IJOBTECH
INTERNATIONAL JOURNAL OF SMART BUSINESS AND TECHNOLOGY

*Vol. 1 No. 1 (2025)*

# Comparison Of CNN And LSTM Strategies For Estimation Investigation Of IKN Relocation

Muhammad Akbar Raafi Rahmatulloh [1], Sugiarto [2], I Gede Susrama Mas Diyasa [3], Sherafim Glory Mei Stephany [4]

[1,2,3] *Department of Digital Business, UPN Veteran Jawa Timur, Surabaya 60294, Indonesia*

[4] *Department of Magister Information Technology, UPN Veteran Jawa Timur, Surabaya 60294, Indonesia*

**Abstract**

As time progresses, information technology has begun to reshape the forms and patterns of communication within society. Social media is one of the services that currently enables more open communication in political and social interactions within communities and nations. A prominent theme in domestic politics is the plan to relocate the nation's capital, which has become a widely discussed topic. The purpose of this research is to understand and analyze public responses captured in comments on YouTube videos related to the issue of relocating the capital city. Additionally, this study aims to evaluate the correlation between two algorithms, CNN and LSTM, in analyzing public sentiment regarding the capital relocation. The data was collected from videos on the capital relocation along with 11,000 comments. After testing, the CNN model achieved an accuracy of 0.975, while the LSTM model achieved an accuracy of 0.966. The analysis revealed both positive and negative sentiments regarding the capital relocation plan. The findings of this research provide policymakers with a more detailed understanding of public perspectives on the capital relocation and demonstrate the benefits of these two algorithms in analyzing textual data with unstructured information.

**Keywords:** *National Capital; Sentiment Analysis; CNN; LSTM.*

**Article History:**

| | | |
|---|---|---|
| **Received** | : | 30 January 2025 |
| **Revised** | : | 24 June 2025 |
| **Accepted** | : | 23 October 2025 |
| **Published** | : | 31 October 2025 |

## 1- Introduction

The decision to move Indonesia's capital from Jakarta to Nusantara represents a strategic effort by the government to tackle various issues plaguing Jakarta. As the country's hub for governance, commerce, and the economy, Jakarta faces significant problems such as traffic congestion, public health challenges, and frequent flooding, all of which stem from its dense population. These challenges have negatively impacted residents' quality of life and created risks for both economic and environmental sustainability in the city.

From the government's perspective, redistributing Jakarta's functions to other cities is seen as a solution to alleviate economic and social burdens. Nusantara, located in East Kalimantan, has been selected as the site for the new capital and the center of economy and governance. The hope is that a more modern and efficient government will be established there. Moreover, this policy is expected to accelerate infrastructure development, attract investment, and create more job opportunities in the region.

However, this policy has sparked reactions among the public and experts, with dissatisfaction reflecting diverse views on the risks and implications of the relocation. Some believe the policy should be implemented to improve the quality of life and promote equitable development, while others are concerned about excessive costs, potential environmental damage, and unaddressed social and economic impacts.

Amidst the intense debate, social media platforms have become a key medium for public discourse, with YouTube serving as a primary channel for comments supporting or opposing the policy. These responses represent public opinions on the capital relocation and provide crucial insights into societal attitudes. However, analyzing sentiment faces challenges such as linguistic and symbolic variations and the vast amount of data involved.

Thus, sentiment analysis plays a critical role. By employing advanced computational techniques, sentiment analysis enables the identification, extraction, and interpretation of meaning embedded in complex sentiments and texts. It not only provides an overview of how Indonesians think and feel about the capital relocation policy but also helps in formulating policies that are more responsive to public aspirations..

[1] **CONTACT**: akbarrafii@gmail.com

This research aims to evaluate and compare the effectiveness of sentiment analysis methods in the context of social media comments regarding Indonesia's capital relocation. Specifically, it designs feedback mechanisms using two popular techniques, Convolutional Neural Networks (CNN) and Long Short-Term Memory (LSTM), to detect positive, negative, and neutral sentiments in the comments. This study aims to provide sharper insights into public attitudes toward the relocation and demonstrate the effectiveness and reliability of each method in addressing this complex task.

## 2- Metodhology

This research examines sentiments regarding the relocation of Indonesia's capital to Nusantara by analyzing comments on YouTube. The techniques employed include library initialization, data crawling from YouTube, and text labeling using word-based learning methods. This is followed by modeling using Convolutional Neural Network (CNN) and Long Short-Term Memory (LSTM) evaluators to identify the best model.

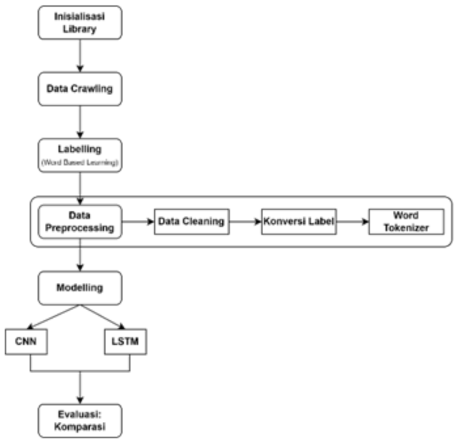


**Figure 1.** Research Flow Chart

This research utilizes several Python libraries to facilitate efficient and accurate data retrieval, analysis, and visualization. For instance, Pandas aids in data manipulation, while Seaborn and Matplotlib support data visualization. For natural language processing (NLP) and sentiment analysis, the NLTK library is used, including stopword removal. YouTube comments were extracted using the YouTube Data API V3 and the apiclient library, while Regular Expression (re) was applied for text cleaning. NumPy facilitated numerical computations, and deep learning modeling was conducted using Keras with layers such as embedding, LSTM, and Conv1D. Additionally, Scikit-learn was employed to split the dataset into training and testing sets.

Data crawling refers to the automated data collection from digital sources like applications, websites, or databases. In this study, data crawling was utilized to download all comments from several YouTube videos discussing the relocation of Indonesia's capital, using the YouTube Data API V3. API keys were acquired through Google Cloud, and video IDs were input for the data retrieval process. For each desired comment, this process was repeated five times. Data from five videos were compiled into a CSV file, totaling 11,185 entries. For sentiment analysis using CNN and LSTM algorithms, only the "comments" were used as the research variable, leading to the creation of a new dataset containing only the comments.

The labeling stage involved sentiment analysis of all text in the dataset, assigning sentiment labels to each text, and storing the dataset with the added sentiment labels. The researchers adopted Word-Based Learning or Word Embedding approaches and the SentimentIntensityAnalyzer library, which is effective for analyzing short text such as YouTube comments. A custom function, label_sentiment, was created to assign a sentiment label (positive, negative, or neutral) to each text. This function was applied to the "Comment" column in the dataset, and the results were saved in a new column named "Labels." The labeled dataset was then exported as a new CSV file called labeled_dataset.csv. Sentiment label distribution was visualized using the countplot function in Seaborn, which displays the count of texts for each sentiment label: positive, negative, and neutral.

Data preprocessing is a crucial step, including cleaning, label conversion, and text tokenization. This involves transforming raw data into a suitable format for analysis by, for example, converting text to lowercase, removing irrelevant symbols, filtering out nonsensical words, and applying stemming. The preprocess_text function ensures data consistency by removing HTML tags, non-alphabetic characters, and stopwords. Sentiment labels were then converted to machine-friendly numerical values: 0 for negative and 1 for positive. The dataset was split into training and testing sets to evaluate the models, using consistent splits to ensure reproducibility. Word tokenization, which breaks text into individual words, was performed to facilitate further analysis.

This research leveraged CNN and LSTM models. CNN was used to classify comment sentiments with its capability to process spatial data, including text transformed into matrix form. To evaluate model performance and prevent overfitting, cross-validation was implemented, dividing data into training and validation sets. Metrics such as loss, accuracy, validation loss, and validation accuracy were measured using binary cross-entropy. CNN was employed to learn local features of the text and generate abstract representations to support sentiment classification. Convolution and pooling layers enhanced feature extraction, while dense layers with a sigmoid activation function facilitated binary sentiment classification.

The LSTM model was used to process sequential data while preserving relevant context, making it effective for recognizing temporal patterns in text data. The model was designed, trained, and evaluated with parameters such as vocabulary size and embedding dimensions to optimize performance. Training involved setting batch size, the number of epochs, and validation splits, while evaluation measured the model's ability to predict unseen data accurately.

In sentiment analysis using a combination of CNN and LSTM models, evaluations were conducted to assess overall performance. Key metrics included Mean Absolute Error (MAE), Mean Squared Error (MSE), and Root Mean Squared Error (RMSE). MAE calculates the average absolute prediction error, MSE emphasizes larger errors through squaring, and RMSE presents errors in the same units as the target variable. Evaluation results were visualized using bar charts to provide a clear representation of model performance.

## 3- Result And Discussion

This analysis delves deeply into public views and opinions regarding the issue of the capital relocation. By gathering data from various sources and processing it comprehensively, the study finds that the majority of the public supports and agrees with the plan.

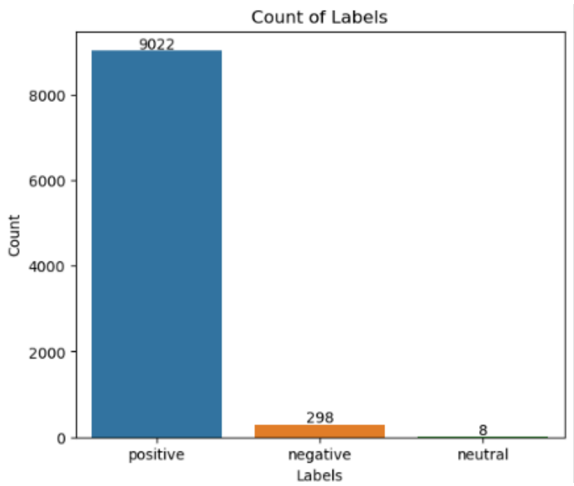


**Figure 2.** Community Sentiment

The chart in the figure illustrates the sentiment distribution in the data, with the majority of sentiments (9,022) being positive, 298 negative, and only 8 neutral. This data was obtained through a manual labeling process, where each comment and opinion was analyzed and classified. This information underscores that most of the public approves of relocating the administrative center to the new location.

### *3-1- CNN Modeling Results*

The first model employs a CNN architecture with an embedding layer sized to the vocab_length and an embedding dimension of 100. This model features a 1D convolutional layer with 128 filters of size 5 and a ReLU activation function, followed by a global max pooling layer to extract key features. To mitigate the risk of overfitting, the model incorporates several fully connected layers with 64 and 32 units, L2 regularization, and a dropout layer with a ratio of 0.5.

During training, evaluation was conducted using loss and validation loss metrics. The results are summarized in the table below.

**Table 1.** Training Process CNN

| Epoch | Loss | Val Los |
|---|---|---|
| 1 | 0.6750 | 0.4102 |
| 2 | 0.4386 | 0.3542 |
| 3 | 0.3809 | 0.3105 |

| | | |
|---|---|---|
| 4 | 0.3052 | 0.2802 |
| 5 | 0.2637 | 0.2635 |

The initial loss value of 0.6750 reflects the model's average error in predicting outputs from the training data. The lower validation loss value (0.4102) compared to the training loss indicates that the model demonstrates good generalization ability and is not overfitting.

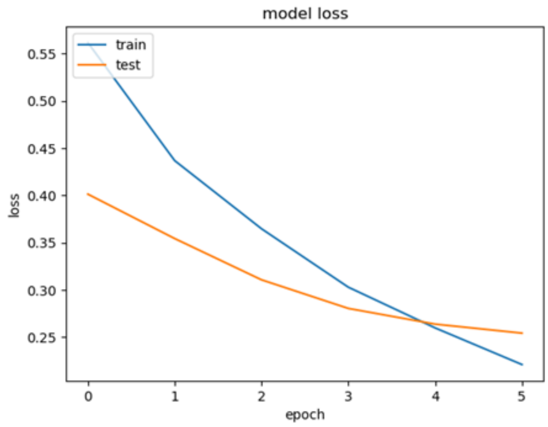


**Figure 3.** Model Loss CNN

### *3-2- LSTM Model Result*

The second model uses an LSTM architecture. The process begins with an embedding layer that transforms sequential input into 100-dimensional vectors with 1,596,100 parameters. The LSTM layer, containing 117,248 parameters, captures temporal patterns and long-term dependencies in the data.

**Table 2.** Training Process LSTM

| Epoch | Loss | Val Los |
|---|---|---|
| 1 | 0,3530 | 0,1332 |
| 2 | 0,1535 | 0,1338 |
| 3 | 0,1446 | 0,1330 |
| 4 | 0,1477 | 0,1318 |
| 5 | 01591 | 0,1305 |
| 6 | 0,1398 | 0,1367 |
| 7 | 0,1466 | 0,1361 |
| 8 | 0,1420 | 0,1317 |
| 9 | 0,1542 | 0,1325 |
| 10 | 0,1405 | 0,1356 |

The loss value of 0.3530 indicates the average error made by the model when predicting outputs from the training data. This suggests the model is still making some prediction errors and has not yet fully understood all the patterns in the training data.

Meanwhile, the validation loss value of 0.1332 reflects the model's average prediction error on validation data. This value represents how well the model performs on new, unseen data. The lower validation loss compared to the training loss (0.1332 vs. 0.3530) indicates that the model is not overfitting to the training data patterns and demonstrates a good ability to generalize.

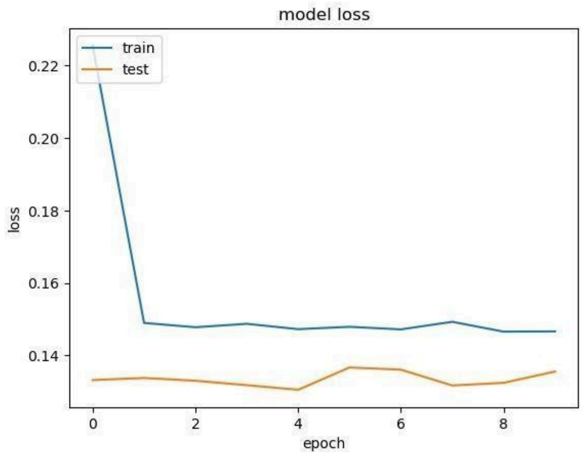


**Figure 4.** Model Loss LSTM

### *3-3- Model Evaluation*

Evaluation and test results were utilized to compare the performance of the two models and determine which one exhibited the best performance. This study implemented two algorithmic models, Convolutional Neural Network (CNN) and Long Short-Term Memory (LSTM), to train the data and measure their accuracy. After undergoing training and testing phases, both models demonstrated high accuracy levels, although there were slight differences in the results.

**Table 3.** Model Evaluation

| Epoch | Train Split | MSE | RMSE | MAE |
|---|---|---|---|---|
| CNN | 10% | 0.018 | 0.135 | 0.027 |
| | 20% | 0.014 | 0.120 | 0.018 |
| | 30% | 0.015 | 0.123 | 0.018 |
| | 40% | 0.018 | 0.135 | 0.022 |
| LSTM | 10% | 0.032 | 0.179 | 0.069 |
| | 20% | 0.032 | 0.180 | 0.072 |
| | 30% | 0.033 | 0.180 | 0.059 |
| | 40% | 0.033 | 0.180 | 0.052 |

The evaluation metrics illustrate a performance comparison between the CNN and LSTM models across different training data sizes (10%, 20%, 30%, 40%). The CNN model showed improved performance as the training data size increased up to 30%, but its performance began to decline when the training data size reached 40%. Meanwhile, the LSTM model remained consistent, with stable MSE, RMSE, and MAE values despite the increase in training data size.

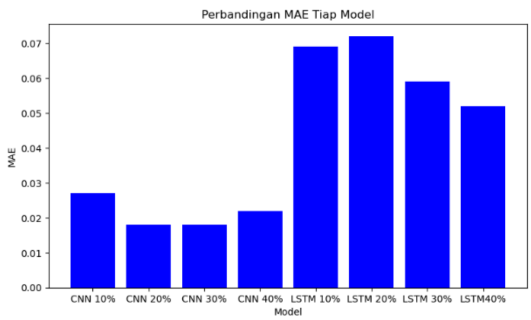


**Figure 5.** MAE Comparison of Each Model

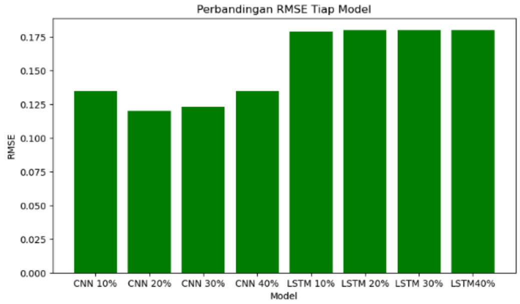


**Figure 6.** RMSE Comparison of Each Model

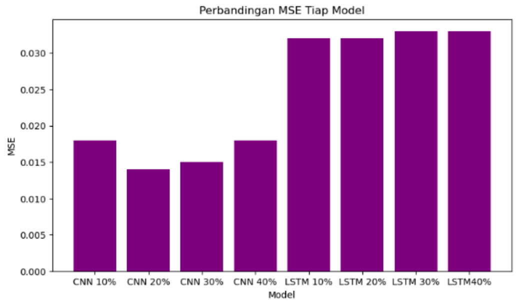


**Figure 7.** MSE Comparison of Each Model

Based on the evaluation results, the CNN model demonstrated superior performance compared to the LSTM model in predicting the target. CNN achieved the best results across all evaluation metrics, with the lowest MAE of 0.018 compared to 0.052 for LSTM, the lowest RMSE of 0.120 compared to 0.135, and the lowest MSE of 0.014 compared to 0.032. These findings indicate that CNN is more effective in solving target prediction problems, making it a more optimal choice for similar data.

## 4- Conclusion

The Convolutional Neural Network recorded a lower Mean Absolute Error compared to the Long Short-Term Memory, with the lowest values being 0.018 for the Convolutional Neural Network and 0.052 for the Long Short-Term Memory. Additionally, the Root Mean Squared Error for the Convolutional Neural Network was also lower at 0.120 compared to 0.135 for the Long Short-Term Memory. Similarly, in terms of Mean Squared Error, the Convolutional Neural Network achieved the lowest value of 0.014, while the Long Short-Term Memory recorded 0.032. Based on these three evaluation metrics, it can be concluded that the Convolutional Neural Network overall demonstrates better performance than the Long Short-Term Memory in predicting the target.

## 5- References

[1] Agrawal, R., & de Alfaro, L. (2023). Predicting the quality of user contributions via LSTMs. *UC Santa Cruz Previously Published Works*. Retrieved from https://escholarship.org/uc/item/32k365xv.

[2] Susanti, D. O., Efendi, A., & Putri, A. S. (2024). The urgency of sharia-crowdfunding as an alternative funding in development of Nusantara's capital city. *PETITA: Jurnal Kajian Ilmu Hukum dan Syariah, 9*(1), 114–128.

[3] Buček, J., Plešivčák, M., & Bačík, V. (2024). One hundred years of national capital-making: The case of Bratislava, Slovakia. *Quaestiones Geographicae, 43*(4), 49–63.

[4] Susanti, D. O., Efendi, A., & Suhaimi, A. (2024). Characteristics of Sharia Crowdfunding as an Alternative to Financing the Development of the National Capital City. *Yuridika, 39*(3), 375–394.

[5] Deng, J, Lu, L., & Qiu, S. (2020). Software defect prediction via LSTM. *IET Software, 14*(4), 443-450.

[6] Minaee, S., Azimi, E., & Abdolrashidi, A. (2019). *Deep-Sentiment: Sentiment Analysis Using Ensemble of CNN and Bi-LSTM Models*. arXiv preprint arXiv:1904.04206.

[7] Alayba, A. M., Palade, V., England, M., & Iqbal, R. (2018). *A Combined CNN and LSTM Model for Arabic Sentiment Analysis*. arXiv preprint arXiv:1807.02911.

[8] Srinivas, A. C. M. V., Satyanarayana, C., Divakar, C., & Sirisha, K. P. (2021). *Sentiment Analysis using Neural Network and LSTM*. IOP Conference Series: Materials Science and Engineering, 1074(1), 012007.

[9] El Koufi, N., Missah, Y. M., & Belangour, A. (2024). *A Hybrid CNN-LSTM Based Natural Language Processing Model for Sentiment Analysis of Customer Product Reviews: A Case Study from Ghana*. Journal of Hunan University Natural Sciences, 51(8).

[10] Purwono, A., Ma'arif, A., Rahmaniar, W., Fathurrahman, H. I. K., Kusuma, A. Z., & Haq, Q. M. (2022). Understanding of Convolutional Neural Network (CNN): A review. *International Journal of Robotics and Control Systems, 2*(4), 739–748.

[11] Upreti, A. (2022). Convolutional Neural Network (CNN): A comprehensive overview. *International Journal of Multidisciplinary Research and Growth Evaluation*, 3(4), 488-493.

[12] Wankhade, M., Rao, A. C. S., & Kulkarni, C. (2022). A survey on sentiment analysis methods, applications, and challenges. *Artificial Intelligence Review, 55*(5), 5731–5780.

[13] Wang, W., & Pan, S. (2018). *Deep CNN-LSTM with Combined Kernels from Multiple Branches for IMDb Review Sentiment Analysis*. *IEEE International Conference on Green Computing and Communications*, 2018, 551–556.

[14] Kumar, A., & Jaiswal, A. (2023). *A CNN-LSTM-Based Hybrid Deep Learning Approach for Sentiment Analysis of Monkeypox Tweets*. *Journal of Computer Virology and Hacking Techniques*, 2023.

[15] Ahmad, S., Saqib, S. M., & Syed, A. H. (2024). *CNN and LSTM Based Hybrid Deep Learning Model for Sentiment Analysis on Arabic Text Reviews*. *Mehran University Research Journal of Engineering and Technology*, 43(2), 183–194.

[16] Dehghani, M., & Yazdanparast, Z. (2023). *Political Sentiment Analysis of Persian Tweets Using CNN-LSTM Model*. *arXiv preprint arXiv:2307.07740*.

[17] Mollah, M. P. (2022). *An LSTM Model for Twitter Sentiment Analysis*. *arXiv preprint arXiv:2212.01791*