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A Bi-LSTM Based Model to Identify Key Information from Political News in the 2024 Indonesian Election Event

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Abstract: Recognizing the Name Entities (NE) such as names, locations, and organizations in the context of election news plays a crucial role in understanding and analyzing political dynamics and public opinion. This study aims to improve the recognition of the entities contained in the text of 2024 Indonesia election news by using the Long Short-Term Memory (LSTM) especially Bidirectional LSTM (Bi-LSTM) algorithm. The proposed method utilizes the LSTM to automatically identify and extract name, location, and organization entities from election news texts. Through a series of experiments, this approach is evaluated in stages i.e. quantitatively and qualitatively. Furthermore, model evaluation using a confusion matrix provides a more detailed picture of the entity classification performance of the Bi-LSTM model. The application of the Bi-LSTM model is promising to be applied in developing such a system to determine the entities of people, locations, organizations, and those that are not included in the three entities in the 2024 Indonesia election news. By grouping NE class and non-NE class with the cross-validation data-splitting scheme, the model provides average precision value of 0.9280, average recall value of 0.9489, average F1 score of 0.9381, and average accuracy value of 0.9489 respectfully. Therefore, it can be convinced that the model achieves good performance in predicting entities in the 2024 Indonesia election news, despite still in predicting a specific entity it needs to be improved.
Keywords: 2024 Election News, Entity Recognition, LSTM, News Analysis, Text Processing.

1. Introduction

In the rapid technological growth era today, obtaining information is very easy. One way to obtain this information is through the internet [1]. The collection of information contained in online news is widespread and massive, one example being election news. Elections are a crucial moment in contemporary democracy that influences the country's political policies. The online news portals emerged along with the growth of an increasingly active audience in seeking information [2]. Therefore, it is crucial to have effective tools to identify and analyze key information contained in election news.

One of the main challenges in understanding election news is identifying important entities involved in the political process. This study focuses on recognizing entities in unstructured text such as people (PER), locations (LOC), and organizations (ORG) [3]. The news used came from detik.com from November 2023 to December 2023. A total of 751 election-related news texts were retrieved. From these news texts, words related to the entities in the election news were identified and tagged.

One of the appropriate techniques for identifying entities is Named Entity Recognition (NER), which is one of the tasks of Natural Language Processing (NLP). NER has proven effective in identifying and extracting text elements such as individual names, organizations, time, location, and so on[4]. In this study, NER is applied to identify entities in election news. Identification of election entities is the first step in analyzing and understanding the content of election news to facilitate information extraction from election news.

LSTM has proven to be a reliable technique for handling sequence data such as narrative sentences, including Indonesian sentences. Several publications that utilize it to solve NLP and NER problems are discussed in this section. Based on the results of a study published in [5], the authors compared the performance of LSTM, BI-LISTM, and GRU in classifying click bait news headlines. The authors stated that GRU provided poorer precision performance, at 96.63%. This figure is slightly below the precision of the LSTM and Bi-LSTM models, which achieved 97.75% and 97.44%, respectively. However, when it is considered to the other three metrics i.e accuracy, recall, and F1-score, the GRU algorithm shows the better performance. The LSTM with Self-Attention Gate to solve the Chinese NER problem is presented in[3]. Compared to the baseline model, the authors' proposed GCRA model provides the significant accuracy improvements of 1.72%, 1.5%, and 1.26% on the MSRA, Literature, and Resume datasets, respectively.

The challenging of NER problem solution of Bahasa Indonesia has also attracted the attention of several researchers, such as those published in [4], [6], [7]. In the study result published in[5], the authors conducted a study to solve the NER problem in Bahasa Indonesian using the Bi-Directional-LSTM CRF technique. The combination of techniques produced an accuracy of 87.77%. This accuracy was achieved using a parameter set with an epoch limit of 50 and a learning rate of 0.001. Meanwhile, in their study [6], the authors utilized the Indonesian chatbot dataset as experimental data for the application of the BI-LSTM technique. The experimental results show quite good accuracy, namely 86.81% with a learning rate of 0.1, 87.44% with a learning rate of 0.01, and 41.19% with a learning rate of 0.001.

In this study, we attempted to explore the Bi-Directional-LSTM (Bi-LSTM) technique applied to a political news dataset sourced from an online news site to identify NER. The research questions we examined in this study are:

1. How to develop an entity recognition system for election news?
2. How to handle uncertainty, ambiguity, and variation in entities that occur in election news, and ensure consistency and accuracy in the identification process?
3. How can the NER method using the LSTM algorithm be applied to entity recognition in election news?

The rest of this paper is presented as follow. Section two discusses the methodology and framework used in the study. The results and discussion of the experiment is presented in the section three, whereas the section four elaborates the conclusion and future works.

2. Method and Material

In the NER mining study, we adopt the Data Mining methodology as proposed [8] known as Knowledge Data Discovery (KDD) technique. The study stage follows the KDD is presented as figure 1. Each activites in the stages is presented in the following sub section.

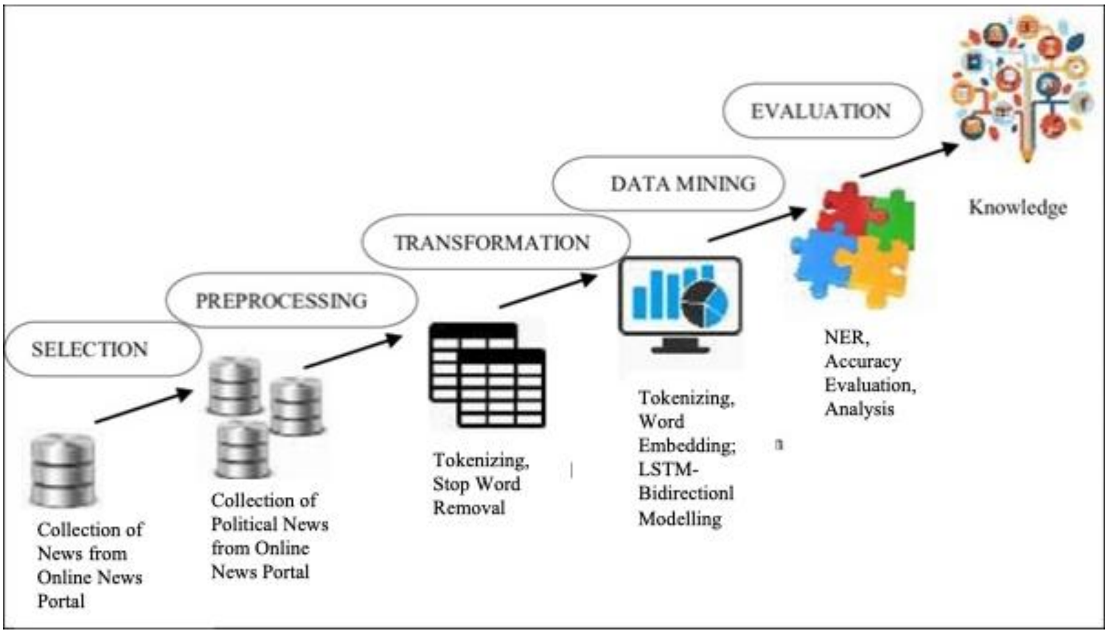

Figure 1: Research Stages

2.1 Dataset

The study data sources are obtained through open data by downloading datasets from existing research. The downloaded dataset consisted of election-related news from the online news site detik.com, specifically related to the 2024 elections. The obtained dataset was then tagged for each word to train the model for testing. The dataset was obtained through open data scraping from detik.com web pages. From the obtained news texts, words related to the election news entity were identified from the predetermined words and then tagged accordingly. There are three entity classes and single non-entity class used, as follow:

1. PER = Person Name Entity
   Examples: Anies Baswedan, Muhaimin, Prabowo, Gibran, Ganjar Mahfud.
2. LOC = Location Name Entity
   Examples: South Jakarta, Cirebon, West Java.
3. ORG = Organization Name Entity
   Examples: TKN (National Campaign Team), TPN (National Winning Team), KPU (General Election Commission).
4. O = For entities outside PER, LOC, and ORG.

2.2 Data Preprocessing

At this stage, a series of crucial initial steps are carried out to ensure that the data used in analysis and model building is of high quality and consistency. The data preprocessing involves several important steps designed to clean, convert, and prepare the data for use in machine learning model.

2.2.1 Data Cleaning

The collected data will undergo a series of preprocessing steps. These steps include removing unused columns, removing punctuation, and converting words to capital letters.

2.2.2 Tagging

The predetermined data is then tagged according to the entities in the election news, as follows:

1. PER for the person's name entity
2. LOC for the location name entity
3. ORG for the organization name entity
4. Outside (O) to mark words that do not belong to any entity.

In the text, each word is assigned a label that corresponds to its entity, or an "O" label if the word does not belong to any entity. This process ensures that each word in the text is annotated with relevant entity information for use in subsequent analysis. This allows each entity in the text to be better identified and analyzed, enabling the use of appropriate machine learning models for entity recognition.

Those 4 tagging is then used as the label (target) of the input data; thus the output LSTM model is the predicted label of each word consumed by the model.

2.3 Bi-LSTM Modeling

LSTM and Bi-LSTM models are implemented to sequentially process these word sequences one by one and store information about the context of previous words in their long-term memory. Machine learning models such as LSTM (Long Short-Term Memory) and Bi-LSTM (Bidirectional Long Short-Term Memory) are often used in known entity recognition (NER) tasks due to their ability to identify long-term dependencies in text data.

The LSTM model is based on the RNN *(Recurrent Neural Network*). An LSTM network is the derivative of RNN which also is formed by 3 layers, that is, an input layer, a single recurrent hidden layer, and an output layer. The specific innovation of LSTM is that there are one or more memory blocks in its hidden layer. Each block of memory contains one or more memory cells. In the standard form, the inputs are connected to all the cells and gates, whereas the cells are connected to the outputs. The gates are connected to other gates and cells in the hidden layer. The single standard LSTM is a hidden layer with input, memory cell, and output gates[9].

Bi-LSTM is a kind of deep learning algorithms which can deliver better performance and faster computation times than machine learning algorithms. Bi-LSTM exploits preceding and following context by processing information from both directions using separate hidden layers. Bi-LSTMs connect two opposing hidden layers to a single output [10]. The advantage of Bi- LSTMs is their ability to capture richer context from text, as information from both directions can be combined. It makes Bi-LSTM more effective in text understanding and tasks such as sentiment analysis, where the context before and after a word or phrase can influence its meaning. The main architecture of Bi-LSTM layer is presented as figure 2. As depicted in Figure 2, Bi-LSTM processes data in two directions. Bi-LSTM utilizes both previous and subsequent context by processing data in both directions with separate hidden layers [11]

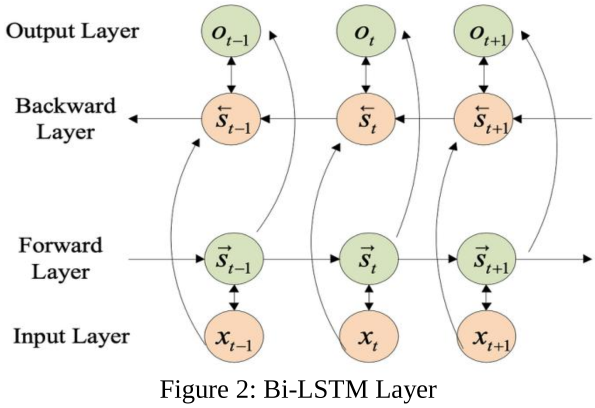

Figure 2: Bi-LSTM Layer

2.4 Model Training and Optimization

Bi-LSTM models are trained using deep learning techniques using the Sparse Categorical Cross-entropy loss function. This function is used for multi-class classification where labels are stored as integers. To prevent over fitting, dropout is applied to certain layers. Model parameters are also optimized with a customized learning rate.

2.5 Model Evaluation

Model evaluation is performed after training the Bi-LSTMNER model. One evaluation method commonly used in classification is the Confusion Matrix. The Confusion Matrix provides a clear overview of model performance by showing the number of correct and incorrect predictions for each class. In the context of NER, we are interested in evaluating the model's ability to recognize entities such as Person, Organization, and Location in election news texts. This evaluation was conducted on a previously separated test dataset to ensure that the evaluation results are a valid representation of the model's performance. To split the dataset into data training and data testing we used the cross-validation scheme since it is assumed the cross validation is more representative compared to random splitting[12]. Cross-validation is a validation technique that divides the data into several subsets, or folds. Each fold is used in turn as a validation dataset, while the remaining folds are used for model training. Accuracy parameter is then used as the performance evaluation criteria in the first step of modelling, whereas in the second step we also evaluate model by using the confusion matrix to compute the model accuracy parameters, i.e., *precision, recall, f1-score, and accuracy*. The Accuracy computation is presented as formula (1) [13].

$$Accuracy = \frac{TP+TN}{TP+FP+FN+TN} \quad (1)$$

Where:

TP : True Positive
TN : True Negative
FP : False Positive
FN : False Negative

2.6 Quantitative Analysis

In the quantitative analysis, the results from the Bi-LSTM model were used. The Confusion Matrix provides a visual representation of model performance by showing how many entities and non-entity thatl correctly and incorrectly classified by the model. This helps understand how well the model can recognize entities such as Individual, Organization, Location, and non-entities in election news texts. Furthermore, this analysis allows for identifying potential improvements or enhancements to the model.

3. Results and Discussion

In this section we present the results of each stage have been conducted as presented in section 2.

3.1. Data Preparation

This stage involves a series of initial steps involving dataset selection and processing. This data preparation aims to ensure the quality and consistency of the data that will be used in further processing. The steps taken at this stage include dataset selection, collection, cleaning, and tagging.

3.1.1. Data Collection

The first step in data preparation is careful data collection. The data required for this study involves news texts related to the 2024 election, covering numerous entities related to political figures, locations, and organizations. The data was obtained through Kaggle open data, which collected 751 news texts from the official detik.com website between November 2023 and December 2023. These texts were then tagged for keywords related to the election.

3.1.2. Data Preprocessing

This stage involves data preparation before proceeding to the analysis and model building stages. Data preprocessing is crucial to ensure the quality and consistency of the data used in further analysis. Table 1 presented the sample of raw data and the cleaning data. The initial data obtained consists of news text and tags in the form of predetermined words. This data is then cleaned by removing punctuation from the tag column. The next step is to select the 'tag' column, which will be converted to a 'word' column. A new column named 'tag' will be created to provide tagging for the entities contained in the 'word' column. Meanwhile, table 2 presents the results after selection and cleaning for the next process.

Table 1: The sample of data cleaning result

author	*publish_date*	*article_text (In Bahasa Indonesia)*	*tag*
Detik News	2023-12-10 23:31:00+07:00	Sekjen PDIP sekaligus Sekretaris Tim Pemenang Nasional (TPN) Ganjar Pranowo-Mahfud MD, Hasto Kristiyanto, ingin debat calon presiden dan calon wakil presiden saling *(The Secretary General of PDIP and Secretary of the National Winning Team (TPN) Ganjar Pranowo-Mahfud MD, Hasto Kristiyanto, wants the presidential and vice presidential candidates to debate each other.)*	['hasto kristiyanto', 'hasto', 'sekjen pdip', 'tpn ganjar-mahfud', 'pemilu', 'politik']
Detik News	2023-12-10 23:09:00+07:00	Mantan Ketua Umum Pengurus Besar Nahdlatul Ulama (PBNU) Said Aqil Siradj mengungkapkan tidak mendukung salah satu pasangan calon di Pilpres 2024. Ia menegaskan… *(Former Chairman of the Nahdlatul Ulama Executive Board (PBNU) Said Aqil Siradj revealed that he does not support any of the candidate pairs in the 2024 Presidential Election. He emphasized tha ....t)*	['said aqil siradj', 'gibran rakabuming', 'pemilu', 'pilpres', 'politik']
…	….	….	….

Table 2: The sample of processed data

word	*tag*
hasto kristiyanto hasto sekjen pdip tpn ganjar mahfud pemilu politik	PER PER PER O ORG ORG PER PER O O
surat pernyataan kpps pemilu pendaftaran kpps pemilu kpps pemilu kpps pemilu kpu	O O ORG O O ORG O ORG O ORG O ORG
pengamanan nataru sumut polda sumut	O O LOC ORG LOC
tkn prabowo subianto	ORG PER PER
tkn prabowo gibran dudung abdurachman	ORG PER PER PER PER

3.1.3. Data Transformation

The final stage of data preparation process is to transform the text data into numerical data so it can be processed by LSTM model. We use the TF-IDF word embedding to represents the final data form. Some important steps in this process include text tokenization, label encoding, and sequence padding to ensure they are of equal length. To ensure that the text data and labels are prepared in a uniform format and that machine learning algorithms can process them, these steps are necessary. Text tokenization is performed to convert text into a sequence of numbers, each number represent a distinct word in the corpus. Text padding is the padding addition to the sequence of numbers so that all sequences have the same length. Label encoding is used to convert the category labels (tag) into numerical format. Label padding is performed to add padding to the encoded labels to match the length of the text sequences. After all data preprocessing stages conducted, the quantity of instant data in the dataset is 751.

3.2. LSTM Modelling

The modelling phase consists of two main activities i.e., model training and model validation. We utilize the Tensor Flow – Python library to build the Bi-LSTM Model. The architecture of the Bi-LSTM Model is depicted as figure 3, whereas the list of parameters is presented in table 3. The brief explanation of figure3 as follow: first the model will receive input with a maximum length of 50 tokens **input: (None, 50)** and will get the same output, **output: (None, 50)**, then it is forwarded to the embedding layer where each token becomes a vector measuring 300 dimensions **output: (None, 50, 300)**.The two-dimension vector is then forwarded to the Bi- LSTM layer where the sequence will be processed and produce a 64-dimensional output for each token in the **output sequence: (None, 50, 64)** which is passed to the dropout layer of 0.5. Finally, the Dense layer function is used to activate Soft Max which provide output to 4 classes, one for each tagging-token in the sequence, as described in sub section 2.2.2 Tagging.

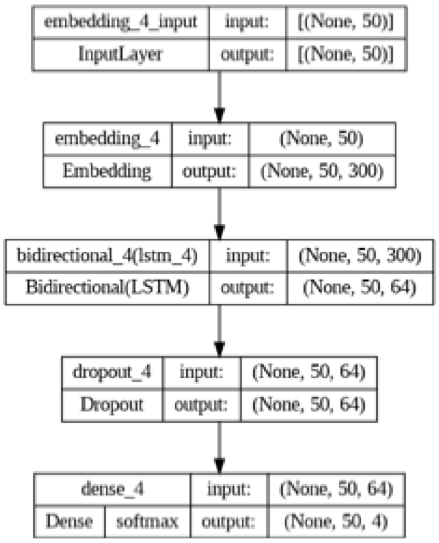

Figure 3: The Bi-LSTM architecture

Table 3: Bi-LSTM parameters

Parameter	*Nilai*
embedding_dim	len(tokenizer.word_index) + 1
units	300
dropout_rate	32
l2_reg	0.5
num_classes	0.01
max_seq_length	len(label_encoder.classes_)
n_folds	max_seq_length
epochs	50
batch_size	64
optimizer	Adam
loss	sparse_categorical_crossentropy
metrics	['accuracy']
shuffle	TRUE
random_state	42

3.3. Model Evaluation

To evaluate the model, we used training-validation scenario utilized the cross-validation dataset splitting scheme. First model evaluation is the quantity performance measurement using the confusion matrix. To perform the confusion matrix, we grouped the label into 2 general classes i.e., positive class that represent the targeted entities ('PER', 'OR', 'LOC') and the negative class which represents non-entity ('O'). After training and validation phase by using the 5-fold cross validation, the confusion matrix with each cell value is the average results is presented as figure 4.

		ACTUAL	
		P	N
PREDICTED	P	116,58	168,09
	N	9,04	6,28

Figure 4: The confusion matrix of the grouped entities class

Based on the confusion matrix, the model performance measurement values are *precision = 0,928, recall=0,9489, f1-score=0,9381*, and *accuracy = 0,9489* respectively. These parameters value shows that the Bi-LSTM proposed performed is promising to be future exploration.

Further investigation is performed to evaluate the model performance in predicting the specific entities. Some of the investigation results is presented as table 4. Based on the results partially showing in table5, it can be summarized some points as follow. 1. Errors in Organization class, the model face difficulty in recognizing the 'ORG' (organization) entity, often it is classified as 'O' or 'LOC', 2. Easier to predict the location class, the model performance is better in identifying the 'LOC' (location) entity, but still makes errors in some instances, 3. Errors in person name, the model in general successfully recognizes the person's name as 'PER', despiteit still make errors when there is ambiguity in the context, and 4. Label confusion, thereare errors in the predicted label mapping, particularly for the 'ORG' class. It indicates the need for improvements in model training or more representative data for this entity.

Table 4: Sample of the comparison between actual and predicted label

Text	*Actual label*	*Predicted*
['zulkifli', 'hasan', 'jokowi', 'kapan', 'labuan', 'bajo']	['PER', 'PER', 'PER', 'O', 'LOC', 'LOC']	['PER', 'PER', 'PER', 'LOC', 'LOC']
['transjakarta', 'bawaslu', 'dki', 'jakarta', 'jabodetabek', 'pemilu', 'vandalisme']	['O', 'ORG', 'LOC', 'LOC', 'LOC', 'O', 'O']	['O', 'O', 'LOC', 'LOC', 'LOC', 'LOC']
['ganjar', 'pranowo', 'ganjar', 'kalimantan', 'timur']	['O', 'O', 'ORG', 'LOC', 'LOC']	['PER', 'PER', 'O', 'LOC', 'LOC']
['bamsoet']	['ORG']	['LOC']
['pemilu', '2024', 'polper', 'jogja', 'jogja']	['PER', 'PER', 'O', 'LOC', 'LOC']	['O', 'O, 'LOC', 'LOC', 'LOC']
['ganjar', 'pranowo', 'ganjar', 'kalimantan', 'timur']	['O', 'O', 'LOC', 'ORG', 'LOC']	['O', 'O, 'LOC', 'LOC', 'LOC']

4. Conclusion and Future Work

The study proposed the Bi-LSTM model development that is capable to automatically identify entities contained election news. Yet the model shows the advantage and drawback as well. The model provides impressive performance in predicting Location class, by resuling the high accuracy and recall values as the proving that the model's ability to recognize location entities ('LOC').The model generally can understand person names ('PER'). However, the error is still occurred when it faced to the ambiguous context or when the same name appears repeatedly in the text. The first drawback still left is that the model struggles to identify organization entities. It is often that the entity 'ORG' is classified as 'O' or 'LOC'. The second deficiency observed was the errors in label mapping. There were errors in the predicted label mapping, especially for the 'ORG' class. This indicates that the model needs further improvement to handle more difficult class prediction errors. The evaluation results using cross-validation show that the model performs well for overall. The average precision value was 0.928, the average recall value was 0.949, the average F1-score was 0.938, and the average accuracy value was 0.949. However, the similarity between the recall and accuracy values indicates that the model may have bias in its predictions toward certain classes.

In the future work we will explore some scenario to overcome those drawbacks. Some scenarios potentially to be investigated such as to utilize the data augmentation to increase the data training volume and variation, especially for organizational entities ('ORG'). We will also elaborate any other model architectures, such as transformer-based models (e.g., BERT) for NER tasks. Further hyper parameter tuning to find a more optimal model configuration is also promising to be studied. The other scenario is improving the data cleaning and tagging to ensure that training data is accurately and cleanly tagged to reduce noise and to improve model training quality.

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Ozzi Ardhiyanto is an undergraduate student in Informatics at Universitas Bhayangkara Jakarta Raya, specializing in Data Science. He has hands-on experience working on personal projects using PHP, Java, Python, MySQL, Flutter, and Laravel. He is passionate about software development, data science, and building practical applications that solve real-world problems. Throughout his studies, he has developed projects ranging from an entity recognition system for election news using Python and LSTM, to a mobile catalog app built with Flutter and Laravel, and a relational school database using Oracle. He is adaptable, a quick learner, and able to work well independently or in a team. He is keen to grow his skills in AI, machine learning, and backend development.