Determining Intent: Sentiment Analysis Based on the Classification of Indonesian Tourist Destination Review Texts

Abulwafa Muhammad [1,*], Sarjon Defit [2], and Gunadi Widi Nurcahyo [2]

[1] Department of Informatics Technology, Doctoral Program of Informatics,
Universitas Putra Indonesia YPTK, Padang, Indonesia
[2] Doctoral Program of Informatics, Universitas Putra Indonesia YPTK, Padang, Indonesia
Email: abulwafa@upiyptk.ac.id (A.M.); sarjon_defit@upiyptk.ac.id (S.D.); gunadiwidi@yahoo.co.id (G.W.N.)
*Corresponding author

***Abstract*—Every day millions of people express their opinions, suggestions and views about accommodation, services, and tourist destinations on the web and online applications. The Google Map website was used to collect a datasets of reviews of tourist destinations in West Sumatra, Indonesia. The aim of this research is to analyze text reviews of tourist destinations so that it is known that Intent Sentiment Analysis (ISA) uses the Deep Learning Recurrent Neural Network (RNN) Long Short-Term Memory (LSTM) variant classification method with support for FastText Embedding feature extraction. The performance of the text classification model was evaluated using split data ratios of 70:30, 80:20, and 90:10. The highest accuracy rate of 97% was achieved with a data split ratio of 90:10. The four models developed succeeded in predicting the intent of sentiment analysis consisting of complaints, suggestions, opinions, statements, and appreciation. This research provides knowledge about what motivates people to write reviews on tourist destinations. This can be used as a reference source by tourist destination management in making destination management policies.**

***Keywords*—Recurrent Neural Network (RNN)-Long Short-Term Memory (LSTM), FastText, Natural Language Processing (NLP), intent sentiment, tourism destination**

I. INTRODUCTION

Every day, millions of people express their opinions, suggestions, and views about accommodation, services, and destinations on the web and online apps [1]. The expression of traveller views through social networking sites [2]. The opinions or reviews of travelers are dispersed, and it is unclear what motivated or prompted them to write the review, the manager or management of tourist destinations should consider these factors when developing better development and management plans [3]. These collections of text become a rich resource that can be used to explore users opinions and emotions about tourist attractions, ultimately leading to better recommendation services for users [4]. Text reviews related to tourist destinations, such as hotels, aim to assess user sentiment towards hotel services [5]. Text on e-commerce websites is analyzed using deep learning techniques to determine the author's intent [6]. Sentiment Analysis (SA) was conducted on a collection of tourist text review data to determine the impact of reviews on return visits to tourist destinations [7].

SA is crucial for analyzing data from tourism visitor review web content to comprehend tourists' requirements and preferences [8]. Efficiently extract user opinions and emotions regarding tourist destinations to enhance recommendation services [9]. SA is usually used to extract information from the text data obtained from Twitter using the Convolutional Neural Network (CNN) method producing accuracy levels of up to 94.47%, 95.4% and 94% respectively, when evaluated using Phone, Laptop, and TV review datasets [10]. However, there is also SA research which uses lexical-based methods to better recognize the polarity of natural language texts by utilizing different polarity features from standard POS tags, such as adjectives, adverbs on the Amazon dataset to explore the polarity of certain texts where a combination of JJ + NN + features is used. VB + RB + VBP + RP achieved a 4.4% improvement compared to baseline1 [11]. A comparative study was carried out on the SA dataset of demonetization cases in India in 2016 using the Naïve Bayes classifier machine learning algorithm and support vector machines. From this analysis it is known that the majority of people in India have a neutral opinion [12]. SA uses the Naïve Bayes algorithm, Support Vector Machines (SVM), Decision Tree, Random Forest and Logistic Regression (LR) classifier in classifying text from Twitter related to electronic products such as laptops, telephones and TVs. This analysis provides knowledge that the Logistic Regression algorithm has the highest accuracy compared to other algorithms used that was 0.93% for laptops, 0.94% for TVs and 0.92% for phones [13]. Comparing the algorithms used for approach and classification in SA, discussing the advantages and disadvantages of the performance of existing machine learning models so that the SA function in Natural Language Processing (NLP) can be optimized [14].

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Most research in SA focuses on Fine-Grained Sentiment Analysis, which classifies responses or opinions into categories such as very positive, somewhat positive, neutral, somewhat negative, and negative. In general, SA research uses algorithms found in machine learning, such as SVM, Random Forest, Naïve Bayes, and several Deep Learning algorithms. There are not many researches has been done to find out the intent, sentiment, or motivation behind writing reviews, online opinions in the form of complaints, suggestions, opinions, questions, or appreciation using a combination of the Recurrent Neural Network algorithm with the Long Short-Term Memory (RNN-LSTM) variant with FastText feature extraction. So we try to propose:

- Text review analysis of tourist destinations to determine Intent Sentiment Analysis (ISA) using the RNN-LSTM deep learning classification method with support for FastText Embedding feature extraction.
- Carry out accuracy testing of the model used with the specified ratio for testing data and test data so that the best performance is known.

II. Related Work

This part will present several publications related to comprehensive sentiment analysis with various methods used. This part also provides support for the background. The development of an artificial neural network whose process works repeatedly (looping) to process input sequence data is known as RNN. The development of the RNN model consists of several variants that can maximize the effectiveness of the architecture, including Long Short Term Memory (LSTM) and Bidirectional Long Short Term Memory (Bi-LSTM) [15]. The application of the RNN method for text classification is widely used because this method has a "memory" where each sample will be processed in the same way with consideration of previous samples [16].

A total of 7,413 tourism data (Online Travel Reviews—OTRs) from Mexico were used to create 14 sentiment analysis systems. These systems were presented and used to evaluate the proposed combination schemes. Three proposed schemes were used to efficiently predict OTR polarity, especially those based on deep learning. The sentiment analysis results were significantly improved individually as well as for 4 out of 5 polarized c lasses [17]. Text data collected from online media reviews will undergo text analytic using various models and methods, including machine learning, deep learning, and other analysis concepts [18]. Text analytic and machine learning are commonly used in text review analyses. They combine multiple methods to produce a deeper understanding [19]. Text representation is crucial for sentiment analysis. It encodes text into a continuous vector by projecting semantics onto points in a high-dimensional space [20].

The study presented in this paper demonstrates that the perceived credibility of online reviews by consumers moderates the impact of review sentiment on product sales, additionally, this study reveals that the perceived credibility of online reviews has varying effects on product sales, which may change the product sales [21]. Rough set theory achieved the highest classification accuracy of 94% when compared to Naïve Bayes, which only achieved 90%, and K-Nearest Neighbors, which achieved 82%. The dataset used for this analysis consisted of reviews of Iraqi language dialect e-tourism [22]. The dataset used for this study consists of reviews of the Iraqi language dialect in e-tourism. It is important to note that all evaluations presented are objective and free from bias [23]. Deep learning-based representation models often outperform machine learning-based models when the text's syntactic structure is complex [24]. The use of deep learning in the tourism industry can aid in the development of marketing strategies for heritage destinations, attracting tourists and achieving long-term sustainable development [25]. The study conducted sentiment analysis on Urdu online reviews using various machine learning and deep learning classifiers, the results showed that the combination of word n-gram features with LR outperformed other classifiers for the sentiment analysis task, achieving the highest F1-Score of 82.05%, the Hidden Attention Long Short-Term Memory (HA-LSTM) network was used in combination with 16 different linguistic features, resulting in improved performance of the language model when compared to other state-of-the-art models. The improvement was up to 2% in terms of F1-Score across three different gold standard datasets [26].

The parameters of the proposed model outperform classical Machine Learning models in sentiment analysis, as demonstrated by the analysis results which show a 91.3% accuracy rate, The model used a hybrid Convolutional Neural Network-Long Short Term Memory (CNN-LSTM) and was trained on both the Airline quality and Twitter airline sentiment datasets [27]. Research using e-commerce product review datasets has shown that there are various methods available for sentiment analysis, including word2vec, Glove, and Term Frequency-Inverse Document Frequency (TF-IDF) with unigram, bigram, and trigram, these methods can provide recommendations, as well as Bidirectional Encoder Representations from Transformers (BERT), Bi-LSTM, RNN, CNN, and other techniques [28]. A survey of sentiment analysis and opinion mining on educational data can be found in [29]. Other research has proposed sentiment analysis models that are capable of detecting positive sentiments even in low-rated conditions for low applications, such as BERT, RNN, and LSTM. Additionally, a review dataset for Zoom Cloud Meetings was analysed [30]. The use of deep learning in tourism can aid heritage tourism destinations in enhancing their marketing strategies for Chinese tourists and achieving sustainable long-term destination development [31]. This can be achieved through the implementation of the BERT method, which utilises a dataset of reviews from Chinese tourists who have visited cultural sites in Melaka [32]. Feature selection using SHapley Additive exPlanations (SHAP) values, a shallow learning algorithm called Paragraph Vector-Distributed Memory (PV-DM), and machine learning classifiers like eXtreme Gradient Boosting (XGBoost) using the NSL-KDD and UNSW-NB15 datasets successfully demonstrated the efficiency of the approach [33].

From the references above, the author is interested in using the RNN-LSTM Deep Learning Algorithm testing method by adding FastText word embedding to tourist destination review data on Google Map. This research was conducted to determine the performance of the algorithm and the effect of adding word embedding on the implementation of text classification. Table I displays the literature related to sentiment analysis using different methods.

TABLE I. SUMMARY OF APPROACHES RELATED TO SENTIMENT ANALYSIS

Authors	Dataset	Method/Tools	Result	Research limitations
Kusumaningrum *et al.* [5]	Online Travel Agent (OTA)-Indonesia Hotel Review	CNN LSTM	the performance for the F1-Score was 0.95 ± 0.03, 0.87 ± 0.02, and 0.92 ± 0.07 for document-level sentiment analysis, aspect-level sentiment analysis, and aspect-polarity detection, respectively	Further research can be developed by applying various kinds of the latest word embedding techniques, such as GloVe, FastText, or BERT (Bidirectional Encoder Representations from Transformers)
Puh and Babac [34]	TripAdvisor data set	Naïve Bayes, Support Vector Machines (SVM), Convolutional Neural Network (CNN), Long Short-Term Memory (LSTM) and Bidirectional Long Short-Term Memory (BiLSTM), TF-IDF, GloVe	The performance of machine and learning models achieved high accuracy in predicting positive, negative, or neutral sentiments and ratings from tourist reviews. The optimal model architecture for both classification tasks was a deep learning model based on BiLSTM. The study's results confirmed that deep learning models are more efficient and accurate than machine learning algorithms.	The appropriate credibility of all explored reviews in our dataset and use of a single data resource
Li *et al.* [35]	Open training data set and 92,905 reviews extrapolated from restaurants in Tokyo	BERT word vector model, LSTM, IAOA mechanism, and a linear output layer	The model achieves significantly better performance compared with other neural networks. The findings provide empirical evidence to validate the suitability of this new approach in the tourism-hospitality domain.	More sentiments should be identified to measure more fine-grained tourism-hospitality experience and new aspects are recommended that can be automatically added into the aspect set to provide dynamic support for new dining experiences
Song *et al.* [36]	20,476 online reviews from 18,387 Tripadvisor users from 2008 to 2019	Latent Dirichlet Allocation (LDA) and logistic regression machine learning methods	The visitor experience explored within this study uncovered multiple facets of sense of place on the Strip and suggested urban design strategies and public space management policies related to the programmatic and physical elements of the Strip sidewalks. The study shows how online reviews can provide strong empirical evidence for visitor experience in built environment projects	One limitation of this study was the potential for this selection bias
Fu and Pan [37]	Tourism review	LSTM	method maintains more than 90% accuracy in comment sentiment detection	The collective volume of our data is far from sufficient for later studies, and we will continue to focus on the construction of the network review dataset in the next studies. For the optimization of the network, we will consider using a bidirectional recurrent neural network to process two polar character sentiment feature sequences to achieve better sentiment detection accuracy.
Gregoriades *et al.* [38]	Hotel reviews I Cyprus-TripAdvisor	Extreme Gradient Boosting (XGBoost), SHAP (SHapley Additive exPlanations)	(1) the filtering and labelling of reviews based on revisit intention, (2) the generation of two topic models for the two hotel categories based on their star ratings, (3) the training and validation of two XGBoost classifiers to predict revisit or non revisit intention for the two categories of hotels, and (4) the interpretation of the patterns embedded in the two trained XGBoost classifiers based on which recommendations for the hotel management can be made	the proposed model overlooks certain factors that could influence revisit intention, such as brand name or contextual variables such as the weather this work does not address fake reviews and does not consider the credibility of the eWOM author as also noted elsewhere
Memiş *et al.* [39]	Turkish financial market tweets	Neural Network, Convolutional Neural Network (CNN), Long Short-Term Memory (LSTM), Gated Recurrent Units (GRU) and GRU-CNN models	The best results for binary and multi-class datasets were observed with pre-trained word embedding with the CNN model (83.02%, 72.73%). When word embedding was employed, the Neural Network model had the best results on the multi-class dataset (63.85%) and GRU-CNN had the best results on the binary dataset (80.56%).	Using additional layers in these models may improve their performances. Use of more specific pre-processing techniques could also improve model performances, as the collected Turkish tweets about the Turkish financial market contain many ambiguous words and phrases that make the pre-processing step difficult. Enlarging the datasets could lead to better results.
Maity *et al.* [40]	Travel reviews on hotels or resorts in trivago web	Trigram and conjunction rule based approach.	The experiment results show significantly better accuracy and precision than the conventional text segregation and sentiment analysis methods	more dataset review

III. RESEARCH METHOD

This part explains the text classification process to determine intent sentiment analysis of tourist destination reviews on Google Maps. Text categories include complaints, suggestions, opinions, statements, and appreciation. To achieve the desired results, we use the RNN LSTM method with FastText embedding feature extraction and model evaluation. Fig. 1 illustrates the intent sentiment analysis framework.

Fig. 1 displays the intent sentiment analysis framework by classifying tourist destination text reviews. The process begins with selecting a dataset, followed by the preprocessing stage. The process stages begin with feature extraction using FastText embedding. The RNN-LSTM model is used to classify tourist destination text reviews. The novelty of the research lies in the development of an LSTM RNN model that utilizes FastText Embedding for intent prediction and text classification. Models are evaluated to determine their accuracy and differentiate them from other models.

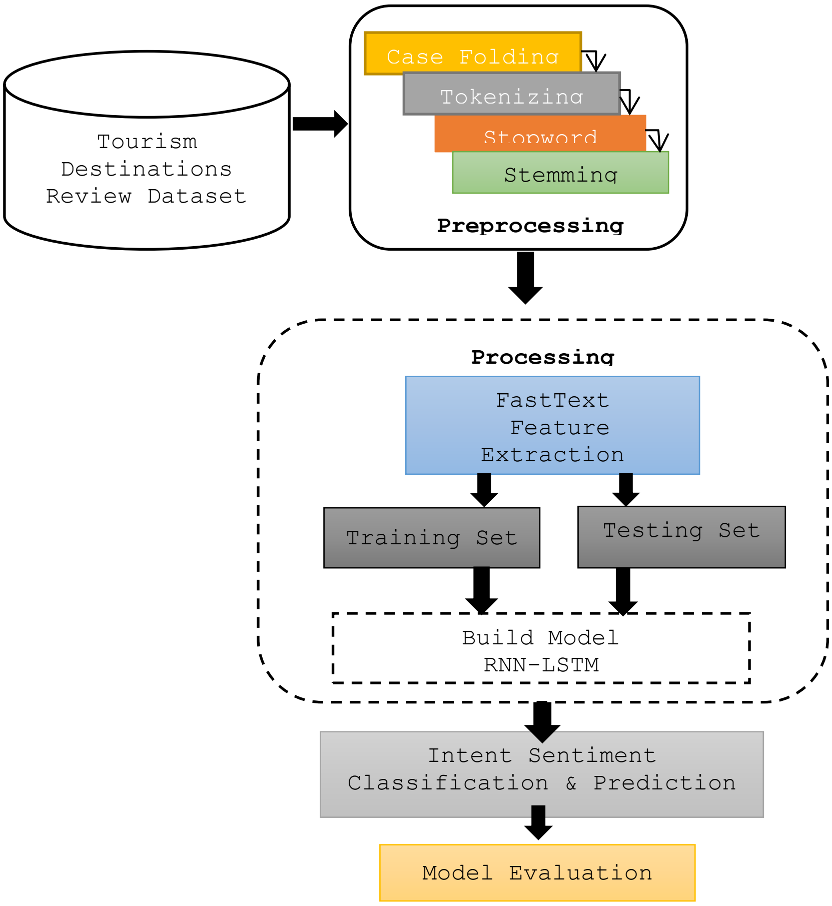


Fig. 1. Intent sentiment analysis framework.

Steps to determine intent sentiment analysis based on text review classification using the RNN-LSTM method with FastText Embedding feature extraction. In the first stage, text reviews of tourist destinations on Google Maps were collected by means of web scraping. The next stage is that the scraping data is cleaned according to the features that will be used as a dataset in this research. The dataset in .csv format is then used for the preprocessing stage (casefolding, tokenizing, stopword and stemming. The dataset that has been preprocessed is divided into data sets and test data and then processed using FastText Embedding. The next stage the RNN-LSTM model is used to carry out text classification review of tourist destinations. The model is then evaluated to measure accuracy and other performance. This evaluation also uses a confusion matrix. Predictions are made using a trained model to predict the intent of review texts (training data) and sentiment analysis of new texts. The next step is to interpret the prediction results as complaints, suggestions, opinions, statements, or appreciation

A. *Tourism Destinations Review Dataset*

According to the online dictionary, a dataset is a collection of separate collections of information that is treated by a computer as a single unit. The dataset used in this research is West Sumatera tourism Destination Reviews on Google Maps, as illustrated in Fig. 2, which consists of 2217 reviews which are devided into testing data and test data. The dataset is saved in the form of a CSV file to assist in reading news documents at the data labeling and text pre-processing stages. The dataset that has been collected is still classified as raw data and there are still many things that are not needed for research so that they interfere withs the analysis process. The dataset used initially consisted of 23 columms. Namely, the Name_column, google_id, place_id, location_link, reviews_link, reviews_per_score, review_img_urls, rating_owner_answer, owner_answer_timestamp, datetime_utc, review_link, review_rating, review_timestamp, review_datetime_utc, review_likes, reviews_id. But in this research, the only columns needed are column name and review_text. So when the labeling process is carried out, the dataset consists of only 3 columns.

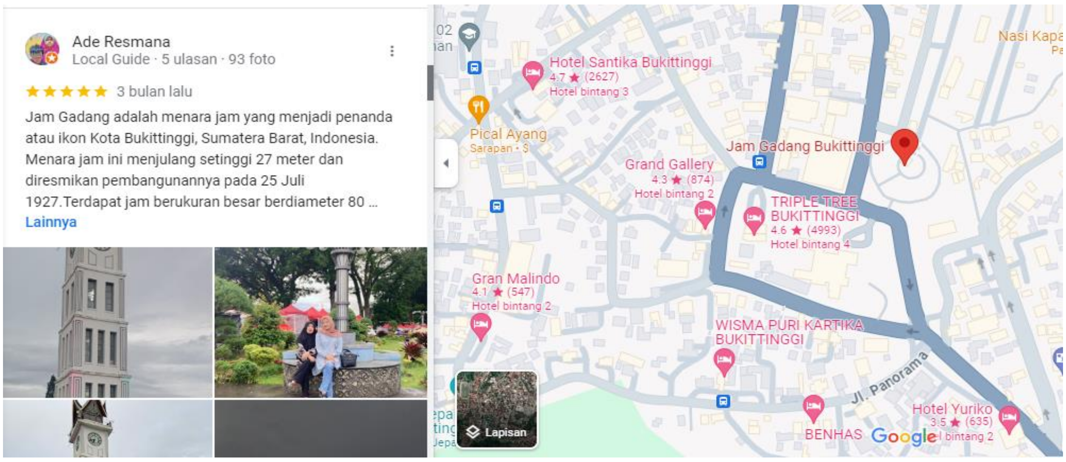
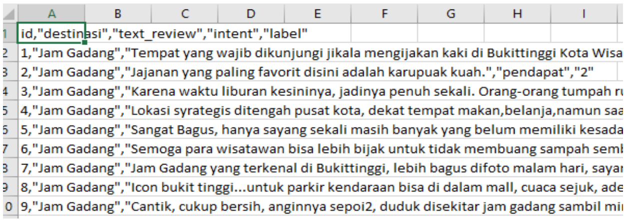


Fig. 2. Tourist destination review.

Fig. 2 shows one of the text reviews of *Jam Gadang* tourist destinations on Google Map. The review text on the Google map will be scraped to produce a text review dataset. This review text dataset will be saved in .csv format. As can be seen in Fig. 3.



	A
1	id,"destinasi","text_review","intent","label"
2	1,"Jam Gadang","Tempat yang wajib dikunjungi jikala mengijakan kaki di Bukittinggi Kota Wisa
3	2,"Jam Gadang","Jajanan yang paling favorit disini adalah karupuak kuah.","pendapat","2"
4	3,"Jam Gadang","Karena waktu liburan kesininya, jadinya penuh sekali. Orang-orang tumpah r
5	4,"Jam Gadang","Lokasi syrategis ditengah pusat kota, dekat tempat makan,belanja,namun saa
6	5,"Jam Gadang","Sangat Bagus, hanya sayang sekali masih banyak yang belum memiliki kesada
7	6,"Jam Gadang","Semoga para wisatawan bisa lebih bijak untuk tidak membuang sampah sem
8	7,"Jam Gadang","Jam Gadang yang terkenal di Bukittinggi, lebih bagus difoto malam hari, saya
9	8,"Jam Gadang","Icon bukit tinggi...untuk parkir kendaraan bisa di dalam mall, cuaca sejuk, ade
10	9,"Jam Gadang","Cantik, cukup bersih, anginnya sepoi2, duduk disekitar jam gadang sambil mi

Fig. 3. Tourist destination review dataset.

Fig. 3 shows multiple datasets stored in .csv format. This review dataset will be used to determine sentiment intent through text classification. Before the classification process begins, the dataset will undergo preprocessing.

B. Preprocessing

Preprocessing is the initial step in analyzing datasets of online reviews. This process includes several stages, case folding, tokenizing, stopword and stemming, to generate more structured data [41]. Review data for Google Maps destinations undergoes several processes to produce clean data for the next stage [42]. Table II shows the preprocessing stages starting from text review (before casefolding) to the after stemming.

TABLE II. PREPROCESSING TEXT REVIEW OF TOURIST DESTINATIONS

Preprocessing	**Preprocessing Result**
Before Case Folding (Text Review)	The area you must visit is the flat land icone...
After Case Folding	the area you must visit is the land icon...
After Tokenization	[area, mandatory, travel, ground, flat, icon]...
After Stopword	area, mandatory, travel, ground, flat, icon...
After Steaming	area, mandatory, travel, ground, flat, icon...

1) Case folding

This stage involves converting all text to lowercase letters. This facilitates the next process, but the punctuation and text structure remain the same as the original review from the web source database [43]. This is the initial step in the preprocessing stage, making the subsequent stage easier to process.

2) Tokenizing

This stage is done after the case folding process is complete. The process of tokenization involves dividing a document into parts. During this stage, phrases and punctuation characters are removed, which can occasionally disrupt the flow of the conversation [44]. At this stage, we process tourist destination review sentences that have been converted to lowercase and stripped of punctuation marks and non-text characters.

3) Stopword

Stopword removal, or filtering, is the crucial preprocessing stage that follows tokenization. This process eliminates words that hold no significance or relevance in the text. All words that lack meaning in the text review are deleted. The input at this stage is the text resulting from the tokenization process, which removes words that lack meaning.

4) Stemming

At this stage, the words or text generated after stopword removal undergo stemming. The process identifies the base word or stem of the filtered word by removing prefixes and suffixes from existing words. The root words of the review text after the stopword stage This simplifies the process of understanding the meaning of words by identifying their basic forms.

C. Processing

1) FastText feature extraction

sWord embeddings provide information about similarities and relationships between words [45]. This method learns word representation by considering subword information. Each word is represented as a set of n-gram characters, which helps capture the meaning of shorter words and allows embedding to understand word endings and beginnings. A vector representation is associated with each n-gram character, while words are represented as the sum of these vector representations. The

Skip-gram model is trained to learn the vector embedding of a word represented by n-gram characters [46]. FastText performs well, can quickly train models on large datasets, and can provide a non-vocabulary representation of words by splitting them into n-grams to obtain their embedding vectors [25]

FastText is a word embedding method that extends word2vec [47]. The FastText integration model builds digital vectors from words that do not appear in the corpus [9]. It is an open source and efficient model. There are built-in pre-trained words available for 157 languages, other than Indonesian, that can be downloaded [48].

Fig. 4 displays the embedding matrix generated by the FastText embedding process. The embedding matrix represents words as numerical vectors, which simplifies the process of classifying tourist destinations.

```
[[ 0.          0.          0          ...   0.           0.0.          ]
 [-0.00228911  0.00067935  0.00098137 ...  0.00226554  -0.00085578  -0.00107767]
 [-0.00320969  0.00078011 -0.00545185 ... -0.00058804   0.00343665   0.00060616]
 [-0.0003645  -0.00017016  0.00132428 ... -0.00037717   0.00045394   0.00062075]
 [-0.00091088  0.00058116  0.00302618 ... -0.00041011   0.00210411   0.0002208 ]
 [-0.00395322 -0.00172261  0.00271979 ... -0.00011283   0.00205711  -0.00113202]]
```

Fig. 4. Matrix embedding using FastText.

2) Training set

The data set that has passed the preprocessing stage is divided into a training data set and a testing data set. The distribution of the data set as training data in this research was carried out by distributing the data set by 90%, 80%, 70%. The goal of dividing this data set is to confidently evaluate the performance of the classification model and determine the optimal data set for its development.

3) Testing set

The division of the dataset into test datasets in this research was carried out by dividing the dataset by 10%, 20%, 30%. This dataset is divided with the aim of evaluating the performance of the model we developed effectively.

4) RNN-LSTM

Recurrent Neural Network (RNN) is a type of neural network architecture that processes input data repeatedly, usually in the form of sequential data. Long Short-Term Memory (LSTM) is a specialized type of RNN architecture designed to overcome the limitations of RNNs in dealing with long-term memory issues can see in Fig. 5.

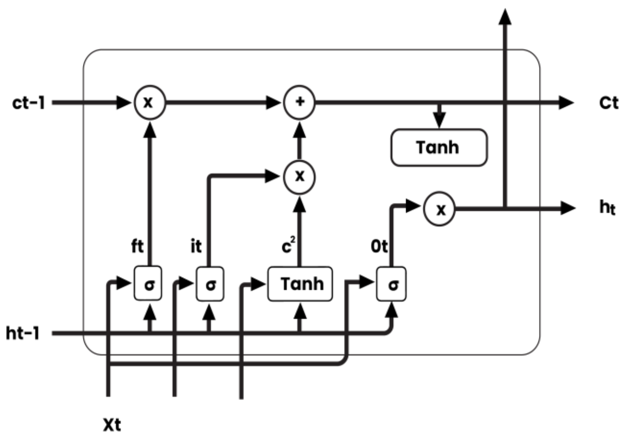


Fig. 5. Long Short-Term Memory (LSTM) architecture.

LSTMs are capable of storing long-term information. The tanh equation is outlined in Eq. (1).

$$\tanh(X) = 2\sigma(2X) - 1 \tag{1}$$

where
σ= sigmoid activation function
x= input data

$$(x) = 1/(1 + \epsilon - X) \tag{2}$$

where:
x = input data
ϵ = mathematical constant (2.71828 18284 59045 23536 02874 71352)

This layer is called the Gate of Oblivion. The outputs ht–1 and xt of the previous step are used as inputs. A sigmoid activation function is used to produce an output of 0 or 1 at Ct–1. The forget gate equation is described in Eq. (3).

$$ft = \sigma(Wf.[ht\text{–}1, xt] + bf) \tag{3}$$

If σ represents a sigmoid function, the weight matrix and bias matrix at the forgetting gate are denoted by Wf and bf, respectively. The weight value of Wf can be found using Eq. (4).

$$W = \left(\frac{1}{\sqrt{\mathrm{d}}} + \frac{1}{d}\right) \tag{4}$$

The next step is to identify the information stored in the cell state. The input gate layer uses the sigmoid layer above the input to decide which part of the cell state to update. The Tanh layer generates new candidates $\tilde{C}t$ that can be incorporated into the cell state. In the next step, the two candidates are merged and the cell status is updated. The input gate equation is described in Eq. (5).

$$i_t = \sigma(Wf\ .[h_t - 1, x_t] + b_i \tag{5}$$

Eq. (6) outlines the new candidate equation Ct, where σ is a sigmoid function and Wi and bi are the weight and bias matrices at the input gate, respectively.

$$\tilde{C} = \tanh(W_c \,.\, [h_t - 1, x_t] + b_c \quad (6)$$

Here, $tanh$ is the Tanh function, and Wc and bc are the cell state bias values. Multiply the old cell state *Ct*–1 by *ft* to remove the given information in the forget gate layer. Then, new information $* \tilde{C}tt$ is added to update the cell state as described in Eq. (7).

$$C_t = f_t \,.\, -1 * C_t + i_t * \tilde{C}_t \quad (7)$$

where:
C_t = Cell state
f_t = forget gate
C_t–1 = Cell state before order *t*
i_t = gate input
$\tilde{C}_t$ = new value that can be added to cell state

The output is determined by the state of the filtered cells. To achieve this, a sigmoid layer is applied to the previous output *ht*–1 and the input *xt*, giving the output gate value *ot*. This value is between 0 and 1 and determines which part of the cell state is output. The cell state Ct is then transformed using the Tanh function to obtain values between −1 and 1. Finally, the transformed cell state value is multiplied by the output gate value or becomes the output HT. The output described in Eq. (8) is printed and sent to the next step in the network.

$$o_t = \sigma\,(W_o . [h_t - 1, x_t\,] + b_o \quad (8)$$

where σ is a sigmoid function, W_o and b_o are the weight matrix and bias value at the output gate, respectively. The equation for the output value of order t is described in Eq. (9).

$$h_t = o_t \times \tanh \quad (9)$$

where ht represents the output value of order t, ot represents the gate output, and Ct represents the Cell state. The tanh function is used.

D. *Intent Sentiment Clasification and Prediction*

Determining the intent sentiment analysis of the tourist destination review dataset by classifying text. In Fig. 6, you can see the distribution of intent labels for the dataset used in this text classification process. The dataset consists of five labels, labeled 0 to 4. Label 0 has 618 text reviews, label 1 has 789 text reviews, label 2 has 477 text reviews, label 3 has 195 text reviews, and label 4 has 141 text reviews.

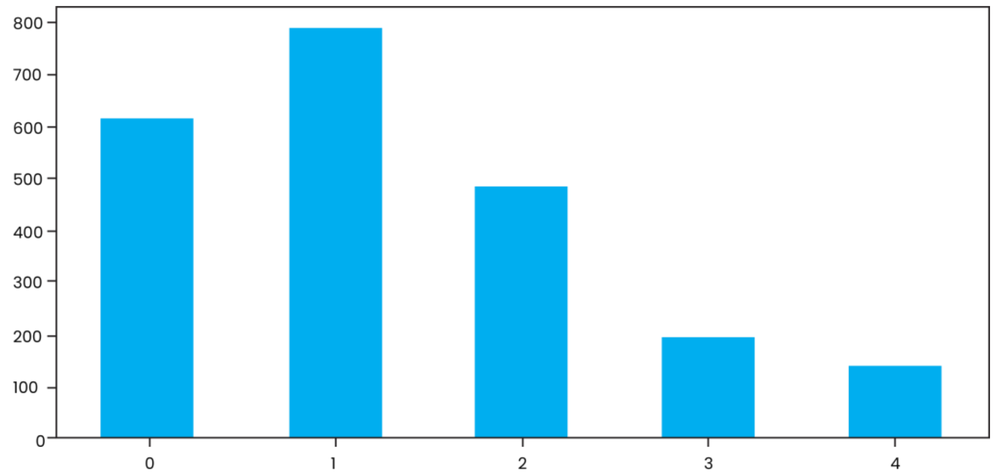


Fig. 6. Distribution of the number of labels intents in the processed dataset.

E. *Model Evaluation*

The evaluation of the model is based on the confusion matrix evaluation metric. This metric displays the number of correct and incorrect predictions for each intent class, providing a clear understanding of the number of accurate and inaccurate predictions for intent classes 0, 1, 2, 3, and 4.

IV. Result and Discussion

The performance of the RNNLSTM model with additional FastText embedding feature extraction was evaluated using an initial dataset consisting of 2217 samples. Jupyter notebook and Python are used as tools to support testing this model. The training dataset is then divided into several subsets, namely (test data-training data) 70:30, 80:20, and 90:10. The confusion matrix is used to find out how well the model works to predict each class. The results of performance evaluation using the confusion matrix can be seen in Figs. 7–9.

Based on the data presented in Fig. 7, it can be observed in the first row that the model is able to accurately predict Class 1 where there are 55 that are actually classified as Class 1 (TP). Number 3 illustrates that there are 3 instances that are actually clearly 1 but are wrongly classified as Class 2. Number 0 describes that there are no instances that are wrongly classified as classes other than Class 1. The second row describes the second class in the classification, the number 79 describes the number of instances correctly classified as Class 2. The number 3 illustrates that there are 3 instances that actually belong to Class 2 but are incorrectly classified as Class 1, the number 2 illustrates that there are 2 instances that belong to Class 2 but incorrectly classified as Class 4. The 3rd row reflects the third class in the classification, where the number 46 describes the number of instances that are correctly classified as Class 3. The number 1 in this 3rd row illustrates that there is 1 instance that actually belongs to Class 3 but incorrectly classified as Class 2. The number 0 illustrates that there are no instances that are incorrectly classified as classes other than Class 3. Row 4 reflects the fourth class in the classification where the number 21 shows the number of instances correctly classified as Class 4. The number 0 in that row illustrates that there are no instances that were incorrectly classified as other than Class 4. Row 5 reflects the fifth class in the classification, where the number 12 describes the number of instances that were correctly classified as Class 5. The number 0 in that row indicates that there were no instances that were incorrectly classified as a class other than Class 5.

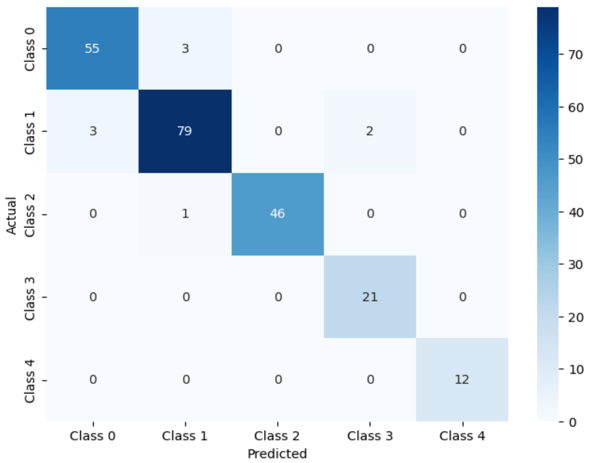


Fig. 7. Confusion Matrixs model RNN LSTM FastText split data 90:10

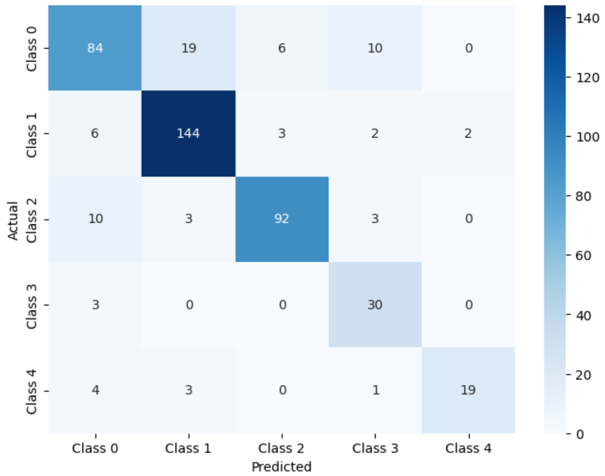


Fig. 8. Confusion Matrixs model RNN LSTM FastText split data 80:20.

Fig. 8 is a confusion matrix image where the first row represents the first class in the classification where the number 84 is the number of instances that are correctly classified as Class 1 True Positives (TP). The number 19 depicts the number of instances that actually belong to Class 1 but are incorrectly classified as another class, False Negatives (FN). The numbers 6 and 10, respectively indicate the number of instances that actually belong to another class but are incorrectly classified as Class 1, False Positive (FP). The number 0 indicates the absence of instances of other classes that were incorrectly classified as Class 1. The second row represents the second class in the classification. The number 144 describes the number of instances that are correctly classified as Class 2. The numbers 2,3,2,2 are the number of instances that actually belong to another class but are incorrectly classified as Class 2. Then the number 0 in this second row indicates that there are no instances from other classes incorrectly classified. And so on for rows 3, 4 and 5.

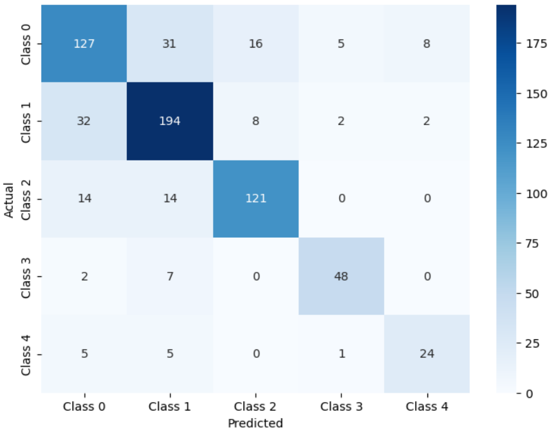


Fig. 9. Confusion Matrixs model RNN LSTM FastText split data 70:30.

In Fig. 9, the first row represents the first class in the classification. Number 127 shows the number of instances correctly classified as Class 1 (True Positives). Numbers 31, 16, 5, 8: Each shows the number of instances that actually belonged to another class but were incorrectly classified as Class 1 (False Positives). There are no numbers in this row that indicate instances of Class 1 that were incorrectly classified as other classes (False Negatives). The second row represents the second class in the classification. Number 194: Indicates the number of instances correctly classified as Class 2 (True Positives). Numbers 32, 8, 2, 2: Each shows the number of instances that actually belonged to another class but were incorrectly classified as Class 2 (False Positives). There are no numbers in this row that indicate instances of Class 2 that were incorrectly classified as other classes (False Negatives). And so on for the next rows representing Class 3 to Class 5.

TABLE III. Classification Report of RNN LSTM FastText Model with 90:10 Split Data

Classification Report	Precision	Recall	F1-Score	Support
Class 0	0.96	0.97	0.97	428
Class 1	0.98	0.98	0.98	551
Class 2	0.97	0.99	0.98	328
Class 3	0.94	0.95	0.94	138
Class 4	1.00	0.90	0.95	106
Accuracy			0.97	1551
Macro avg	0.97	0.96	0.96	1551
Weighted avg	0.97	0.97	0.97	1551

Accuracy: 0.97

Table III shows the accuracy validation results for the 90:10 split data. Table IV shows the accuracy validation results for the 80:20 split data and Table V shows the accuracy validation results for the 70:30 split data.

TABEL IV. CLASSIFICATION REPORT OF RNN LSTM FASTTEXT MODEL WITH 90:10 SPLIT DATA

Classification Report	Precision	Recall	F1-Score	Support
Class 0	0.79	0.71	0.74	119
Class 1	0.85	0.92	0.88	157
Class 2	0.91	0.85	0.88	108
Class 3	0.65	0.91	0.76	33
Class 4	0.90	0.70	0.79	27
Accuracy			0.83	444
Macro avg	0.82	0.82	0.81	444
Weighted avg	0.84	0.83	0.83	444

Accuracy: 0.83

Table III shows that the model has an accuracy level of 0.97, which means 97% of all predictions made by the model are correct. Apart from that, for each class, precision, recall, and F1-Score can also be seen so that the model's performance in classifying each class is known. The precision value for class 0 is 0.96, which means 96% of the items classified as class 0 by the model are actually Class 0. The recall value for class 0 is 0.97, which means the model identifies 97% of the items that are actually Class 0. The F1-Score value of 0.97 shows a balance between precision and recall. The support value for class 0 is 428, this shows the number of samples in class 0. This is also seen for Class 1 to Class 4.

Meanwhile in Table IV it can be seen that the accuracy for the 80:20 data split is 0.83, meaning the model is able to make 83% predictions correctly. It can be seen that each class has a precision, recall F1-Score and support value. For example, for Class 1, the precision value is 0.85, then the recall value is 0.92, for the F1-Score value is 0.88 with support of 157.

TABLE V. CLASSIFICATION REPORT OF RNN LSTM FASTTEXT MODEL WITH 90:10 SPLIT DATA

Classification Report	precision	recall	F1-Score	support
Class 0	0.71	0.68	0.69	187
Class 1	0.77	0.82	0.79	238
Class 2	0.83	0.81	0.82	149
Class 3	0.86	0.84	0.85	57
Class 4	0.71	0.69	0.70	35
Accuracy			0.77	666
Macro avg	0.78	0.77	0.77	666
Weighted avg	0.77	0.77	0.77	666

Accuracy: 0.77

Evaluation of the split data model with a ratio of 70:30 can be seen in Table V. The model accuracy is 0.77 or 77% capable of carrying out classification correctly. Each class has different precision, recall F1-Score and support values. As an example, we can see for Class 2, where the precision value is 0.83, recall is 0.81, F1-Score is 0.82 and support is 149.

```
Review: ['bangun kuno tempoe doloe pandang indah kuliner manja unjung']
True sentiment: [4]
Intent sentiment: [4]
-------------------------------
Review: ['tinggal sejarah awat pandu ramah kuasa sejarah istana adat minangkabau rinci moga awat']
True sentiment: [2]
Intent sentiment: [2]
```

Fig. 10. Tourism destinations intent sentiment analysis review results.

This model successfully predicts sentiment intent based on text review classification using training data, as shown in Figs. 10 and 11 show intent Sentiment Analysis with new review.

Performance evaluation of the RNN LSTM model using FastText Embedding feature extraction revealed a high level of accuracy. The purpose of this research is to develop a sentiment analysis model based on text classification. Table VI shows a comparison between this study and previous text classification studies. The developed RNN LSTM model has excellent results in training and test evaluation.

```
1/1 [==============================] - 0s 94ms/step
Teks Review: pelayanan  memuaskan, tempat bagus
Intent Sentimen: pendapat
```

Fig. 11. Intent sentiment analysis with new review.

TABLE VI. COMPARISON WITH PREVIOUS RESEARCH

Author	Text Classification	Dataset	Result
Mahadevaswamy and Swathi [49]	BiLSTM	Amazon product review dataset	Highest accuracy of 91.4%
Sedqy *et al*. [50]	BiLSTM	The Twitter website during the conflict between Ukraine and Russia	Accuracy of 91.79%
Sangeetha and Kumaran [51]	(PCCHHO-RNN-LSTM	Amazon user review dataset	PCCHH-RNNLSTM accuracy 95.8%, precision 95.4%, recall 95.6%, and F-measure 95.2%, respectively.
Islam *et al*. [30]	BERT and hybridization of RNN and LSTM	zoom cloud meetings app using user reviews on google play	BERT 0.67, RNN 0.53, LSTM 0.47
Kong and Zhang [52]	Text-CNN	Hotel Review	Accuracy 0.92
RNN LSTM FastText Embedding	RNN LSTM	Review of tourist destinations google map	Highest accuracy 97%

V. Conclusions and Future Works

The dataset used in this research was obtained by reading reviews of tourist destinations on the Google Maps website. A text classification model is developed to accurately determine review sentiment. The model successfully identifies the intent behind writing a review of a destination, including complaints, suggestions, opinions, statements and appreciation. The models underwent testing using deep learning algorithms, specifically RNN/LSTM, separately. Maximum accuracy reaches 97% with data set division 90:10, 80:20, 70:30. However, this research has several weaknesses, including the use of a limited dataset. It is hoped that future research can use a larger and more diverse dataset. This research should be tested using a combination of existing text classification methods and a combination of word embeddings to get more reference results. It is necessary to develop meaning sentiment labels based on cultural developments and community behavior.

Conflict of Interest

The authors declare no conflict of interest.

Author Contributions

Abulwafa Muhammad identified the problem and the process of solving it by designing a development model. He collected and analysed data, conducted experiments and took responsibility for new findings. He was diligent in conducting a thorough literature review to ensure that the research was within the academic context. He also took the lead in drafting and writing the manuscript, incorporating valuable insights and revisions from the supervisors, Prof. Sarjon Defit and Dr. Gunadi Widi Nurcahyo, and responding to their comments. The advisor provided guidance, direction and supervision throughout the research process. By providing feedback on the research direction, the research objectives were refined. All authors had approved the final version.

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