AN IMPROVED CLASSIFICATION MODEL FOR IGBO TEXT USING N-GRAM AND K-NEAREST NEIGHBOUR APPROACHES

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Abstract

This paper presents an improved classification model for Igbo text using N-gram and K-Nearest Neighbour approaches. The N-gram model was used for text representation and the classification was carried out on the text using the K-Nearest Neighbour model. Object-Oriented design methodology is used for the work and is implemented with the Python programming language with tools from Natural Language Toolkit (NLTK). The performance of the Igbo text classification system is measured by computing the precision, recall and F1-measure of the result obtained on Unigram, Bigram and Trigram represented text. The Igbo text classification on bigram represented text has highest degree of exactness (precision); result obtained with three N-gram models has the same level of completeness (recall) while trigram has the lowest level of precision. This shows that the classification on bigram Igbo represented text outperforms unigram and trigram represented texts. Therefore, bigram text representation model is highly recommended for any intelligent text-based system in Igbo language.

Keywords: Igbo Language; Text Classification; Text Mining; K-Nearest Neighbour; N-Gram; Similarity Measure

1. INTRODUCTION

The extraction and management of useful information that are hidden in the huge quantity of textual documents has generated big concern to Information Technology (IT) professionals; together with its unstructured nature [1]. It is difficult and uneconomical to explore the useful information present in the unstructured text documents of web pages, textual content management system, news articles, etc. This is faced with lack of sophisticated text analysis model for discovery new information in their unstructured manner [2]. The need for systematic organization and management of free available online documents for proper utilization and decision making is emphasized in [3]. As a result of this, text mining and data mining have gained great interest with the intense of converting the data into valuable facts [4]. In [5], it is approximated that about 500 companies lose about $12 billion in value annually because of their inability of exploiting unstructured textual data and this practically implies that performing text analysis may increase the organization’s competitive advantage.

Text Mining (TM), gotten from the meaning textual data mining, is called a knowledge extraction from text. Discovering or extracting knowledge, ideas from text simply means extracting interesting but hidden patterns or trends from textual documents. Text mining is a quite novel research that has created great concern on researchers, due to a continuous increase of electronic text. It is also has been to be of great business values. This is proved by [6] statement: “As the mainly natural means of saving information is textual data, textual data mining is assumed to comprise a higher profitable potential than data mining. It is pointed that a research done shows that more than 70% of the business information is hold in a textual document. TM involves difficult tasks because of the unstructured nature of the textual data; one has to perform these tasks in order to put the text in a structured format before analysis can be performed on it [7]. Text mining adopts models and algorithms from natural language processing, data mining, machine learning, and data retrieval system to extract knowledge from the text automatically [8] [9]. Text mining is a multidisciplinary field and involves many subtasks such as text summarization, text classification, entity extraction, clustering, semantic and
sentiment analysis [10]. This work focuses on text classification. Text classification is a task of assigning predefined categories to textual documents [11][12].

The advancement of Information Technology (IT) has gone a long way of bringing in Igbo, one of the three Nigerian major languages evolved [13]. It has advanced to the extent one can operate (Windows 7 and above operating system), create documents, reports news online, search and publish articles online with this language. As there is vast increase in information stored in text format of this language, there is need for an intelligent text-based system for proper management of the data [14]. It is necessary to have means to organise and manage the data generated with these languages effectively. These needs have motivated for this research to develop an improved model to classify Igbo textual documents for proper organisation and management.

In addition, text mining is gaining popularity as a result of increase in textual documents in different languages in the world. Most text mining models majorly deals on processing foreign languages (like English, French, Latin, Chinese, Arabic, Spanish, and Japanese) documents. Little or no research has been done to apply the text mining techniques on Igbo textual document.

1.1 Overview of Igbo Language

According to [15], a language is a way of communication between people who share common code, in form of symbols. The Igbo language is one of the three major languages (Hausa, Yoruba and Igbo) in Nigeria and largely spoken by the people in the eastern part of Nigeria [13]. Igbo language has many dialects but the standard Igbo is used formally and is adopted for this research. Standard Igbo has thirty-six (36) alphabets (a, b, c, h, d, e, f, g, gb, gh, gw, h, i, j, k, kw, lp, m, n, nw, ny, o, ọ, p, r, s, sh, t, u, u,v, w, y, z), consisting of eight (8) vowels and twenty-eight (28) consonants. The 28 consonant characters are “b, ch, d, f, g, gb, gh, gw, h, j, k, kw, kp, l, m, n, nw, ny, o, ọ, p, r, s, sh, t, v, w, y, z” and 8 vowels characters are “a, e, i, ọ, o, u, u, y”. There are nine consonants characters that are digraphs: “ch, gb, gh, gw, kp, kw, nw, ny, sh” [16]. It uses a Roman Script and it is a tonal language with two distinct tones, high and low. Igbo is an agglutinative language, in which words are built by stringing different morphemes or words together [15].

2. Review of Related Works

Some papers related to the work were studied, analysed and discussed as follows:

[17] proposed an improved way of classifying Arabic text based on Kernel Naïve Bayes (KNB) classifier to solve the non-linearity problem of Arabic text classification. Experimental results and performance evaluation on the collected dataset of Arabic topic mining corpus showed effectiveness of the proposed KNB classifier against other classifiers.

The performance of five mostly used feature selection methods (Chi-square, Correlation, GSS Coefficient, Information Gain and Relief F) on Arabic text classification is examined in [18]. An approach of combination of feature selection methods based on the average weight of the features was used. The results of experiments carried out using Naïve Bayes and Support Vector Machine classification model show that finest classification results were obtained when done feature selection using Information Gain method. The results also prove that the combination of numerous feature selection methods outperforms the finest results gotten by the individual methods.

The work in [19] surveyed three feature selection techniques (filter, wrapper and embedded) and their effects on text classification. The survey proved that filter method should be adopted if the result is needed in lesser time and for large dataset; and wrapper method should be adopted if the accurate and optimal result is needed. It was also observed that the performance of different algorithms differ according to the data collection and desires.

[20] compared the performance of various text classification systems in different cases using feature selection with stemming and without stemming on Arabic dataset. Various text classification algorithms such as Decision Tree (D.T), K-Nearest Neighbours (KNN), Naïve Bayesian (NB) Method and Naïve Bayes Multinomial (NBM) classifier were adopted. The result showed the classification accuracy for Decision Tree, Naïve Bayesian method and Naïve Bayes multinomial is better than K-Nearest Neighbours (KNN) in all tested cases.
Three feature reduction techniques on Arabic text is presented and compared in [21]. Stemming, light stemming and word clusters techniques were used. The effects of the listed techniques were studied and analyzed on the Arabic text classification system using K-Nearest Neighbour algorithm. The result from the experiments shows that stemming reduces vector sizes, and hence enhances the classification accuracy in terms of precision and recall.

[22] proposed a new system for text classification based on Binary Particle Swarm Optimization and Reduced Error Pruning Tree- BPSO/REP-Tree hybrid. The Binary Particle Swarm Optimization – BPSO/REP is adopted for the feature selection process and the “Reduced Error Pruning Tree - REP” is used for the classification process. The experiment is done on an Arabic data-set, collected from the BBC-Arabic website using the Weka tool.

An approach for computing range-based rules from numerical data to develop classification and characterization models is proposed in [23]. Their experimental results show the proposed approach performs better than the commonly used rule mining methods.

These related research works are mainly on English language; Asian languages (like Chinese and Japanese); European languages (like French, German and Spanish); and Arabic. Small or no work on this research area has been done on Igbo, a Nigerian language. This work looked at problems / challenges in mining textual data in an Igbo language, developed a system that extracts useful features in Igbo text for the classification of the document.

3. MATERIALS AND METHODS

This section discusses the processes (figure 1) involved in developing and implementing efficient and robust text classification model that extracts features from Igbo textual corpora for the classification of the documents based on predefined categories. The system uses K-Nearest Neighbour model based on similarity measurement to automatically classify Igbo text documents.

![Architecture of Igbo Text Classification System](image)

Figure 1: Architecture of Igbo Text Classification System
3.1 Igbo Text Collections

The text classification of the Igbo text starts with the collection of Igbo textual data documents. The Unicode model was used for extracting and processing Igbo texts because it is one of the languages that employ non-ASCII character sets and its processing needs UTF-8 encoding [13]. UTF-8 makes use of multiple bytes and represents complete collection of Unicode characters. This is achieved with the mechanisms of decoding and encoding as shown in Figure 2. Decoding converts text in files in an Igbo character sets into Unicode while encoding write Unicode to a file and converts it into an appropriate encoding [24]. A sample of an Igbo text is displayed in figure 3.

![Figure 2. Igbo Text Unicode Decoding and Encoding](image)

Kpaacharụ anya makana projekto nkuziihe a achoghị okwu ntughe, ndị ichoghị ka ha ụgu ga ahụ ime-ngo iji. Ọbụrụ na icooro ịrị projekto nkuziihe a were rụọ ọrụ, pikinye ”Jiko”. A na-akwunye projekto nkuziihe na komputa nkunaka ịrị mee ime onyonyo. Komputa nkunaka banye na projekto nkuziihe ọcha

![Figure 3: Sample of Igbo Text Document](image)

3.2 Igbo Text Pre-processing

Text pre-processing is an essential task and an important step in a text classification system. This module transformed unstructured input of Igbo text into a more understandable and structured format ready for further processing [25]. The text pre-processing task in this work covers text normalization, Igbo text tokenization and Igbo stop-words removal.

3.2.1 Text Normalization

In this process, the Igbo textual document is transformed to a format that makes its contents consistent, convenient and full words for an efficient processing. All text cases are converted to lower cases. The diacritics and noisy data are removed. The noisy data is assumed to be data that are not in Igbo dataset. A list is created for these data and the normalization task process is done following the algorithm in [13].

3.2.2 Igbo Text Tokenization

Tokenization is the task of analyzing or separating text into a sequence of discrete tokens (words). The tokenization procedure in [13] is used in the system.

3.2.2.1 Igbo Stop-words Removal

Stop-words are language-specific functional words; the most frequently used words in a language that usually carry no information [26]. There are no specific amounts of stop-words which all Natural Language Processing (NLP) tools should have. Most of the language stop-words are generally
pronouns, prepositions, and conjunctions. This task removes the stop-words in Igbo text. Some of Igbo stop-words are shown in Figure 4.

Figure 4. Sample of Igbo Stop-words List

In the developed Igbo text classification system, a stop-word list is created and stored in a file. This is automatically loaded to the system whenever the system is in operation. Any Igbo word with less than three character length is assumed not to carry useful information and is removed in this process [27]. The removal of the stop words in the proposed system is done following the designed algorithm for the work in [13].

3.3 Text Representation

Text representation involves the selection of appropriate features to represent a document [28]. The text document representation is one of the issues resulting from natural language peculiarities that need to be resolved for the success of any research in the text related fields [13]. The approach in which text is represented has a big effect in the performance of any text-based applications [29]. It is strongly influenced by the language of the text. According to [12], text data represented using vector space model which is a conventional text representation model, results to high dimensional data and may also contain lots of redundant or irrelevant features that may affect the performance of a text classification system.

In Igbo language, compounding is a common type of word formation and many compound words exist. Compound words play high roles in the language. They can be referred as Igbo phrases that make sense only if considered as a whole. Majority of Igbo terms, key words or features are in phrasal structure [13]. The semantic of a whole is not equal to the semantic of a part. N-gram model, recommended by [13] is adopted for the representation of the system text features because of the compounding nature of the language.

3.4 Feature Selection

Feature selection is the task of choosing relevant features from a textual document to be used for a text-based task. This is put in place to reduce the dimension feature space of a system to improve its performance. It involves the identification of relevant features to be used in the system without affecting its accuracy [30]. This process will serve as a filter; muting out irrelevant, unneeded and redundant attributes / features from Igbo textual data to boost the performance of the system. Improving the feature selection will improve the system performance. The goal of feature selection is summarised in threefold:

i. Reducing the amount of features;
ii. Focusing on the relevant features; and
iii. Improving the quality of features used in the system process.

The Mean Term Frequency-Inverse Document Frequency (Mean TF-IDF) model is adopted for the feature selection in this system.

3.5 Text Classification

Text Classification is a text mining application that automatically assigns one or more predefined labels to free text items based on their content [12]. Currently, the amount of the Igbo available text data in the web is increasing daily as the Information Technology (IT) has inculcated the use of Igbo language in its operation. This huge size makes the process of classifying it manually a very difficult and time consuming task. Therefore, the trend of automatically classifying text data is introduced. Although a lot of works have studied classification of English texts, few or no work have studied the classification of Igbo texts. K-Nearest Neighbour (KNN) text classification model is adopted for the system.
3.5.1 **K-Nearest Neighbour (KNN) Classifier**

KNN text classification model classifies test document regards to the k- nearest training documents in the documents set. KNN is a good model for text classification [31]. It is chosen because it is a simple and effective means of classifying text. The KNN algorithm works with three major parameters:

1. **Similarity / Distance metric:** The distance metric is used to compute the difference between two data instances in order to measure the similarity. The distance metric in calculated by getting the distance between input test document instance and training document set instances. Choice of distance metric acts vital task in the efficient and effective performance of the proposed text classification model. The Igbo text classifier uses the Euclidean distance metric to compute the distance between two neighbours.

2. **K-Value Selection:** K-value represents the neighbourhood size. This is one of the input parameters used to determine the class.

3. **Computing the Class Probability:** The assignment of a data instance into a class is simply based on voting. This is illustrated using figure 3.16.

Given a test document \( t \) to classify, k-NN model positions the text document’s neighbours amidst the training documents. It then uses the document class of the k nearest / most similar neighbours to guess the class of the test document.

The procedure of the proposed KNN text classifier based on similarity measurement is shown in algorithm 1.

**Algorithm 1: K-Nearest Neighbour Classifier**

**Procedure:** Find the class label

**Input:** k-value, the number of nearest neighbours; \( V \) – Testing data set; \( W \) – Training data set;

**Output:** C, Label set of testing data set

1. Input Training data file
2. Input Testing data file
3. Perform pre-processing
4. Select relevant features
5. For each \( v_i \) in \( V \) and each \( w_i \) in \( W \) do
   - Calculate \( d(v_i, w_i) \) based on distance measure
6. Determine the similarity or dissimilarity based on the computed distance \( d \).
7. Determine the k-value.
8. To decide whether the document belongs to a class;
   i. Assign \( C = \{ \} \), a set or list that holds the class labels
   ii. For each \( v_i \) in \( V \) and each \( w_i \) in \( W \) do
   iii. \( \text{Neighbours} (v_i) = \{ \} \)
   iv. if \( |\text{Neighbours}(v_i)| < k \) then
   v. \( \text{Neighbours} (v_i) = \text{closest} (v_i, w_i) \cup \text{Neighbours} (v_i) \)
   vi. \( \text{End if} \)
   vii. if \( |\text{Neighbours}(v_i)| = k \) then
   viii. \( C = \text{test Class} (\text{Neighbours} (v_i) \cup C) \)
   ix. \( \text{End for} \)
9. Exit Classifier

In the algorithm 4, a text document is given a class label by votes of its neighbours. For instance, assuming \( K = 1 \), then classifier will assign the document to label of its most similar neighbour. The \( \text{Neighbours} (v_i) \) returns the k-nearest neighbours of \( v_i \); and \( \text{closest} (v_i, w_i) \) returns the closest element of \( w_i \) in \( v_i \).
The choice of k-value will be dependent on the number of neighbours, distance metric and decision rule. The decision for choice of k is heavily dependent on the actual distribution of v and w. Figure 5 shows the illustration on how the KNN performs its classification.

In figure 5, the green circle represents the test instance and is to be grouped either into blue square category or into red triangle category regards to the k-value. For example if k-value = 3 (solid outline circle), the green circle is categorized into red triangle instance class label due to existence of 2 triangle instances and 1 square instance in internal circle. If k-value =5 (dashed outline circle), the green circle is categorized into blue square instance class due to existence of 3 blue square instances and 2 red triangle instances in the external circle.

![Figure 5: Illustration of KNN Algorithm](image)

### 3.5.2 Similarity Measure

A similarity measurement quantifies the similarity between two documents that reflects the degree of closeness or separation of documents [33]. The similarity score is defined in order to determine the similarity between documents. Different features of the documents are quantified and similarity algorithm is employed across the features to get the similarity score between the documents.

Euclidean distance metric is used to produce the similarity scores between the documents. The documents that have minimal similarity score are likely to be more similar while those with maximal similarity score are likely to be dissimilar. The text documents in the same class will appear to be most similar neighbours.

**Definition:** If $X = (x_1, x_2, ... x_n)$ and $Y = (y_1, y_2, ...y_n)$ are two points in n-dimensional Euclidean space, then the distance (d) from X to Y or Y to X is given by the formula:

$$d^2(X,Y) = d^2(Y,X) = (x_1-y_1)^2 + (x_2-y_2)^2 + ... (x_n-y_n)^2$$



### 3.6 System Performance Evaluation

The system performance is evaluated by computing the precision, F1-measure and Recall. Precision is defined as the quotient of total TPs and sum of total TPs and FPs. Precision point is known to as a point of correctness.

**Precision** = \[\frac{TP}{TP + FP}\] ................................................................. 2

Recall of the classification system is described as the quotient of total TPs and sum of total TPs and total FNs. Recall level measures completeness.

**Recall** = \[\frac{TP}{TP + FN}\] ................................................................. 3

F1-Measure is single function that joins recall and precision points. When the F1-measure is high, it means that the overall text classification system is high.

**F1-Measure** = \[\frac{(2 * Precision * Recall)}{(Precision + Recall)}\] ........................................... 4

= \[\frac{2TP}{2 (TP + FP + FN)}\] ................................................................. 5

In summary, computation of precision, recall and f1-measure required four input parameters: TP, FP, TN and FN.
i. TP - total of text documents accurately allotted to document class.
ii. FP - total of text documents wrongly allotted to document class.
iii. FN - total of text documents wrongly rejected from document class.
iv. TN - total of text documents correctly rejected from document class.

These parameters are input to the evaluator. They are obtained from the classification result. Figure 9 displays the performance measure module of the Igbo text classification system.

4. EXPERIMENTS

This involves the practical method of putting into work all the theoretical design of the proposed model. The Igbo text classification system is implemented with Python and tools from Natural Language Toolkit (NLTK).
Figure 6 displays the Text classification module of the system. The K-value and N-gram model are the input parameters required to supply before classification can be done. The value of K determines the number of most similar / nearest documents to consider when assigning the class label / name. The document (s) to classify is selected from the testing documents set.

Figure 7 shows the display of result obtained when similarity measurement is performed on Igbo text documents using Euclidean distance metric function. Figure 8 is a display of Igbo Text Classification System Result on Bigram Represented Text when k =1.

Figure 9 shows the classification performance measure result chart. The result shows that the recall, precision and F1 for unigram are 1.00, .80 and .89 respectively. The recall, precision and F1 for bigram are 1.00, .90 and .95 respectively. The recall, precision and F1 for Trigram are 1.00, .62 and .82 respectively. Recall measures the degree of completeness. The result shows Igbo text classification on the text represented with the three models (unigram, bigram and trigram) has the same level of recall (completeness). This means all the text documents that were given to the classifier, were given a label name. Precision measures the degree of exactness. The classification
with bigram has highest degree (0.90) of exactness (precision) while trigram has the lowest degree (0.62) of exactness. F1 measures the classification system accuracy by taking into consideration the precision and recall to calculate its value. F1-measure is at its finest score (value) at 1 and at its worst at 0. Bigram represented text classification has the highest value (0.95) of F1 while Trigram has the lowest value (0.82).

Table 1 gives the summary of classification result obtained on Unigram, Bigram and Trigram text representation. A total of 10 testing documents are used for the experiment. In Unigram, eight documents are correctly assigned a class label while two are incorrectly assigned a class label. In bigram, 9 documents are correctly assigned a class label while one is incorrectly assigned. In trigram, 7 documents are correctly assigned a class label while 3 are incorrectly assigned a class label.

6. CONCLUSION

In this work, an improved model for representation and classification of Igbo texts using N-gram and KNN model based on the similarity measure is developed and implemented. This model richly represented Igbo text using N-gram model of length 3 (Unigram, Bigram and Trigram) considering issues of collocations and compounding that play high role in the language. The relevant features were selected with Mean TF-IDF technique. The text classification was performed on the selected features using K-Nearest Neighbour technique based on similarity measure. The similarities between the Igbo text documents are measured with Euclidean distance metric.

The performance was measured by computing the classification accuracy of Unigram, Bigram and Trigram represented text. The result showed that the classification performed on bigram represented text has higher performance than unigram and trigram represented texts.

The model will be of high commercial potential value and will be useful in any text based intelligent system on the language. It will also motivate other researchers to develop interest in doing more research on how to bring Information Technology fully into Igbo, one of the three Nigerian major languages to the benefit of people and society.

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