Word2vec Architecture in Sentiment Classification of Fuel Price Increase Using CNN-BiLSTM Method

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Abstract: − Fuel price increases have been a frequent problem in recent years, mainly due to unstable international price fluctuations. This research uses sentiment analysis to examine the increase in fuel prices and its impact on public sentiment. Sentiment analysis is a data processing method to obtain information about an issue by recognizing and extracting emotions or opinions from existing text. In this research, two architectures, Word2vec Continous Bag of Words (CBOW) and Skip-gram, were tested with different vector dimension sizes in each architecture using the CNN-BiLSTM hybrid deep learning method. The results showed that the CBOW model with 300 vector dimensions produced the best performance with 87% accuracy, 87% Recall, 89% Precision, and 88% F1-score on the tested Indonesian language dataset.

Keywords: CNN-BiLSTM, Hybrid deep learning, Sentiment analysis, Twitter, Word2vec

INTRODUCTION

The increase in fuel prices is a problem that has often occurred in recent years, one of which is caused by the unstable rise in international fuel prices (Mujahidin, Prasetio, & Utomo, 2022). The Indonesian government began to set fuel price increases in early September 2022 (Kurniasih & Suseno, 2022) The rise in fuel prices has become a hot topic of conversation in the community, causing pros and cons. Based on Twitter's financial report for the third quarter of 2021, active Twitter users reached 211 million, and Indonesia is one of the countries with active Twitter users (Wahyu Kurniawan & Maharani, 2020). Twitter is a platform widely used for research in sentiment analysis because Twitter has a feature called tweets. In sentiment analysis, tweets are a suitable object because the public opinion expressed in Tweets is generally text.

The sentiment analysis process automatically extracts information from data about a particular issue (Buntoro, 2017). This technique is increasingly used to analyze information from social media platforms like Twitter and Facebook (Wardani, Ummi Arfah, Sojuangon Lubis, & Alwashliyah Medan Coresponding Author, 2022). Despite significant research in this field, several challenges still need to be addressed, including improving model performance, reducing processing time, and adapting techniques to specific data types and domains (Wardani et al., 2022).

Deep learning has recently become increasingly popular in the case of text classification due to the use of large and complex datasets. Machine learning has several areas for improvement, including training processing times that tend to be long and poor accuracy (Widayat, 2021). In addition to single deep learning, combining deep learning models is also increasingly used. Research (Chandra & Jana, 2020) proves hybrid deep learning performs better than machine learning.

In text classification, deep learning cannot directly process data in text form, so text data must be converted into vector form (Huang, Chen, Zheng, & Dong, 2017). The development of machine learning into deep learning is followed by the development of word feature extraction, namely word embedding (Intan Af et al., 2021). Word embedding is one of the most popular word representations in NLP. Word

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embedding can capture the context of words in documents, semantic and syntax similarities, and relationships with others . Training word vectors requires a large dataset and a considerable amount of time. However, pre-trained word vector word embedding can be used repeatedly in other NLP tasks (Putri, Amalia, Nababan, & Sitompul, 2021).

Word2vec is a popular word embedding technique commonly used in sentiment analysis. It was first developed in 2013 by Mikolov et al (Mikolov, Chen, Corrado, & Dean, n.d.). According to Mikolov, there are two architectures for Word2vec: Continuous Bag of Words (CBOW) and Skip-gram. Although these architectures operate differently, they both represent words similarly. Additionally, words with similar meanings are represented by closely located word vectors (Putri et al., 2021). The performance of the Word2vec model can be affected by various parameters during training, including vector dimension and window size (Jatnika, Bijaksana, & Suryani, 2019; Putri et al., 2021).

Differences in architecture, vector dimension, and window size that can affect the performance of Word2vec motivate this research. This study's search for architecture, vector dimension size, and windows dimension of word2vec differs. However, it is carried out on a deep learning method, namely hybrid deep learning CNN-BiLSTM using Indonesian language datasets.

LITERATURE REVIEW

Many studies have used Machine Learning and Deep Learning approaches in sentiment analysis. Research (Chandra & Jana, 2020)has compared the performance of machine learning and deep learning in sentiment analysis. The models used in machine learning are Naive Bayes, MNB Classifier, Bernoulli Classifier, Logistic Regression, Stochastic Gradient Descent, Linear SVC, and NuSVC Classifier. In deep learning, the LSTM-CNN hybrid model is used. In both classification processes, hybrid LSTM-CNN obtained the highest accuracy results of around 85% to 97%.

The use of deep learning in sentiment analysis has gone through many innovations, such as combining or hybrid several deep learning algorithms. As done in research (Shen, Wang, & Sun, 2017) by combining the CNN algorithm with BiLSTM. The first experiment compared BiLSTM and CNN-BiLSTM. The second experiment is CNN-BiLSTM with pre-trained word embedding. Then the 3CNN-BiLSTM model with pre-trained word embedding. From the three experiments, CNN-BiLSTM with pre-trained word embedding obtained a high accuracy of 89.7% .

Selection of appropriate word embedding for sentiment analysis as an extractive feature is also essential. Hitesh et al., 2019 conducted research (Hitesh, Vaibhav, Kalki, Kamtam, & Kumari, 2019)sentiment analysis by comparing several words embedding Bag-of-words, TF-IDF, and Word2vec using machine learning Random Forest algorithm. Among the word embedding comparisons, it is found that word2vec produces higher accuracy performance than other traditional word embedding with an accuracy of 86.87%. This is explained because Word2vec can capture semantic meaning in sentences and then be represented into vectors to see words with high (Hitesh et al., 2019).

Word2vec, in its settings, has different dimensions of vector size and window size for each architecture. Kurniawan et al., 2020 (Wahyu Kurniawan & Maharani, 2020) conducted research by comparing the Continuos Bag Of Words (CBOW) and Skip-gram architectures. This research uses SVM machine learning as a classification method. The data used in this study are Indonesian tweets with the corpus used, namely Wikipedia Indonesia. This study found that the 100-dimensional skip-gram model provided the best classification results with 64.4% precision, 58% recall, and 61.1% f-score.

In addition to using different dimensions, Word2vec has other parameters, such as a combination of evaluation methods and different dimension sizes on each architecture. In research (Muhammad, Kusumaningrum, & Wibowo, 2021), research has been conducted on the combination of evaluation methods and dimension sizes for each architecture. Researchers used the Hotel Reviews Indonesian dataset with the Long-short Term Memory (LSTM) deep learning classification method. In this study, Skip-gram was obtained with the Hierarchical Softmax evaluation method, and a vector dimension of 300 obtained good results, namely an accuracy of 85.96%.

Applying word2vec word embedding in hybrid deep learning can also produce better performance. Wang Yue et al., 2021(Yue & Li, 2020a) have conducted sentiment analysis research on the CNN-BiLSTM hybrid deep learning method with Word2vec word embedding without pre-trained with the

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greatest accuracy result of 91.48%. This research explains that using the Word2vec-CNN-BiLSTM method can work well because of Word2vec's ability to place words with similar meanings in close positions. In addition, the CNN-BiLSTM hybrid gives good results because of CNN's ability to extract features and BiLSTM, which can learn two-way short-term memory (Yue & Li, 2020a).

METHOD

The flowchart of this research can be seen in Figure 1. The system starts by collecting Tweets data on Twitter, extracting Wikipedia, preprocessing, pre-trained Word2vec using Wikipedia, dividing data into test and train data, word embedding, classification using CNN-BiLSTM, and finally evaluating with test data.

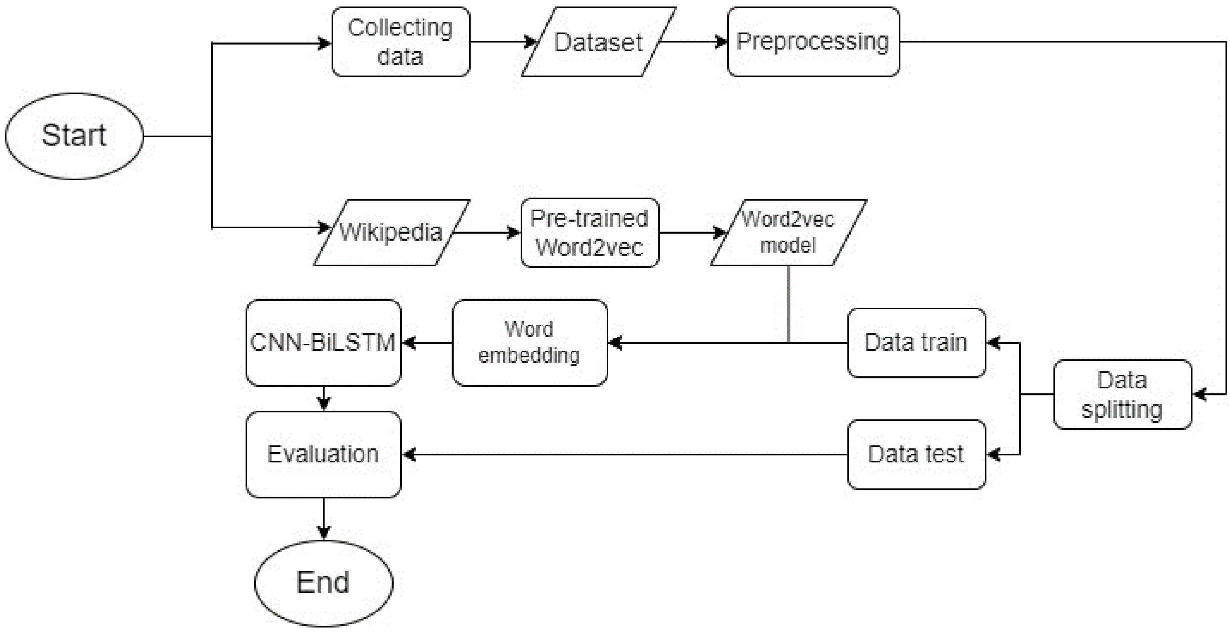

Fig. 1 System Flowchart

Collecting data

Data is collected using crawling or retrieving from Twitter social media. At this stage, the author uses the Twitter API key with the keyword "BBM naik." The data collected was 19,843. An illustration of the dataset label can be seen in Table 1

Table. 1 Labelled Dataset

Tweet	Label
@bachrum_achmadi Sirait.. Sirait.. Kok otak lu cetek amat ya. Harga minyak turun, BBM diturunkan. Harga minyak naik, BBM Dinaikan. Begitu aja terus. Kalau lu goblok jangan pamer ya. Lu mau rakyat jadi bingung gitu...	2
Setelah Harga BBM 2x Naik, SPBU Vivo Tetap Ramai.	0
Kunjungan terhadap salah satu warga sebagai pedagang yang terdampak kenaikan BBM, Puji Tuhan walaupun harga BBM naik, namun ibu ini mengalami kenaikan omzet sebagai pedagang barang Klontong	1

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Pre-processing

Preprocessing is converting data into a format to make it more effective and efficient to get more accurate results, reduce computing time, and make the data size smaller without reducing the information so that it can be processed and used to build the system (Asroni, Fitri, & Prasetyo, 2018). Examples of results from preprocessing can be seen in Table 2. The preprocessing stages carried out in this study are described as follows:

a. Dataset cleaning
   Data cleaning is a stage to clean the entire data by removing data containing HTML tags, URL removal, mention removal to remove the "@" sign, punctuation removal to remove all punctuation marks, and number removal to remove all numbers in the sentence.
b. Case folding
   Case folding is the process of making all letters in a sentence lowercase.
c. Tokenizing
   Tokenization is separating words in sentences into single words.
d. Normalization
   The normalization process is a process that helps change words that are not standard, typos, slang words, and other words.Stopwords removal (Alvi Rahmy Royyan & Erwin Budi Setiawan, 2022). This research uses the KBBI dictionary, a meaningless dictionary made manually and accessed from the internet.
e. Stopwords removal
   Using the literary library to reduce the dimensionality of the data and remove words that are not contained in sentiment elements, such as personal pronouns, conjunctions, and prepositions (Rosid, Fitrani, Astutik, Mulloh, & Gozali, 2020).
f. Stemming
   Word stemming is used for the process of converting words into root words. This stage is quite important in text-based classification (Rosid et al., 2020).

Table. 2 Preprocessed Text

Before Preprocessing	After Preprocessing
@Denny kalau harga bahan bakar minyak naik, otomatis biaya pembangunan infrastruktur ikut naik. blegug!	harga bahan bakar minyak naik otomatis biaya bangun infrastruktur naik bodoh
Dukung penyesuaian harga BBM, demi Indonesia ~ DKI Jakarta - #BBMSubsidi #BBMBersubsidi #BantuanBBMUntukRakyat #BLTBBMTepatSasaran #SubsidiTepatSasaran #SemuaDemiKesejahteraan #CerdasPakaiBBM #BijakPakaiBBM https://t.co/5KzMIUFAoO	dukung sesuai harga bbm indonesia dki jakarta

Word2vec

The next stage in this research is pre-trained word embedding using 2 Word2vec architectures, namely Continous Bag of Words (CBOW) and Skip-gram Word2vec. The corpus used is the latest Indonesian Wikipedia in 2021. An illustrates of the difference between CBOW and Skip-gram architecture can be seen in Figure 2 below.

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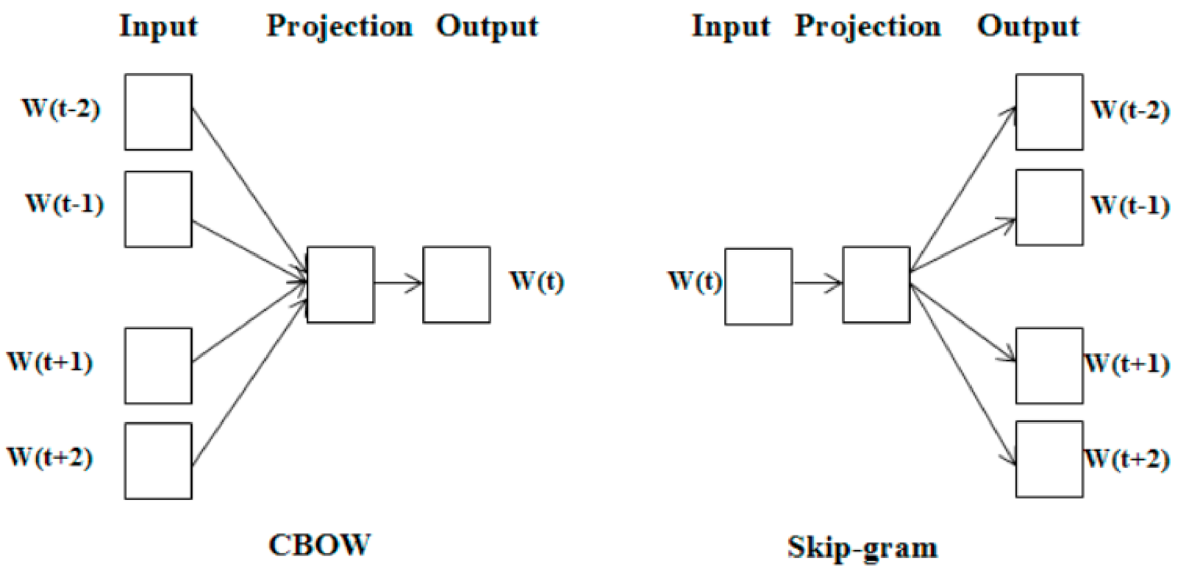

Fig. 2 CBOW and Skip-gram architecture

The two architectures work oppositely in that CBOW can predict the target word based on the context or surrounding words so that the position of a particular word in its neighboring word order does not matter. CBOW takes a faster time to train, and the accuracy is slightly better. In contrast to CBOW, Skip-gram works better with less training data and can predict words around a given word.

In this study, we implemented Word2vec using the gensim library and the window size, mint_count, and workers parameters commonly used in previous studies considering that they have obtained the best results. However, different vector dimension sizes and different architectures were used in this study. The explanation of the parameters is explained as follows:

a. The vector's dimension is the nodes' size in the hidden layer. This study uses dimensions 100, 200, and 300 for each architecture.
b. Sg is a parameter to select the Word2vec algorithm. The value is 0 for CBOW and 1 for Skipgram. In this study, we used both architectures.
c. Window size is the distance between the context word and the target word. This research uses a window size of 5 for each architecture.
d. Mint_count is the minimum frequency of occurrence of a word in the corpus. The mint count used is 1 for each architecture.
e. Hs is a parameter to select the hierarchical softmax or negative sampling evaluation model. Value 1 for hierarchical softmax and 0 for negative sampling. In this research, we use parameter one or Hierarchical softmax.

CNN-BiLSTM

Hybrid deep learning CNN-BiLSTM adopts a hybrid Neural Network model built and used to classify short text emotions. CNN is known for extracting as many features as possible from text. BiLSTM can store the chronological order between words in the document, so it can ignore unnecessary words using the delete gate (Yue & Li, 2020b).

In this stage, convolution and max pooling layers are applied for feature extraction to extract high level features. The output of this stage is the input of the next stage.

Each combination of CNN and Bi-LSTM models has a unique architecture and advantages (Bharal & Vamsi Krishna, n.d.) :

1. CNN is famous for extracting as many features as possible from the input text using maximal pooling layers.

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2. BiLSTM can store information in future memory by using two hidden states together. Moreover, it can ignore unnecessary textual information by using a forgetting gate.

A hybrid deep-learning system for sentiment classification will be built at this stage. The author uses deep hybrid learning to find the advantages of combining two or more classification methods and to cover the shortcomings of each method. The methods used in this research are Convolutional Neural Network and Bidirectional Long Short term Memory. The architecture of the hybrid model can be seen in Figure 3 (Bharal & Vamsi Krishna, n.d.) :

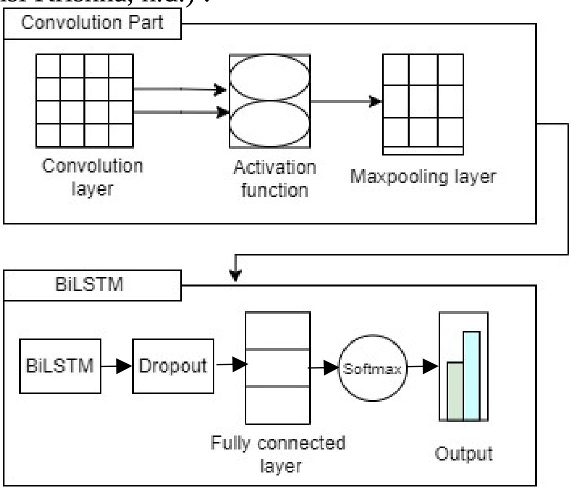

Fig. 3 CNN-BiLSTM Architecture

Evaluation

In this study, the evaluation will be carried out using an evaluation matrix after building the model. The evaluation matrix is used to measure the classification results to determine the effectiveness of the model that has been built. The evaluation matrix can also be used to examine the performance and quality of the model built (Munawar, 2020). The evaluation matrix used in this research is as follows :

1. Confusion Matrix
The evaluation matrix is used as an indicator to measure the classification results to see the model's effectiveness. The evaluation matrix is also used to assess the quality of the model. The following evaluation metrics used in this study are described in Table 3.

Table. 3 Matrix Confusion

Classification	Positive Prediction	Negative Prediction
Actual positive	True Positive (TP)	False Positive (FP)
Actual Negative	False Positive (FP)	False Negative(FN)

2. Accuracy
Accuracy is the ratio of accurate predictions for positive and negative values to the overall data. The accuracy equation can be seen in the equation (1)

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

3. Precision
Precision is the ratio of accurate positive rate predictions to positive results with the following equation (2).

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$$\text{Precision} = \frac{\text{TP rate}}{(\text{ TP rate+FP rate })} \quad (2)$$

4. Recall
Recall is the ratio of true positive predictions to the overall true positive data with the following equation, the equation to calculate recall can be seen in the equation (3).

$$\text{Recall} = \frac{(\text{TP}}{(\text{ TP rate + FN rate })} \quad (3)$$

5. F1-score
F1-score is calculated by taking the average value of the precision and recall results to calculate model performance with the following equation (4)

$$\text{F1} - \text{Score} = \frac{(\text{ 2}*\text{Recall}*\text{precision})}{(\text{ Recall+Precision })} \quad (4)$$

RESULT

Sentiment of fuel price increase

Based on the data collected using the Twitter API and labeled in this study, there are 19,843 datasets with positive data of 6,406, neutral 6,238, and negative 6,840. The distribution of data with labels is illustrated in Figure 4, with labels "1" as positive, "0" as neutral, and "2" as negative.

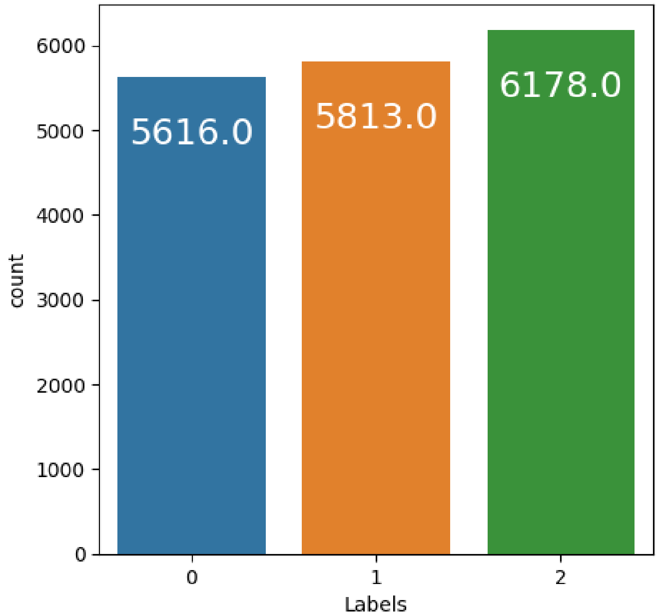

Fig. 4 Dataset Distribution

CNN-BiLSTM parameter

The CNN-BiLSTM hybrid parameters we use in this study are shown in Table 4. The output of Word2vec will be inputted into the CNN layer, and the CNN output will be entered into the BiLSTM layer; we use 10 epochs in this study.

Table. 4 CNN-BiLSTM Layer

Hybrid Layer	Output Shape
CNN	(None, 64, 64)

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Max pooling1d	(None, 32, 64)
BiLSTM	(None, 256)
Dense 1	(None, 128)
Dropout 1	(None, 128)
Dense 2	(None, 32)
Dropout 2	(None, 32)
Dense 2	(None, 3)

Dimension Vector Combination of Word2vec

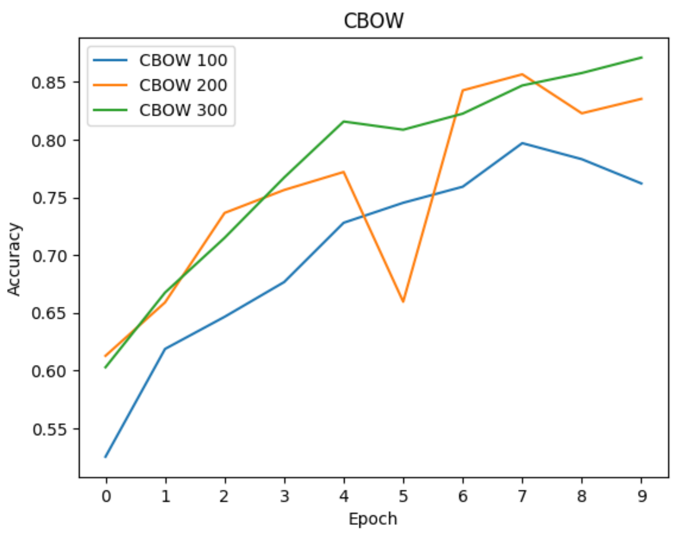
The test results on each CBOW and Skip-gram architecture with dimensions 100, 200, and 300 for each architecture can be seen in Table 5 with the value of accuracy, recall precision, and F1-score.

Table. 5 CBOW and Skip-gram performance

Architecture	Accuracy	Recall	Precision	F1- Score
CBOW 100	76%	92%	92%	81%
CBOW 200	84%	84%	85%	84%
CBOW 300	**87%**	**87%**	**89%**	**88%**
Skip-gram 100	72%	90%	89%	73%
Skip-gram 200	83%	93%	90%	85%
Skip-gram 300	80%	95%	92%	80%

CNN-BiLSTM train and loss

Figure 5 shows the train and loss graphs of the CNN-BiLSTM model using the CBOW word2vec architecture. Figure 6 shows the train and loss graphs of the CNN-BiLSTM model for the Skip-gram word2vec architecture.



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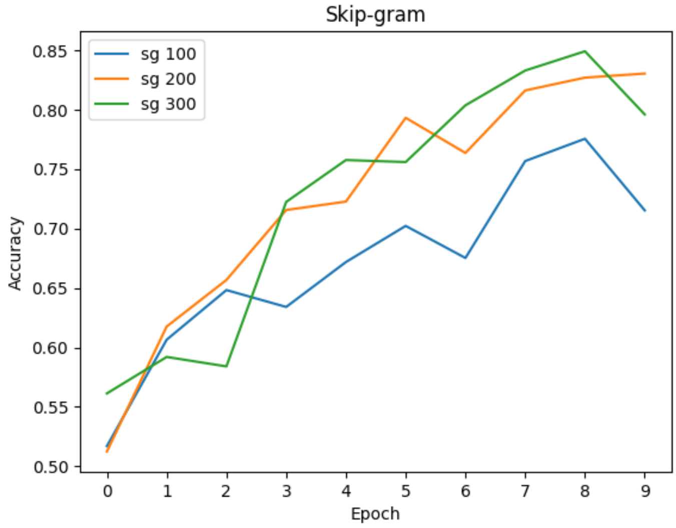

Fig. 5 CBOW-CNN-BiLSTM train and loss **Fig. 6** Skip-gram CNN-BiLSTM train and loss

DISCUSSIONS

Tests were conducted to see the effect of architecture and different dimension sizes on the Word2vec model on sentiment classification. The main research conducted by Mikolov (Mikolov et al., n.d.) explains that the parameters used for each architecture are around 50-600. We do the research by testing three different vector dimensions in each architecture, namely with sizes 100, 200, and 300.

The selection of the Word2vec architecture model can affect the performance of the deep learning model. The average results of different architectures show this. This study found that the CBOW architecture model with a dimension size of 300 produced better accuracy. CBOW has slightly better accuracy for frequently occurring words (Mikolov et al., n.d.). Many words frequently appear in the dataset tested in this study so that CBOW can work better. In addition, hybrid deep learning, namely CNN-BiLSTM, can also work well because when the built word vector passes through the CNN-BiLSTM model, it will significantly help extract implicit features from the word vector (Liu, Zhang, Luo, Lian, & Liu, 2020).

CONCLUSION

Research on sentiment classification of fuel price increases has been completed with a dataset of as many as 19,843 with positive, neutral, and negative labels. The method used is hybrid deep learning CNN-BiLSTM. This research compares how the two Word2vec architectures work by comparing different model architectures and vector dimension sizes. The results showed that the CBOW model with 300 vector dimensions worked better on this dataset with 87% accuracy, 87% Recall, 89% Precision, and 88% F1-score. However, Word2vec requires a longer time and a larger laptop CPU size for training. For future research, it is expected that researchers can use the latest word embedding, such as Bidirectional Encoder Representations from Transformers (BERT).

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