ISSN 2460-9056
http://socj.telkomuniversity.ac.id/ijoict/
Intl. Journal on ICT
Vol. 9, No. 1, Jun 2023. pp. 73-85
doi: /doi.org/10.21108/ijoict.v9i1.756

Sentiment Analysis of Tourist Attraction Review from TripAdvisor Using CNN and LSTM

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Abstract

The tourism sector has an important role in driving the economy. In order to identify the positive or negative tourists, one way is to group them using deep learning sentiment analysis. The data used the tourist attraction dataset from TripAdvisor from several categories such as water and amusement park, nature, and museum. The methods used in this research are convolutional neural network (CNN) and long short-term memory (LSTM). In addition, Word2vec for feature extraction and Synthetic Minority Over-sampling (SMOTE) for handling imbalanced datasets will be used for this research. There are several scenarios used to perform sentiment analysis, with original train data, with SMOTE train data, and with hyperparameter tuning. The use of SMOTE and hyperparameter tuning on train data improves model performance on some categories of data. The highest performance obtained on water and amusement park, nature, and museum category data is 94%, 93%, and 94% respectively for F1-score, 62%, 65%, and 60% respectively for macro F1-score.

Keywords: Sentiment Analysis, Tourist Attraction, Deep Learning, CNN, LSTM.

I. INTRODUCTION

Tourism is one of the sectors that is being developed by the government because it is considered to have a very important role in development in Indonesia as an economic engine that can reduce unemployment, especially people who live in tourism areas [1]. In 2019, the tourism industry directly contributed 4.8 percent of GDP [2]. The increase in the use of social media occurs very rapidly from day to day which makes social media a very important source of information. At this time, social media is used to express opinions that occur currently. One of the popular social media that is a source of tourist reviews is TripAdvisor [3], [4]. Based on the data on TripAdvisor, water and amusement park, nature, and museum are the most popular categories in Indonesia.

Due to the high number of visits, there are both positive and negative responses from tourists. The way to see whether the response is positive or negative is to categorize the response. In categorizing responses, sentiment analysis is the right thing to do.

Sentiment analysis research related to tourist attractions has been done before [4]–[7]. For research using deep learning, Risca Naquitasia et al [6] conducted sentiment analysis of halal tourism with the methods used CNN and CNN-BiLSTM. The accuracy results obtained when classifying with CNN are 93.9% better than CNN-BiLSTM for accuracy of 93.4%. Jovita Nurvania et al [3] conducted sentiment analysis on TripAdvisor

Received on 07 Jul 2023. Revised on 12 Jul 2023. Accepted and Published on 18 July 2023.

which contains questions from foreign tourists who will visit the island of Bali but are hindered by the COVID-19 pandemic. The analysis method used is LSTM. The accuracy results provide accuracy, precision, and recall of 71.67%, 72.97%, 95.3%, 82.7%. Af'idah et al [7] conducted sentiment analysis on Tripadvisor which contains questions from foreign tourists who will visit the island of Bali but are hindered by the COVID-19 pandemic. The analysis method used is LSTM. The accuracy results provide accuracy, precision, and recall of 71.67%, 72.97%, 95.3%, and 82.7% when using preprocessing and undersampling.

Based on the results of the study, the method used only performs sentiment analysis using one type of tourist attraction data generically so it cannot compare methods optimally. In this research, sentiment analysis will be carried out using tourist attraction dataset in Indonesia which has several categories, namely water and amusement parks, nature, and museum. The method used in this research is deep learning. In previous studies, deep learning methods were considered effective in conducting sentiment analysis before. The deep learning methods used are CNN and LSTM. Then, the two methods used are compared with the metric measurement method.

II. LITERATURE REVIEW

Research on tourist attraction analysis has been done before. Research on sentiment analysis of tourist attraction reviews has been carried out by Ahmad Rifa'I et al in [5] using tourist attraction data in West Kalimantan on google maps. Labels on the data consist of positive and negative. The method used in sentiment analysis is Naive Bayes whose test evaluation uses a confusion matrix of tourist attractions in West Kalimantan. The highest and lowest accuracy performance generated was 76% and 38%. This proves that testing on different data is highly influential in determining the performance of the model.

For research on tourist objects on TripAdvisor, other research has been conducted by Arifiyanti et al [4] using data reviews of Mount Bromo attractions on Tripadvisor. The feature extraction method used is TF-IDF. The classification methods used in this study are naïve bayes, decision tree, and logistic regression. Decision tree outperforms each method in performing sentiment analysis. The accuracy results obtained during testing on naïve bayes, decision tree, and logistic regression were 88%, 91%, and 88% respectively. Another study using TripAdvisor data was conducted by Siti Khomsah [8] using hotel review data. The use of labels with a rating of 1-3 is negative and a rating of 4-5 is positive. Observations showed that there were many negative words in rating 3. The study gave the highest accuracy of 93% in the use of Random Forrest and Extra Tree.

Sentiment analysis research related to tourist attractions has been done before with LSTM and CNN. Risca Naquitasia et al [6] conducted sentiment analysis of halal tourism. The methods used are CNN and CNN-BiLSTM. The results obtained when performing classification with an accuracy of 93.9% for CNN and 93.4% for CNN-BiLSTM. Jovita Nurvania et al [3] conducted sentiment analysis on Tripadvisor which contains questions from foreign tourists who will visit the island of Bali but are hindered by the COVID-19 pandemic. The analysis method used is LSTM. The accuracy result when using only data preprocessing of 65% is better than using only undersampling of 61%. However, combining preprocessing and undersampling gave the highest result 71%. This proves that preprocessing and undersampling provide good results.

Af'idah et al [7] conducted sentiment analysis on tourist attractions in Bali. The method compared word2vec models from architecture, evaluation method, and dimension. The word2vec architectures used were CBOW and Skip-gram. The word2vec evaluation method consists of hierarchical softmax and negative sampling. There are three dimensions compared, namely 100, 200, and 300. The classification method used is LSTM-CNN. The experimental results obtained for the architecture comparison obtained an accuracy result of 96.76% for skip-gram and 96.73% for CBOW. For the dimension of word2vec, it is concluded that the larger the dimension size is not always good. This is because the features become complex which usually leads to overfitting. Dimension sizes of 100, 200, 300 have an accuracy of 96.90%, 96.77%, and 96.57% respectively.

A. Sentiment Analysis

Sentiment analysis is a research topic derived from text mining research that is used to analyze public opinion [8]. Sentiment analysis is a method for analyzing opinions, sentiments, evaluations, judgments about some specific objects such as services, products, or events that are determined whether they are positive or negative [9].

B. *TripAdvisor*

TripAdvisor is a platform characterized by user-generated content for price comparison of booking recommendations for transportation, accommodation, restaurants, and others. The most highlighted thing about TripAdvisor is the responses or comments given by travelers to the service experiences and places they visit where other travelers can read the comments to consider making decisions [10]. The comments given have five rating categories that have a value from 1 to 5.

C. *Convolution Neural Network*

Convolutional Neural Network (CNN) is a deep learning method used to process multi-dimensional data. CNN consists of a series of layers that can transform a volume into a smaller volume. Usually, this method is used for image classification and for now based on related research that has been discussed, many use CNN to conduct sentiment analysis [6]. The architecture of the CNN method is convolutional layer, pooling layer, and fully connected layer [11]. In sentiment analysis, Input is converted to embedded vector by embedding layer. Convolution layer is a layer used to perform the convolution process used to extract features in the input. After that, it will be forwarded to the pooling layer which aims to reduce the dimensions of the features that can speed up computation. Finally, the data will be flattened which changes the results in the polling layer into one column and forwarded to the fully connected layer for sentiment classification. An illustration of the CNN architecture is shown in Fig. 1.

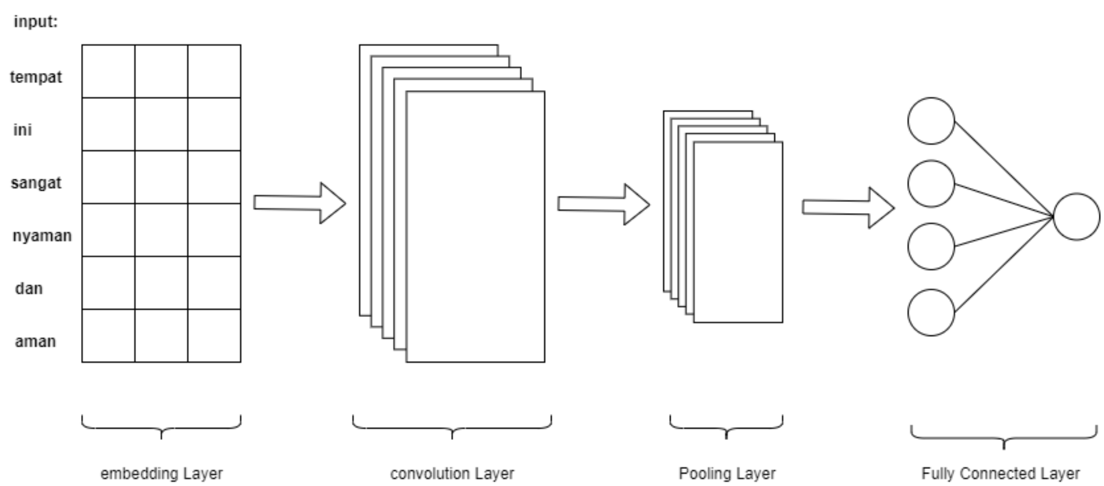

Fig. 1 CNN Architecture Illustration

D. *Long Short-Term Memory*

Long short-term memory (LSTM) is an improved algorithm model of Recurrent Neural Network (RNN). LSTM performance can produce more capabilities than RNN because it can remember information over a long period of time [7]. The LSTM method consists of three parts, namely forget gates, input gates, output gates, and cell state [3]. Input gates are used to receive new information that is added to the cell state. Forget gates are used to delete information that is no longer needed. Output gates are used to retrieve information in the cell state as output.

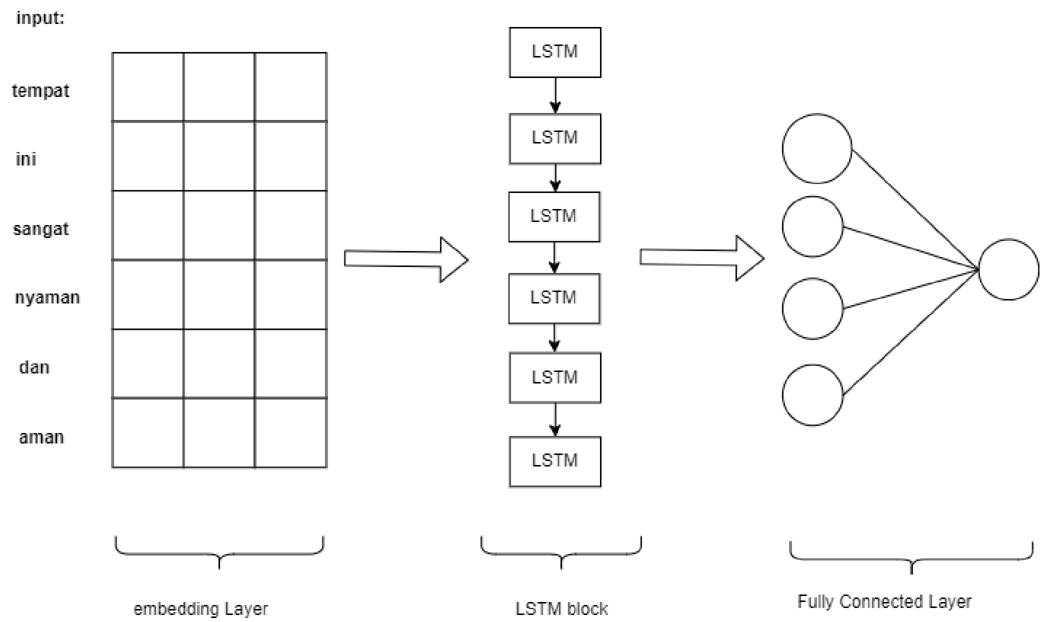

Fig. 2 LSTM Architecture Illustration

In the LSTM architecture illustration in Fig. 2 shows the process by which sentiment analysis is performed. First, Input is converted to embedded vector by embedding layer. The result of the embedding vector is then processed into LSTM blocks. It is then passed to the fully connected layer for sentiment classification.

E. Synthetic Minority Over-sampling (SMOTE)

SMOTE is an oversampling technique used to balance a data set. This approach works by including a synthetic sample in the minority class. However, SMOTE does not perform oversampling based on direct sample copies. Instead, some additional examples are created outside of the original dataset to prevent overfitting, which is an advantage of this algorithm [12].

F. Word2Vec

Word2vec is a method widely used technique for word embedding. This approach offers an arrangement based on syntactic equivalency as well as the syntactic interpretation of words. This method places related words closer together in the vector space while placing unrelated words farther apart. Word2Vec converts words into vectors by using neural networks. A vector space is produced once the text has been provided as an input [7].

G. Metric Measurement

The metric measurement that will be used is confusion matrix which contains 4 categories: True Positive (TP), True Negative (TN), False Positive (FP), and False Negative (FP). Then the precision, recall, F1-Score and macro F1-Score will also be seen with the following calculations.

1) Precision

Precision is the proportion of True Positive (TP) out of the total number of predict positive.

$$Precision = \frac{TP}{TP + FP} \tag{1}$$

2) Recall

Recall is the proportion of True Positive (TP) out of the total number of actual positive.

$$Recall = \frac{TP}{TP + FN} \tag{2}$$

3) F1-score

F1-score is the harmonic average of precision and recall.

$$F1 - Score = \frac{2 * Precision * Recall}{Precision + Recall} \tag{3}$$

4) Macro F1-score

Macro average is average of performance in classes model. Macro F1-score is used to see the average F1-score performance of each class, so that classes can be treated equally.

$$Macro\ F1 - Score = \frac{\sum_{i=1}^{n} F1 - Score_i}{n} \tag{4}$$

III. RESEARCH METHOD

Figure 3 is a flowchart of system design to conduct sentiment analysis research. There are 6 main processes performed, including data crawling, data preprocessing, feature extraction, data splitting, over sampling and evaluation.

A. Data Crawling and Labelling

The data collection process is carried out by taking data on Tripadvisor which contains reviews of tourist attractions in Indonesia with the categories of water and amusement parks, nature, and museum. The dataset consists of text reviews and ratings. The rating on the dataset is 1-5. In crawling data, it will be done using the beautifulsoup library in python. Then the label will be given positive if the rating is 4 - 5 and negative if the rating is 1 - 3. Ratings of 3 are labelled as negative because there are many negative words in the text review [13]. The amount of data obtained is as follows in table I.

TABLE I
RESULT OF DATA CRAWLING AND LABELLING

Data Category	**Sentiment**		**Total**
	Positive	**Negative**	
Water and amusement park	11975	1543	13966
Nature	9624	1325	10949
Museum	3463	340	3803

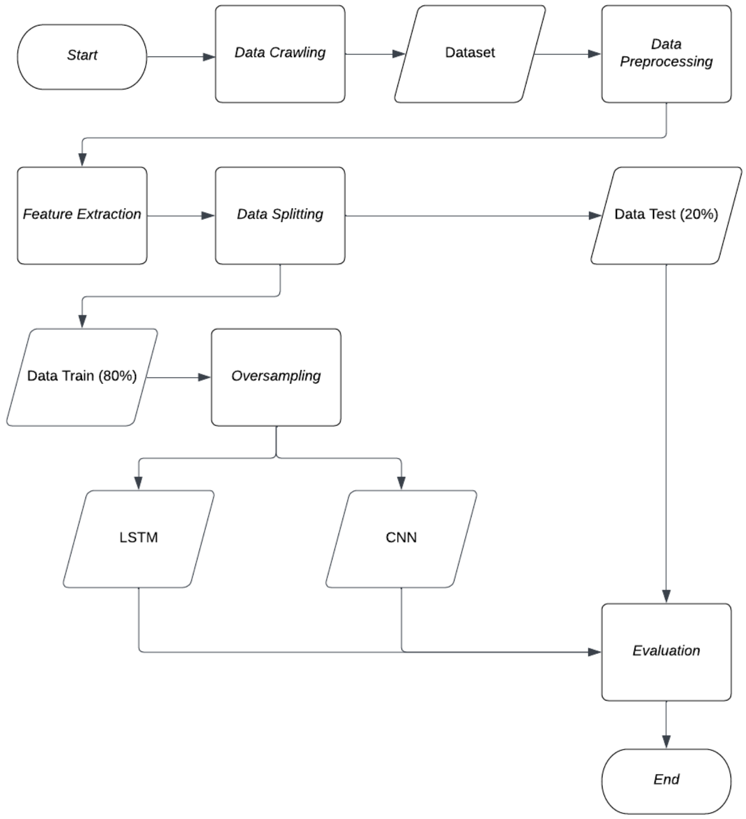

Fig. 3 System Design

B. *Data Crawling and Labelling*

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C. Data Pre-processing

The data collected will be pre-processed to transform the raw data into data that is ready for use. The steps in data preprocessing are as follows.

1) Lower Casing

Lower casing aims to convert all uppercase letters into lowercase letters. The purpose of lower casing is so that all words are equivalent from a combination of uppercase and lowercase letters.

2) Cleansing Data

Cleansing data aims to delete data that is not needed. deleted data in the form of url, tag, email, date, emoji, punctuation, number, stopword, and whitespace.

3) Tokenization

The tokenization process is used to break the sentence into words. Each word contained in the sentence is separated by a space.

4) Remove Stopword

In sentiment sentiment analysis, stopwords have no meaning and information in performing sentiment analysis so they must be removed. The stopword dictionary used in this research is the Indonesian-language corpus in NLTK version 3.8.1.

5) Normalization

Normalization is the process of converting nonstandard words into standard words. Changing standard and non-standard words uses a normalization dictionary. The normalization dictionary used in this reseach provided by Adytyo from his Github [14].

6) Stemming

Stemming aims to remove affixes and suffixes from words and turn them into a root words. The stemming process used in this research is the Python library. The stemming library used in this research is Sastrawi version 1.0.1.

D. Feature Extraction

Data in the form of text will not be used in training and testing models. Therefore, the text will be extracted into a feature that can be used. For feature extraction, word2vec will be used. Based on research [7], word2vec model that will be used is skip-gram. The skip-gram method has the advantage of overcoming rare words [8]. The way skip gram works is between the context word and the target word. Context word is the main word in the sentence while the target word is the word around the context word. There is a parameter used to determine the number of target words before and after the context word called window size [13]. The dimension used is 200 [7].

E. Splitting and Oversampling Dataset

The dataset will be divided into 2 parts, namely 20% training data and 80% test data. Training data is used as training for the model created. Training data will combine every category of training dataset such as water and amusement park, nature, and museum. Test data is used as an evaluation result of the model that has been trained. Oversampling is a sampling technique by adding data that is useful for balancing classes. The oversampling algorithm to be used is the Synthetic Minority Oversampling Technique (SMOTE). SMOTE does not perform oversampling based on direct sample copies. Instead, some additional examples are created outside of the original dataset to prevent overfitting [12]. SMOTE used to balance class in train data. The resulting amount of data after splitting and oversampling is as follows in Table 2.

TABLE II
RESULT SPLITTING DATASET AND OVERSAMPLING TRAINING DATA

Testing Data	Training		Testing
	Without SMOTE	With SMOTE	
Water and amusement park	22,973	40,096	2,794
Nature			2,190
Museum			761

F. Model for Sentiment Analysis

The architecture of the models used are CNN and LSTM as shown in Figure 1 and Figure 2. Each model will be used early stopping will be used. Early stopping is a strategy used to avoid overfitting the model by monitoring a training and validation performance [15]. In this experiment, the accuracy will be monitored. Patience is a value that the model tolerates if there is no consecutive improvement. The patience value used in early stopping is 7.

In this process, hyperparameter tuning with random search will be performed as scenario to optimize model. The random search algorithm is an alternative to grid search, which tests every combination of hyperparameters. The random search algorithm selects and tests random combinations of hyperparameters, which requires less time and calculation to get results [16]. For CNN and LSTM architecture consists of several layers that will be done hyperparameter tuning. In the CNN architecture, the hyperparameter tuning settings used are as follows.

1) Convolution1D: the filter used is at least 32-64 with 16 each interval. Kernel size used is from 3-5.
2) MaxPooling1D: the size used is 2-5.
3) Fully Connected: the units used are 32-128.

In the LSTM architecture, the hyperparameter tuning settings used are as follows.

4) LSTM block: for units used 10-260 with 40 at each interval.
5) Fully Connected: the units used are 32 to 128.

G. Evaluation

Evaluation of the model will be seen in the method with early stopping and with hyperparameter tuning. The results of the performance are accuracy, recall, precision, and f1-score. The use of performance metric evaluation results will be shown in a table.

IV. RESULTS AND DISCUSSION

In this research, the data obtained during the data crawling process on TripAdvisor with the categories of water and amusement park, nature and museum amounted to 22,973 data. After obtaining the data, labelling is done to determine the sentiment class with positive and negative labels. The data set is then divided into 80%

for train data and 20% for test data. The training data consists of the combinations of several training data categories, namely water and amusement park, nature, and museum. In this experiment, the use of SMOTE increased the training data from 22,973 data to 40,096 data. The test data in each data category are 2,794 data for water and amusement park, 761 data for nature and 2190 data for museum. In the experimental phase, three scenarios are used, with the original training data, with data oversampled using SMOTE, and with hyperparameter tuning.

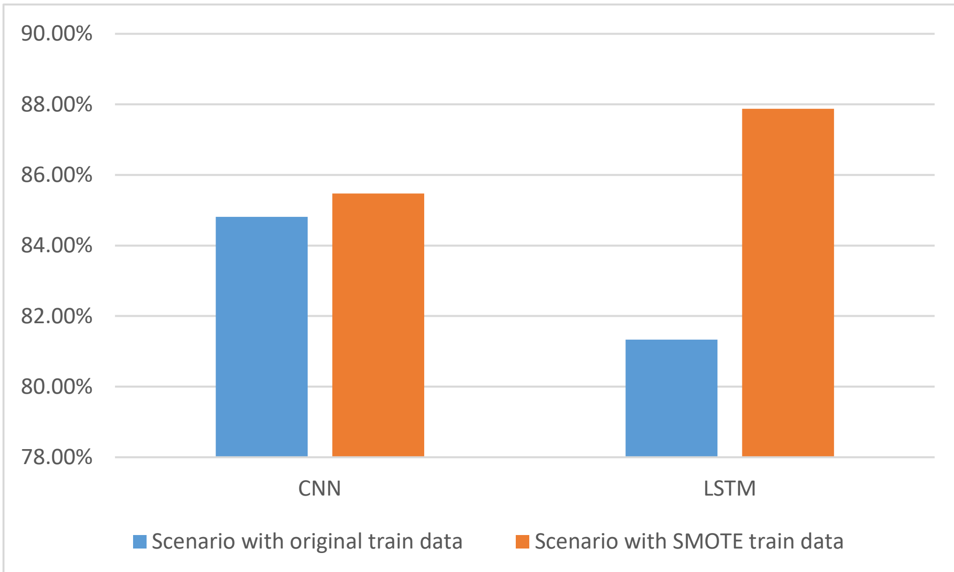

Fig. 4 Accuracy Validation Result in Training Model

In the model training in Fig. 4, it can be seen that the use of SMOTE in the scenario can improve the performance of the model. The use of SMOTE on the CNN model can have a 0.66% increase in validation accuracy, while the use of SMOTE on the LSTM model can have a 6.55% increase in accuracy. Using SMOTE on the LSTM has a greater performance improvement effect than on the CNN.

TABLE III
RESULTS WITH ORIGINAL TRAIN DATA EXPERIMENT USING TEST DATA

Testing Data	Precision		Recall		F1-score		Macro F1-score	
	CNN	LSTM	CNN	LSTM	CNN	LSTM	CNN	LSTM
Water and amusement park	88%	**89%**	**95%**	89%	**92%**	89%	**62%**	51%
Nature	**91%**	89%	**95%**	89%	**93%**	89%	**64%**	63%
Museum	**92%**	91%	**95%**	90%	**94%**	91%	57%	**61%**

In the model evaluation results in Table III, LSTM has a good performance in precision on water and amusement park data. However, the average performance of using CNN has better performance than LSTM in precision, recall, F1-score and macro F1-score in test data categories. Thus, in the evaluation of the resulting model, the performance of using CNN is better than that of using LSTM. In terms of macro f1-score, the results obtained range from 57% to 64%, which can be considered average.

TABLE IV
RESULTS WITH SMOTE TRAIN DATA EXPERIMENT USING TEST DATA

Testing Data	**Precision**		**Recall**		**F1-score**		**Macro F1-score**	
	CNN	**LSTM**	**CNN**	**LSTM**	**CNN**	**LSTM**	**CNN**	**LSTM**
Water and amusement park	**93%**	88%	**90%**	**90%**	**92%**	89%	**59%**	56%
Nature	**92%**	91%	88%	**91%**	**90%**	91%	**65%**	64%
Museum	89%	**92%**	87%	**92%**	**88%**	92%	**60%**	**60%**

In the model evaluation results in Table IV, when using SMOTE on train data, the use of CNN has a good average performance in terms of precision, F1 score, and macro f1-score. However, the use of LSTM has a good average recall. It can be seen that the use of CNN with SMOTE has improved performance as it has the highest f1-score and macro f1-score in all of data category. Therefore, in the next scenario, SMOTE will be used in hyperparameter tuning scenario with random search. After experimenting with SMOTE train data and hyperparameter tuning, the result of the confusion matrix is shown in Fig. 5.

TABLE V
RESULTS WITH SMOTE TRAIN DATA AND HYPERPARAMETER TUNING EXPERIMENT USING TEST DATA

Testing Data	**Precision**		**Recall**		**F1-score**		**Macro F1-score**	
	CNN	**LSTM**	**CNN**	**LSTM**	**CNN**	**LSTM**	**CNN**	**LSTM**
Water and amusement park	**92%**	87%	**97%**	95%	**94%**	91%	**60%**	56%
Nature	90%	**91%**	95%	**96%**	92%	**93%**	60%	**64%**
Museum	88%	**92%**	95%	**94%**	91%	**93%**	56%	**58%**

In the model evaluation results in Table V, when using hyperparameter tuning, CNN has a better performance in precision, recall, F1 score, and macro F1-score in the water and amusement park data category. However, LSTM has a better average performance than CNN in precision, recall, F1 score, and macro F1-score on test data categories. Result of this scenario, hyperparameter tuning can optimize the LSTM model in F1 score than without hyperparameter tuning in Table 4.

In the scenario performance using CNN in Fig. 5, it can be seen that CNN with SMOTE has increased the average macro F1-score performance model in each data category. In the performance scenario with LSTM in Figure 6, it can be seen that LSTM with SMOTE has significantly improved performance on F1-score and macro F1-score. It has been demonstrated that the use of SMOTE can improve the performance of the model. The use of CNN in hyperparameter tuning in Fig. 4 decreases macro f1-score. However, in Fig. 5, the use of LSTM can increase macro f1 score. From all the experiments, it can be seen that the use of LSTM has improved the performance in each scenario, rather than the use of CNN.

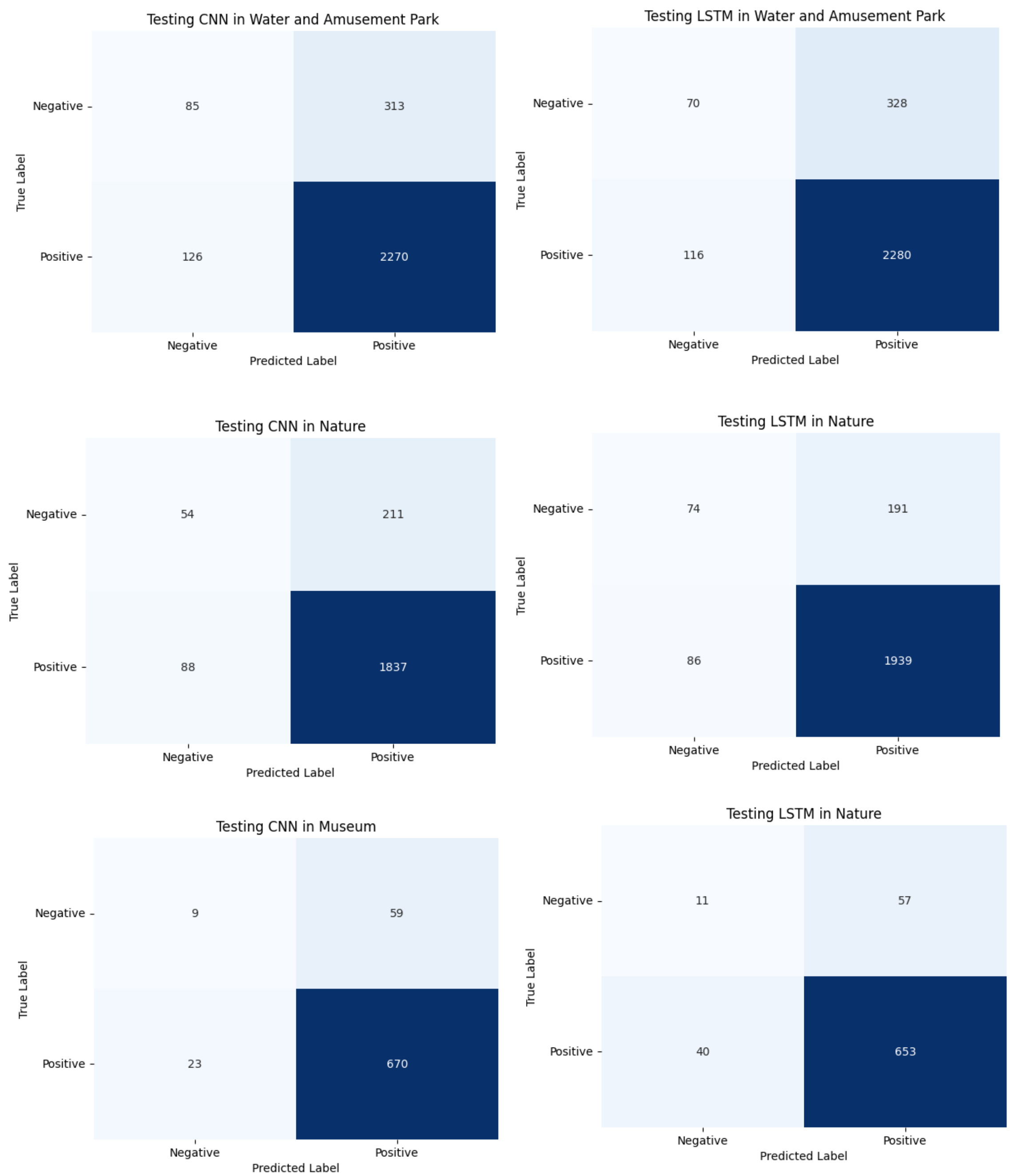

Fig. 5 Result of Confusion Matrix in SMOTE Training Data and Hyperparameter Tuning Experiment Using Test Data

V. CONCLUSION

In this research, sentiment analysis of tourism place data in Indonesia is carried out which consists of several categories, namely museum, nature tourism, and water parks and entertainment. The data used has three sentiments, namely positive and negative. The models used are CNN and LSTM. The use of LSTM and CNN is compared with 3 experiments, with original data train, with SMOTE data train, and with hyperparameter tuning. The results of using SMOTE in LSTM can improve the model performance results. On average, the use of SMOTE on CNN and LSTM can improve the performance of the model. The use of hyperparameter tuning in this scenario improves the performance of the LSTM model compared to the previous results scenario, but not for the CNN model. The highest performance results obtained are in water and amusement park, nature, and museum of 94%, 93%, and 94% respectively for F1-score, 62%, 65%, and 60% respectively for macro F1-score. In this research, the F1-score macro has a performance of 60%-65% which can be considered average so that improvement is still needed to get a better result.

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