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AN INTEGRATED MODEL OF NATURAL LANGUAGE PROCESSING TECHNIQUE AND CASE-BASED REASONING FOR SUPPORTING STUDY PROGRAM ACCREDITATION

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Abstract. *Academic quality assurance is an important issue for higher education. This study presents an integrated model of Natural Language Processing (NLP) and Case-Based Reasoning (CBR) to support accreditation. The model uses NLP techniques to extract information from accreditation documents. Feature extraction uses Latent Dirichlet Allocation (LDA) to determine the topic model. The result of feature extraction is as input to the CBR system. CBR provides recommendations based on previous similar cases. The Jensen-Shannon Divergence algorithm is used to measure the similarity of cases with a mean similarity of 81.57%. The results of this study demonstrate the potential of NLP and CBR to increase the effectiveness of the accreditation process and provide insights for future research in this area.*
Keywords: Accreditation, Latent Dirichlet allocation, Natural language processing, Case-based reasoning

1. **Introduction.** Academic quality assurance is an essential issue in higher education. This is to ensure that higher education standards are achieved systematically and sustainably. It also seeks to develop a quality culture and realize quality higher education.

Previous studies have discussed the urgency of accreditation for higher education quality. The advantages of quality assurance for higher education were examined in [1,2]. Additionally, [3] benchmarked to map educational program objectives to student learning outcomes using the Accreditation Board for Engineering and Technology (ABET) standards, and [4] proposed an assessment of student learning outcomes based on log files from the e-learning system. Other researchers mentioned the importance of a quality assurance system for the development of higher education [5]. Unfortunately, they have not proposed a model to assist the accreditation process.

According to [6], this research develops model to analyze the relationship between university accreditation and student experience. Natural Language Processing (NLP) is used to extract features from accreditation reports. These features are explanatory variables in an automatic linear regression model where the dependent variable is student experience. This model has proven useful for comparing accreditation reports and can help prospective students in choosing a university. However, the parameters of these models have different results for different institutional accreditation reports. Furthermore, [7] extracted children's social case document features using topic modeling with Latent Dirichlet Allocation (LDA). It succeeded in clustering children's social case topics, but the accuracy of the results has not been discussed.

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NLP techniques can process text as input to the Case-Based Reasoning (CBR). A combination of them can solve various problems, for example, diagnosing schizophrenia disorders [8], processing construction accident report documents to reduce future accidents [9,10], and green building design based on experience [11]. However, this approach's effectiveness depends on the case's quality in the case base and the NLP techniques used to extract the case features.

We use NLP technique to extract features from accreditation documents. Then, the extracted features are used as input for the CBR system. This model evaluates the results of field assessments based on accreditation report documents. This research proposes an accreditation assessment model to answer the following research questions: a) how to extract features from accreditation report documents, and b) how to retrieve accreditation cases from the case base effectively.

2. Proposed Model.

This study proposes an integrated model of NLP technique and CBR. The main contribution of this study is to help assess the adequacy of the self-evaluation document applied to Indonesia's accreditation process. The model (Figure 1) consists of four modules: NLP, Case Representation, CBR, and Testing Method.

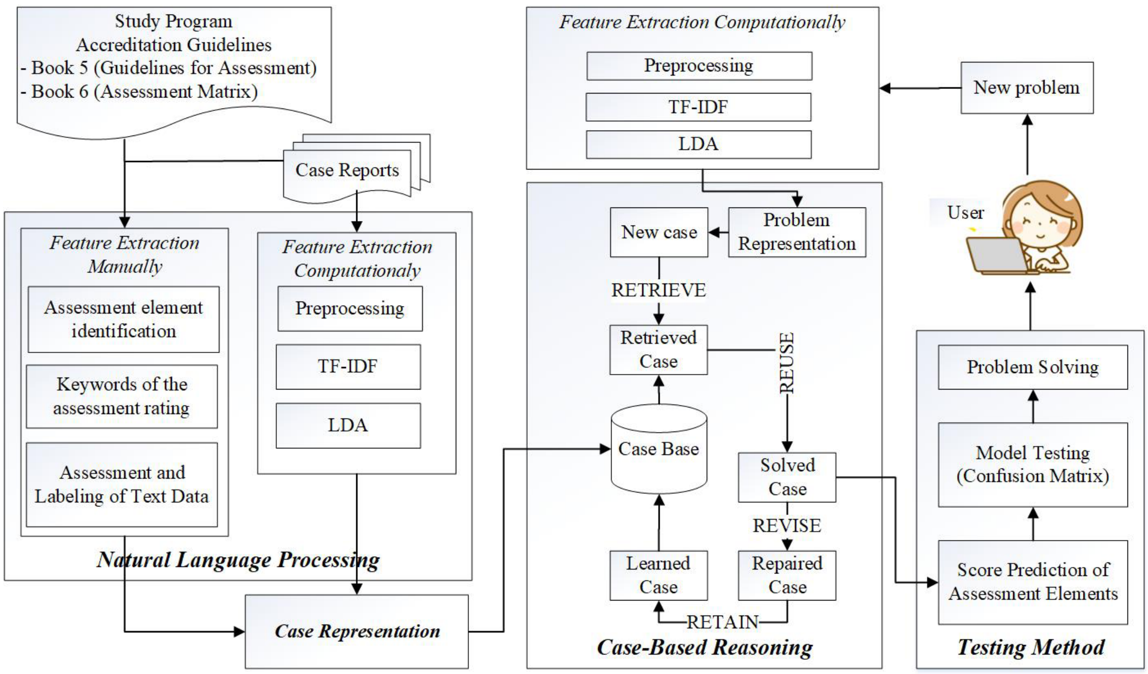

FIGURE 1. The framework of the NLP-CBR model

2.1. Natural language processing.

The NLP technique extracts features in the study program accreditation report document. It is further adapted to identify features to represent a case of accreditation. In this study, feature extraction has been done in two ways, namely manually and computationally. Manual feature extraction is performed by an expert. This is to identify scoring elements, define keywords, and label text data. The expert identifies keywords to characterize the assessment elements.

On the other hand, computational feature extraction uses the Natural Language Toolkit (NLTK) Library [12] and the Sastrawi Library [13] in the Python programming language. NLTK is a Python-based platform developed to process text data. Sastrawi is a simple Python library which allows you to reduce inflected words in Indonesian to their base form. This computation involves preprocessing, Term Frequency Inverse Document Frequency (TF-IDF), and determining Latent Dirichlet Allocation (LDA) topics.

Preprocessing is necessary to ensure that the document mining results are in an appropriate form for use in the following process. It involves tokenization, stemming, lemmatization, and stop word removal [14]. Tokenization is the process of breaking down a text into smaller units, usually words or sentences. Stemming is a text normalization technique that aims to reduce words to their base. Lemmatization is a sophisticated text normalization technique that reduces words to their dictionary form. Stop word removal is the process of allowing for common and non-informative words.

TF-IDF is an algorithm to transform the text into a meaningful representation of numbers, and is used to fit machine algorithm [15]. TF indicates how often a term appears in a document (Equation (1)).

$$TF = \frac{number\ of\ times\ the\ term\ appears\ in\ the\ document}{total\ numbers\ of\ terms\ in\ the\ document} \tag{1}$$

IDF is a calculation of the logarithm of the number of documents with a document frequency of one term (Equation (2)).

$$IDF = \log\left(\frac{number\ of\ the\ documents\ in\ the\ corpus}{number\ of\ documents\ in\ the\ corpus\ containing\ the\ terms}\right) \tag{2}$$

TF-IDF of a term in the document is calculated by multiplying TF and IDF (Equation (3)).

$$TF\text{-}IDF = TF * IDF \tag{3}$$

LDA is a statistical model that tries to capture the latent topics in a collection of documents [16]. The basic idea is that documents are represented as random mixtures over latent topics, where a distribution over words characterizes each topic [17].

2.2. **Case representation.** In the CBR, case representation mainly focuses on what to store in the case base and on how to structure a case to describe its content [18]. A case represents a set of features reflecting its problem and solution parts. The features allow all collected accreditation case reports to be transformed into a spreadsheet.

2.3. **Case-based reasoning.** CBR is a paradigm, a concept, and an automatic problem-solving mechanism [18]. The CBR cycle consists of the following:

1) Retrieve: for the given problem, find the most relevant and similar cases in the case base.

2) Reuse: A solution to the target problem is adopted in retrieved cases.

3) Revise: If the retrieved solution cannot match the target problem, some adjustments will be made to the retrieved solution.

4) Retain: After successful application confirmation of the retrieved, the target issue and solution will be added to the case base for future use.

2.4. **Testing method.** A CBR system is needed for previous cases that have been stored in a case base of cases to be used to solve current problems. Retrieve cases using the similarity algorithm to solve new cases by finding the highest score prediction of assessment elements with the similarity of the previous point. This process will produce recommendations for improving the quality of study programs when the similarity is highest with old cases that need a better accreditation level. This process is also tested with a confusion matrix to determine accuracy, precision, recall, and F1 score [19]. This study uses a confusion matrix for 3-class classification, i.e., Very Good, Good, and Fair. Unlike binary classification, there are no positive or negative classes here. What we must do here is to find TP, TN, FP, and FN for each class.

3. Result and Discussion.

3.1. Data collecting.
The primary data in this study is documented from the accreditation reports of undergraduate programs. The text data from National Accreditation Board for Higher Education (*Badan Akreditasi Nasional Perguruan Tinggi or BAN-PT*) is available in Indonesian. There are seven standards in the accreditation guidebook. However, this study is limited to standard 1 (Vision, Mission, Goals, Objectives, and Achievement Strategies). Standard 1 has three assessment elements (EP), as shown in Table 1. Each element has five ratings, i.e., "Very Good", "Good", "Fair", "Poor", and "Very Poor" with a scale of values from 0 to 4. This study uses data on the first three levels and ratings, as shown in Table 2.

Table 1. Assessment elements of Standard 1

EP	Descriptor of assessment
EP1	Clarity and realistic vision, mission, goals, and objectives of the study program.
EP2	Target achievement strategy with a clear timeframe and supported by documents.
EP3	Effective outreach is reflected in the level of understanding of the parties involved.

Table 2. Labels on score-based assessment elements

EP	Labels of assessment elements		
	Very Good (4)	Good (3)	Fair (2)
EP1	Vision, mission, goals, and objectives are apparent and very realistic.	Vision, mission, goals, and objectives are clear and realistic.	Vision, mission, goals, and objectives are clear but unrealistic.
EP2	Target achievement strategy: 1) with clear and very realistic time stages 2) supported by complete documents.	Target achievement strategy: 1) with clear and realistic time stages 2) supported by complete documents.	Target achievement strategy: 1) with clear and quite realistic time stages 2) supported by sufficiently complete documents.
EP3	Well understood by all academics and academic staff.	Well understood by some academics and academic staff.	Need to be understood by academics and education staff.

Qualitative assessment by assessors is expressed in the form of a qualitative description. A qualitative report and score were obtained from the research data from the BAN-PT document. Scores are presented numerically on a scale from 0.00 to 4.00. Data texts were obtained from 123 study program accreditation documents. Next, scores on the assessment elements were categorized and labeled based on consultation with experts. Scores above 3.51 are labeled as Very Good, 3.00 to 3.50 as Good, and below 3.00 as Fair. Each assessment element (EP) consists of 123 study programs (PS). In other words, each EP has 123 cases. The information obtained from the PS forms after having been verified by interviews and observations (after that, called case descriptions) has a length of between 55 and 250 words. Next, each EP contains 123 case records consisting of case id (CID), study program id, assessment element id, case descriptions, score, and label. An example of an accreditation case record can be seen in Table 3.

3.2. Text feature extraction.
Feature extraction is a process to find the feature values contained in the document for text processing [20]. This study has two processes, namely manual and computational.

TABLE 3. Sample of an accreditation case record

CID	PS	EP	Case descriptions	Score	Label
C001	PS001	EP1	*Visi PS: Menjadi pusat pendidikan dan inovasi big data yang unggul dan inovatif berstandar internasional dalam bidang Bio Informatika di ASEAN. Visi, misi dan tujuan realistik dan saling terkait untuk menghasilkan lulusan yang handal, berdaya saing tinggi, beretika dan berwawasan nasional dan global. Penyusunan VMTS melalui berbagai tahapan yang melibatkan berbagai pihak misalnya Founders, dewan penasehat industri, lembaga penelitian, mitra strategis, top management, jurusan, tenaga kependidikan dan pemangku kepentingan.**	3.5	Good

***In English:** The study program's vision is to become a superior and innovative big data education and innovation center with international standards in the field of Bio Informatics in ASEAN. Visions are realistic and interrelated missions and goals to produce reliable, highly competitive, ethical graduates with a national and global perspective. The preparation of VMTS went through various stages involving various parties, for example, founders, industry advisory boards, research institutions, strategic partners, top management, departments, educational staff, and stakeholders.

The first is manual feature extraction to find document keywords. The selection of keywords refers to the accreditation assessment guide. All documents are searched for keywords. For example, the keywords in EP1 regarding the clarity and realistic vision, mission, goals, and objectives of the study program. The 123 documents were broken down into words. The manual process selected keywords related to the characteristics of "Very Good", "Good", and "Fair" were determined. The manual selection takes the top 10 words often appearing in the accreditation case content corpus. Then, weight is attributed to it according to the frequency of appearance in the document. For example, the results of selecting keywords and weight from EP1 for the label "Very good" contains the following keywords: "involve" (34), "linkages" (29), "stakeholder" (28), "clear" (27), "realistic" (27), "document" (18), "external" (17), "internal" (15), "very" (14), and "stages" (7).

The second is text processing using NLTK and Sastrawi in Python. The NLP techniques have been used to find the topic model for each EP. Tokenization, stemming, lemmatization, and stop word removal are used to process the text in each EP. These are all essential techniques for training efficient and effective NLP models.

TF-IDF calculations used the ScikitLearn library in Python. Data text will be processed with TF-IDF by calling the `TfidfVectorizer` function to find out the weight of a word appearing in the document so that it can be seen how relevant a word is in a document. According to Equation (3), TF-IDF calculation works by constructing a vector that contains the weight of each word that appears in the entire corpus for each case description. For example, the calculation using TF-IDF from EP1 in PS001 is shown in Figure 2.

Term and Frequency
[vmts (0.104222), bagai (0.386538), tahap (0.193269), libat (0.088317), bagai (0.386538), pihak (0.154286), misal (0.226590), founders (0.259911), dewan (0.226590), nasehat (0.259911), industri (0.240419), lembaga (0.199688), teliti (0.199688), mitra (0.259911), strategis (0.259911), top (0.259911), management (0.259911), jurusan (0.259911), tenaga (0.182542), didik (0.136609), pangku (0.122320), penting (0.120965), stakeholder (0.173778)]

FIGURE 2. TF-IDF result from EP1 in PS001

The following feature extraction process determines topic modeling in the document with LDA. LDA is a generative model that unsupervised allocates weight values to the words contained in a document as a topic representation. The size of the vector depends on the numbers of words for each document in a corpus. So, each document will have a variety of vectors.

The LDA operation will generate two models, and each is represented in a vector. The first vector contains the distribution vector of words with their weights forming a topic. The second vector includes the distribution of topics with weight for each document. The first vector distribution then becomes the LDA model to estimate the distribution of topics for new documents without repeating the LDA operation.

In an experiment to find topics using LDA, it is necessary to iterate to find the optimal number of LDA topics. These topics can be seen from the intersection line graphs of coherence and perplexity. Iterations were carried out 40 times for each EP. The number of topics obtained is EP1 $= 26$, EP2 $= 14$, and EP3 $= 14$. After receiving the optimal number of topics, a topic is performed from each document. An example of a topic from document EP1 is presented in Figure 3.

No. topic	Topic Model
Topic 1	(0, '0.061*"visi" + 0.060*"misi" + 0.050*"jelas" + 0.047*"tujuan" + 0.037*"sasar" + 0.036*"kait" + 0.025*"realistik" + 0.024*"ada" + 0.022*"libat" + 0.021*"vmts" + 0.019*"rumus" + 0.018*"sudah" + 0.018*"penting" + 0.018*"pangku" + 0.018*"milik" + 0.016*"realistis" + 0.015*"ps" + 0.015*"saling" + 0.013*"internal" + 0.012*"eksternal"'),
...	...
Topic 26	(25, '0.042*"libat" + 0.028*"ada" + 0.027*"pimpin" + 0.023*"didik" + 0.023*"internal" + 0.020*"kait" + 0.020*"vmts" + 0.019*"susun" + 0.019*"pihak" + 0.018*"eksternal" + 0.018*"kepala" + 0.018*"ketua" + 0.018*"kantor" + 0.015*"dalam" + 0.014*"cara" + 0.013*"target" + 0.013*"visi" + 0.011*"sasar" + 0.010*"program" + 0.010*"prodi"')

FIGURE 3. LDA model with 26 topics

3.3. **Case representation.** The experimental output uses LDA topic modeling to obtain text features representing case features. Case representation mainly focuses on what to store in the case base and how to structure a case to describe its content [21]. In this study, the case problem part contains the requirement of users (case description), the features of the LDA topic, and the label's prediction. The case solution part describes PS, EP, case description, keywords, score, label, and the features of the LDA topic.

3.4. **Case retrieval.** Case retrieval is usually regarded as the most critical step within the CBR cycle. The target of this process is to find the cases in the case base that are closest to the new problem. To achieve this aim effectively, similarity measures are adopted to measure the closeness between the target and stored cases. According to [22], the Jansen Shannon Divergence (JSD) can analyze changes in topic content. This is very useful because a case may be discussed in multiple documents. With JSD, it is hoped that the model will be able to recognize case patterns to retrieve them with such a relationship.

The LDA operation produces two models represented in a vector. The first vector contains the distribution vector of words with weights forming a topic (words over topic distribution). The second vector includes the distribution of topics with their weights for each document (topic over document distributions). The first vector distribution (words over topic distribution) then becomes the LDA model to estimate the distribution of topics for new documents without repeating the LDA operation.

Furthermore, after the topic model vector of the new case (P) is obtained, similarity calculations are performed with all topic model vectors from the old cases (Q) in the case base. Calculation of the similarity of this topic model is carried out with JSD formulation (Equation (4)).

$$JSD(P\|Q) = \frac{1}{2}\sum_{i}\left[P(i)\log\left(\frac{P(i)}{\frac{1}{2}P(i)+Q(i)}\right) + Q(i)\log\left(\frac{Q(i)}{\frac{1}{2}P(i)+Q(i)}\right)\right] \tag{4}$$

Implementation of JSD calculation in Python is implemented for each EP. The calculation is done randomly to get the highest JSD score. Testing data used is 24 cases in each EP. Based on the results of these calculations, the average JSD scores for each EP are presented in Figure 4.

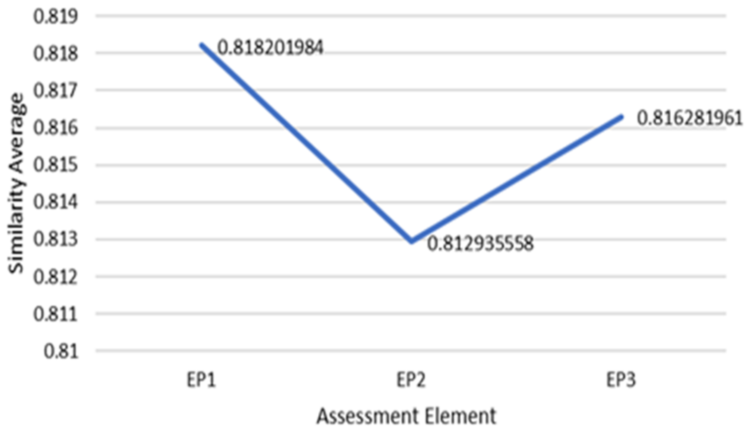

FIGURE 4. Average similarity with JSD

3.5. **Model evaluation.** The evaluation focuses on CBR model performance, especially in the case retrieval section. It is to find similar cases. Like the new case description, the text similarity algorithm finds old case documents in the case base. The dataset is divided into two: data stored in the case base, called reference data, and data that will be used to evaluate similarity calculations, called new data. Of the 123 cases, the comparison used was 80% reference data (99 cases) and 20% new data (24 cases).

The parameters used for evaluation are Accuracy, Precision, Recall, and F1. All these parameters are used to measure each EP. At the same time, the results of the calculations are presented in Figure 5. Compared to model without TF-IDF, the highest accuracy, precision, recall, and F1 values are 50%, 40%, 41%, and 34%. These could be better performances.

Metrics	EP1			EP2			EP3		
	Very Good	Good	Fair	Very Gcood	Good	Fair	Very Good	Good	Fair
TP	2	14	2	5	9	3	4	9	3
TN	15	3	20	14	8	18	15	7	16
FP	3	4	1	4	1	2	3	3	3
FN	4	3	1	1	6	1	2	5	2
SUM	24	24	24	24	24	24	24	24	24
Performance measures									
Accuracy	71%	71%	92%	79%	71%	88%	79%	67%	79%
Precision	40%	78%	67%	56%	90%	60%	57%	75%	50%
Recall	33%	82%	67%	83%	60%	75%	67%	64%	60%
F1	36%	80%	67%	67%	72%	67%	62%	69%	55%

FIGURE 5. Confusion matrix

The NLP technique succeeded in processing the accreditation report and extracting them into characteristics of assessment elements. These results are used as input to the CBR system. Then, retrieving cases from the case base was effective with a high similarity value.

4. **Conclusion.** This study has developed an integration model for NLP and CBR, which is necessary to support the accreditation of study programs.

In the case retrieval process, similarity text measurement is used to find similarities between new and old cases. The JSD algorithm is used to measure the case similarity with a similarity result of 81.82% (EP1), 81.29% (EP2), and 81.62% (EP3). For each assessment element and its label, evaluating model uses Accuracy, Precision, Recall, and F1 parameters. The lowest accuracy value is 67% on EP3-Good, and the highest is 92% on EP1-Fair. The lowest precision value is 40% on EP1-Very Good, and the highest is 90% on EP2-Good. The lowest recall value is 33% on EP1-Very Good, and the highest is 83% on EP2-Very Good. The lowest F1 value is 36% on EP1-Very Good, and the highest is 80% on EP1-Good.

In future research, increasing the amount of data variations will improve performance in prediction labels.

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