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Development of the Minangkabau Local Language Translation Machine Based on Stemming

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***Abstract*— Indonesia is an archipelagic country that has hundreds of ethnic groups and regional languages. One of the well-known regional languages is the Minangkabau language (BM) which is dominantly used in several areas in Sumatra which are in the Austronesian family. The habit of the Minangkabau people in their daily life is to always use the Minangkabau language (BM) in communicating. Usually, the Minang tribe always communicates every day using the Minangkabau language, so that it is unique for the people around them, thus creating curiosity to know BM. So this research was conducted to translate BM into Indonesian. The purpose of this research is to translate BM into Indonesian. By using the translation engine of the Minangkabau Language Stemming Algorithm (SBMK). The data processed were 600 basic words in printed dictionaries and sentences in 12 BM documents. The level of accuracy of the translation results from this study is 98.33% for basic words and 94.68% for sentences in the document. The resulting algorithm is very precise to translate and process the basic word spelling checker in BM words and documents into Indonesian.**

Keywords— language, Minangkabau, translation engine, spelling checker, basic words.

I. INTRODUCTION

The Minangkabau language is a regional language used by the Minangkabau people from the Minangkabau Highlands in West Sumatra, South Sumatra, and the west coast of the Mukomuko region [1]. The Minangkabau language (BM) is very popular with its various dialects, such as Agam, Batu Sangkar, Pesisir, Solok, and Pariaman [2]. BM has several unique words in prefixes, insertions, suffixes, combinations, and disconnected affixes. In prefixes consisting of ba-1, ba-2, maN, paN-, pa-, ta, no, di, sa, ka, raw, and basi, insert -il, -al, -ar, -am, and iŋ, endings -an, -kan, I, and –lah, compound ba-Kan, ba-1, no-Kan, pa-Kan, ba-lah, standar-lah, stale-lah, man-pa-Kan , no-pa-Kan, no-sa-Kan, sa-paN, di-pa-sa-Kan, and interrupted affixes Ka..an, Ka..no, paN..an. The uniqueness that exists in the Minangkabau language is in the insertion affix, where of the five insertion words in Minangkabau language, only il, ar, am are widely used, which are not too productive[3]. Morphologically rich language, and morphological and ambiguous analysis plays an important role in most Natural Language Processing (NLP) tasks[4]. NLP is a branch of artificial intelligence that focuses on natural language processing. The language that would understood by the computer requires a process first so that the user's wishes can be clearly understood by the computer[5]. Stemming is a sub-field of NLP, which is a phase process in pre-processing finding the root or root word in a particular word [6][7][8]. Stemming is widely used in application development, especially in terms of Information Retrieval (IR), and text mining, to improve system performance [9][10][11]. The stemming function here is to cut or separate the basic words with affixes, both prefixes, insertions, suffixes, or combinations [12], [13].

The stemming algorithm had widely used for many cases, such as determining similarities in submitting thesis titles using Nazief & Adriani stemming [14], Then compare two Indonesian stemmers Porter and Arifin Setiono, to find out which stemmer is more effective in determining the root word [15]. Arifin and Setiono also proposed a new algorithm similar to Nazief, but adding affixes to words to be omitted, resulting in a more effective root word [16]. Stemming on tweet documents to analyze the public opinion of Indonesian tweets about presidential candidates of the Republic of Indonesia in 2014 using Naive Bayes classification, Maximum Entropy classification, and Support Vector Machines[17]. ECS stemming reduces the number of terms generated at the preprocessing stage by using the Clustering method[18]. Affix grouping based on Indonesian morphology stemming algorithm Enhanced Confix Stripping (ECS), New Enhanced Confix Striping (NECS) stemming algorithm, and UG18 stemming algorithm[19].

The stemming methods that exist in each language are different from each other, where Indonesian stemming has a different morphology from the Minangkabau language stemming. Stemming for the Minangkabau language is more complicated because several affixes will be removed to get the root word. Stemming regional languages using the Rule-Based Approach which produces an accuracy rate of 96.94% with a total of 120 incorrect words corrected to 20 incorrect words[20], modification of the Enhanced Confix Stripping stemmer method, using data in the form of text/poetry in the Madurese language [21].

II. MATERIAL AND METHOD

2.1 The Spell Check

Spell Check, is the process of checking for spelling errors of words in the text and providing solutions for errors automatically. Errors that arise can be caused by the use of the wrong words, and typing and coding errors. Spelling errors are divided into two, namely non-word errors and real-word errors. Non-word errors occur because the typed word is not in the dictionary, the word is in the dictionary but is wrong in the context [22][23]. The challenges in making a spelling checker are in the process of finding the wrong word and providing suggestions in the form of the right word to replace the mistake word, as well as the process of recognizing grammar in sentences, whether ambiguity and words that do not exist in the dictionary are also known as Out of Vocabulary (OOV) While errors in non-words the process of checking excessive letters and spelling words [24].

2.2 Minangkabau language (BM)

Minangkabau language (BM) has three types of word meanings (phonemes) [25]. The three phonemes are 5 vowels, namely a, i, u, e, and o; 20 consonants, and 6 diphthongs, namely id̄, ud̄, aw, ay, uy, ed̄ [26]. The smallest words (morphemes) in BM consist of 1 to 4 syllables that have meaning [27]. Morphological morpheme processes are grouped into seven groups of affixes which are presented in Table 1.

Table 1. BM Affix Group

No	Group	Affix
1.	Prefix	*ba-1, ba-2, maN, paN-, pa-,ta, no, sa, baku, baka, basi, ka, bapa, tapa, maN pa, sa pa*
2.	Insert	*-il, -al, -ar, -am, iŋ*
3.	Suffix	*-an, -kan,i, dan lah*
4.	Disconnected Affix	*ka..an, ka..no, paN..an*
5.	Combination of prefix and s uffix	Combination of prefix and suffix *(ba K an, ba- i, no- Kan, pa-Kan, ba- lah, ba ku- lah, basi- lah),* Combined Suffix and Prefix (*MaN- pa- Kan, no- pa- Kan, No- sa- Kan, sa-pa N, di-pa-sa-Kan*)
6.	Combination of prefix and c ombination of suffix	*maN..pa..Kanlah, maN..sa..Kanlah dipa..Kanlah,disa..Kanlah, baku..lah, b asi..lah, sapaN..lah*
7.	Other disconn ected affixes	*ba2..ka..an,ba2..paN..an, sa..paN.an*

Based on the group of affixes in Table 1, word formation can be done using Equation (1).

$$kd = [aw] + [akh] + [dk] + [sis] + gab \qquad (1)$$

Where kd is a basic word in documents and sentences, aw is a prefix, akh is a suffix, ds is a basic word, sis is an insertion in a sentence, and gab is a combination of affixes. The part of the word that is combined with the root word will form an affix. The Minangkabau Language Stemming Algorithm (SBMK) process begins with finding the word to be stemmed in the dictionary. If a word is found, it becomes the root word and the process stops. If the word is not found, then the deletion process is carried out starting from the deletion of the prefix, the deletion of the suffix, the removal of the insert, the deletion of the interrupted affix, and the deletion of the combined. All processes refer to checking in the Minangkabau language dictionary. If the word you are looking for is not found in the dictionary, then the word you are looking for becomes the root word.

Documents containing variations in various forms of letters and punctuation, need to be uniformed through a preprocessing process with the aim that the data used is free of noise. The preprocessing stage includes case folding, tokenizing, stopword removing, and stemming processes[28]. Case Folding is the process of changing the entire text in a document into lowercase letters, such as 'a', 'b', etc., tokenizing is the process of separating a document into parts, and removing some characters, such as punctuation marks. Stopword Removing is the process of removing words that have no meaning, such as 'and', 'or', 'by'[29]. Stemming is the process of separating root words from prefixes (prefixes), insertions (infixes), suffixes (suffixes), and combinations (confixes)[30].

The stages of the process of checking the spelling and translation of the Minangkabau language are presented in Fig. 1.

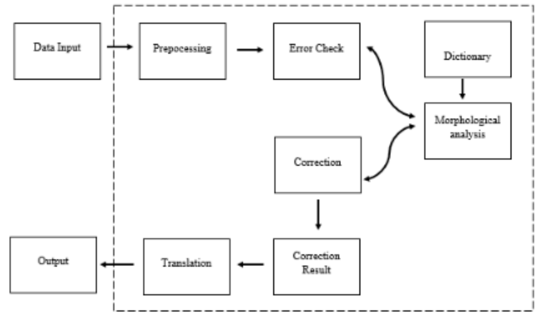


Fig. 1. Stages of the Translation Process

Fig. 2, describes the process carried out in checking the spelling of the Minangkabau language, starting from the pre-processing stage, before proceeding to the next stage, a language dictionary is needed to check words according to the morphological analysis of the language used. The preprocessing stage consists of processes, such as case folding, which removes all periods and punctuation marks in a document, then proceeds with the tokenizing process, which is the process of separating each syllable, then the stopword removing process, which removes words. words that have no meaning, such as the word and, or, by, etc. Then there is the stemming process, which is to remove existing affixes such as prefixes, insertions, and suffixes. Then proceed to the error detection and error correction process. After checking and correcting errors which refers to the analysis of the morphology of the language, then it produces results in the form of words in the document. Next, carry out the language translation process, according to the EYD rules in Indonesian. The algorithm of the translation process is presented in the following pseudocode in Fig. 2.

```
Translasi Algorithm
   Input      : KD,Kata, Kal
   Output     : KD, Kata, Kal
      Initialization preg_match
      If (cekKamus($_1_KD)){
       $data['kata1']='$_1_KD;
         $data['kata2']='$_2_Kata;
           $data['kata3']='$_3_Kal;
      Else
      If (preg-match 'KD'){
         If (preg_match('KD'){
            Return Tampil KD;
              Return Arti KD;
            End if
         Else
            If (preg-match ('Kata')){
              If (preg_match ('Kata')){
                Return Tampil Kata;
                  Return Arti kata;
                End if
         Else
              If (preg-match('Kal')){
                Return hapus Kal;
                  Return Arti Kal;
                End if
              End If
            End If
```

Fig. 2. Translation Pseudocode

The translation algorithm in Fig. 1 is based on the grouping of basic words, words, and sentences in the morphology of the Minangkabau language. The translation process is carried out starting from the root word. This algorithm processes basic words, words, and sentences in the document which will produce basic words, words, and sentences in the Minangkabau language. Base words, words, and sentences will be validated with the database. Basic words, words, and sentences found in the database will be processed to produce basic words, words, and sentences that have been translated into Indonesian. Like the word, "barangkek" will be "depart".

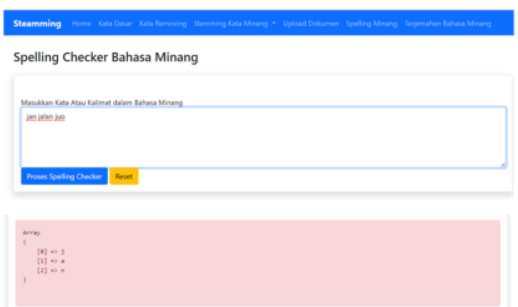
III. RESULT AND DISCUSSION

The translation algorithm was tested on 600 basic words. The choice of words tested was based on the groups of vowels and consonants in the database. The translation algorithm was also tested on 12 Minangkabau language folklore documents. Each test result is validated by an expert and the formula to determine the level of accuracy in the word is presented in Equation (2). Accuracy values for words that were successfully translated in the document using Equation (3).

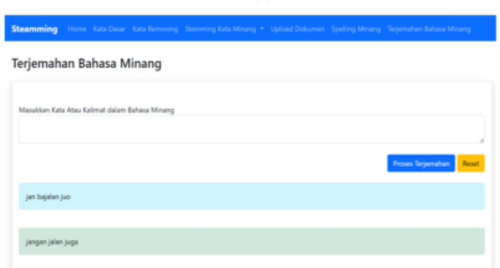
$$\text{Word Translation Acc} = \frac{\sum SW}{\sum IW} \text{x } 100\% \qquad (2)$$

$$\text{Doc Translation Acc} = \frac{\sum SD}{\sum ID} \text{x } 100\% \qquad (3)$$

Where $\sum SW$ is the number of successful word translations, and $\sum IW$ is the number of words tested. $\sum SD$ is the total translation of documents, and $\sum ID$ is the number of test documents. The algorithm application is implemented using the PHP Programming Language with test data in the form of a dictionary stored in a MySQL database. One of the test results using the application is presented in Fig. 4.



(a)



(b)

Fig. 4. Testing interface (a) Spelling Checker, (b) Translator results

Table 2. Test results on the word

No	Group	Word Count	Word Translate	Accuracy (%)
1.	prefix	387	385	99.00
2.	insert	11	10	91.00
3.	suffix	96	93	97.00
4.	affix	59	57	97.00
5.	Combination of prefix and suffix	18	17	94.00
6.	Combined prefix and combined suffix	24	23	96.00
7.	Another disconnected affix	5	5	100.00
	Total	600	590	
Average				98.33

Table 3. Test results on words in the document

No	Tittle	Word Count	Word Translate	Accuracy (%)
1.	Asal usul Maninjau.txt	199	190	95.00
2.	Mande.txt	72	65	90.00
3.	Cerita Minang.txt	112	100	89.00
4.	Mengutaroan Cinto.txt	1,403	1,320	94.00
5.	Barubek.txt	394	372	94.00
6.	Di rumah Puti Galang.txt	453	435	96.00
7.	Talaraik dek harato.txt	1,722	1,700	99.00
8.	Mandapek Malu.txt	518	480	93.00
9.	Di tingga Marantau.txt	193	180	93.00
10.	pituah bapak jo mande.txt	477	464	97.00
11.	Malin Kundang.txt	399	350	88.00
12.	Marantau.txt	507	450	89.00
Total		6,449	6,106	
Average				94.68

Based on the test results in Table 2 and Table 3, the average accuracy level of translators from the SBMK algorithm is obtained, namely:

$$Accuration = \frac{Word\ Trans\ Accu + doc\ Trans\ Accu}{2} \qquad (4)$$

$$= \frac{98.33\% + 94.68\%}{2} = 96.50\% \qquad (5)$$

With an accuracy result of 96.50%, it makes the translation algorithm reliable, and has advantages in translating words, sentences in documents. Another advantage of the translation algorithm is that it can work very well and can also identify words and spelling checkers in sentences.

IV.CONCLUSSION

The translation algorithm is a standard stemming algorithm for the Minangkabau language which can be implemented for translating words and sentences in documents. The translation algorithm can determine the spelling checker for words and sentences in the document. The system produces an accuracy rate of 96.50% from 600 words and 12 documents containing.

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