INTRODUCTION

Translation is the process of converting text or speech from one language into another while maintaining its original meaning, nuances, and context. Munday et al. (2022) stated that translation is the changing of two different languages between source text in the SL and a targert text in the TL. This linguistic practice dates back to ancient times when civilizations interacted through trade, diplomacy, and cultural exchange. As societies evolved and globalization accelerated, the demand for translation services surged, leading to the development of translation as a profession. The evolution of translation can be traced through various historical milestones, from early human endeavors to facilitate communication across language barriers to the establishment of translation as an academic discipline and profession.

Throughout history, translation has played a crucial role in fostering cultural exchange, facilitating commerce, advancing knowledge dissemination, and promoting understanding among diverse linguistic communities. The act of accurately transferring a message from one language, known as the source language (SL), to another, known as the target language (TL), is known as translation. According to Newmark (1988, p5), rendering the meaning of the SL the TL without omitting the author's intention is what defines translation in his opinion. Similar definition is also mentioned by Larson (1984, p. 3) stating that translation consists of translating the meaning of the source language into the receptor language.

For the translation to be successful, accuracy is necessary throughout the process. People can now communicate in multiple languages because of technological advancements and linguistic diversity. There is more to translation than merely translating a text from the source language (SL) into the target language (TL) equivalent. Finding the equivalent meaning or message in the source language to convey into the target language is another aspect of translation, which goes beyond simply translating words and phrases from the source language into the target language. Through a translator, people can get accurate and clear information without having difficulties understanding the information that is given by foreigners (Dewi et al., 2016). To translate a text from source language into target language, the translator should consider the process of translating.

In recent decades, technological advancements, particularly in machine translation and computational linguistics, have revolutionized the translation industry. Automated translation tools, such as neural machine translation and natural language processing algorithms, have significantly enhanced the efficiency and accuracy of translation processes, albeit with certain limitations compared to human translation. Despite technological advancements, human translators remain indispensable for tasks requiring cultural sensitivity, context comprehension, and linguistic creativity. Moreover, the increasing demand for translation services in various domains, including literature, legal, medical, and technical fields, underscores the enduring significance of human expertise in translation. The sharp rise in the use of technology tools in the translation process has rendered human translators more invisible than ever. The importance of the role played by human translators, however, cannot be denied or understated (Rojo, 2018).

Machine translation (MT) has gained significant attention in recent years due to its efficiency and advancements (Wang, 2024). These advancements revolutionized translation, transforming it from a time-consuming task to a rapid and scalable process through the use of computational linguistics, artificial intelligence, and machine translation. This has democratized access to multilingual communication by breaking down language barriers and fostering global connectivity through the use of translation machines like Google Translate, DeepL, and others. These machines offer real-time translation capabilities, customizable options, and utilize various techniques to deliver accurate and contextually appropriate translations across multiple languages

In this study, the researcher uses the DeepL to examine its performance by conducting an error analysis. According to Weis (2024), DeepL is a highly-touted online translation tool powered by advanced neural network technology. Considered to be a much more sophisticated tool than Google Translate, DeepL has garnered much positive reception from users. The DeepL algorithm utilizes artificial intelligence to replicate human intelligence when translating documents. According to various tests, DeepL Translation seems to offer more natural translations, capturing nuances that are often missed by Google Translate. DeepL offers a free version of its tool available for anyone to use. To take advantage of their full suite of features, they have subscription-based options available. Along with machine learning technology, DeepL takes advantage of user feedback and ratings to help improve the quality of translations. DeepL offers a free version of its tool available for anyone to use. To take advantage of their full suite of features, they have subscription-based options available. Along with machine learning technology, DeepL takes advantage of user feedback and ratings to help improve the quality of translations. Because of some of these advantages that DeepL has and also its performance is better than Google Translate, the researcher chose DeepL to be used in this research as a Machine Translation.

The use of DeepL for translation by utilizing advanced artificial neural network technology to produce translations is often recognised for its naturalness and accuracy. However, despite its merits, the accuracy and quality of DeepL translations need to be further scrutinized, especially in the context of error analysis. In this study, the researcher aims to assess the performance of DeepL by conducting error analysis using Costa's Taxonomy of Machine Translation Error. By applying Costa's taxonomy (2015), the researcher sought to identify and classify the types of errors present in the translations produced by DeepL, thereby gaining insight into its weaknesses. Costa's taxonomy for machine translation error analysis is a structured framework for categorizing and analyzing errors in machine translation. It is based on linguistic principles and aims to capture nuances of translation quality beyond mere accuracy. The key components of Costa's taxonomy are as follows:

1. Semantic errors: These are mistakes in the meaning of the translated text. This can be a mistranslation, where the meaning is completely altered, or a sense dislocation, where the translation is logically incorrect or nonsensical.
2. Syntactic errors: These are mistakes in the structure of the translated text. This category includes problems with word order, agreement, and tense.
3. Lexical errors: Lexical errors involve problems with individual words or phrases. This can include mistranslations, inappropriate word choices, or the addition or omission of words. These errors can make it hard to understand the text.

4. Pragmatic Errors: When the translation does not match the source text, it is a pragmatic error. This can be because of a misunderstanding of the culture or context, the wrong language register, or a failure to convey the right tone or style.

Costa's taxonomy provides a systematic framework for identifying and analyzing the shortcomings of machine translation systems. It categorizes errors according to linguistic dimensions, allowing researchers to gain deeper insights into the specific types of errors that occur and to target improvements in machine translation algorithms accordingly. Additionally, Costa's taxonomy considers linguistic factors beyond mere word-for-word accuracy, facilitating a more comprehensive assessment of translation quality that aligns with human perception and understanding.

This research aims to investigate the errors made by DeepL in translating a short story entitled *Dolly and Her Little Red Umbrella* from English to Indonesian. The errors are classified by using Costa's taxonomy. This study employs Costa's taxonomy as a systematic framework for classifying these errors. By categorizing the errors according to linguistic dimensions such as semantic, syntactic, lexical, discourse, and pragmatic, this research endeavors to provide a comprehensive analysis of the shortcomings in DeepL's translation performance. This investigation will provide insights into the specific types of errors encountered in the translation process, which will inform potential improvements to enhance the accuracy and quality of machine translation outputs.

There are some previous studies investigating errors produced by various machine translation (MT) systems. Alkatheery (2023) in his research entitled *Google Translate Errors in Legal Texts: Machine Translation Quality Assessment*, conducted a study to evaluate the quality of Neural Machine Translation (NMT) of legal texts from Arabic into English, specifically focusing on Google Translate. The study used manual evaluation to assess the quality of NMT output and diagnosed legal discourse features of English NMT output. The findings revealed that the introduction of NMT to Google Translate has not solved common issues related to errors in MT output. Though Google Translate provided a comprehensible output, lexical and syntactic errors were seen in the data. The paper also suggested that Google Translate failed in translating several factors of legal discourse. The research concluded that machine translation, though it provided a comprehensible output, could not translate legal structures and terminology perfectly.

The second previous study was conducted by Amilia and Hasni (2023) entitled *Investigating Subtitle Error Typology In Unofficial Movie Streaming Website By Using FAR Model*. This study was intended to investigate the types of errors in the movie subtitles available on a movie online streaming, LayarKaca21 (LK21). The research method applied is descriptive case study. The data were collected by comparing the English version of the subtitles, the LK21's version, and the Indonesian subtitles on Netflix. The movie taken as a data source was of the animation genre, entitled *How to Train Your Dragon: The Hidden World*. The data found were analyzed based on Pederson's typology of subtitle errors, FAR Model standing for Functional Equivalence, Acceptability, and Readability. The errors were classified into distinct categories: functional equivalence errors, including semantic and stylistic discrepancies; acceptability errors encompassing grammatical, spelling, and idiomatic inaccuracies; and readability errors involving segmentation and spotting, reading speed and line length, as well as punctuation and graphics. Throughout the analysis, a total of 716 errors were identified, comprising 316 functional equivalence, 105 acceptability, and 295 readability errors. The outcomes of the investigation unveiled that the majority of errors within LK21 predominantly fell under the functional equivalence category. Such errors inherently possess the potential to significantly hinder viewers' comprehension of the conveyed messages in the movies or series they engage with.

The third previous study was *Assessment of Google and Microsoft Bing Translation of Journalistic Texts*, According to Almahasees (2018), Machine Translation (MT) systems are commonly utilized by end users since MT is available freely or at a low cost. The increasing demand for MT services nowadays means that ensuring the acceptability of the output to the potential users of such systems is a necessary task. The paper evaluates the capacity of two prominent systems, Google Translate and Microsoft Bing Translator, in producing acceptable English translations of journalistic texts written in Arabic. To do so, the study has adopted Linguistic Error Analysis of Reference and of Error Classification described in Reference . The Results of the study show that both systems obtain outstanding results with > 90 percentage accuracy in the area of orthography and grammar. In addition, both systems obtain good results in the areas of lexical and grammatical collocations of 79.8% for Google and 74.5% for Bing. The two systems achieved good results in these categories because they have recently adopted Neural Machine Translation, which imitates the human brain to perform translation and learns from previously translated texts by humans.

This research investigates the errors made by DeepL in translating a children's story from English to Indonesian, specifically focusing on using Costa's taxonomy to classify the errors. The similarities between this study and three previous studies is that all studies assess the quality of machine translation (MT) output and employ some form of error analysis to categorize the mistakes. Two studies conducted by Alkatheery & Amilia compare the MT output to a human-generated translation considered the "correct" version. This study focuses on a children's story, while Alkatheery targets legal texts and Amilia targets movie subtitles. Almahasees investigates journalistic texts. Machine Translation that is analyzed in this study is DeepL, whereas Alkatheery explores Google Translate, Amilia explores subtitles (likely not generated by a single system), and Almahasees compares Google Translate and Microsoft Bing Translator. The theory used in this study utilizes Costa's taxonomy, while Alkatheery classified the MT errors by lexical errors, syntactic errors, omission, and legal register-related errors, Amilia uses FAR Model (Functional Equivalence, Acceptability, Readability) and Almahasees uses Linguistic Error Analysis of Reference and Error Classification. Overall, this study adds to the existing research by examining a different domain (children's story) and using DeepL as the MT system. It also applies Costa's taxonomy, offering a fresh perspective for error analysis in machine translation.