An Extractive Text Summarization based on Candidate Summary Sentences using Fuzzy-Decision Tree

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***Abstract*—This study aims to predict candidate summary sentences in extractive summary using the Fuzzy-Decision Tree method. The fuzzy method is quite superior and the most widely used in extractive summaries, because Fuzzy has advantages in calculations that are not cryptic, so it is able to calculate uncertain possibilities. However, in its implementation, the fuzzy rule generation process is often carried out randomly or based on expert understanding so that it does not represent the distribution of the data. Therefore, in this study, a Decision Tree (DT) technique was added to generate fuzzy rules. From the fuzzy final result, important sentences are obtained that are candidates for summary sentences. The performance of our proposed method was tested on the 2002 DUC dataset in the ROUGE-1 evaluation. The results showed that our method outperformed other methods (baseline and sentence ranking) with an average precision of 0.882498, Recall 0.820443 and F Measure 0.882498 with CI for F1 0.821-0.879 at the 95% confidence level.**

Keywords*—*Text summarization; extractive; fuzzy; decision tree

I. Introduction

The development of information and communication technology, especially the internet, has an impact on increasing the number of publications of articles on websites or online media which are very useful for decision-making processes and movements regarding everyday life for humans. However, reading the entire text or obtaining relevant information on a particular topic becomes a tedious and time-consuming task. Automated text summarization is recognized as a solution to this problem, because automatic text summaries generate summaries that include all key relevant information quickly without losing the original intent of the text.

There have been many different methods and approaches in the field of text summarization. One approach is abstractive and extractive text summarization. In an abstract summary, sentences generated by summaries are called new sentences, or paraphrases, that use words that are not in the text to generate summaries. Abstract summarization is much more complex and relatively more difficult than extractive summarization. In contrast to abstractive text summarization, the results of the extractive summary consists of fully extracted content, just as the summary result is a sentence or word extracted from the original text [1].

Based on the latest three-year literature, the extractive approach is quite widely used [2] [3]. Several different approaches handled the process of extracting text summarization, one of which is the Frequency-based term weighting approach [4]. The rule-based approach is a study by Naik & Gaonkar [5], which provides the rule-based summarizer with the highest average accuracy, f Measure, and recall values, but has never been tested with broader data contradictions.

In making a summary, the concept of classification can be used by classifying sentences into two groups, namely sentences that are included in the summary (which are important sentences) and sentences that are not included in the summary (sentences that are not important). The fuzzy method has often been used in classification cases and gives good results in both classification and prediction. Fuzzy has the advantage in that its calculations are not rigid (fuzzy), so that it is able to take into account uncertain possibilities [6] [7]. The fuzzy approach is quite widely used in extractive summaries [8]. The fuzzy logic approach is a commonly used method because it can prevent data inconsistencies involving the human role of reviewing sentences and agreeing to select specific sentences to create a summary sentence [9]. The fuzzy system works with different features or multiple inputs from the index. The score for each feature is then passed to the fuzzy inference system as input for later use of IF THEN rules in human knowledge.

Although the fuzzy method is quite superior in extractive summary, in this case, fuzzy has a complexity in terms of determining the rules or basic rules used during inference. Some fuzzy cases use rules obtained by experts, namely humans, while humans can be subjective and can make mistakes. It is feared that this does not reflect the actual data representation. From these problems, a special method is needed for determining the rules of the fuzzy inference system (FIS). Therefore, in this study, the rule to determine candidate summary sentences from FIS will be generated using a Decision Tree. Thus the rules used in the inference engine will represent the actual situation.

In this paper, we propose a text summarizing method that begins by predicting the candidate summary sentences and then compares them with the reference summary results provided by the expert (dataset used is DUC 2002). The proposed summary method is a fuzzy rule-based system for identifying and selecting sentences. To create a fuzzy rule, we use a Decission Tree. Auto-generated text summaries can reduce reading-related cognitive efforts, especially with large amounts of textual information [10]. Contribution to this work is to propose an automatic text summarizing method by predicting candidate summary sentences using fuzzy and decission tree (fuzzy-decission tree) methods in extractive summarizing areas, comparing the proposed method with other methods. The remainder of this paper is organized as follows. Section II describes related work. Section III details this method. Section IV reports experiments for performance evaluation and discussion. Section V discusses conclusions and future work.

II. Related Work

This section analyzes the state of research on automatic text summarization from the last few years using a fuzzy logic approach. The things analyzed include algorithms, datasets, text features, performance, and comparison measures used. Fuzzy logic and NLP are interconnected [11] to solve tasks such as text addition, sentiment analysis, and knowledge representation. This is because fuzzy logic overcomes the problem of inaccuracy and ambiguity of human language by providing a description of the dataset with a linguistic concept defined as a fuzzy set [12]. The following are some of the works that use fuzzy logic in text summarization.

Research conducted by Megala et al., 2014 compares the performance of the fuzzy logic method with the artificial neural network method in summarizing the text. The method is tested by non-automatic evaluation using legal documents. As a result, fuzzy logic is superior in measuring f-measures compared to artificial neural networks, namely 0.46 for fuzzy logic and 0.42 for artificial neural networks [13]. Researchers Megala et al., 2015 again summarized text with fuzzy logic to extract the size, produce a summary and classify segments using Conditional Random Fields (CRF). The evaluation was carried out with legal decision documents, showing that it yielded 0.26 for the f-measure and the method was able to classify all segments in the case [14].

The next research is multi-document summarization using cross-document relationships using fuzzy on news. There are three jobs being carried out, among others: extracting sentence components, performing semantic relationships between text units using Cross-document Structure Theory (CST), and scoring sentences using fuzzy logic. The summary results are obtained from the sentences with the highest ranking. Evaluation reached 0.33 for ROUGE-1 with a 2002 DUC [15]. Summarizing text research with a new model by combining three methods. CLA is used to overcome redundancy, this model uses CLA to reduce redundancy problems, PSO is used to assign feature weights, fuzzy logic is used for sentence assessment. The features used to select important sentences include keywords, sentence length, nouns, thematics, and sentence positions. Method performance excels at f-measure 0.48 when tested on the 2002 DUC dataset [9]. Research on an automatic summary system with a fuzzy approach to extract some features to get important information on student assignment texts. This summary system was tested on a collection of text responses from students to assignments given in a Virtual Learning Environment (VLE). The proposed model is then compared with the method of score, Baseline, sentence and model with ROUGE [16].

Text summary for single document using fuzzy logic approach by extracting sentence features and calculating word scores [17]. Choose a summary sentence by calculating the weight of the sentence and compiling it into a summary. Sentence weights are obtained from calculating word scores and extracting sentence features with fuzzy inference. So that the sentences that stand out are based on fuzzy inference measurements which will later be included in the summary. The method was evaluated using ROUGE-N on the DUC 2002 dataset and then compared with other methods, and the results were superior to the comparison method. The next research is to develop a text summary using fuzzy models in many documents [18]. The fuzzy method is used to handle the uncertainty of feature weights. In this model, the cosine similarity is added to solve the redundancy problem. The evaluation was carried out using ROUGE at DUC 2004. As a result, the proposed method performed higher than the comparison method (Yago Summarizer, TexLexAn, PatSum, ItemSum, and MSSF). In recall measurement, the result is superior, namely 0.1555 on Rouge-2, but lacking in precision when compared to the Patsum method [19].

Extractive summary research that produces an abstract summary. Abstractive summary is obtained by combining the extractive sentence selection process (which uses fuzzy logic) and the long-term two-way short-term memory (Bi-LSTM) method to update the network weights, so it is called the Fuzzy long short-term memory (FLSTM) method. The fuzzy approach is used to get the most important and relevant sentences by extracting information from the document. Important and relevant sentences obtained from the fuzzy extraction method are then used as input for the Bi-LSTM method to produce an abstract summary. The model was then evaluated using ROUGE on the DUC and CNN datasets. The proposed model shows better performance empirically than other comparison methods [20].

Subsequent text summarizing research proposes the integration of two methods, namely the Restricted Boltzmann Machine and Fuzzy logic, hence the name FRBM (Fuzzy Restricted Boltzmann Machine). These two methods have different ways of producing precise summary sentences, but these two methods have something in common, namely, they are unsupervised methods used to summarize text. The summary generated by fuzzy logic is then integrated with the summary generated by the Restricted Boltzmann Machine. The advantage of the FRBM model is that in dealing with noise during training, it is more resistant than RBM [21].

Automatic text summarization uses three different algorithms. It is a two-tailed score for local contextual information (LCIS), key term weighting by sentence, and a fuzzy graph sentence score (FGSS). The LCIS score was used to identify the LCIS, the weighting was used to increase the weight of the important terms, and the fuzzy graph sentence score was used to document the centroid by calculating the appropriate fuzzy graph sentence score. It exhibits superior averages compared to previous studies and requires no training or testing [22].

The next research, summarize unsupervised extractives with fuzzy logic method. Fuzzy logic is used because it is based on natural language that is easy to understand. This summary is built using the Python language. The features used include position, bitcoin, tritoken, cosine similarity, thematic sentence length, numerical data and TF-ISF. The method was tested on the UCI, BBC and DUC 2004 datasets using the ROUGE-1 evaluation. The results conclude that fuzzy logic makes feature extraction sharper and more precise [23]. The next extractive summary research is to summarize the text documents of students' essay assignments using the fuzzy C-Means method. The feature used in this research is the sentence weighting feature. The summary obtained is the sentence with the highest weight in the cluster [24].

In the next research, extractive summaries combine three approaches, namely fuzzy, evolutionary and clustering. The workings of this model begins with clustering, namely grouping sentences according to their similarities. Then extract the significant sentences of each cluster. An evolutionary optimization approach is used to find the optimal weights for text features. Fuzzy inference is used to determine the final score of the sentence. The proposed model was tested on three datasets namely CNN, DUC 2021 and DUC 2022. The results show that the hybrid method produces a good summary [3].

III. PORPOSED METHOD

In this section, the proposed method of summarizing extractive techniques using fuzzy and decision tree methods is proposed. Fuzzy method is used to extract features, while decision is used to help fuzzy in making rules (rule based). The proposed model is described in Fig. 1 and is broken down into five main steps, as follows:

A. Preprocessing

Preprocessing is the initial stage for text summarization. Some of the pre-processing steps needed in this research are as follows: Removing punctuation and special words that are not used. Segmentation, the process of separating text into sentence units. Tokenization is the process of separating words from each sentence. Stop word removal, removing a collection of unused words. And steamming is the process of converting each word to its basic form by removing prefixes, affixes and suffixes.

B. Features used

At this stage, describe the extracted features. Feature extraction is used to get important sentences from text sources that have been preprocessed before. This feature ensures the importance of each sentence that goes into the summary. So that the summary contains sentences with high scores. Therefore, selecting the right features can have a big impact on the quality of the summary. In this study, used seven extracted features for each sentence in the input data. The seven features are:

1) Sentence position: The key concept here is that sentences that appear at the beginning or end of the input text are considered more important than other sentences. So for the initial and final sentences, initialize 1 and those that are not the initial and final sentences are initialized 0 [25].

Score (S_i) = 1 for First and Last sentence,

0 for other sentences (1)

2) Sentence lenght (in document): The sentence length feature in the document is used to filter out short sentences such as the author's name, address and date that might be found in news documents. Sentences that are too short are not expected to be part of the summary [5]. So that in this feature normalization of sentence length is carried out, namely the ratio of the number of words that appear in the sentence to the number of words that appear in the longest sentence of the document [25].

$$Score\ (Si) = \frac{No.of\ a\ word\ occurring\ in\ S_i}{No.Word\ Occurring\ in\ longest\ Sentence\ from\ document} \quad (2)$$

3) Sentence length (in paragraph): In this feature, short sentences may not represent the topic of the document because the words contained in it are few. Thus, long and short sentences are given low scores. The value of sentence length in paragraphs is calculated based on the equation: [26]

$$Score\ (Si) = \frac{No.of\ a\ word\ occurring\ in\ S_i}{No.Word\ Occurring\ in\ longest\ Sentence\ from\ paragraph} \quad (3)$$

4) Thematic word: This feature is quite important in text summarization because terms that appear frequently in a document may be related to the topic. The thematic word count indicates the words with the maximum relativity possible [25]. After getting the thematic words in the text, then look for the ratio of the number of words in the sentence that appears in the thematic word to the length of the sentence (the number of words in the sentence).

$$Score\ (S_i) = \frac{No.Thematic\ word\ in\ S_i}{Length\ (Si)} \quad (4)$$

5) Title word: This feature is used to find the number of words in the title that appear in the sentence. Words in sentences that also appear in the title is given a high score [6]. Calculate score for this feature which is the ratio of the number of words in a sentence that appears in the title to the length in that sentence (the number of words in that sentence).

$$Score\ (S_i) = \frac{No.Title\ word\ in\ S_i}{No.word\ occuring\ in\ S_i} \quad (5)$$

6) Numerical: In the summary, text or sentences containing numbers are considered informative. So in this feature, sentences with a lot of numerical data need to be considered to be included in the summary. The way to calculate it is to calculate the ratio of the number of numeric data in a sentence divided by the length of the sentence [21].

$$Score\ (S_i) = \frac{No.Numerical\ data\ in\ S_i}{\text{No.word occuring in } S_i} \quad (6)$$

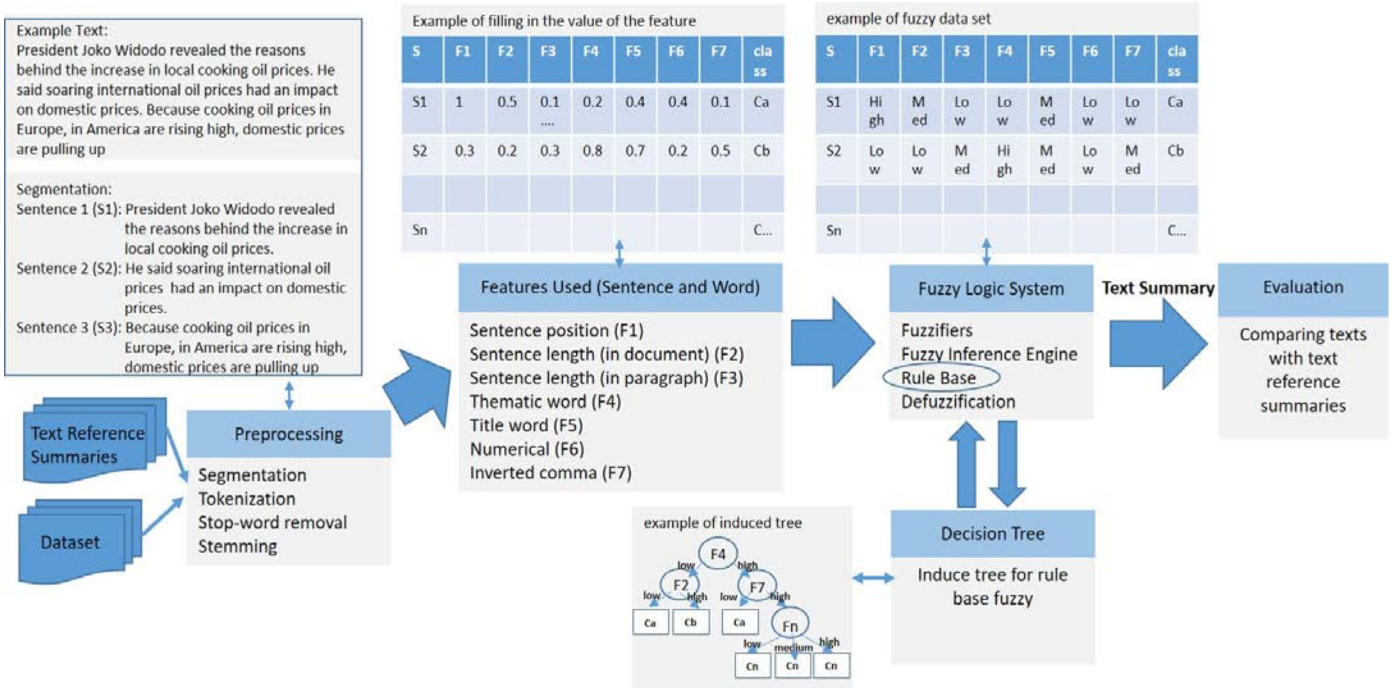

Fig. 1. The Proposed Method of Summarizing Extractive Techniques using Fuzzy and Decision Tree.

7) Inverted comma: Inverted commas usually indicate direct conversation, title or name, and also contain important information [26]. The inverted comma is calculated using the following equation.

$$Score\ (S_i) = \frac{No.Inverted\ comma\ in\ S_i}{No.word\ occuring\ in\ S_i} \quad (7)$$

C. Fuzzy Logic System

Fuzzy logic has often been used for various applications because fuzzy logic is easy to understand, flexible and tolerant of inaccurate data. One of the characteristics of fuzzy logic is the use of verbal instructions described in fuzzy sets and rules. The way the fuzzy logic system works there are four parts as follows:

1) Fuzzifiers: The first process in the Fuzzy system is to transform raw crisp values into membership values through membership functions. This means that the membership function for each fuzzy set must be determined first. In this section, the input is the value of text summarizing features (in the form of numbers), which by using the membership function will be converted into lingiustic. The membership function used for this summary model is the Triangular Membership Function (TMF). Where each feature has three fuzzy sets, namely: high, medium and low.

2) Fuzzy inference engine: This section is the main part of fuzzy logic. Here will be calculated formulas so as to produce output. There are two things that serve as a reference for this calculation, namely the membership function in the previous section and also the fuzzy rule. So that fuzzy input is needed from the fuzzifier in making decisions based on rules. For our proposed summary model, the inference used is Mamdani fuzzy inference (FIS). Due to its simple and most common min-max operating structure it is used in many applications. In addition, Mamdani is more suitable for text summarization systems because it can capture expert knowledge which allows us to describe abilities in a more insightful and more human-like way. To process it using the help of MATLAB.

3) Rule base: The rule design process is an important part in the fuzzy classification algorithm. In this study, to help activate the rule, the decision tree method was used in designing the if-then rules. From the results of making the decision tree, 33 if-then rules are obtained. To see a more detailed explanation of the decision tree method, see section 3, part d.

4) Defuzzification: converting linguistic inference results back into sharp outputs. In this study, the centroid defuzzification method was chosen for us to use. This method is the default method where it works by returning the center of the area under the curve.

D. Decision Tree (for Rule Fuzzy)

Decision tree is one of the most famous studies to describe the decision-making process based on existing knowledge. Each branch of the decision tree can be converted into a decision rule, and all these decision rules can generate a decision rule base (Mu et al., 2019). Therefore, in this research, each feature value that is input in fuzzy where the linguistic fuzzifier process has been made instead of the membership function of each feature, will be used as training data for the decision tree algorithm to produce a decision model. To produce a decision tree, the C4.5 algorithm is used to process the training data. This stage begins with calculating the entropy value that will be used to calculate the gain value for each feature. The feature with the highest gain value will then be set as root. The formulas for calculating entropy and gain are shown in Equation (8) and Equation (9). The step of calculating entropy and gain for each feature is repeated continuously until all features are partitioned.

$$Entropy(S) = \sum_{n=1}^{c} - {p_i}^2 \log p_i \quad (8)$$

$$Gain(S,A) = Entropy(S) - \sum_{v \in Values(A)} \frac{|S_v|}{S} Entropy(S_v) \quad (9)$$

From the decision tree that has been made, 33 if-then rules are obtained which will be used in the fuzzy process. Fig. 2 below shows one of the rules formed from the results of the decision tree.

IF (Thematic is medium) and (Sentence length in a paragraph is high) and (Sentence length in a document is medium) and (Sentence position is high) and (Numerical is low) and (Inverted Comma is low) and (Tittle word is medium) THEN (sentence is Yes)

Fig. 2. Sample IF THEN RULE Results from Decision Tree.

E. Evaluation

In the evaluation of this research, the results of the text summary from the system will be compared with the reference summary from the expert (human). In the evaluation used the Recall-Oriented Understudy for Gisting Evaluation (ROUGE) which was used to measure the similarity between system generated summaries and human reference summaries (Lin & Hovy, 2003). The ROUGE evaluation produces three measures, namely: recall, precision and f-measure. The measure is calculated by counting the words that overlap between the computer-generated summary and the human-generated ideal summary. Precision is the number of n-grams that appear together in the system summary and reference summary divided by the total number of n-gram reference summaries. Whereas Recall is the number of n-grams that appear together in the system summary and the reference summary divided by the total number of n-grams in the system summary. Precision and recall ranged from 0 to 1. When the precision score was 1, all n-grams in the text summary were in the reference summary. F-Measure is a combination of precision and recall, which is a weighted harmonic average of precision and recall. The study of Steinberger & Jezek, 2009 showed that automated evaluation using the unigram version of ROUGE-N, namely ROUGE-1 correlated well with human evaluations based on various statistics. Therefore, this study uses the evaluation of the system summary results with ROUGE-1.

IV. Experiment and Result

This section describes the evaluation of the performance results of the Fuzzy Decision Tree method. Shows a comparison of our proposed Method with other methods. The Baseline method and the Sentence method are also implemented to be used in the evaluation process as a comparison to the Fuzzy-Decision Tree method.

A. Compared Methods

1) Fuzzy-decision tree: In our Fuzzy-Decision Tree method, the first start by setting the fuzzy set in three input variables: high, medium, low (for each feature). The selected sentences must represent an informativeness or indicate the level of importance of a sentence classified in the output variable as YES/NO. To assist our work in designing fuzzy models, used the Fuzzy Logic Toolbox in MATLAB. The type of inference, used is Mamdani. To help create an IF THEN rule, used the Decision Tree method.

2) Baseline: The baseline system is the basic information collected before a program starts. For comparison if using DUC 2002, use Baseline-1 DUC 2002. Baseline-1 is the first 100 words from the beginning of the document as determined by DUC 2002 https://www-nlpir.nist.gov/projects/duc/duc 2002/baselines.html [25].

3) Sentence ranking: Sentence method selects sentences based on word frequency. First of all choose fetch keywords. After that it calculates the frequency of each keyword such as how often it appears from the maximum frequency this keyword is taken and calculates the number of frequency weights. And the last one is extracting high-frequency sentences [27].

B. Dataset

In this experiment, 10 data were taken in the form of text documents from the DUC 2002 dataset. So that the total words in this experiment were 3803, the total sentences were 242 sentences. Each text document contains an average of 380 words and an average of 24 sentences. Data for evaluation, 10 reference summary documents have been provided by language course experts based on the desired key concepts. The total data consists of 2122 words and 98 sentences. Each reference text document contains an average of 212 words and eight sentences. As an evaluation of the comparison between the summary data generated by the system and the reference summary data, used n-gram statistics. Measurement with n-gram ROUGE has a 95% confidence level so that it is highly correlated with human judgment.

C. Result and Discussion

For evaluation of summary texts, this study uses a set of ROUGE metrics that have become the standard for automatic summary evaluation. Evaluation is done by comparing the results of the summary of the system with the results of the summary of human references. To compare summaries, n-grams are used. ROUGE-I is consistently highly correlated with human judgment and has high recall and significance test precision with manual evaluation results. So in the experiment of summarizing the text, the ROUGE-1 measurement was used. Table I shows the comparison of the summary results of the proposed method, namely the Fuzzy-Decision Tree with the summary results of the baseline and summary results of the sentence method from the 2002 DUC collection.

TABLE I.

PERFORMANCE COMPARISON

Document	**Fuzzy-Decision Tree**			**Baseline**			**Sentence Ranking** [27]		
	R	**P**	**F1**	**R**	**P**	**F1**	**R**	**P**	**F1**
AP880911-0016	0.75	0.825	0.78571	0.33333	0.5	0.4	0.72727	0.65306	0.68817
AP900621-0192	0.82609	0.83333	0.82969	0.36522	0.36207	0.36364	0.69565	0.65574	0.67511
AP900621-0186	0.85586	0.94059	0.89623	0.43243	0.61538	0.50793	0.7027	0.77228	0.73585
AP880821-0008	0.85938	0.9322	0.89431	0.34375	0.46809	0.3964	0.78906	0.71631	0.75093
AP880228-0013	0.76866	0.88793	0.824	0.40299	0.53465	0.45958	0.87313	0.84783	0.86029
AP880508-0070	0.808	0.93519	0.86695	0.4	0.65789	0.49751	0.736	0.77966	0.7572
AP881025-0196	0.74803	0.84071	0.79167	0.33071	0.53165	0.40777	0.65354	0.72807	0.68879
AP880808-0040	0.89011	0.84375	0.86631	0.51648	0.63514	0.5697	0.65934	0.61224	0.63492
AP900103-0077	0.86957	0.90909	0.88889	0.48913	0.6	0.53892	0.61957	0.75	0.67857
AP880914-0027	0.82873	0.87719	0.85227	0.34807	0.55752	0.42857	0.80663	0.90123	0.85131
Average	**0.820443**	**0.882498**	**0.849603**	**0.396211**	**0.546239**	**0.457002**	**0.726289**	**0.741642**	**0.732114**

R = Recall, P = Precision, F1= F Measure

The application of the ROUGE-1 metric resulted in the performance of the tested method on 10 data taken from the DUC 2002 dataset which is presented in Table I. From the table it is shown that the Fuzzy-Decision Tree method has superior performance in all documents tested except for the AP880228-0013 document, where the sentence method outperforms the Fuzzy-Decision Tree in the evaluation of recall 0.87313 and F1 0.86029.

Table II highlights the average performance results of F-Measure, Recall and Precision produced by the Fuzzy-Decision Tree method, the Baseline method and the sentence ranking method. From the table, it shows that the Fuzzy-Decision method has the best average, namely the average F Measure is 0.882498, the average precision is 0.882498 and the average recall of 0.820443 with CI for F1 0.821-0.879. Followed by the performance of the sentence ranking method which is close to the Fuzzy-Decision Tree method, namely the average F-Measure is 0.732114, the average precision is 0.741642 the recall average is 0.726289 with a CI for F1 of 0.678-0.786. Considering the dataset used is DUC 2002, which is news text, the results are reasonable, because the performance for Recall and precision will be higher if the text used is short text.

The results show that the Fuzzy-Decision Tree performance is significantly better than baseline summary and Sentence ranking. Then compared the performance of the Fuzzy-Decision Tree summary and other summarizers by checking for precision and recall. In this case, the best precision and recall of Fig. 3 and Fig. 4, provide strong evidence of its feasibility in text summarization applications.

Fig. 5 describes the results of the method based on the performance confidence interval (CI). The CI and f measures of the method indicate that the systems cannot be considered equal. The performance of the Sentence ranking method is almost close to the Fuzzy-Decision Tree method, while the Baseline method remains the farthest. This is because the Baseline method only selects the first sentence of the original text. Poor performance of Baseline method due to its simplicity compared to other methods. The sentence ranking method is close to the fuzzy decision tree because the sentence ranking method is based on word frequency, where word frequency represents most of the summary content. And this shows that there is a correlation between one of the features in the Fuzzy-Decision Tree method, namely the thematic word feature because it counts themes that often appear in a document that may be related to the topic.

TABLE II. SUMMARY OF PERFORMANCE COMPARISON

Method	**R**	**P**	**F1**	**C1 for F1**
Fuzzy-Decision Tree	**0.820443**	**0.882498**	**0.849603**	**0.821-0.879**
Baseline	0.396211	0.546239	0.457002	0.408-0.506
Sentence	0.726289	0.741642	0.732114	0.678-0.786

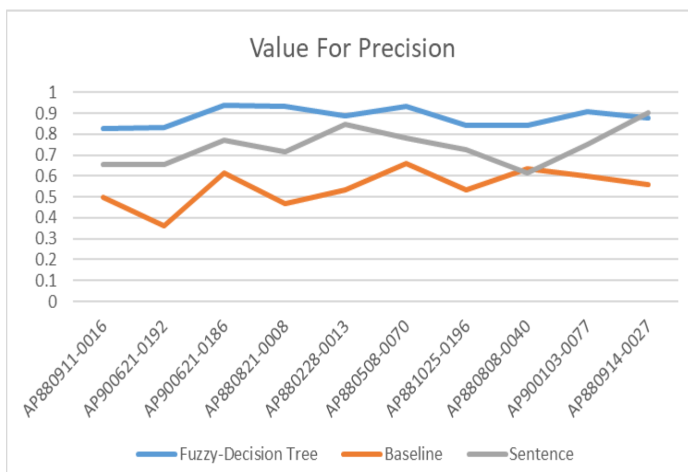

Fig. 3. Precision Result Comparison.

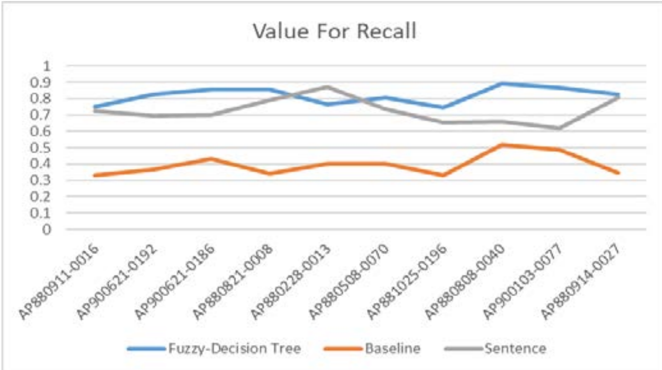

Fig. 4. Recall Result Comparison.

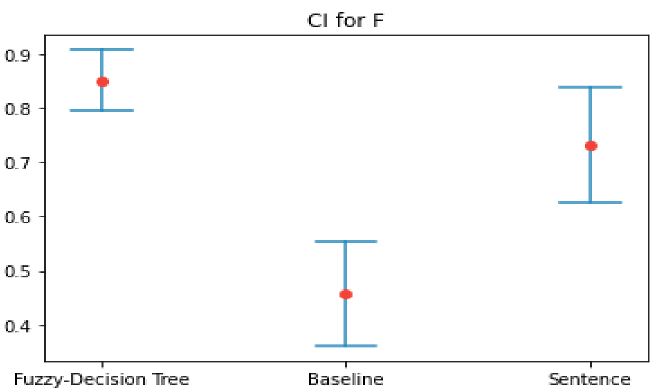

Fig. 5. Confidence Interval (CI) for F1.

V. Conclusion and Future Work

In this study a text summarization is proposed that starts by predicting candidate summary sentences and then compares it with the results of a human-given reference summary. The summary method proposed is a system with a fuzzy approach that identifies and selects important sentences based on important features. Important features in this study include: sentence position, sentence length in the document, sentence length in paragraphs, thematic words, title words, numeric data and inverted commas. Fuzzy logic is used because it is believed to be able to handle uncertain information such as language ambiguity. To optimize the creation of a fuzzy rule base, a decision tree method is added so that the built rules reflect the actual data representation. Contributions in this paper include: 1. Combination method between fuzzy logic and decision tree (fuzzy-decision tree) which has never been applied to extractive summary research before; 2. Comparison of the proposed method (fuzzy-decision tree) with other methods (baseline and sentence ranking).

Evaluation of the proposed method shows that our method outperforms other methods included in the comparison method, namely baseline and sentence ranking. By evaluating ROUGE-1, our method excels with mean precision 0.882498, mean drawdown 0.820443 and F Measure 0.882498 with CI for F1 0.821-0.879 at 95% confidence level tested in single-document test data. However, the performance of the method has not been tested on multi-documents.

For our next work that is part of this research is to add other important features that have not been used in our proposed summary, such as the similarity feature between sentences thereby reducing sentence redundancy in the summary, and the word frequency feature for making summaries. The results are more informative comparing with other more diverse summary methods and adding focus to summary results not only on quality but also on more diverse summary quantity such as 20%, 30% or 40% summary.

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