SENTIPUBLIKO: Sentiment Analysis of Repost Jejemon Messages using Hybrid Approach Algorithm

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Abstract. Jejemon language becomes a form of communication dialect. It was a form of expression used by a particular social group unknown as Jejemon. However, the Jejemon expression has different formats ranging from a basic form of changing letter to number, lowercase letter to uppercase letter, inserting shortcut texts into more complicated format. This paper aims to classify Jejemon tweet whether it is a positive, negative or neutral sentiment through sentiment analysis techniques. Experiment included translation of Jejemon formatted tweet, reduction of sentiment scores on repost tweets and sentiment classification. Analysis of experiment results involves Paired T-Test, confusion matrix, precision, recall, f-score and accuracy. Evidently, translated Jejemon tweet resulted 78.5% similar from the actual message using cosine similarity algorithm. Furthermore, Paired T-Test shows no significant difference between new sentiment scores from translated expression and actual sentiment scores using Hybrid Algorithm. Sentiment analysis metrics such as precision, recall, f-score and accuracy show acceptable values of 71%, 76%, 71% and 73% respectively.

1. Introduction

Human language is constantly changing. It happens across time and social groups. These changes on human language yields negative perception from people who are unable to cope with new vocabulary or new visual representation. The downside of the new trends might result possible miscommunication between social groups.

In the Philippines, several languages were invented to cater specific social groups. Predominantly, millennial and member of the third sex are the most socially active group in terms of modern language expression [1]. They developed new language semantics such as Jejemon (p30pL3, o+h3r, p4c3s) [2] and bikemon (Aglipay, Chiquito, Churchill). However, the most controversial language trend in 2016 is Jejemon [3].

Nevertheless, Jejemon language users suffered from weak speaking ability and mangled word spelling as observed by English teachers. They average 12 text messages everyday. Each jejem message normally is composed of symbols and phonetics. However, the advent of technological communication medium focuses on social connection such as social media created new Jejemon followers in Twitter aside from JEJETYPING, wearing a jeje-hat and jeje-photos online [4].

The overwhelming success of Jejemon language lead to an award as Word of the Year in 2010 by the Filipinas Institute of Translation Incorporated based on significant impact on Filipino life in terms of socio-cultural, political, social and economic [5].

As an influential millennial language, Jejemon expression is a result of self-expression which designed to resolve concerns on limited available space provided by text messages and Twitter [5].
However, it is significantly important beyond translation to understand the actual feeling behind the person’s message or opinion.

Classification of one’s opinion can be done through sentiment analysis. It can classify opinion whether positive, negative or neutral via polarity score. Unfortunately, other factor to consider is the impact of repost known as retweeting in Twitter towards sentiment classification in a document level. This paper is designed to classify the sentiment of a phenomenon language developed by Jejemon generation. Its complexity to analyze the Jejemon expression using natural processing language is the key motivation of this paper. In classifying Jejemon tweets whether “positive sentiment” or “negative sentiment” relies on sentiment polarity value.

Hybrid algorithm developed by Ilao and Fajardo [6] will be used to determine sentiment polarity values that was proven better than SentiWordNet and VADER algorithm as tested to different political datasets. Furthermore, integration of string similarity algorithm in reducing sentiment polarity score for repost or retweet messages will provide better understanding of the side effect of repost messages in a document level sentiment evaluation.

The paper is organized by sections. Section 1 elaborated Jejemon language origin, sentiment analysis and possible issue on repost message. Section 2 enumerated vital concepts related to the paper. Section 3 discusses the detailed stages of sentiment analysis. Section 4 described characteristics of collected instances. Section 5 cited statistical instrument and sentiment analysis measurement to provide performance analysis. Section 6 explained performance and evaluation of translation, dataset and algorithms. Lastly, Section 7 presented the general conclusion of the study.

2. Review of Related Literatures

2.1. Jejemon Word Structure

J ejemon language became popular in 2010 based on the limited space available for text messages and tweets [5]. It is primarily composed of alphabet known as Jejebet.

Jejebet uses Roman alphabet (a-z), Arabic numerals (0-9) and other special characters (@, !, ~, ?, .). However, Jejemon word is more than jejebet alphabet. It has several types of pattern namely alternating capitalization, over-usage of the letters H, X or Z and mixture of numeric characters and English alphabet [5] as shown in Table 1.

| Characteristics of Jejemon                          | Example               |
|----------------------------------------------------|-----------------------|
| Insertion of unnecessary numbers and letters.      | phfue or p0w          |
| Unique orthography based on how the words sound    | eHyUoeW               |
| Unconventional use of punctuations                 | psenxa na ha!!        |
| Numbers to substitute letters                       | bzt4h                 |
| Alternate use of lower and upper case              | WE wNt 2 BE~ P0wh.    |
| Use of onomatopoiec lexis/emotional language       | tnx p0wh jejeje       |
| Lengthening of vowels and consonants               | TAMAAAA!              |
| Substitution of spelling                            | M@q                   |

2.2. Jejemon Translation

J ejemon translation is available online. One particular online translator is Jejemon Translator found in http://173.254.110.65/jejeschool/index.php. It is capable to translate English language to Jejemon expression as shown in Figure 1.
Figure 1. English Language to Jejemon Language Translation.

It was applied to transform the English thesis document version [7] to jejenese or Jejemon language document version available in iskwiki.upd.edu.ph. It shows the reliability of the Jejemon translator as an effective technical tool. The jejemon document revision demonstrated combination of three Jejemon techniques namely numbers to substitute letters, symbols to substitute letters and alternate use of lowercase and uppercase letters.

An alternative online Jejemon translator can be found http://akosijairah.blogspot.com/2010/04/Jejemon-translator-v3_28.html as shown in Figure 2. The translated expression is comprised of case conversion, p0wh insertion and modification of word to a totally different spelling.

Figure 2. English Language to Jejemon Language Translation.

2.3. Dictionary Substitution Approach

Dictionary Substitution Approach is a technique commonly identified as search and replace approach. The key characteristic is to match word from the corpus. However, when multiple entries are found from the corpus, randomize word will be selected from list possible alternative [8].

Jejemon language does not follow specific pattern. Through Dictionary substitution approach it can replace non-standard Jejemon token into a meaningful context of English or Filipino word. English or Filipino sentence found in Table 2 was translated to Jejemon equivalence from three sources. It shows three different techniques of Jejemon translation.
Table 2. Sample Online English Expression Translated into Jejemon Expression

| English Sentence | URL Source of Jejemon Translator | Jejemon Expression |
|------------------|----------------------------------|--------------------|
| I would like to know more about you, care to tell me your name? Hehehehe! | https://pinoychronicle.wordpress.com/Jejemon/ | i wuD LLYK to knOw moR3 bOut u. crE 2 t3l3 mE yur N@me? jejejeje! |
| Online Jejemon Translator (http://173.254.110.65/jejeschool/index.php) | 1 wUD 77yk +0 kn0w mUhr3 4b0U+ U’, cr +0 +377 m3 U’r nm3?’n j3j3j3h3! |
| Online Jejemon Translator (http://akosijairah.blogspot.com/2010/04/jejemon-translator-v3_28.html) | i WOULD Lyk To KNow more about u, CeyRTo Tell me uR nMe, n0H? JEJEJEjE LOLz! |

2.4. Lexicon-Based Algorithm
Lexicon-based Algorithm works by defining rules to classify the opinion which is created by tokenizing every sentence in each document and testing if the token or word is present in the database [8]. It is based on rule which is composed of antecedent and consequent. An antecedent defines a condition and consists of either a token or a sequence of tokens. This process provides a technique to single out positive, negative or neutral about the subjective opinion [9][10][11].

It uses sentiment lexicon to assign a polarity value. A lexicon is comprised of words or phrase where each label is categorized based on polarity value whether positive or negative orientation [12]. In building a sentiment lexicon have three strategies namely hand-craft elaboration, automatic expansion from an initial list of seed words and corpus-based approach.

A comparative study [13] on Lexicon-based review involving AFINN, General Inquirer, Micro-WNOP, Opinion Lexicon, SentiSense, SentiWordNet, Subjectivity Lexicon and WordNet-Affect. The investigation resulted 78% accuracy towards SentiWordNet which utilizes WordNet corpus.

2.5. String Similarity Algorithm
String based similarity measurement defines the similarity of strings in terms of the longest prefix common to both strings. It is applied to several fields namely data cleaning, data integration, error checking or pattern recognition [14]. It uses either character-based or term-based technique [15]. The commonly used string based similarity measurement. It is a term-based technique known as edit distance algorithm which performs minimum number of insertions, deletions or substitutions to string1 to string2 [14].

The comparative study on edit distance algorithms namely Q-gram similarity, cosine similarity and dice coefficient similarity. The study resulted in favor of cosine similarity algorithm with an average accuracy of 63% [16]. Cosine similarity algorithm measures two-finite-dimensional vectors of the same dimension [15]. Furthermore, cosine similarity was applied to analyze the similarity of sentiment scores from SentiWordNet and the similarity of each sentiment score contributed to product review rating prediction [17].

2.6. Hybrid Polarity Score Algorithm
Each synset polarity score is derived by computing the average of SentiWordNet algorithm and VADER algorithm as elaborated in Equation 1, Equation 2 and Equation 3 [18]. Normally, VADER polarity score use compound score to determine the sentiment classification. However, Ilao’s Hybrid algorithm used VADER’s positive and negative scores to derived sentiment score.

\[
\text{Hybrid positive score} = \frac{(\text{SentiWordNet Positive Score} + \text{VADER Positive Score})}{2} \quad (1)
\]

\[
\text{Hybrid negative score} = \frac{(\text{SentiWordNet Negative Score} + \text{VADER Positive Score})}{2} \quad (2)
\]
Over-all Hybrid Score (OHS) = (Hybrid positive score – Hybrid negative Score) \hspace{1cm} (3)

Where:
- If OHS >0, then sentiment is “Positive”.
- If OHS<0, then sentiment is “Negative”.
- If OHS=0, then sentiment is “Neutral”.

The number of occurrences of positive, negative and neutral tweets will determine the over-all sentiment of the entire population of collected political tweets. The hybrid approach was experimented to different political datasets. The experiment yielded 88.33% accuracy better than SentiWordNet and VADER algorithm.

3. Methodology
The study was designed to implement sentiment analysis approach as illustrated in Figure 3.

![Figure 3. Jejemon Repost Hybrid Polarity Score Algorithm Conceptual Framework](image)

It involves several stages such as data cleaning, removal of irrelevant words, dictionary substitution and loan translation approach, tokenization, stemming, feature extraction, hybrid sentiment polarity score approach (SentiWordNet Score, VADER score, Filipino Score, Recurrence Percentage Reduction Score), and sentiment classification.
3.1. Pre-Processing

3.1.1. Data Cleaning
It involves elimination of unwanted expression such as removal of punctuations, website URL, emoticons, special characters and apostrophes.

3.1.2. Removal of Irrelevant Words
It is intended to remove irrelevant contents such as slang words [19], stop words, Jejemon expression (example: poWH, jejeje, xD) and non-Jejemon formatted text.

3.1.3. Dictionary Substitution and Loan Translation Approach
Jejemon lexeme might contains abbreviation or shortcut text in English or Filipino expression. A CSV file and Text file will stored shortcut English text, shortcut Filipino text and Jejemon most sentimental words. When translated lexeme is found from the seedlist, detected text will be replaced into its actual value. It also involves translation of Jejemon expression to purely English expression, purely Filipino expression and combination of both languages.
Translation utilized enchant libraries [20] and collection of Filipino words from Tagalog dictionary [21] to cross-checked spelling or possible word suggestion in transforming complicated Jejemon expression.
Furthermore, customized Tagalog dictionary was constructed from collection of rubbish words of English or Filipino words will resolve some ambiguity coming from Jejemon expression translation.

3.1.4. Tokenization
The process of tokenization segments where Jejemon expression might be in the form of paragraph, sentences and word into a lexeme (single word).

3.1.5. Stemming
In this stage, Jejemon lexeme will subjected to extraction of base word by simplifying plural form to singular or by removing prefix, suffix and infix.

3.2. Feature Extraction

3.2.1. N-gram Approach
The study will implement a hybrid approach in classifying the given Jejemon expression whether positive, negative and neutral sentiment. The two lexicon-based algorithms that was proven effective by Ilao’s study in 2019 combined SentiWordNet and VADER algorithm polarity scores as shown in Equation 1, Equation 2 and Equation 3 in which uni-gram and tri-gram approach were implemented by the said algorithms respectively.

3.2.2. Part-of-Speech (POS) Tagging
Each English lexeme will be tagged via StanFord POS Tagger. Each tag will determine whether the lexeme can be a source of sentiment of SentiWordNet.
However, Filipino lexeme will not undergo POS Tagging procedure. The study will used Tagalog Corpus in identifying positive and negative political words.

3.3. Hybrid Approach

3.3.1. SentiWordNet Polarity Score
SentiWordNet polarity score features positive, negative and neutral scores. Nonetheless, Hybrid approach requires positive and negative elements of its derived polarity score.
3.3.2. VADER Polarity Score

Classification of sentiment using VADER normally uses compound score. However, hybrid approach will apply positive score and negative score as shown in Equation 1.0 and Equation 2.0.

3.3.3. Filipino Sentiment Polarity Score

Filipino sentiment polarity score will be applied for Filipino expression based on Equation 4.0. For every detected positive or negative word from collected list of commonly used tagalog political sentiment word will be scored as 1 point.

\[
\text{Filipino Polarity Score (FPS)} = \frac{\text{Number of Positive Words} - \text{Number of Negative Words}}{\text{Number of Words in the Tweet}}
\]  
(4)

Where:
- If FOSS >0, then sentiment is “Positive”.
- If FOSS<0, then sentiment is “Negative”.
- If FOSS =0, then sentiment is “Neutral”.

If translated expression is 85% classified as an “English Expression”, Over-all Sentiment Polarity Score will be computed by Equation 1, Equation 2 and Equation 3. If translated expression is 85% classified as “Filipino Expression”, Over-all Sentiment Polarity Score will be derived by Equation 4. Otherwise, Over-all Sentiment Polarity Score will be calculated by Equation 5.0.

\[
\text{Average Polarity Score (APS)} = \frac{\text{OHS} + \text{FPS}}{2}
\]  
(5)

Where:
- If APS>0, then sentiment is “Positive”.
- If APS <0, then sentiment is “Negative”.
- If APS =0, then sentiment is “Neutral”.

3.3.4. Cosine Similarity

Cosine Similarity algorithm will be used to determine if there are some similarities between posts. If cosine similarity returns a string similarity value of 70%, there exists a significantly identical tweet between the lists of collected tweets which is considered as a repost message.

3.3.5. Recurrence Percentage Reduction Score

After string similarity algorithm identified similarity between tweets, Equation 6.0 and Equation 7.0 will define reduction score from previously derived value and generate a new polarity score for repost message.

\[
\text{Relative Frequency Rate} = \left( \frac{\text{number of item repost}}{\text{total number of post messages}} \right) \times 100
\]  
(6)

\[
\text{Recurrence Percentage Reduction Score} = \text{Over-all Hybrid Score} - \left( \text{Relative Frequency Rate} \times \text{Over-all Hybrid Score} \right)
\]  
(7)

3.3.6. Sentiment Classification

The study was designed to perform sentiment analysis in a document level. Each Jejemon expression will be classified whether positive, negative or neutral sentiment. The classification is dependent on the Over-Hybrid Score (OHS), Filipino Polarity Score (FPS) or Average Polarity Score (APS) as described by case scenario listed below.

Case 1: Jejemon Expression translated as English Expression
- If OHS >0, then sentiment is “Positive”.
- If OHS<0, then sentiment is “Negative”.
- If OHS =0, then sentiment is “Neutral”.

Case 2: Jejemon Expression translated as Filipino Expression
- If FOSS >0, then sentiment is “Positive”.
- If FOSS<0, then sentiment is “Negative”.

Case 3: Jejemon Expression translated as Tagalog Expression
- If FPS >0, then sentiment is “Positive”.
- If FPS<0, then sentiment is “Negative”.
- If FPS =0, then sentiment is “Neutral”.
If \( \text{FOSS} = 0 \), then sentiment is “Neutral”.

Case 3: Jejemon Expression after translation falls below 85% classified as Filipino or English Expression

If \( \text{APS} > 0 \), then sentiment is “Positive”.
If \( \text{APS} < 0 \), then sentiment is “Negative”.
If \( \text{APS} = 0 \), then sentiment is “Neutral”.

Afterward classification, each identified sentiment will be counted individually; the highest number of frequencies between positive, negative or neutral will generally determine the over-all sentiment classification of the collected instances.

4. Data Source
The dataset was collected from Twitter accounts namely Jejemonilao and Jejemonkami from January 15, 2020 up to February 29, 2020 as stated in Table 3, Table IV, Table V and Table VI with 131 instances.

Tweets have a maximum number of 37 tokens, minimum number of 3 tokens and an average of 12 tokens per instance.

Jejemonilao tweets followed Jejemon format available in http://akosijairah.blogspot.com/2010/04/Jejemon-translator-v3_28.html considered as controlled environment. However, uncontrolled environment instances were extracted from Jejemonkami tweets. Tweets were formatted based on preference of participants from any available Jejemon patterns. Moreover, collected dataset is comprised of purely English Jejemon tweet, purely Filipino Jejemon tweet and combination of both.

| Original Expression | Jejemon Format Domain | Expression | Frequencies |
|---------------------|-----------------------|------------|-------------|
| Government plays a good job during Taal Eruption. | Online Resource (Controlled Environment) | G0V3rNm3nt pLaYZ a G00D J0B DuRiNg TaAl ErUpTioN. | 39 |
| Personal Preference (Uncontrolled Environment) | goVerNmEnt pLyz a goOD job duRiNg Taal eRUPtioN p0WH. | 92 |

| Tweet Post Tweets | Frequencies |
|-------------------|-------------|
| Single Post | 116 |
| Repost | 15 |

| Jejemon Tweet used Languages | Frequencies | No. Instances under Controlled Environment | No. Instances under Uncontrolled Environment |
|-----------------------------|-------------|------------------------------------------|---------------------------------------------|
| English | 113 | 35 | 78 |
| Filipino | 14 | 1 | 11 |
| Combination | 4 | 3 | 3 |
Table 6. Sentiment Classified Frequencies

| Sentiment Classification | Frequencies |
|--------------------------|-------------|
| Positive                 | 29          |
| Negative                 | 76          |
| Neutral                  | 26          |

5. Measurement of Algorithm Performance

Algorithm performance will be validated by means of paired T-Test, accuracy, recall, f-score and precision using Equation 8, Equation 9, Equation 10 and Equation 11 via confusion matrix values as shown in Table 7.

Table 7. Confusion Matrix

| Actual  | Predicted |  |
|---------|-----------|---|
|         | Negative (F) | Positive (T) |
| Negative (F) | FF | FT |
| Positive (T)  | TF | TT |

Accuracy = \( \frac{FF + TT}{FF + FT + TT} \) (8)

Precision = \( \frac{TF}{FT + TF + TT} \) (9)

Recall = \( \frac{TT}{TT + TF} \) (10)

F-Score = \( \frac{2 \times \text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}} \) (11)

Where:

FF: the frequency of correctly predicted negative emotion.
FT: the frequency of incorrect predicted negative emotion.
TF: the frequency of incorrect predicted positive emotion
TT: the frequency of correct predicted positive emotion.

6. Experiment

The study evaluated the translation success rate of Jejemon instances to counterpart language via string similarity algorithm presented in Table 8. Each instance from each domain is compared to the actual expression.

Similarity Percentage is based cosine similarity value of translated expression against actual expression. Similarity values fall from 70% and above were classified as “Strong Similarity” otherwise considered as “Weak Similarity”.

Table 8. Similarity Percentage of Translated Expression and Actual Expression

| Jejemon Format Domain                  | No. of Strong Similarity (70% and Above) | No. of Weak Similarity (Below 70%) | Average Cosine Similarity Percentage |
|----------------------------------------|----------------------------------------|-----------------------------------|-------------------------------------|
| Online Resource (Controlled Environment) | 92%                                    | 7%                                | 81%                                 |
| Personal Preference (Uncontrolled Environment) | 73%                                    | 27%                               | 76%                                 |

Table 9 shows the lowest and highest similarity percentage of the entire dataset per language. The controlled group’s translation similarity percentage ranges from 23% up to 100%. The factors which affect translation success rate are word case, missing letters that were omitted by Jejemon expression when translated lead to a different English or Filipino expression due to ambiguity, proper
space between Jejemon expression and single/plural forms. However, uncontrolled group’s similarity percentage ranges 24% up to 100%. Significant difference from controlled group, uncontrolled group’s factors are special characters such as Ê, é, Ñ, @, or ü; repetition of letters namely “z”, “s”; two representation of 8 either “te” or “ate”, “i” either “!” or “1”, “a” either “4” or “@” and Filipino word interchangeably used “po” or “poh”.

Table 9. Cosine Similarity Percentages per Language

| Jejemon Format Domain | Languages   | Lowest Similarity Percentages | Highest Similarity Percentages | Average of Similarity Percentage |
|-----------------------|-------------|-------------------------------|--------------------------------|---------------------------------|
| Online Resource (Controlled Environment) | English     | 23%                           | 100%                           | 81%                            |
|                       | Filipino    | 89%                           | 89%                            | 89%                            |
|                       | Combination | 67%                           | 89%                            | 74%                            |
| Personal Preference (Uncontrolled Environment) | English     | 25%                           | 100%                           | 78%                            |
|                       | Filipino    | 24%                           | 100%                           | 39%                            |
|                       | Combination | 25%                           | 70%                            | 55%                            |
| Average               |             | 42%                           | 91%                            | 69%                            |

Furthermore, Table 9 presented the lowest similarity percentage is 23% under English language of Controlled Environment. The event was brought by several wrongly translated words due to ambiguity. Some Jejemon tweets have missing letters, translation of the given scenario relies on selection from a given list of suggested words. Other scenario, some words should be express in capital letter.

While English and Filipino expression (combination) of Uncontrolled Environment gained the lowest value of 70% under highest similarity percentage. Uncontrolled Environment encountered similar condition from Controlled Environment where missing letters might be rubbish word or an abbreviation but it cannot be disregarded. For example, “plyz” was replaced by “plys” based on the suggested words from English or Tagalog Dictionary where it should the word “plays”. There are scenarios where an English word was taken as a Filipino word or vice versa.

After Jejemon translation, the new dataset comprised of English, Filipino or combination underwent pre-selection. As stated on previous studies on machine translation on several Filipino dialects, accuracy rates are 70.67% [22] and 69.5% [23]. Pre-selection of instances will be based on similarity percentage between 70% up to 100%. Qualified instances are revealed in Table 10.

Table 10. New Instances after Pre-Selection

| Languages | Controlled Environment | Uncontrolled Environment |
|-----------|------------------------|--------------------------|
| English   | 33                     | 64                       |
| Filipino  | 0                      | 2                        |
| Combination | 1                    | 1                        |
| Total     | 34                     | 67                       |

Table 10 shows 12% decreased on the number of instances under the controlled environment from 39 instances down to 34 instances. Similarly, 27% decreased on uncontrolled environment instances from 92 instances down to 67 instances. It also shows the most retained translated tweet is English tweet with 94% retention. While Filipino tweets suffered the most reduction with 18% retention out of 11 instances.
Table 11. Paired T-Test of Computed Sentiment Scores

|                  | Mean   | N  | Mean Difference | p-value | Interpretation |
|------------------|--------|----|-----------------|---------|----------------|
| **Uncontrolled** |        |    |                 |         |                |
| New Score        | -.073824 | 6  | -.002619        | .821    | Not Significant |
| Original Score   | -.071204 | 7  |                 |         |                |
| **Controlled**   |        |    |                 |         |                |
| New Score        | -.062557 | 3  | .016663         | .257    | Not Significant |
| Original Score   | -.079220 | 4  |                 |         |                |
| **Similarity Reduction** | | | | | |
| New Score        | -.163912 | 2  | -.017796        | .246    | Not Significant |
| Original Score   | -.146115 | 3  |                 |         |                |

Table 11 described the relationship between different sentiments’ scores namely new score is derived from translated expression, original score is derived from the actual expression. Furthermore, cosine similarity found instances with 70% similarity considered as repost messages. All repost sentiments’ scores underwent either 1% or 3% reduction. As stated in Table 11, p-value results are 0.821, 0.257 and 0.246. They are greater than 0.05 which implied there is no significant difference between new scores and original scores under controlled environment, uncontrolled environment and after application of recurrence percentage reduction scores.

Table 12. Confusion Matrix of Controlled Environment

|               | Predicted |         |         |         |
|---------------|-----------|---------|---------|---------|
| Actual        | Negative (F) | 11      | 1       |         |
|               | Positive (T)    | 7       | 6       |         |

Table 13. Confusion Matrix of Uncontrolled Environment

|               | Predicted |         |         |         |
|---------------|-----------|---------|---------|---------|
| Actual        | Negative (F) | 31      | 3       |         |
|               | Positive (T)    | 9       | 11      |         |

Table 12 and Table 13 shown number of positive and negatives instances classified correctly or incorrectly. It appears 59 instances out of 79 instances were classified correctly and 20 instances were classified incorrectly.
Table 14. Sentiment Analysis Metric Summary

| Jejemon Format Domain | Label   | Precision | Recall | F-Score | Accuracy |
|-----------------------|---------|-----------|--------|---------|----------|
| Online Resource       | Positive| 46%       | 86%    | 60%     | 68%      |
| (Controlled Environment) | Negative | 92%       | 61%    | 73%     |          |
| Personal Preference   | Positive| 55%       | 79%    | 65%     | 78%      |
| (Uncontrolled Environment) | Negative | 91%       | 78%    | 81%     |          |
| Average               |         | 71%       | 76%    | 71%     | 73%      |

Table 14 shows both negative sentiments resulted high precision with at least 91% and lowest precision value is 46% under Positive Controlled Environment. While, recall highest value is 86% falls under positive sentiment of Controlled Environment Domain; however the rest of the recall values are 61% up to 79%. Lastly, the highest f-score value is 84% under the negative sentiments of Uncontrolled Environment Domain whereas the remaining values are within 60% up to 84%.

The hybrid model provided accuracies of 68% (Controlled Environment Domain), 79% (Uncontrolled Environment Domain) and an average of 74% from collected Jejemon format domain. Generally, average scores of precision, recall, f-score and accuracy resulted 70% and above in term of classification performance towards the different Jejemon format domains.

7. Conclusion

This paper experimented on sentiment analysis solely focus on Filipino fascination in expressing their idea through Jejemon language.

However, Jejemon language raised issues on millennial English proficiency. Jejemon language as a form of communication is normally expressed through short-text and special representation of word or expression. Furthermore, Jejemon expression offered several language structure ranging simple to complicated techniques.

In general, the study of machine translation from Jejemon expression into counterpart language namely English, Filipino or combination (English and Filipino) yielded successful conversion based on the cosine similarity done. The similarity rates of translated expression against actual expression gained 76% and 81% for controlled and uncontrolled environment.

Even though some instances were not converted exactly as compared to actual expression, paired T-Test shows no significant difference between original polarity score and new polarity score derived from the two dataset domains. Moreover, repost messages that underwent reduction through recurrence percentage reduction technique do not shows significant difference from the two domains based on the available data.

Sentiment classification through hybrid approach resulted positively in terms of consistency and accuracy based on the average precision, recall and accuracy such as 71%, 76% and 73%. Average F-score of 71% signifies the acceptable classification performance since there is an uneven representation of sentiment instances from collected domains.

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