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Leveraging Convolutional Neural Networks and Random Forests for Advanced Sentiment Classification of Social Media Responses on Public Services

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ABSTRACT

In the digital era, social media has become a significant channel for citizens to express their opinions on government services. In Indonesia, particularly in the context of municipal issues, understanding public sentiment is essential to improving public service delivery. This study analyzes user comments from Facebook, Instagram, Twitter, and YouTube to capture public responses toward local government performance. Departing from previous studies that typically employ binary or three-level classifications, this research implements a five-category sentiment scheme: Very Good, Good, Fair, Poor, and Very Poor. A hybrid model combining a Convolutional Neural Network (CNN) for feature extraction and a Random Forest (RF) classifier is proposed to address this multi-class task. The model achieves 87% accuracy, outperforming the individual CNN and RF models. The results demonstrate the potential of social media–based sentiment analysis to enhance public service quality in Indonesia.

I. INTRODUCTION

The government plays a critical role in delivering high-quality public services that meet the diverse needs of the population. The effectiveness of these services is strongly influenced by public satisfaction and acceptance of government policies. Consequently, community feedback serves as a key indicator for assessing government performance and contributes significantly to maintaining social stability in Indonesia [1][2].

Social media platforms such as Facebook, Instagram, Twitter, and YouTube have become prominent channels through which citizens voice complaints, suggestions, and aspirations regarding various urban issues. The sentiments expressed in these online comments—ranging from highly positive to highly negative—offer valuable insights into public perceptions of service quality [3]. The abundance of user-generated content on these platforms underscores the importance of developing reliable analytical methods to interpret sentiment at scale.

This study aims to examine public sentiment toward government services by classifying social media comments into five distinct categories: very poor, poor, fair, good, and very good. To accomplish this, a hybrid model integrating a Convolutional Neural Network (CNN) for feature extraction and a Random Forest (RF) classifier for final prediction is utilized. Both techniques have demonstrated strong potential in previous sentiment analysis and text classification research.

The primary contribution of this study is to provide policymakers with deeper insight into public perceptions across different urban settings in Indonesia. Furthermore, the proposed hybrid approach advances methodological developments in sentiment analysis by demonstrating that neural feature extraction combined with an ensemble classifier can yield improved performance in multi-class text classification. These findings can support the development of more responsive public service policies and enhance the evaluation of government performance.

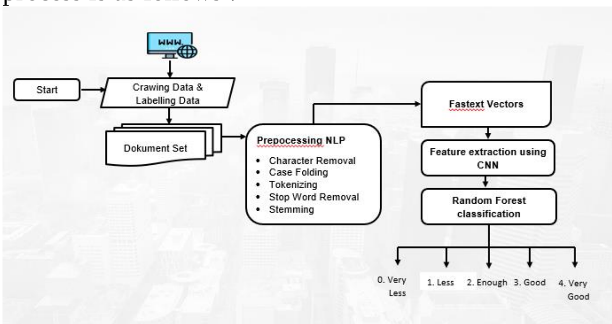
A substantial body of literature has explored various machine learning and deep learning algorithms for sentiment analysis, particularly those employing CNNs and RFs. Wang et al. [4] introduced a CNN-based model for sentiment classification using continuous numerical data, achieving improved outcomes over traditional techniques, though dataset characteristics limited its application. Yang et al. [5] implemented a CNN–RF hybrid approach for image classification, achieving high accuracy but with limited relevance to text-based sentiment tasks.

More recent studies by Kastrati et al. [6] and Sitaula et al. [7] applied CNN architectures to sentiment analysis of social media content; however, these studies generally relied on binary or three-class sentiment labels and did not address the challenges posed by more granular multi-class schemes. George and Sumathi [8] also explored a CNN–RF hybrid model, though their work focused primarily on product reviews rather than the public service domain.

This research addresses these limitations by adopting a five-level sentiment taxonomy that better captures the nuances of public opinion. The integration of CNN and RF enables the extraction of richer text features and supports more accurate multi-class classification. Additionally, applying the Continuous Bag-of-Words (CBOW) technique for text vectorization enhances the representation of linguistic context, thereby strengthening the model's ability to interpret diverse sentiment expressions in social media comments.

II. METHOD

This research seeks to examine public sentiment regarding public services as articulated on social media. The analysis process involves collecting data, processing text, and classifying responses into sentiment categories using a combination of a Convolutional Neural Network (CNN) and a Random Forest (RF) algorithm. The research process is as follows :



Gambar 1. System Design Diagram

A. Crawling Data

In this study, 8,000 comments from four social media platforms—Twitter, Facebook, Instagram, and YouTube—were analyzed. The distribution of data per platform is as follows: 2,000 comments from Twitter, 2,000 from Facebook, 2,000 from Instagram, and 2,000 from YouTube. The sentiment data was unbalanced, with most comments labeled "Good" and "Very Good," while "Poor" and "Very Poor" were less common. The sentiment labeling was performed manually by the research team, who assigned labels based on an analysis of the emotions expressed in the comments.

B. Labelling Data

Sentiment labeling typically employs positive and negative categories for binary categorization. This research employs multiple classification categories due to its multi-label nature. The author employs five categories designated by numbers for labeling purposes: 0 = very poor (very less) 1 = poor (less), 2 = fair, 3 = good, and 4 = very good.We conducted hand labeling, as illustrated in the table below :

TABEL I
THE DATASET IS IN THE INDONESIAN LANGUAGE

Senti ment	Comments
1	Ini bukan waktunya bicara ,tapi kerja kerja & kerja , bantu rakyatnya ??????
2	Sepatutnya pak gubernur yg punya inisiatif,,terjadi banjir karena apa,, mungkin tata kotanya kurang,atau masalah masifnya penggundulan hutan dan pertambangan sehingga sungai menjadi dangkal,, apa memang faktor alam karena curah hujan tinggi,,
3	Kerja cepat bukan kerja dibuat lelet bravo pak bas menteri PUPR ☺
3	Bgmn cara cek bg kami yg blm pernah mndaptkan Dana Bansos??
1	gubernur cap kecap vs panglima pembangunan
0	Peras terus.. tikus berdasi, tikus berseragam yg semakin hidup sedangkan org yg bukan bagian dri mereka hanya di jadikan tumbal.
4	Mantap terima kasih pak presiden semoga adanya kegiatan ini indonesia semakin maju dan melek teknologi.
5	Salut dan mantaap pelayanan Dukcapil demi tertib administrasi
Etc..	Etc…

Grading Features

According to the Big Indonesian Dictionary (KBBI), a sentence is a unit of language that has final intonation and can consist of clauses. Sentences are used in both spoken and written forms. In the context of education, a sentence is also a complete linguistic structure that conveys meaning. Therefore, in sentiment assessment, sentences are categorized into five levels: very poor, poor, fair, good, and very good, based on word choice and meaning.

Sentences are categorized as very poor if they contain very negative words, such as profanity, insults, or abusive language. Examples include statements that use abusive language or mention insults against certain groups, such as the police or certain agencies. Such sentences contain very derogatory sentiment and reflect extreme disapproval.

If a sentence expresses milder negative sentiments, such as rejection, disappointment, or lies, it is categorized as poor. For example, sentences expressing disappointment with the inequality of social assistance or rejection of certain policies can be considered poor, because they convey criticism or complaints that are milder but still negative.

Sentences that are considered to contain neutral or informative sentiments, such as questions, suggestions, or information that is neither overly supportive nor oppositional. Sentences with clear information, such as questions about fund allocation or suggestions about the education system, fall into this category because they are neutral and do not contain overly strong opinions.

Finally, sentences that contain positive sentiment, such as approval, appreciation, or praise, are categorized as good or very good, depending on the strength of the sentiment. Sentences that express gratitude, praise for someone's performance, or strong expressions of support such as "I strongly agree" fall into this category. These types of sentences show strong positive feelings towards the topic being discussed.

C. Preprocessing NLP

Text preprocessing involves several important steps. First, the text is cleaned to remove irrelevant elements such as HTML tags, URLs, and special characters. Next, the text is reformatted using case folding, converting all letters to lowercase to maintain consistency. We also handle informal language by converting abbreviations and non-standard words into standard forms. Slang and emojis are treated with care, where emojis that have emotional meaning are retained for sentiment analysis, while irrelevant slang is removed. Stopwords in Indonesian that do not contribute significantly to sentiment analysis are also removed from the dataset. [4].

D. Feature Extraction Using CNN

After the text preprocessing stage, the next step is to extract features from the text data using a Convolutional Neural Network (CNN). This model uses CNN to extract text features relevant to sentiment analysis. The CNN model used consists of 30 layers, starting with an embedding layer that converts text into a vector representation with dimensions (None, 70, 300). After that, there are 11 convolution layers (Conv1D), each using a 3x3 filter to capture local features in the text. Each convolutional layer is followed by a ReLU activation layer, which increases the model's non-linearity, and a MaxPooling1D layer to reduce feature dimensions, speed up training, and prevent overfitting. This model produces a 128-channel feature representation in the last layer, which is then further processed for classification [11].

E. FastText Vectors

The text input is subsequently transformed into a vector representation utilizing the Continuous Bag-of-Words (CBOW) model. This procedure transforms the text into a numerical vector format suitable for processing by machine learning algorithms [11]. CBOW enables the algorithm to forecast words based on their contextual surroundings, which is highly advantageous for sentiment analysis.

F. Random Forest Classification

The model classifies features extracted from the CNN using the Random Forest algorithm. This algorithm is a group method that builds multiple decision trees and generates predictions by majority voting across them. The classification results, based on the extracted features, are grouped into five sentiment categories [13]. This research uses Random Forest to enable more accurate sentiment analysis [8].

G. Confusion Matrix

Researchers employ the confusion matrix to assess the efficacy of classification algorithms, particularly in the context of class imbalance. This table comprises four cells: True Positives (TP), True Negatives (TN), False Positives (FP), and False Negatives (FN), as illustrated below:

- Accuracy: The accuracy test evaluates the closeness between the predicted and actual values. Correct data classification allows the accuracy of the prediction results to be determined [14].
- Precision: Precision is a metric that quantifies the ratio of pertinent information retrieved by the system to the overall information retrieved, irrespective of its relevance [14]
- Recall: Recall refers to the ratio of pertinent information recovered by the system in relation to the total relevant information included in the dataset, irrespective of the system's success in retrieval [14].
- F1-Score: Mathematically, the F1-score represents the harmonic mean of precision and Recall.

The formula for this equation is as follows [15] :

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} = 100\%$$

$$Precision = \frac{TP}{FP+TP} = 100\%$$

$$Recall = \frac{TP}{FN+TP} = 100\%$$

$$F - Measure = \frac{2PR}{P+R} = 100\%$$

The quantity of positive comments accurately identified as positive by the system is termed TP; negative comments accurately identified as negative are referred to as TN; and positive remarks erroneously classed as negative are designated as FN.

III. RESULT AND DISCUSSION

To assess the efficacy of the suggested methodology, the researchers gathered 8,000 urban community data points and classified them into five sentiment categories : very good, good, fair, poor, and very poor. The researchers split the dataset into 20% for testing and 80% for training. Using the CNN model, they extracted features from the dataset, which had the following attributes :

TABEL 2
DATA SET DESCRIPTIONT

Attributes	Description	Label
Sentiment	Opinions or perspectives based on heightened emotions	0-5
Comments	Public response to issues in the city	8000 total entries

The Continuous Bag-of-Words (CBOW) model transforms text into vector representations in the initial phase. Subsequent to processing the dataset, the researchers input it into the Convolutional Neural Network (CNN) model. This research employs a CNN model comprising 30 layers. The procedure commences with an Input Layer that acquires text input and transmits it to the Embedding Layer, which transforms the text into a vector representation with dimensions (None, 70, 300). This vector quantitatively encodes the words, facilitating subsequent processing.

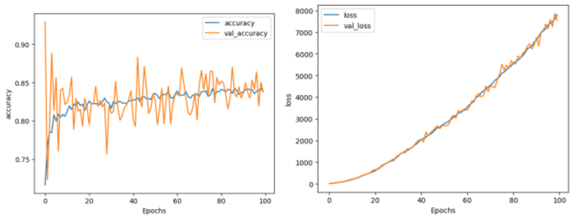
Next, eleven Conv1D layers extract features from the text data. Each convolutional layer includes a BatchNormalization layer to normalize the output and a ReLU Activation layer to introduce non-linearity. These layers progressively produce richer, more complex feature maps, starting with Conv1D (None, 70, 16) and ending with Conv1D (None, 4, 128), resulting in a feature representation with 128 channels.

After the convolutional stage, the MaxPooling1D layer reduces feature dimensions and computational complexity by selecting the maximum value within a defined window. This step lowers the risk of overfitting and accelerates training. The GlobalAveragePooling1D layer then summarizes the extracted features into a single average value per channel, reducing the number of parameters the model must process and improving its generalization."

This model ends with a Fully Connected Layer (Dense) with 100 neurons, which connects all neurons from the previous layer to perform final classification based on the extracted features.

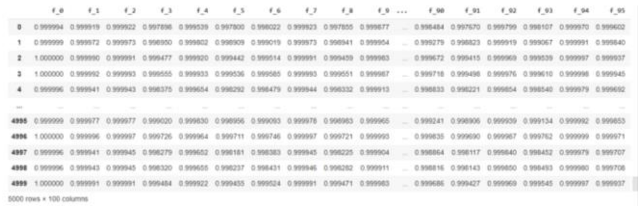
Overall, this architecture comprises 30 layers: input, embedding, convolution, normalization, activation, pooling, and fully connected. This model has 3,988,504 parameters, including 324,420 trainable and 3,664,084 non-trainable. The complexity of this model enables deep, accurate feature extraction from text data, which it then uses for sentiment classification.

This research extends the application of Convolutional Neural Networks (CNNs) to improve sentiment analysis model performance. We implemented CNN layers to extract more in-depth features from text data. To optimize the model, we trained it using 100 epochs and evaluated its accuracy. The results of this experiment show an accuracy of 0.8381 with a loss value of 7530.02. Despite the loss value exceeding expectations, the achieved accuracy remains satisfactory given the model's complexity and the data characteristics used. These results demonstrate the model's ability to identify patterns in text with sufficient precision. The following image shows the training results and performance of the tested model :



Gambar 2. CNN Accuracy (left) and CNN Loss (right)

Subsequently, for the classification procedure, we employed the scikit-learn module in Python and picked 100 features from the Random Forest for RF classification. The CNN features are used as output. :



	f_0	f_1	f_2	f_3	f_4	f_5	f_6	f_7	f_8	f_9	...	f_90	f_91	f_92	f_93	f_94	f_95
0	0.999994	0.999919	0.999922	0.997898	0.999539	0.997800	0.998022	0.999923	0.997855	0.999677	...	0.998484	0.997670	0.999799	0.998107	0.999970	0.999602
1	0.999999	0.999972	0.999973	0.998950	0.999802	0.998909	0.999019	0.999973	0.998941	0.999954	...	0.999279	0.998823	0.999919	0.999067	0.999991	0.999840
2	1.000000	0.999990	0.999991	0.999477	0.999920	0.999442	0.999514	0.999991	0.999459	0.999983	...	0.999672	0.999415	0.999969	0.999539	0.999997	0.999937
3	1.000000	0.999992	0.999993	0.999555	0.999933	0.999536	0.999585	0.999993	0.999551	0.999987	...	0.999718	0.999498	0.999976	0.999610	0.999998	0.999945
4	0.999996	0.999941	0.999943	0.998375	0.999654	0.998292	0.998479	0.999944	0.998332	0.999913	...	0.998833	0.998221	0.999854	0.998540	0.999979	0.999692
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...
4995	0.999999	0.999977	0.999977	0.999020	0.999830	0.998956	0.999093	0.999978	0.998983	0.999965	...	0.999241	0.998906	0.999939	0.999134	0.999992	0.999853
4996	1.000000	0.999996	0.999997	0.999726	0.999964	0.999711	0.999746	0.999997	0.999721	0.999993	...	0.999835	0.999690	0.999987	0.999762	0.999999	0.999971
4997	0.999996	0.999941	0.999945	0.998279	0.999652	0.998181	0.998383	0.999945	0.998225	0.999904	...	0.998864	0.998117	0.999840	0.998452	0.999979	0.999707
4998	0.999996	0.999943	0.999945	0.998320	0.999655	0.998237	0.998431	0.999946	0.998282	0.999911	...	0.998816	0.998143	0.999850	0.998493	0.999980	0.999708
4999	1.000000	0.999991	0.999991	0.999484	0.999922	0.999455	0.999524	0.999991	0.999471	0.999983	...	0.999686	0.999427	0.999969	0.999545	0.999997	0.999937

5000 rows × 100 columns

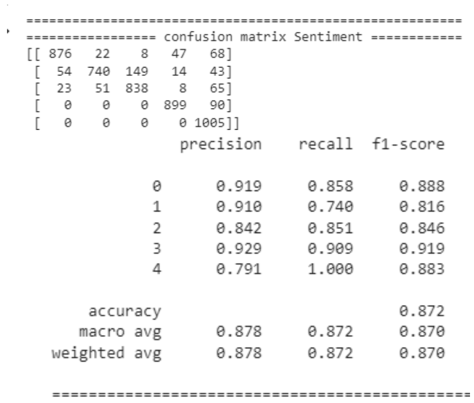
Gambar 3. CNN Feature Output

Based on Figure 3, the CNN output shows the features extracted from the text and the probability that the text belongs to a particular class. The CNN output table has 100 columns and 5000 rows. Columns f_0 to f_99 represent text class labels. Each row contains a text with corresponding feature values. Values between 0 and 1 indicate the probability that the model will classify the text into a particular class. The higher the value, the greater the likelihood that the model will classify the text into that class.

TABEL 3
PREDICTION RESULTS FOR DATASET

Predicted Outcome	Human Categorization	System Categorization
True	5000	4229
False	0	771

From the classification error analysis, it was found that classes' 3' and '4', or good and very good, were the most difficult to distinguish. For example, comments such as "the government's performance is good but needs to be improved further" and "the government's performance is quite good" are often misclassified because of subtle differences in meaning. This indicates the need for a deeper understanding of subjectivity in sentiment labeling, which can be addressed in future research.



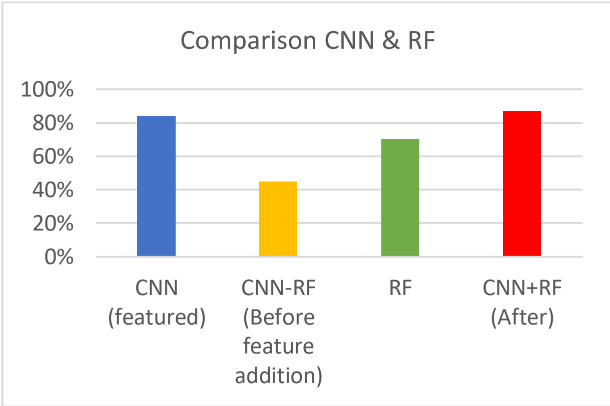
```
=========================================================
================ confusion matrix Sentiment ===========
[[ 876   22    8   47   68]
 [  54  740  149   14   43]
 [  23   51  838    8   65]
 [   0    0    0  899   90]
 [   0    0    0    0 1005]]
              precision    recall  f1-score

           0      0.919     0.858     0.888
           1      0.910     0.740     0.816
           2      0.842     0.851     0.846
           3      0.929     0.909     0.919
           4      0.791     1.000     0.883

    accuracy                          0.872
   macro avg      0.878     0.872     0.870
weighted avg      0.878     0.872     0.870

=================================================
```

Gambar 4. Performance of CNN and Random Forest Models (Confusion Matrix)



Gambar 5.Comparison Between CNN and RF

The model's overall accuracy is calculated as (TP + TN) / total predictions, yielding 0.878. The model accurately recognized 87.8% of the comments in the training dataset.

Precision is defined as the ratio of true positives (TP) to the total number of optimistic predictions (TP + FP). The model's precision is 0.919, indicating that 91.9% of comments expected to be positive were correctly identified.

Recall is determined by dividing the count of true positives (TP) by the total number of actual positive cases (TP + FN). The model's recall is 0.858, indicating that it accurately recognized 85.8% of the positive comments in the training dataset.

The confusion matrix shows that the model performs well overall. Although the accuracy, precision, and recall are already quite good, there is still room for improvement. The model could be more precise, meaning it would misclassify fewer positive tweets, and have a higher recall, meaning it would correctly classify more positive tweets.

TABEL 4
COMPARISON BETWEEN CNN AND RF MODELS

Comparison CNN & RF	Sentiment
CNN (With Features)	84%
CNN-RF (Before Feature Integration	45%
RF Model	70%
CNN+RF (After Integration)	87,2%

The comparison of the CNN and RF models reveals that the CNN alone achieves 84% accuracy, while the RF model achieves only 70%. However, after integrating the CNN-extracted features into the RF model, the CNN-RF hybrid model achieves an accuracy of 87%. These results demonstrate that combining the two models enhances the model's ability to classify sentiment more accurately, as shown in Table 4.

Figure 5 compares the performance of different sentiment classification models using oversampling strategies, as illustrated in the table and graphic. The initial model is a CNN using the primary methodology, achieving 87.2% accuracy during the feature extraction phase. The second model integrates a CNN with a Random Forest (RF) and achieves 45% accuracy before incorporating additional features. The third model, Random Forest, attained an accuracy of 70%.

The inclusion of up to 100 CNN characteristics in the fourth model, which integrates CNN and RF, resulted in a substantial accuracy boost to 87.2%. Consequently, diverse oversampling methodologies, the integration of CNN with RF, and feature extraction can enhance the precision of sentiment classification models.

Using 100 CNN features in the hybrid model not only achieves higher accuracy but also better handles class imbalance in the data. The oversampling used here helps reduce class imbalance in the dataset, a challenge in multi-class sentiment analysis. The integration of CNN for deeper feature extraction and RF for ensemble-based classification provides a significant performance improvement over separate models.

Thus, the results of this sentiment analysis can be used to formulate more responsive government policies. For example, if the 'Very Bad' class dominates in certain public sectors, such as health services or infrastructure, this can serve as a basis for more targeted intervention policies. Conversely, if 'Very Good' dominates, these policies can be maintained or expanded in related sectors to further improve service quality.

IV. CONCLUSION

This research demonstrates that sentiment analysis of urban community feedback can be improved effectively by combining a Convolutional Neural Network (CNN) with a Random Forest classifier. Using a dataset of 8,000 metropolitan responses categorized into five sentiment levels—very good, good, fair, poor, and very poor—the hybrid model achieved an accuracy of 87.2% after training the Random Forest on 100 CNN-extracted features.

Comparative experiments using oversampling techniques further show that the hybrid CNN–Random Forest model consistently outperforms each model. The results substantiate that integrating deep learning–driven feature extraction with ensemble-based classifiers significantly enhances the effectiveness of multi-class sentiment analysis.

Future research should explore alternative machine learning and deep learning models to broaden the understanding of sentiment classification effectiveness. Expanding the dataset with larger and more diverse samples is expected to improve generalizability. Additionally, assessing the influence of various data preprocessing strategies may yield further performance gains.

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