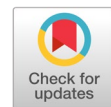


An enhanced pivot-based neural machine translation for low-resource languages



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ABSTRACT

This study examines the efficacy of employing Indonesian as an intermediary language to improve the quality of translations from Javanese to Madurese through a pivot-based approach utilizing neural machine translation (NMT). The principal objective of this research is to enhance translation precision and uniformity among these low-resource languages, hence advancing machine translation models for underrepresented languages. The data collecting approach entailed extracting parallel texts from internet sources, followed by pre-processing through tokenization, normalization, and stop-word elimination algorithms. The prepared datasets were utilized to train and assess the NMT models. An intermediary phase utilizing Indonesian is implemented in the translation process to enhance the accuracy and consistency of translations between Javanese and Madurese. Parallel text corpora were created by collecting and preprocessing data, thereafter, utilized to train and assess the NMT models. The pivot-based strategy regularly surpassed direct translation regarding BLEU scores for all n-grams (BLEU-1 to BLEU-4). The enhanced BLEU ratings signify increased precision in vocabulary selection, preservation of context, and overall comprehensibility. This study significantly enhances the current literature in machine translation and computational linguistics, especially for low-resource languages, by illustrating the practical effectiveness of a pivot-based method for augmenting translation precision. The method's dependability and efficacy in producing genuine translations were proved through numerous studies. The pivot-based technique enhances translation quality, although it possesses limitations, including the risk of error propagation and bias originating from the pivot language. Further research is necessary to examine the integration of named entity recognition (NER) to improve accuracy and optimize the intermediate translation process. This project advances the domains of machine translation and the preservation of low-resource languages, with practical implications for multilingual communities, language education resources, and cultural conservation.



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1. Introduction

Machine translation (MT) is a fast-expanding field within language technology. The utilization of neural machine translation (NMT) and other advancements in machine learning has led to a notable enhancement in the accuracy and proficiency of automatic translation [1]. However, despite the substantial advancements in translating widely spoken languages like English, Spanish, and Chinese,

there are still considerable challenges when it comes to translating low-resource languages such as Javanese and Madurese, which have limited resources available [2]–[5].

Indigenous languages hold immense cultural value as they carry deep historical meaning and contribute to the unique character of a community [6], [7]. Indigenous languages serve as vital stores of culture and history, while also contributing significantly to the social and economic cohesion of communities. The extinction of these languages may result in the deterioration of cultural identity and diminish the depth of local knowledge systems. The diminishing use of regional languages like Javanese and Madurese impacts cultural preservation and undermines the sense of belonging and national identity within a multilingual society [8], [9]. Indigenous languages frequently face the risk of extinction or a significant decrease in usage due to the rapid pace of globalization. This issue is worsened by the absence of literacy and documentation of the local languages that already exist, resulting in local languages in Indonesia being classified as low-resource languages [10], [11].

Machine translation technology plays a crucial role in this context. The declining utilization of regional languages such as Javanese and Madurese results in diminished access to literature, cultural expressions, and localized knowledge systems. Consequently, communities may see a deterioration of social ties and a decline in the intergenerational transfer of cultural heritage. Developing machine translation for local languages in Indonesia is essential to enhance inclusion, safeguard cultural variety, and foster a robust national identity [12]–[14]. Machine translation in Indonesia facilitates access to digital resources, documentation, and literature in local languages, hence enhancing its exposure and use among a wider population [15].

Furthermore, the advancement of machine translation might facilitate the more effective recording of indigenous languages, encompassing the transcribing of old writings and their translation into different languages for the purpose of comparative analysis and additional investigation [16]–[18].

Numerous studies have examined the difficulties of translating low-resource languages, especially the scarcity of linguistic resources, parallel corpora, and technical emphasis on these languages. Recent study underscores the necessity of augmenting linguistic datasets and formulating approaches capable of addressing the dialectal variations and grammatical intricacies characteristic of low-resource languages such as Javanese and Madurese. Pivot-based methodologies have shown to be a viable tactic in the realm of machine translation for indigenous languages. Previous research indicates that utilizing an intermediary language with extensive linguistic resources, such as Indonesian, can markedly improve translation quality, particularly when direct parallel corpora between two languages are scarce.

Although machine translation has the capacity to safeguard and advance indigenous languages in Indonesia, there are several notable obstacles, particularly for languages with little resources, such as Javanese and Madurese. Several of these barriers include: 1) Insufficient Training Data: Adequate parallel translation data is necessary for training NMT models [19], [20]. Regrettably, the accessibility of such data is very restricted or virtually non-existent for Javanese and Madurese [21]. This impedes the model's capacity to acquire and generate accurate translations; 2) Dialect Variation: Regional languages frequently display diverse dialects and localized variants. For instance, Javanese exhibits several notable dialects, such as Central Javanese, East Javanese, and West Javanese [22]. The Madurese language encompasses several dialects, including the Bangkalan, Pamekasan, Sumenep, and Kangean dialects [23]. To generate translations that are appropriate and meaningful in each context, the Neural Machine Translation (NMT) model must be capable of adapting to these differences; 3) Scarce Technology Resources: The development and implementation of language technology are often given more priority to languages with a bigger customer base and market presence. Less commonly spoken languages are frequently overlooked in the advancement of technology and study [24]; 4) Linguistic difficulties: Every language possesses distinct semantic and grammatical frameworks. The syntax and morphology of Javanese and Madurese provide unique challenges, making machine translation efforts more arduous.

A pivot-based strategy is a highly successful option for overcoming this difficulty. This project primarily addresses the difficulty of enhancing translation accuracy between Javanese and Madurese, two

low-resource languages characterized by insufficient parallel data and linguistic resources. Frequent faults in direct translation procedures encompass syntactic discrepancies, lexical inconsistencies, and neglect of dialectal variances. This project intends to alleviate these issues and enhance overall translation quality by employing Indonesian as a pivot language.

Translation from Javanese and Madurese can be enhanced by utilizing an intermediary language that possesses greater linguistic assets, such as Indonesian. This approach has the potential to enhance the precision of translation and expedite the advancement of translation models for languages that have limited resources.

This research aims to assess the effectiveness of the pivot-based technique in enhancing artificial neural machine translation for Javanese and Madurese languages. Additionally, it explores the importance of this approach in preserving and promoting regional languages.

Potential Impact of This Study: 1) Language Preservation: Aid in the conservation and advancement of indigenous languages, maintain cultural legacy, and guarantee the transmission of local wisdom to subsequent generations; 2) Technological advancement significantly contributes to the development of language technology, particularly for languages with limited resources; 3) Enhancing the accessibility of digital information and literature for those who speak Javanese and Madurese, hence promoting inclusion in the digital era; 4) Enhance the efficiency of documenting historic texts and other resources in local languages to facilitate their study and preserve cultural heritage

2. Literature Review

Machine translation operates by converting text from one language to another. Machine translation relies on the availability of parallel corpora to identify the number of linguistic resource pairings between two languages [25]. High-resource languages get advantages from having abundant parallel corpora, which are essential for effectively training robust neural machine translation (NMT) models [26]. Conversely, low-resource languages face a significant scarcity of data. The limited number of bilingual texts that are accessible sometimes lack consistency in terms of quality [27], which adds more complexity to the training process. The limited availability of resources impedes the model's capacity to acquire knowledge and provide precise translations, hence posing challenges in attaining the same degree of expertise shown in languages with abundant resources. The size of parallel corpora does not have a minimum criterion to classify a language pair as high, low, or extremely low resource. Even in the early stages, several research regarded 1 million parallel phrases as a low resource [28]. Recent studies classify a language pair as having low or very low resources if the parallel corpora available for NMT trials are less than 0.5 million and 0.1 million [29]–[32], respectively. However, it is important to note that these values are not absolute measures of corpus size.

The level of complexity increases as low-resource languages frequently display substantial dialect diversity [33], [34]. For instance, Javanese and Madurese have several dialects that possess distinct linguistic characteristics. A model trained on a certain dialect may exhibit poor performance when applied to a different dialect, resulting in mistakes and a diminished ability to capture contextual significance. The presence of diversity within the language itself introduces an additional level of intricacy to the work of translation, necessitating the use of adaptable and proficient models that can effectively manage these variances [35], [36]. Consequently, low-resource languages are frequently disregarded, leading to less focus and investment. The challenge is exacerbated by the computing requirements for training NMT models [37], making it difficult for initiatives that specialize on low-resource languages to get the requisite computational resources [38], [39].

The challenges of machine translation modelling lie in the complexities of syntactic and morphological components [40], [41], which pose difficulties for models to acquire and properly anticipate. Existing models sometimes struggle to accurately represent the intricate semantic subtleties and cultural settings present in these languages, which can result in translation mistakes and the loss of intended meaning.

Although facing these difficulties, the emergence of transfer learning and multilingual NMT models has brought about renewed optimism. Transfer learning is the process of improving a pre-trained model on a language with limited resources by using information acquired from a language with abundant resources [42], [43]. Nevertheless, this method still needs the availability of parallel data for further improvement. Simultaneously training multilingual models allows for the transfer of information across languages, providing substantial advantages for low-resource languages. Unsupervised and semi-supervised learning techniques have demonstrated encouraging outcomes as well [32], [44]. These methods utilize monolingual data and a limited amount of parallel data to train neural machine translation (NMT) models [45]. Although these approaches have potential, they need complex training regimens and have not attained the same degree of precision as supervised methods.

The pivot-based method is a very effective technique. The utilization of an intermediary language with more linguistic capabilities, such as Indonesian, can enhance the translation process for Javanese and Madurese. This approach leverages the more extensive linguistic assets of the intermediate language to enhance the quality of translation and expedite the building of the model.

In the context of multilingual machine translation, a pivot language refers to a third language that may be utilized to merge two or more distinct languages. The pivot model facilitates the connection between the source language corpus and the pivot language, as well as between the pivot language and the target language [46], as seen in Fig 1.

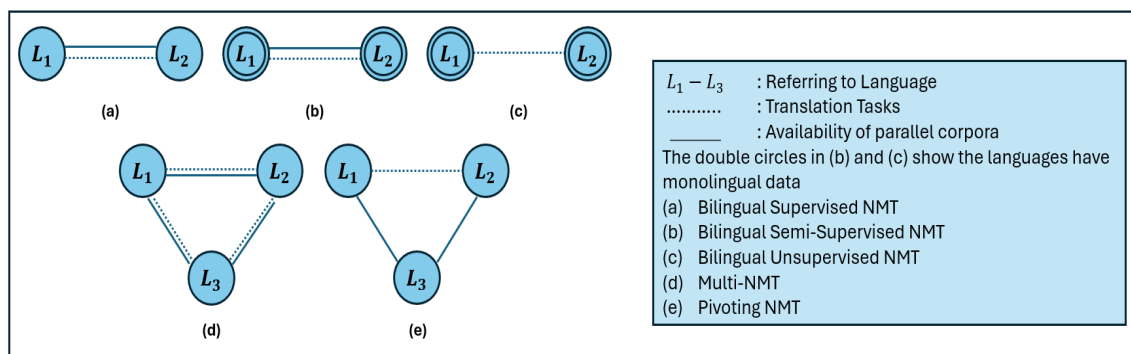


Fig. 1. NMT technique can be used for language pair translation

Several prior research examining the utilization of pivot language yielded varying outcomes. For instance, Cheng et al [47] conducted a study where they used English as an intermediary language to translate from Spanish to French and German to French. They used different amounts of corpus data and observed an improvement in BLEU accuracy value. Specifically, they achieved a 2.80% increase in accuracy for translating from Spanish to French and a 2.23% increase for translating from German to French [48]. In that research, it shown that employing German as a pivot language for translating from French to Czech resulted in a 2.60% improvement in the accuracy score measured by BLEU. Furthermore, in other study where they employed Spanish as an intermediary language to translate Chinese to Catalan [49]. The translation achieved a BLEU score of 38.92%, indicating improved accuracy compared to translations without an intermediary language.

Incorporating pivots in Neural Machine Translation (NMT) involves training a three-way translation model that incorporates the source, pivot, and destination languages. Ren et al [50] employed an expectation-maximization technique, treating the target phrase as a variable. Lu et al [51] incorporated many supplementary layers into both the encoder and decoder, whereas Johnson et al [52] utilized all elements from a single model. Both techniques train models for multiple language pairs that include English. However, for non-English languages, an extra separator must be used to remove tokens from non-target languages, as demonstrated by Ha et al [53].

In Indonesia, the Pivot language is employed to address the limited availability of regional bilingual parallel corpus data, namely for language pairings like Pontianak Malay and Bugis , [54] which are still

challenging to locate. Currently, there have been just two research on the utilization of pivot language, specifically Indonesian, for translating regional languages using Neural Machine Translation. These studies focus on machine translation of Madura-Sunda language [55] and Pontianak Malay-Bugis language [56]. Nevertheless, considering the multitude of distinct regional languages in Indonesia, more investigation into other linguistic variations remains imperative.

3. Method

This research method consists of 5 stages, which are simply illustrated with a flow chart starting from the process of data collection and parallel text corpus creation, model development, training process, prediction and evaluation. Details of the implementation process carried out during the research are illustrated in Fig 2.

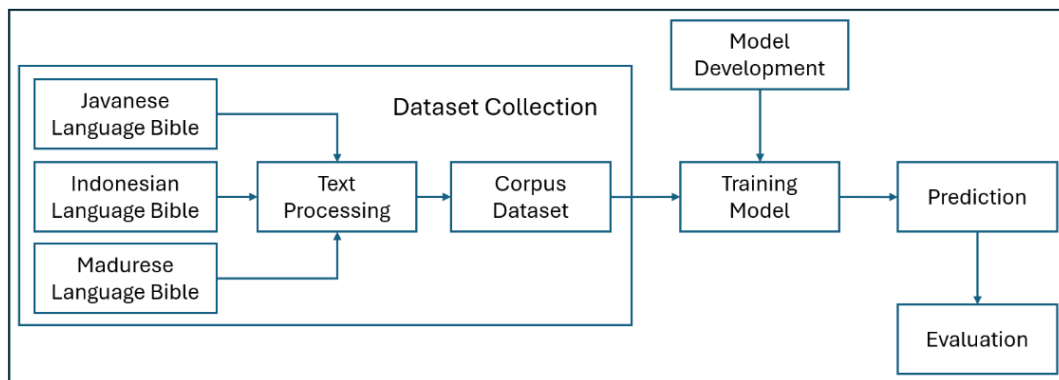


Fig. 2. Block diagram of the research in general

3.1. Data Collection

The research process that has been carried out begins with the collection and construction of corpus datasets for Javanese, Indonesian and Madurese. The process of collecting and building the corpus is shown in Fig 3.

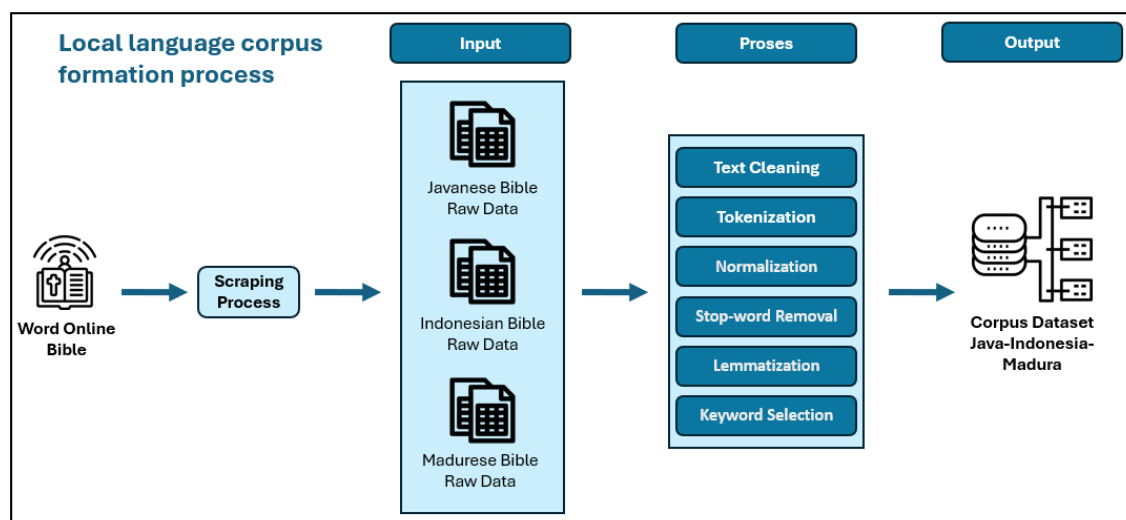


Fig. 3. Local language corpus formation process

The corpus formation process begins with a scraping process from the online biblical web page (<https://alkitab.mobi/>) for Javanese, Indonesian and Madurese. The result of the scraping process is a file with .xls format. With a total of more than 90,000 pairs of sentences, text processing is carried out starting from text cleaning, tokenization, normalization, stop word removal, lemmatization and keyword selection. The six processes are carried out to form a corpus with the format that will be used. The result

or output of this process is a pair of corpus datasets for Javanese - Indonesian and Indonesian - Madurese, then the process will continue with the process of model formation, training and evaluation.

3.2. Creation of a parallel Text Corpus

During the step of creating a parallel corpus, a pivot language, specifically Indonesian, is employed to establish a connection between Javanese and Madurese. The present corpus data comprises three languages: Indonesian, Javanese, and Madurese. The datasets for Indonesian, Javanese, and Madurese were obtained from prior study data. The outcomes of generating a parallel text corpus by utilizing a pivot language are depicted in Fig 4.

Javanese		Indonesian		Madurese
Ing jaman kuna sing wiwitan mula Gusti Allah nitahaké jagad.	→	Pada mulanya Allah menciptakan langit dan bumi.	→	E bakto Allah nyepa'agi alam dunnya,
Gusti Allah nuli ngandika, "Anaa padhang." Banjur ana padhang.	→	Berfirmanlah Allah: "Jadilah terang." Lalu terang itu jadi.	→	Allah adhabu, "Mara tera'!"
Mengkono wis dadi soré lan ésuks; yakuwi dina kang katelu.	→	Jadilah petang dan jadilah pagi, itulah hari ketiga.	→	Kabadha'an laju tera'.
Mengkono wis dadi soré lan ésuks; yakuwi dina kang kapat.	→	Jadilah petang dan jadilah pagi, itulah hari keempat.	→	Malem la lebat pas agante laggu.
Mengkono mau rampungé dumadiné jagad lan sainsiné kabèh.	→	Demikianlah diselesaikan langit dan bumi dan segala isinya.	→	Jareya are se kapeng tello'.
				Malem la lebat pas agante laggu.
				Jareya are se kapeng empa'.
				Daddi alam dunnya la mare ecepta'agi kabbi.

Fig. 4. Translation Processes from Javanese to Indonesian and Madurese

3.3. Model Architecture

The implementation stage of the neural network translator machine with the transformers architecture of the attention mechanism has several stages as in Fig. 5. The neural network translation engine using Indonesian as the pivot language, translating from Javanese to Indonesian, and Indonesian to Madurese. The parallel text corpus data amounted to 30,000 lines of Javanese and Madurese sentences. and Madurese, 30,000 lines of Javanese and Indonesian, and 30,000 lines of Indonesian and Madurese.

Fig 5 illustrates the structure of the Machine Translation (MT) system employing the Pivot and Transformer models. The method utilizes a Java-Indonesian parallel corpus, comprising of sentence pairs in Javanese and their corresponding translations in Indonesian. Subsequently, this data undergoes pre-processing and tokenization steps. The Pivot Transformer architecture serves as an intermediary between Javanese and Madurese languages.

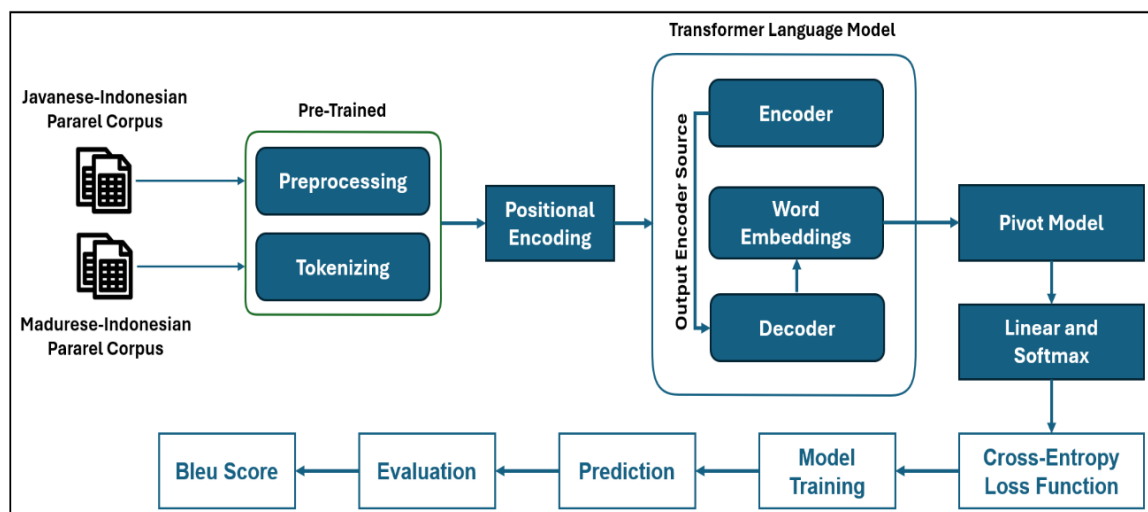


Fig. 5. NMT Architecture with Pivot and Transformer

The model consists of two primary components: an encoder and a decoder. The encoder converts the input text into a higher-level representation, while the decoder generates the translated text. Upon undergoing positional encoding [57], the data proceeds into the Transformer Language Model. This approach is designed to translate text from the Javanese language to the Indonesian language. The evaluation of the translation outcomes is conducted using the BLEU score.

Algorithm: Pivot-Based NMT using Transformer Models

Input:

- T_{JW} : Text in Javanese (source language)
- $M_{JW \rightarrow IN}$: Transformer model for translating Javanese to Indonesian
- $M_{IN \rightarrow MD}$: Transformer model for translating Indonesian to Madurese
- $Tokenizer_{JW}$: Tokenizer for Javanese
- $Tokenizer_{IN}$: Tokenizer for Indonesian
- $Tokenizer_{MD}$: Tokenizer for Madurese

Output:

T_{MD} : Text in Madurese (Target language)

Steps:

1. **Initialize Tokenizers and Models**
 - Load $Tokenizer_{JW}$: for Javanese
 - Load $Tokenizer_{IN}$: for Indonesian
 - Load $Tokenizer_{MD}$: for Madurese
 - Load $M_{JW \rightarrow IN}$ transformer model
 - Load $M_{IN \rightarrow MD}$ transformer model
2. **Translate Javanese to Indonesian**
 - Tokenize T_{JW} using $Tokenizer_{JW}$
 - $tokens_{JW} \leftarrow Tokenizer_{JW}(T_{JW})$
 - Generate Indonesian translation using $M_{JW \rightarrow IN}$
 - $tokens_{IN} \leftarrow M_{JW \rightarrow IN}.generate(tokens_{JW})$
 - Decode the output tokens to get Indonesian text
 - $T_{IN} \leftarrow Tokenizer_{IN}.decode(tokens_{IN})$
3. **Translate Indonesian to Madurese**
 - Tokenize T_{IN} using $Tokenizer_{IN}$
 - $tokens_{JW} \leftarrow Tokenizer_{IN}(T_{IN})$
 - Generate Madurese translation using $M_{IN \rightarrow MD}$
 - $tokens_{MD} \leftarrow M_{IN \rightarrow MD}.generate(tokens_{IN})$
 - Decode the output tokens to get Madurese text
 - $T_{MD} \leftarrow Tokenizer_{MD}.decode(tokens_{MD})$
4. **Output Madurese Translation**
 - Return T_{MD}

To develop a pivot-based neural machine translation (NMT) system for translating from Javanese to Madurese, we can employ a multi-step approach that includes an intermediary translation step through Indonesian that shows in Algorithm 1. The inputs consist of the source text written in Javanese (T_{JW}), transformer models designed for converting Javanese to Indonesian ($M_{JW \rightarrow IN}$) and Indonesian to Madurese ($M_{IN \rightarrow MD}$), as well as tokenizers specific to each language. The result will be the translated text in Madurese (T_{MD}).

The approach starts by initializing the tokenizers and models. Initially, we initialize the Javanese tokenizer ($Tokenizer_{JW}$) to transform the Javanese text into tokens that can be processed by the model. Additionally, we initialize the tokenizer for Indonesian as ($Tokenizer_{IN}$) and the tokenizer for Madurese as Load ($Tokenizer_{MD}$). Next, we initialize the transformer model ($M_{JW \rightarrow IN}$) for the purpose of translating text from Javanese to Indonesian. Additionally, we load the model ($M_{IN \rightarrow MD}$) to facilitate translation from Indonesian to Madurese.

To begin the process of translation, the initial stage is transforming the Javanese text (T_{JW}), into tokens using the ($Tokenizer_{JW}$). The tokenized output, represented as ($tokens_{JW}$) is then inputted into the Javanese to Indonesian model, denoted as ($M_{JW \rightarrow IN}$). This model creates the translated tokens in Indonesian, represented as $tokens_{IN}$. The Indonesian tokens are then transformed into text format T_{IN} through the utilization of the TokenizerIN tokenizer.

In the second phase, the intermediate Indonesian text T_{IN} undergoes tokenization using the $Tokenizer_{IN}$ to generate $tokens_{IN}$. Subsequently, these tokens are fed into the Indonesian to Madurese model $M_{IN \rightarrow MD}$ which produces Madurese tokens ($tokens_{JW}$). Ultimately, the tokens are transformed into the Madurese text T_{MD} by the utilization of ($Tokenizer_{MD}$). The completed translation is outputted as the resultant Madurese translation T_{MD} . This technique efficiently utilizes the pivot language (Indonesian) to improve the precision of the translation from Javanese to Madurese, overcoming difficulties associated with the scarcity of direct parallel corpora between two low-resource languages.

The training procedure for neural network models requires careful configuration of variables and parameters to guarantee optimal performance as shown in Table 1. The word embeddings are configured with an embedding dimension of 512, which enhances the ability to capture the semantic nuances of the words with great effectiveness.

Table 1. Parameter value

Parameter	Value
Word Embeddings (embed_size)	512
Layer	6
Dropout	0.1
Activation	Softmax
Loss	Categorical Cross entropy
Optimizer	Adam
Epoch	10000

The model is designed with a solitary layer, prioritizing simplicity while concentrating on the fundamental aspects of the translation work. To mitigate overfitting, a dropout rate of 0.1 is implemented, which involves randomly discarding units throughout the training process. The utilized activation function is SoftMax, a frequently used function in classification problems that transforms logits into probabilities. The selected loss function is categorical cross-entropy, which is commonly used for multi-class classification problems [58]. This option guarantees that the model's predictions are accurately compared to the true distribution. The optimizer employed is Adam, renowned for its efficiency and efficacy in managing sparse gradients. The model is trained for 10,000 epochs, providing ample time to acquire knowledge of the underlying patterns in the data. This comprehensive setup offers a thorough understanding of the structure and hyperparameters of the neural network model, guaranteeing that each element is meticulously adjusted to attain optimal outcomes in the translation assignment [14], [59]. For the pivot model results are shown in Fig 6.

```

Saved: javanese-indonesian-train.pkl
Saved: javanese-indonesian-test.pkl
Saved: indonesian-madurese-train.pkl
Saved: indonesian-madurese-test.pkl
Model: "pivotmodel"

```

Layer (type)	Output Shape	Param #	Connected to
inputs (InputLayer)	[(None, 57)]	0	[]
embedding (Embedding)	(None, 57, 128)	539776	['inputs[0][0]']
enc_padding_mask (InputLayer)	[(None, 1, 1, 57)]	0	[]
transformer_encoder (TransformerEncoder)	(None, 57, 128)	659712	['embedding[0][0]', 'enc_padding_mask[0][0]']
transformer_encoder_1 (TransformerEncoder)	(None, 57, 128)	659712	['transformer_encoder[0][0]', 'enc_padding_mask[0][0]']
dec_inputs (InputLayer)	[(None, 57)]	0	[]
transformer_encoder_2 (TransformerEncoder)	(None, 57, 128)	659712	['transformer_encoder_1[0][0]', 'enc_padding_mask[0][0]']
embedding_1 (Embedding)	(None, 57, 128)	432896	['dec_inputs[0][0]']
transformer_encoder_3 (TransformerEncoder)	(None, 57, 128)	659712	['transformer_encoder_2[0][0]', 'enc_padding_mask[0][0]']
look_ahead_mask (InputLayer)	[(None, 1, 57, 57)]	0	[]
dec_padding_mask (InputLayer)	[(None, 1, 1, 57)]	0	[]
transformer_decoder (TransformerDecoder)	((None, 57, 128), (None, 8, 57, 57), (None, 8, 57, 57))	1187456	['embedding_1[0][0]', 'transformer_encoder_3[0][0]', 'look_ahead_mask[0][0]', 'dec_padding_mask[0][0]']
transformer_decoder_1 (TransformerDecoder)	((None, 57, 128), (None, 8, 57, 57), (None, 8, 57, 57))	1187456	['transformer_decoder[0][0]', 'transformer_encoder_3[0][0]', 'look_ahead_mask[0][0]', 'dec_padding_mask[0][0]']
transformer_decoder_2 (TransformerDecoder)	((None, 57, 128), (None, 8, 57, 57), (None, 8, 57, 57))	1187456	['transformer_decoder_1[0][0]', 'transformer_encoder_3[0][0]', 'look_ahead_mask[0][0]', 'dec_padding_mask[0][0]']
transformer_decoder_3 (TransformerDecoder)	((None, 57, 128), (None, 8, 57, 57), (None, 8, 57, 57))	1187456	['transformer_decoder_2[0][0]', 'transformer_encoder_3[0][0]', 'look_ahead_mask[0][0]', 'dec_padding_mask[0][0]']
dense_16 (Dense)	(None, 57, 3382)	436278	['transformer_decoder_3[0][0]']

```

Total params: 8797622 (33.56 MB)
Trainable params: 8797622 (33.56 MB)
Non-trainable params: 0 (0.00 Byte)

```

Fig. 6. Pivot Model for Javanese – Indonesian – Madurese

4. Results and Discussion

The BLEU metric is utilized in the model scoring process to assess and quantify the degree of correspondence between the output and the length of the phrase. This study aims to run the experiment five times, and the outcomes are shown in Table 2 to evaluate the performance of direct LSTM based neural machine translation (NMT) without using a pivot language.

Table 2. Javanese-Madurese Direct LSTM based NMT Translation Result

Metric	Experiments 1	Experiments 2	Experiments 3	Experiments 4	Experiments 5
BLEU 1	0.555432	0.668029	0.589123	0.521456	0.643210
BLEU 2	0.423164	0.536297	0.448765	0.487492	0.505421
BLEU 3	0.381973	0.570239	0.390432	0.423784	0.451284
BLEU 4	0.252184	0.358512	0.261298	0.203215	0.332178

The Javanese Indonesian Madurese language translation utilizing the pivot transformer approach yielded superior results compared to the LSTM based NMT direct translation method. The evaluation of the pivot transformer method using the BLEU measure can be found in Table 3.

Table 3. Javanese-Indonesian-Madurese Pivot Transformer Result

Metric	Experiments 1	Experiments 2	Experiments 3	Experiments 4	Experiments 5
BLEU 1	0.768029	0.785324	0.798234	0.812345	0.826541
BLEU 2	0.670123	0.702541	0.715342	0.732154	0.748231
BLEU 3	0.635482	0.653879	0.669523	0.681293	0.695432
BLEU 4	0.521384	0.529874	0.541298	0.558731	0.572389

Fig 7 demonstrates that the translation outcomes achieved by utilizing Indonesian as an intermediary language are often superior.

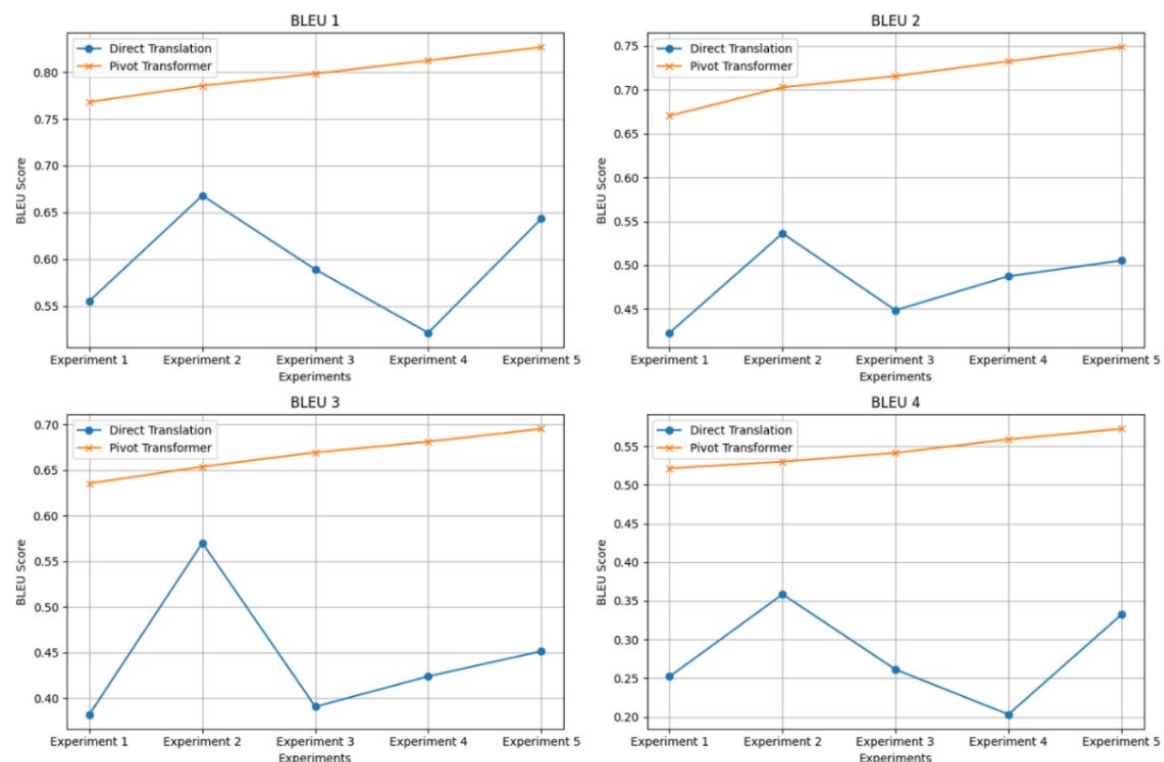


Fig. 7. Comparative analysis of translation test outcomes between Direct LSTM based NMT Translation and Pivot Transformer

This is evidenced by the consistently superior BLEU scores seen in all tests and n-grams, in comparison to the straight translation from Javanese to Madurese. More precisely, the translations using Indonesian exhibit higher BLEU-1 scores, which assess the precision of individual words, suggesting superior word selection and utilization. Furthermore, the BLEU-2, BLEU-3, and BLEU-4 scores, which consider longer word sequences and the maintenance of phrase and sentence structures, also demonstrate notable enhancements.

The higher ratings suggest that the Indonesian translation more effectively maintains the context and nuances of the original Javanese text, leading to a more precise and genuine Madurese translation. By examining the gaps in regional languages, specifically Javanese and Madurese, as shown in Table 4, this study may illustrate the effectiveness of utilizing an intermediary language to bridge linguistic disparities and enhance the translation quality across languages with limited resources.

Based on the test results and comparative observations between the direct translation method and the pivot method, it can be concluded that using the pivot method for translation machines in languages with limited resources, particularly in Indonesia, offers several advantages.

- **Enhanced Precision:** The pivot-based method regularly produces higher BLEU scores, suggesting superior word selection and a greater preservation of the original meaning. Precision is of utmost importance in guaranteeing that the translated text accurately reflects the original content, hence enhancing the overall dependability of the translation.
- **Improved Context Preservation:** Greater BLEU scores for longer n-grams (such as BLEU-3 and BLEU-4) indicate that the pivot-based method is extremely successful in maintaining the context and subtleties of the source language. This feature enables the translation of text in a more authentic

and contextually suitable manner, accurately capturing nuanced meanings and idiomatic phrases that may be overlooked in a literal translation.

- **Improved Readability:** Translations that make use of Indonesian as an intermediary language tend to exhibit more fluency and coherence. The enhanced legibility of these translations facilitates comprehension and enhances the overall reading experience, especially for writings targeting a wide readership or for professional and scholarly goals.

Table 4. Identification of gaps between Javanese and Madurese languages

Gap Identification	Javanese	Madurese
Phonology (Sound System)	It has variations in pronunciation, especially between the dialects of Central Java (Solo, Yogyakarta) and East Java (Surabaya, Malang). Example: the pronunciation of “a” at the end of a word can change to “o” in the Solo dialect.	It has consonants that are not found in Javanese, such as /t/, /d/, and /s/. There are also differences in intonation and word stress.
Morphology (Word Forms)	Has a language level system (ngoko, madya, krama) that determines word usage based on politeness and social context.	It does not have as complex a grading system as Javanese, but still has some different polite forms depending on the situation.
Syntax (Sentence Structure)	Sentences often follow the subject-object-predicate (SOP) order, although variations in structure can occur depending on dialect and context.	More flexible in sentence structure but tends to follow the subject-predicate-object (SPO) order.
Lexicon (Vocabulary)	It has many different vocabularies at each language level. In addition, there are many loanwords from Sanskrit, Arabic and Dutch.	Has a distinct vocabulary and is often influenced by Javanese, Malay and Arabic. Some words have very different meanings in a Javanese context.
(Language Use in Social Context)	Highly influenced by social and cultural context. Language use depends on who is speaking and to whom. Language levels play an important role in daily communication	Less bound by language level, but still considers social status and age in interactions.

- The continuous elevation in scores seen across all studies serves as evidence of the resilience of the pivot-based strategy. The stability of the technique demonstrates its consistent performance across multiple situations and datasets, instilling confidence in its suitability for diverse text kinds and translation scenarios.
- Utilizing Indonesian, a language with abundant linguistic resources and advanced computational tools, greatly improves the translation process. The presence of abundant corpora, advanced language models, and comprehensive linguistic databases in Indonesian enhances the precision and efficiency of translations. This resource use also enables the training of machine translation models, resulting in enhanced performance and scalability.
- (Additional information on broader impacts) This strategy not only enhances translation quality but also has considerable ramifications for language teaching and learning resources, particularly in multilingual environments such as Indonesia. The provision of precise translations for regional languages facilitates educational efforts aimed at teaching and preserving indigenous languages, perhaps incorporating these resources into school curriculum and community language learning activities.
- (Increased impact on language preservation) The implementation of machine translation technology with a pivot-based method can aid in the preservation of endangered indigenous languages. As globalization intensifies language extinction, utilizing such technology to generate digital resources and record languages is crucial for cultural preservation. These initiatives can facilitate the preservation of linguistic legacy for future generations.

- The pivot-based technique can mitigate the uncertainties that frequently occur in direct translations by incorporating an intermediary stage. This intermediary language functions as a sieve, clarifying vague concepts and expressions, so yielding a more exact ultimate translation.
- The utilization of an intermediary language facilitates the acquisition of cross-linguistic insights, which can augment the quality of translation. The intermediary translation can effectively capture cultural and contextual nuances that are more accurately conveyed in Indonesian, resulting in a more comprehensive and knowledgeable translation into Madurese.
- The capacity to adapt to complicated sentence patterns is significantly enhanced by the pivot-based method. The intermediary stage facilitates the decomposition and reassembly of complex syntactic structures, resulting in more linguistically accurate translations in the destination language.

By including these additional factors, we can see that the pivot-based method not only improves the accuracy and clarity of the translation, but also utilizes linguistic resources and knowledge to improve the overall quality and reliability of the translation process. But aside from the greatness of the pivot method, we will point out some examples of translation failure processes that occur. Table 5 shows the examples of failures in the translation process between Javanese, Indonesian, and Madurese may arise from discrepancies in syntax, morphology, or the improper application of idioms.

Table 5. Translation Failure in Pivot Method

Javanese	Indonesian Translation	Madurese Translation	Translation Failure
<i>Aku arep mangan sega</i>	<i>Saya akan makan nasi</i>	<i>Sengkok badha makan bhubur</i>	Bhubur in Madurese should be “porridge,” not “rice.” The translation is wrong because the word “sega” (Javanese: rice) is translated as bhubur which means porridge in Madurese.
<i>Sira iku pinter banget</i>	<i>Kamu sangat pintar</i>	<i>Be' reya penter pole</i>	The translation is wrong because pole should not be used here, because in the Madurese context, pole is more often used to emphasize repeated actions, not for affirmation.
<i>Ojo lali lungo menyang omah</i>	<i>Jangan lupa pergi ke rumah</i>	<i>Jha lunga ka bhumi</i>	The translation is wrong because bhumi in Madurese refers to “land” or “earth,” not “house.” The correct word should be langgar or pondhuk.
<i>Aku lagi ngombe banyu</i>	<i>Saya sedang minum air</i>	<i>Sengkok odik minum ajem</i>	The wrong translation occurs in the word ajem, which should be banyu in Madurese translated as ais or ombak for “water,” not ajem which means “chicken” in this context.
<i>Wong kae pancen wicaksana</i>	<i>Orang itu memang bijaksana</i>	<i>Oreng etta e' jheca</i>	The translation is wrong because jheca does not contain the correct meaning for the word “bijaksana” in Madurese. The correct word is bijaksana or parjuga.

The reasons for the unsuccessful translations from Javanese to Indonesian and Madurese can be categorized into three primary aspects. Cultural or idiomatic errors frequently arise when prevalent phrases in Javanese and Indonesian are directly translated into Madurese, disregarding significant cultural disparities. These idioms may lack accurate equivalents, leading to divergent or erroneous interpretations in the target language. Secondly, lexical discrepancies frequently constitute a significant source of translation failure. Seemingly straightforward terms in Javanese or Indonesian, when translated literally, can acquire radically altered meanings in Madurese due to distinct cultural nuances or regional usage. Terms such as “banyu” (water) in Javanese may be erroneously translated as “ajam” (chicken) if the contextual usage in Madurese is not comprehended. Third, syntactical problems frequently occur in translation. Variations in word order or sentence structure among Javanese, Indonesian, and Madurese may produce phrases that appear peculiar or convey incorrect meanings. The varying arrangement of subject, predicate, and object across multiple languages may lead to misunderstanding in message

transmission; thus, it is crucial for the translation model to comprehend and appropriately modify the sentence structure.

5. Conclusion

The study shows that utilizing Indonesian as a mediator language greatly enhances the quality of translations from Javanese to Madurese, resulting in better BLEU scores for all n-grams in comparison to straight translation. This demonstrates enhanced precision, retention of context, and improved legibility. This approach enhances translation metrics and facilitates the preservation and revitalization of the original language by increasing its accessibility in digital format, hence supporting documentation and educational applications. The pivot-based method is a dependable and effective technique for generating native translations. Nevertheless, the method has its constraints, such as the possibility of mistake spreading and the bias that may arise from using the pivot language. Future studies should investigate the integration of named entity recognition (NER) to improve accuracy by accurately translating specified entities. The integration of Named Entity Recognition (NER) may be executed by initially pre-training the NER model on an extensive Indonesian corpus, thereafter, fine-tuning it on Javanese and Madurese texts to discern key entities such as names, locations, or culturally distinctive terminology. The efficacy of this integration may be evaluated using precision, recall, and F1-score, in conjunction with conventional BLEU scores, to determine the extent to which named items are retained in translations. Enhancing the intermediate translation step can also minimize mistakes and enhance the quality of the result. The pivot-based technique not only enhances translation accuracy but also has significant implications for the preservation of endangered languages. This strategy facilitates the development of language learning tools, the creation of bilingual or trilingual dictionaries, and the enhancement of cross-linguistic communication in multilingual societies. Additional research should explore the suitability of the pivot-based approach for other language pairings, particularly for less widely spoken languages, and utilize sophisticated machine learning methods and comprehensive linguistic resources to enhance the outcomes. This method has the potential to be integrated into language education policy, enhancing the promotion of local languages in educational contexts by offering more reliable translation tools, so assuring their sustained use and relevance in daily life. Conducting extensive study on the long-term effects of pivot-based translation on language acquisition and preservation might be advantageous. Essentially, this method may assist in creating precise bilingual or trilingual dictionaries, expanding language learning resources, and improving translation services in cultures with many languages. This study highlights the essential role of machine translation in encouraging language preservation and developing linguistic diversity through technology, hence overcoming linguistic divides, and sustaining cultural identity. Moreover, subsequent study may investigate the scalability of this approach within larger datasets or multilingual contexts by conducting parallel training in additional languages to assess the wider relevance of pivot-based methodologies in the preservation of endangered languages. As a result, it promotes language preservation and cultural understanding. By incorporating Named Entity Recognition (NER) and resolving existing constraints, the method's efficacy may be further improved for both linguistic research and practical implementations.

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