Jurnal Ilmiah Profesi Pendidikan
Volume 10, Nomor 4, November 2025
ISSN (Print): 2502-7069; ISSN (*Online*): 2620-8326

The Translation of Multilingual Signboards in Mataram City Using Google NMT

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Article History
Received : September 16th, 2025
Revised : October 23th, 2025
Accepted : November 10th, 2025

Abstract: This research investigates the use of Google Neural Matching Translation (GNMT) in translating multilingual signboards in Mataram City into multiple languages. In this paper, the accuracy, readability, and quality of GNMT translations are evaluated to observe their appropriateness in selected well-turned communication environments. Following previous studies, the current study will investigate accuracy, readability, and quality of GNMT translators outputs on translating multilingual signboards in Mataram city compared to its sets produced by human translators. Field work was carried out between June 9 and July 4, 2025 on Jl. Majapahit, Mataram City, West Nusa Tenggara. The population was all multilingual public signboards in Mataram City, while the sample was those along Jl. Majapahit in Mataram. A total of 209 signs (both monolingual and multilingual) were purposively sampled for accuracy, readability and the quality. The results of the study revealed that GNMT achieved a mean score of 4.37 in terms of accuracy and intelligibility as compared to human's score 5.0. It is good in translating transparent structured texts but does not well with translation cultural idiomatic expressions, where human post editing for adding context make it consistent and informative. On the whole, GNMT delivers 100% OCR success in multilingual signboard translation; it overcomes on clear language but fails to deal with idiomatic expressions and culturally sensitive ones such as name of foods which are indicative that humans are the most suitable part to handle context dependent or culture specific issues.

Keywords: GNMT, Multilingual, Signboards, Translation Accuracy, Translation Readability

INTRODUCTION

In the age of tourism and digital globalization, actual information is something that must be available in any public space including tourist areas such as Mataram City, West Nusa Tenggara. According to Badan Pusat Statistik Provinsi Nusa Tenggara (2025), the number of foreign tourists (wisman) entering through Bizam Lombok in December 2024 was 6,108 people, an increase of 23.47 percent compared to November 2024. The highest number of foreign tourist visits by region came from ASEAN with 3,329 people, Europe with 1,781 people and Asia (except ASEAN) with 433 people. Zhu et al., (2024) also said that if Neural Machine Translation (NMT) is performing better in high-resource language pairs, it still faces challenges with low resource and idiomatic outputs. Initial findings in Mataram indicate difficulties including multilingual signboard discolouration, non-standard layout and low textual contrast that may impede understanding and lead to misunderstanding and malorientation in navigation and safety related settings.

This is consistent with a study by Baharuddin et al., (2024) investigated translation equivalence of multilingual signboards in Lombok's religious tourism destinations by employing Baker's equivalence theory. The research also showed that sign translation entails language as well as equivalence at lexical, grammatical, textual, pragmatic (or semiotic), and even moral levels and the necessity of cultural or contextual sensitivity. Nevertheless, the study did not address evaluating Google Neural Machine Translation (GNMT), suggesting a future work to be performed in Mataram City's multilingual settings.

Researchers also still have challenges in the educational environment which, according to research by Baharuddin et al., (2022) explained that the theory of translation still cannot be applied properly by students so that the edits are not much different from the results of Google translation. While according to Alhaisoni &

Alhaysony (2017) said that almost all EFL students in Saudi Arabia use Google Translate, mainly to help understand vocabulary, writing, and reading, but for translation activities it is used in a lower frequency. However, the problem is they assume that the results of google translate translation is the most appropriate translation. Then, Wardana et al., (2022) found that after assessing students ' abilities on translated texts, it turned out that their abilities were still limited. Many students are very fond of using Google Translate without implementing appropriate learning strategies to understand grammar or contextuality.

The growth of AI driven translation systems such as GNMT is however an opportunity to solve language problems on public signage. "The GNMT system translates "whole sentences at a time, rather than piece by piece. The system uses" this." Methodological overview GNMT uses an artificial neural network to generate translations that are more human sounding and sometimes more accurate than those generated with the phrase-based systems that it replaced. Its incorporation with image to text technology ensures quick retrieval of multilingual information for the benefit of tourists and residents. However, there are still concerns regarding GNMT's performance in pragmatic scenarios (i.e., texts with cultural/technical nuance) as discussed by Wu et al., (2016) and Koehn & Knowles, (2017).

Wu et al., (2016) said that MT systems show difficulty such as GNMT, which is well performed to high-resource language including English and Mandarin language, but not for complex morphological language like regional Indonesian languages. Koehn & Knowles, (2017) also noted that such an NMT system tends to misunderstand polysemous expressions in terms of diverse context. Translation challenges are only further complicated in Mataram City, where signs combine Indonesia, English and regional languages amidst environmental considerations like lighting, color contrast and difficult-to-make out text. This problem requires a more in-depth study of how GNMT works under these conditions.

Based on book from Baker (2018), it states that translation is a complex and multifaceted endeavor that requires a nuanced understanding of linguistic structure, cultural context, and pragmatic considerations. However, If GNMT is effective, it can also help improve the accessibility of information for tourists and residents and contribute to tourism and public services in the vicinity. The availability of this application in mobile phones can help people understand without human help. Instead, pointing out its shortcomings could potentially inspire robust translation models that take local environmental conditions into account. This will facilitate better communication in the neighborhood around Mataram.

This research adds to what we know about machine translation when many languages are involved. Specifically, it looks at how well a particular system handles the Indonesian language as well as the dialects used with the aim of building better translation tools. The study also suggests ways to improve how images are well prepared before processing, adjusting features with things like colors, fonts, or backgrounds. As a result, this allows for a more useful translation system where people who speak different languages come together.

METHODS

Research Design

From 9th June to 4th July 2025, researchers examined sign boards on Jl. Majapahit in the city of Mataram, West Nusa Tenggara. The focus of the researchers was multilingual signs throughout Mataram; however, data collection was only carried out on Jl. Majapahit. The researchers selected 209 signboards in which there are Monolingual and Multilingual signs. The research took place in four phases: 1) observing how these signs appear where people actually use them; then, 2) using technology from GNMT, the OCR feature to pull text from the signs; 3) machine translation turns everything into a standardized language; finally, the researcher checks the accuracy and readability and draws conclusions. This initial observation phase records the signs that are organically present within its environment. First, we convert text images into usable text through optical character recognition by Creswell, (2014) After this, the machine translation software converts the texts by Wu et al., (2016) We judge these translations for their veracity along with how easily they flow with reference to, according to Nababan et al., (2012). Patterns in the data emerge using thematic analysis by Braun & Clarke (2006). We look at the translated text next to the original, check for consistent strength, how well it reads, How accurate it is, its overall quality. In the end, the researcher draws conclusions by combining all the analyzes to obtain the final result.

Research Time and Place

From June 9 to July 4, researchers collected information on Jl. Majapahit in the city of Mataram, on the island of Lombok, Indonesia along the way with a variety of signboards and also various kinds of languages in it. This location seemed ideal for checking how well machine translation handles realworld writing, specifically looking at Google's system when converting public notices. Jl. Majapahit with activity, a hub for shops both homegrown alongside well known brands based on the researcher's direct observation on location in 2025. Consequently, it's a perfect spot for this investigation because the area provides real world examples of multiple languages readily available, fitting our research goals.

Population, Sample, and Sampling Technique

This research looked at every sign displaying multiple languages in public areas of Mataram City, yet focused on those lining Jl. Majapahit. Altogether, we examined 209 signs - some used a single language, others featured more than one. Instead of counting people, qualitative studies look at groups of things sharing qualities important to the investigation by Creswell (2014). Consequently, this research focuses on every multilingual signboard - those showing Indonesian, English, Arabic, Sasaknese, or Javanese alongside others, found along Jl. Majapahit in shops and public spaces. Along Jl. Majapahit in Mataram, the research focused on the main areas.The researcher chose this place because the signs in many languages show how diverse the street life of this city is. The researcher chooses a sign based on several important points. Some have only one language, others mixed languages. All writing should be clear-no missing pieces. In addition, researchers can easily photograph and study each sign. In this way, researchers gather useful information to test how well machine translation works with real-world public notices. To collect the data, the researchers deliberately selected all the signboards. Researchers also took the languages that best reflect the languages spoken around Jl. Majapahit, Mataram city. Instead of just picking up any signboards, or aiming for just numbers, researchers want a signboard that offers rich and varied signage for translation according to Palinkas et al., (2015) Therefore, once collected researchers also collect data that is good or not good for further analysis.

Data Source

Researchers took data on the city of Mataram, a bustling place in West Nusa Tenggara province that is teeming with languages as people visit and cultures blend, into the study site. The researchers gathered information from signs-some in one language, others mixing two or more-found where people shop, where cultural sites such as cultural parks, places of worship, health care or other places likely to be visited by locals or tourists. These signage displays a wide variety of language pairs, deliberately chosen to test how well machine translation works with the original text.

Figure 1. Monolingual Signboard
Source: Researcher's documentation (2025)

Around Jl. Majapahit in the city of Mataram, researchers saw a sign that read " DILARANG MASUK." It served as an example for our work. Because the original writing appeared in Indonesian - not English - it matters when we consider how well machine translation works on signs, specifically using one system called GNMT. The place where this text was found is open to everyone, serving both practical needs alongside showcasing local culture; therefore, it highlights just how many languages exist within Mataram City.

Figure 2. Multilingual Signboard
Source: Researcher's documentation (2025)

On figure 2, on Jl. Majapahit in Mataram City, we spotted a signboard that said "JALUR EVAKUASI/EVACUATION ROUTE". It gave details in Indonesian alongside English. It served as just one piece researchers looked at. A signboard displaying two languages offered a chance to see how well GNMT software worked with bilingual text. The spot itself was meant to help everyone as usual.

Figure 3. Multilingual Signboard
Source: Researcher's documentation (2025)

Based on Figure 3, around Jl. Majapahit in the city of Mataram, researchers found a sign that looks three languages, namely in Indonesian, English, and Sasak language. It became part of what we examined for this project. Since it handles multiple languages, this tool can prove useful for evaluating how well Google Translate software works with complex mixed text. The signboards were found in places where people gather, showing the variety of languages and cultures that exist in the city of Mataram.

Data Collection Procedures

The Data for this study were collected through several systematic steps to ensure readability, accuracy, and quality in analyzing multilingual signboard translations in Mataram City.

1. ***Documentation***
   Take photos of monolingual and multilingual nameplates, especially along Jl. Majapahit, the city of Mataram, was taken as the main source of data to observe the real translation results in public spaces.

2. ***Image-to-Text Conversion***
   Collected images were processed using Optical Character Recognition (OCR) to extract written text from each already captured signboards and converted it into digital form for further analysis.

3. ***Translation Using GNMT***
   The translated text is then translated from Indonesian to English through Google Neural Machine Translation (GNMT) to evaluate the accuracity, readability, and overall quality of the translation.

4. ***Documentation Analysis***
   The original text that was the result of the OCR output, and the GNMT translation were compared to identify translation errors, problems, and possible improvements for more effective automatic translation.

Research Instruments

The instruments needed in this study are the following:

Table 1. Description of Research Instruments Used in the Study

Instruments	**Purpose**
Observation Sheet	Recorded the location, type, language, and visual condition of each signboard.
OCR Output Record Form	Documented the text extracted by OCR and noted any recognition errors.
GNMT Translation Evaluation Sheet	Assessed the GNMT translation based on accuracy, readability, and overall quality.
Translation Comparison Table	Compared the original text, OCR result, and GNMT translation, and identified types of translation errors.

This instrument is designed to ensure comprehensive data collection and systematic evaluation of multilingual signage translation on Jl. Majapahit, Mataram City. In the final step or in the Translation Comparison Table, the researchers also included an equivalnce analysis

Fithri et al., (2025). **Jurnal Ilmiah Profesi Pendidikan,** 10 (4): 3098 – 3107
DOI: https://doi.org/10.29303/jipp.v10i4.4100

column according to Baker (2018) because based on Baker (2018) equivalence at the word level means an equivalence relationship between lexical units (words) in the source language and the target language. He explains that not all words have direct equivalents due to differences in culture, concepts and language structure.

Data Analysis Technique

The data were analyzed using a thematic analysis created by Braun & Clarke (2006). At the beginning, the extracted text and GNMT output were compared to identify patterns of accuracy, readability, and translation quality. Then, the signboards data were coded and categorized to find the right GNMT translation results according to their classification. Finally, triangulation between documentation, GNMT OCR results and human translation, and in-depth analysis confirmed the validity of the study. The passage was written clearly and concisely. It provides practical information regarding research methods, procedures, tools, materials, or instruments. Specific criteria that have been established or established by the researcher in the collection and analysis of data are carried out in the next section.

FINDINGS AND DISCUSSION

Findings

RQ1. How accurate and readable are Google NMT translations on multilingual signboards in Mataram?

The researchers checked how well the GNMT worked on the signboars around Jl. Majapahit, the city of Mataram, with a focus on the truth of the translation but in addition also how people are easy to understand. Researchers did this by comparing observations, OCR, GNMT, and also human translation to analyze everything from initial results to final meaning, then considering GNMT and human results.

1. Section A : Observation Sheet

Looking at signs in Mataram, we noticed most communicated their message well. They were easy to read alongside having all necessary information. Specifically, examples four and five appeared both clear yet thorough. However, example three was readable though lacking some details. Conversely, examples one and two had everything needed, however the dim colors coupled with poor contrast made them difficult to decipher, as shown in Figure 4. Signage stayed mostly clear when only one language was used; however, wear, light, where things were positioned. These aspects sometimes made the writing hard to read. Consequently, getting accurate text from images proved trickier.

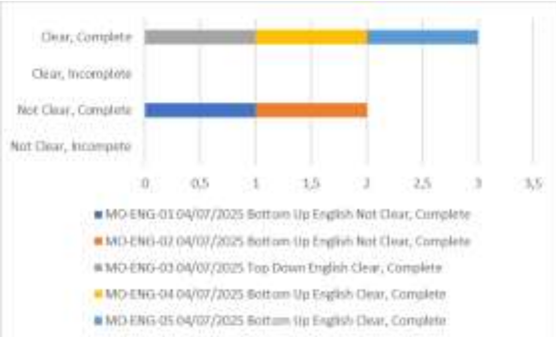

Figure 4. Results of monolingual signboards in Mataram

From the observation results, it was found that all multilingual signboards in Mataram were categorized as *clear and complete*, as shown in Figure 5. Each sample, labeled MU-ENID-SS-01 to MU-ENID-SS-05, displayed readable text with consistent language arrangement and minimal visual damage. This condition indicates that the multilingual signboards were generally well maintained and effectively designed for public readability. The clarity of signboards also supported the accuracy of the Optical Character Recognition (OCR) process, allowing precise text extraction. Overall, the study highlights that multilingual signboards in the observed areas provides easily accessible and well structured information for both local and international audiences.

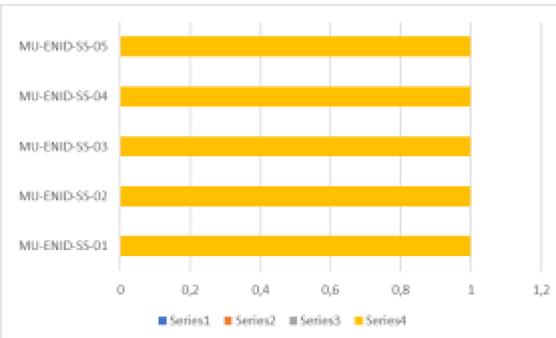

Figure 5. Observation Sheet (Multilingual)

2. Section 2 : OCR Output

The researchers used OCR to get the writing off those monolingual or multilingual signboards. It checked how well the system could turn what was printed into something a computer understands. How clear the signs were mattered, blurry or faint ones led to mistakes, so not everything got copied correctly.

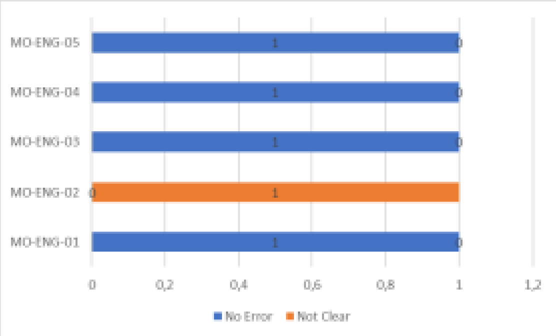

Figure 6. OCR output results of monolingual signboards in Mataram

Figure 6 shows the text reader did well on four out of five tests (MO-ENG-01, MO-ENG-03, MO-ENG-04, likewise MO-ENG-05), no mistakes there. But test MO-ENG-02 didn't come through clearly; poor light along with low contrast messed up how letters were read. So, while things went smoothly when pictures were good, brightness and colors still matter for getting accurate results.

Figure 7. OCR output results of mutilingual signboards in Mataram

The optical character recognition system flawlessly read all six signs. Numbered MU-ENIND-01 through MU-ENIND-06 in multiple languages on Figure 7. Evidently, these signs boasted crisp printing, easily different lettering, likewise strong differences in color between the writing also its backdrop. When signs across languages look alike with enough space between letters, character recognition works well. Because of this, we could then confidently move onto machine translation.

3. *Section C : GNMT Output*

Here are translations from signboards in different languages, created using automated tools in GNMT. Researchers looked at how well they got the right meaning, scoring that out of five alongside how naturally those English, Indonesian or even local language versions were read. A score reflected clarity that a higher number meant better translation quality. Figure 8 below already reveals that translation quality is inconsistent across instances. Some signs are clear enough to read, Although not entirely accurate, the translation is exact, however, the original meaning is sometimes lost. Some other versions have the correct meaning, although some are too formal or use strange expressions. This shows how well the system handles everyday expressions across languages, but it still needs improvement to capture cultural, natural and mixed meanings. According to Saputra (2022) the accuracy of Google Translate varies depending on the type of text being translated. In this case Google Translate can not deal with such diversity on signboards.

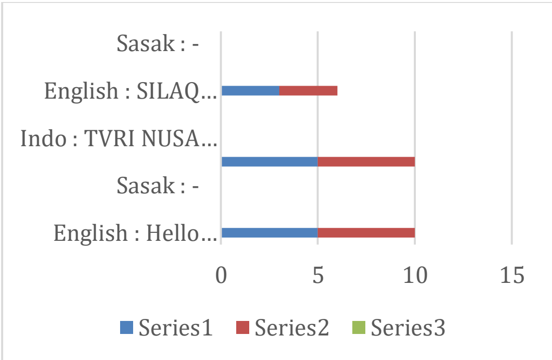

Figure 8. GNMT output accuracy and readability scores for signboards in
Mataram

4. *Section D : Human Translation Output*

Researchers have also examined how well people translate signboards into different languages. We produced score of five based on the accuracy and how smoothly the translation was read. Interpreters gave the right meaning, good and in accordance with the signboards, with the intention that locals and foreign tourists could understood it properly and without difficulty.

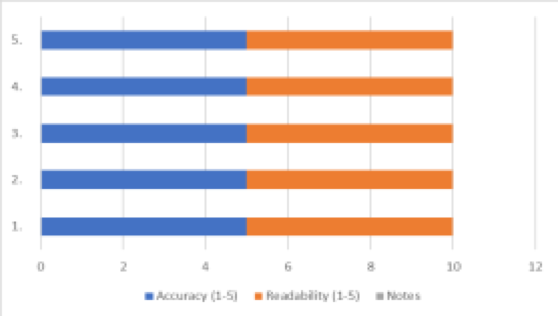

Figure 9. Human translation accuracy and readability scores for signboards in Mataram

In Figure 9 the researcher also showed each of the five examples well done on accuracy, they are also easy to understand. These similarities show translators skillfully blending the right words with the right cultural nuances. People generally choose better words, sayings, also easier to understand the culture than GNMT when translating. This shows that although GNMT translates quickly, one can also submit translations quickly but precisely for sure.

Table 2. The Comparison of Translation Accuracy and Readability Scores between GNMT and Human Translation.

NO	Type of Language	Average Accuracy (Human)	Average Accuracy (GNMT)	Average Readability (Human)	Average Readability (GNMT)
1)	MO-ENG (Monolingual, English)	5	4,6	5	4,6
2)	MO-IND (Monolingual, Indonesia)	5	4,5	5	4,5
3)	MU-ENIND (Multilingual English, Indo)	5	4,2	5	4,2
4)	MU-ENID-SS (Multilingual English, Indo – Side by Side)	5	5	5	5
5)	MU-INAR (Multilingual Indo, Arab)	5	5	5	5
6)	MU-INJA (Multilingual Indo, Java)	5	3	5	3
7)	MU-INSA (Multilingual Indo, Sasak)	5	5	5	5
8)	MU-ENIDSA (Multilingual English, Indo, Sasak)	5	5	5	5
9)	MU-INARSA (Multilingual Indo, Sasak, Arab)	5	5	5	5
	OVERAL AVERAGE	**5**	**4,6**	**5**	**4,6**

Look at how good the translation was, people still did their best judgment to get the correct meaning. GNMT results reached 4.6 out of 5 for each of them, indicating that it is still not appropriate in some translations, especially those that contained cultural nuances. Basically, while it was almost true, it was not quite as perfect as a human translation. In addition, the human translation showed things more clearly, although GNMT correctly translated simple things, but humans are better at translating small things, feelings that lay behind words. So, when context or culture is important, engaging people is the best key.

RQ2. How is the translation quality of Google NMT comparing to human translation of multilingual signboards?

This study explored how well the translation of GNMT compared to the results of work done by humans. In this case paid attention to the truth, how easily the translation flowed, plus indicated exactly where something went wrong. The researchers also noted which versions readers preferred in addition to mistranslations or other inaccuracies obtained in the translation. We carefully looked at each translation example using the same scoring guidelines to compare the original sign, the GNMT translation, and also the way humans translate it. Here was a table showing how well each approach performed in different areas.

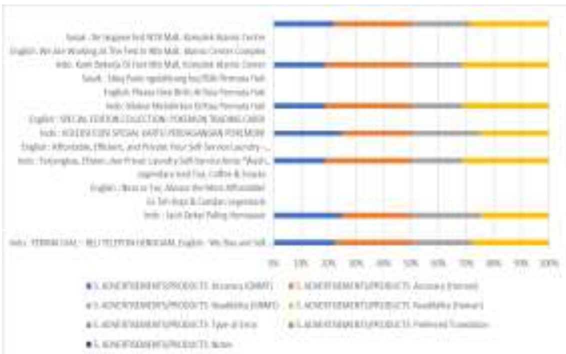

Figure 10. Comparison Table (Advertisement Category)

DOI: https://doi.org/10.29303/jipp.v10i4.4100

One type of signboards was advertising. In the ad category, researchers looked at GNMT translations compared to human translations. Look at Figure 10 above, both were generally good in terms of correctness and how easy they were to produce the right translation. however, humans consistently did a better job of capturing what felt right, taking culture into account as well. Translation from GNMT usually worked well, although it could sometimes feel a bit imprecise, especially when dealing with marketing stuff. Humans just loved the way humans wrote it because their version was clearer, better impressed, and to the point about what they wanted to convey or convince others.

Table 3. The Comparison of Translation Accuracy and Readability Scores between GNMT and Human Translation

NO	Type of Signboards	Average Accuracy (Human)	Average Accuracy (GNMT)	Average Readability (Human)	Average Readability (GNMT)
1)	Food Stalls/Restaurant	5	4	5	4
2)	Retail	5	4,2	5	4,2
3)	Institutions	5	4,6	5	4,6
4)	Hotel/Accomodations	5	5	5	5
5)	Advertisements/Products	5	3,8	5	3,8
6)	Traffic/Prohibitions	5	4,8	5	4,8
7)	Public Services	5	4,2	5	4,2
	OVERALL AVERAGE	**5**	**4,3714286**	**5**	**4,3714286**

The above was the result of GNMT and human translation compared the quality. Seen from the various types of signboards located on Jl. Majapahit, the figures above showed the typical translation of GNMT and Human results. human translations got perfect results with an average of 5 while GNMT was also quite good with an average of 4.37. this showed that GNMT did not capture enough detail with good translation or understand the context as humans did in translating.

Discussion

Signboards were well displayed using GNMT so they were accurate and easy to read. After taking measurements along with OCR GNMT displayed almost every sign (all advertising majors that had multiple languages, two or more) looked almost the same as the initial visual, also displayed some good signs. According to research by Castilho et al., (2018) why it is good that a text is written, clarity, organization, there is something missing that really makes a good person on the machine. Thus, since these signs were very easy to see, they became more accurate.

Optical Character Recognition (OCR) also worked well, generated four out of five monolingual texts correctly, in addition there were multilingual signboards. Because of this success, GNMT most likely started with clear text so its work had to be believable. One example of English, code MO-ENG-02, had difficulty reading because of how light or dark it was considered as well. Based on these findings by Zhou et al., (2020) the environment was important when using a computer to translate text from images although the translation system is good, its success depended on clear text at the beginning.

Humans generally judge translations made by humans as perfect with perfect accuracy in addition to their easy reading as well. The GNMT translation results were close, although they did not quite match the corresponding results. Previous results suggest a similar pattern where machines handled text with ease, but there were errors in the writing or whatever was deeply rooted in the culture. A recent view confirmed that, noting that technology often flowed smoothly but sometimes lost close meaning when faced with signboards that mixed language with cultural references such as in advertising.

When evaluating translations on various signboards, human translations score better. An average of 5.0 versus 4.37 with GNMT. The difference was most noticeable with advertisements or descriptions of goods (GNMT got 3.8, human translation is still at 5.0) because they often relied on convincing language in addition to understanding the local culture. Basically, this GNMT worked well when writing was simple. However, it had difficulty with cultural context, turns of phrase, or signboards that were advertisements where used to really convince someone. GNMT worked well for fast and everyday translations, but people still needed to check everything to make sure everything really fit, was precise and meant what it was intended to. According to Gaspari et al., (2020) combining machine translation with human editors gave the best results when translating for actual use.

CONCLUSION

The researchers found GNMT worked well on signboards around Jl. Majapahit, Mataram City, where people did a lot of activities. GNMT gave 4.37 for how accurately and easily readable the translation results were, while humans had an average result of 5.0. GNMT is good at reading any type of signboards such as hotel labels, government buildings, salespeople labels, basically anything that was easy where the words meant exactly what was written. It showed that GNMT translated typical city sign boards or specific notices well. In addition, the results of the analysis showed that each multilingual signboard was perfectly visible, ensuring smooth translation processing. Translation errors occurred when encountering unique writing, slang, or colorful references. Road signs on Jl. Majapahit that had interesting local phrases or flavors were often missing something important during translation as well, this showed that why people still needed to review human translation still needs to be side by side with GNMT to keep the meaning and culture intact.

ACKNOWLEDGMENT

The author would like to express sincere gratitude to the English Education Department, University of Mataram, for the guidance, facilities, and academic support provided throughout the completion of this research. Special thanks are extended to the supervisors and lecturers for their constructive feedback and encouragement, as well as to colleagues and participants who contributed valuable insights during the data collection and analysis process. Their contributions were essential in the successful completion of the study titled *"The Translation of Multilingual Signboards in Mataram City Using Google NMT."*

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