.

$$\text{Recall} = \frac{\text{TP}}{\text{TP+FN}} \quad (6)$$

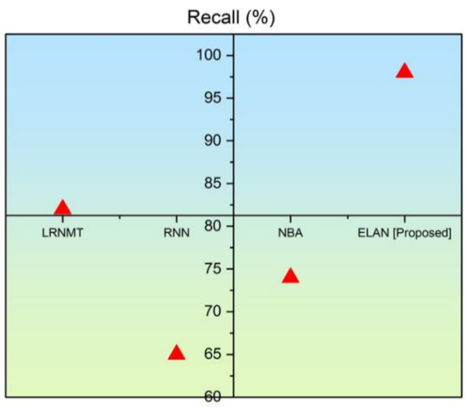

Figure 5: Comparison of Recall

Table 4: Outcomes of Recall

Methods	Recall (%)
LRNMT	82
RNN	65
NBA	74
ELAN [Proposed]	98

The phrase computation time describes the long a computer or other electronic equipment needs to complete a certain activity or operation. Depending on the complexity and speed of the action being done, it is often measured in seconds, milliseconds, or even microseconds. Computation time is a major element for many applications, especially in areas like scientific computing, machine learning, and high-performance computing where massive volumes of data and intricate algorithms need to be handled rapidly and effectively. Depending on the exact tools and techniques employed, the quantity and complexity of the text being translated, among other factors, the computation time for human-machine mutual translation of English for the news might vary significantly. Nonetheless, it is feasible to produce high-quality translations in a little period with the appropriate tools and procedures in place. In the suggested method the computation time is low compared to the existing approach. Figure 6 displays the computation time for the suggested strategy. Table 5 displays the results of the recommended method.

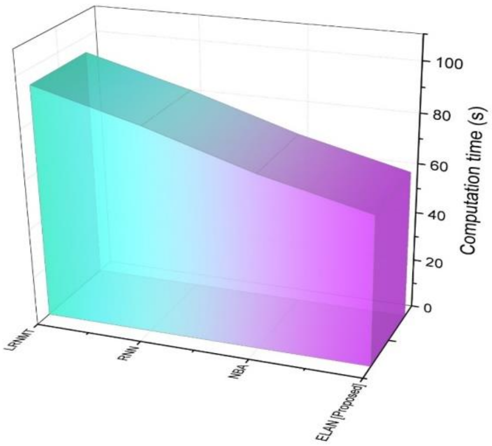

Figure 6: Comparison of Computation time

Table 5: Outcomes of Computation time

Methods	Computation time (s)
LRNMT	94
RNN	83
NBA	70
ELAN [Proposed]	60

V. Conclusion

In contexts where a rapid translation of huge quantities of text is required, such as in the area of localization or international commerce, human-machine mutual translation is a technique that is often used. Large amounts of material can be translated fast by machine translation systems, but they often create translations that aren't precise or nuanced enough for use by professionals. The human-machine mutual translation may provide translations that are both quick and precise by fusing the speed of machine translation with the precision and knowledge of human translators. As a result, we recommended the EUDICO Linguistic Annotator (ELAN) in English for human-machine mutual translation. This research made use of the English news dataset. The existing approaches used for comparison are the Low-resource neural machine translation (LRNMT) method, recurrent Neural Network (RNN), and naive Bayesian Algorithm (NBA). Performance measures such as translation quality, precision, BLEU, recall, and computation time are assessed. According to the assessment findings, the EUDICO Linguistic Annotator is a valuable tool for academics working in the area of human-machine mutual translation of English news since it enables them to examine language data and enhance machine translation programs built on linguistic annotations.

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