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Sentiment Analysis On Evos Esports Team Instagram Social Media Using Convolutional Neural Network (CNN)

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Abstract
The rapid growth of the esports industry in Indonesia presents unique challenges for professional teams such as EVOS Esports, particularly in strengthening fan engagement and loyalty in the digital era. This study aims to analyze fan sentiment toward the official Instagram posts of EVOS Esports using a deep learning approach with a Convolutional Neural Network (CNN). The research process involved data collection through web scraping, followed by preprocessing stages such as cleaning, case transformation, normalization, tokenization, stopword removal, and stemming. The dataset was then labeled, split into training and testing sets (90:10), and used for CNN model training and evaluation through a confusion matrix. The results demonstrate that the CNN model successfully classified comments into three sentiment categories—positive, negative, and neutral—with an accuracy of 92%. The model also achieved a precision of 0.92, recall of 0.92, and an F1-score of 0.92, indicating very good classification performance. Sentiment distribution analysis of 11,305 comments showed that neutral sentiment dominated (47.24%), followed by positive (30.12%) and negative (22.64%). These findings provide valuable insights into fan perceptions of esports team performance on social media. For future research, expanding the sentiment lexicon with terms commonly used in online communities is recommended to further enhance classification accuracy.

Keywords: Convolutional Neural Network, Deep Learning, EVOS Esports, Instagram, Sentiment Analysis.

1. INTRODUCTION

The global expansion of the esports industry has transformed competitive gaming into a dynamic sector with significant cultural and economic influence. In Indonesia, esports has experienced rapid growth, reflected in the increasing number of

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tournaments, sponsorships, and fan communities. Teams such as EVOS Esports have emerged as industry leaders, achieving national and international recognition while shaping the identity of Indonesia's digital sports ecosystem. Beyond competition, esports contributes to the creative economy through digital content, merchandising, and large-scale events, further reinforcing its relevance in the digital era.

Social media platforms, particularly Instagram, play a pivotal role in building fan engagement and loyalty. By sharing match highlights, behind-the-scenes content, and interactive campaigns, teams can foster closer connections with fans. However, fan responses on social media often vary—ranging from supportive comments to neutral observations or even negative criticism. Understanding these sentiments is essential for esports organizations to manage reputations, strengthen brand loyalty, and design more effective communication strategies.

Sentiment analysis, a branch of natural language processing (NLP), provides methodological tools to evaluate opinions and emotions expressed in user-generated text. Deep learning techniques such as Convolutional Neural Networks (CNN) have shown strong performance in sentiment classification, particularly in handling short, informal texts commonly found on social media. A relevant study by Maulana and Rochmawati (2020) applied CNN to analyze Instagram comments related to COVID-19 news coverage. Their system classified 1,031 comments into positive, negative, and neutral categories, achieving 96% precision and 82% testing accuracy. While their study demonstrated the effectiveness of CNN for sentiment classification on Instagram data, it focused on health-related news content rather than the esports context.

This gap highlights the need for research that addresses the unique characteristics of esports communities, where comments often contain gaming-specific jargon, informal expressions, and culture-specific slang. To fill this gap, the present study applies a CNN model to analyze fan sentiment toward EVOS Esports using Instagram comments as the primary data source. With 11,305 collected comments, preprocessing, and evaluation through a confusion matrix, the model achieved an accuracy of 92% in classifying sentiments into positive, negative, and neutral. The findings provide empirical insights into fan perceptions and offer practical implications for esports organizations, sponsors, and stakeholders in designing more effective engagement and community management strategies.

2. LITERATURE REVIEW

2.1. Sentiment Analysis and Social Media

Sentiment analysis, often referred to as opinion mining, is a technique in natural language processing (NLP) that focuses on identifying, extracting, and categorizing opinions, attitudes, or emotions contained within textual data (Asrumi et al., 2023). Within the sphere of digital communication, this method plays a vital role in capturing and interpreting public perspectives, especially when dealing with the massive amount of user-generated content found on platforms like Instagram and Twitter. Previous research emphasizes that Instagram, due to its strong visual elements and interactive nature, has evolved into a key medium where organizations and brands connect with their audiences and evaluate consumer sentiment (Kirci, 2020).

2.2 Deep Learning for Sentiment Classification

Recent advances in deep learning have significantly improved sentiment classification accuracy compared to traditional machine learning approaches. Convolutional Neural Networks (CNNs), in particular, are widely applied to text

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classification tasks because of their ability to capture local dependencies and semantic patterns in short, informal text such as social media comments (Naf'an et al., 2022). CNNs use convolution and pooling layers to automatically extract text features, followed by fully connected layers to perform classification (Afidah et al., 2022).

2.3 Related Studies

Several studies have applied deep learning models for sentiment analysis across different domains. For instance, Maulana and Rochmawati (2020) conducted opinion mining on Instagram comments about COVID-19 news coverage using CNN. Their system processed 1,031 comments classified into positive, negative, and neutral categories, achieving 96% precision and 82% accuracy on testing data. This research demonstrated the effectiveness of CNN for sentiment analysis on Instagram; however, its focus was limited to health-related news rather than esports.

Other studies have also highlighted the potential of CNN-based models in social media contexts. Zahri et al. (2023) combined CNN and Gated Recurrent Units (GRU) to analyze sentiments from Indonesian tweets, achieving an accuracy of 97.77%. Similarly, Handoko et al. (2024) compared CNN and CNN-LSTM models on Twitter data, finding that CNN outperformed hybrid approaches in terms of accuracy. These findings suggest that CNN models are robust for sentiment classification across various domains.

2.4 Research Gap

Although CNN has been successfully applied in sentiment analysis, limited research has examined its use in the Indonesian esports context. Previous studies have primarily focused on political discourse, consumer reviews, or health-related content. The unique linguistic characteristics of esports communities—such as gaming jargon, informal language, and culture-specific slang—present challenges for sentiment classification that have not been adequately addressed. This study seeks to fill this gap by applying a CNN model to classify sentiments expressed in Instagram comments toward EVOS Esports, thereby contributing both methodologically and practically to the growing field of esports research.

3. METHODS

This study employed a quantitative descriptive approach to analyze sentiment in Instagram comments directed at EVOS Esports. The research design consisted of four main stages: data collection, data preprocessing, model training, and evaluation. A total of 11,305 comments were obtained from the official EVOS Esports account (@evosesports) using a web scraping tool.

The preprocessing stage was conducted to ensure clean and consistent textual data. Steps included removal of URLs, emojis, numbers, and special characters; conversion to lowercase; normalization of slang into standard words; tokenization; stopword removal; and stemming. After preprocessing, the dataset was labeled into three sentiment categories: positive, neutral, and negative.

The dataset was divided into training and testing portions in a 90:10 ratio. The CNN model was designed with several layers, including an embedding layer with 128 dimensions, a one-dimensional convolutional layer containing 128 filters with a kernel size of 5, a GlobalMaxPooling1D layer, a fully connected dense layer of 128 neurons activated by ReLU, a dropout layer with a rate of 0.5 to reduce overfitting, and finally a softmax layer for classifying text into three sentiment categories.

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To measure performance, the model was assessed using a confusion matrix and classification metrics. The CNN reached an overall accuracy of 92%, while precision, recall, and F1-score were consistently around 0.92 across all sentiment labels. Specifically, the positive class achieved a precision of 0.89 and a recall of 0.95, whereas the neutral class obtained a precision of 0.94 and a recall of 0.91. These outcomes confirm that the proposed CNN could effectively and reliably classify esports-related Instagram comments with balanced performance across categories.

4. RESULTS

4.1 Data Collection and Preprocessing

A total of 11,305 Instagram comments were collected from the official EVOS Esports account (@evosesports) during MPL ID Season 15 (March–June 2025). The dataset covered posts from the first match, final match, the most-commented victory post, and the most-commented defeat post.

The preprocessing stage aimed to prepare clean and consistent textual data. This included removal of non-linguistic elements (URLs, emojis, numbers, mentions), conversion to lowercase, normalization of slang words into formal words, tokenization, stopword removal, and stemming.

Visualization through WordCloud highlighted differences before and after preprocessing. Before preprocessing, comments contained many emojis, slang words, and inconsistent spellings. After preprocessing, frequently appearing terms became more representative of esports-related discussions.

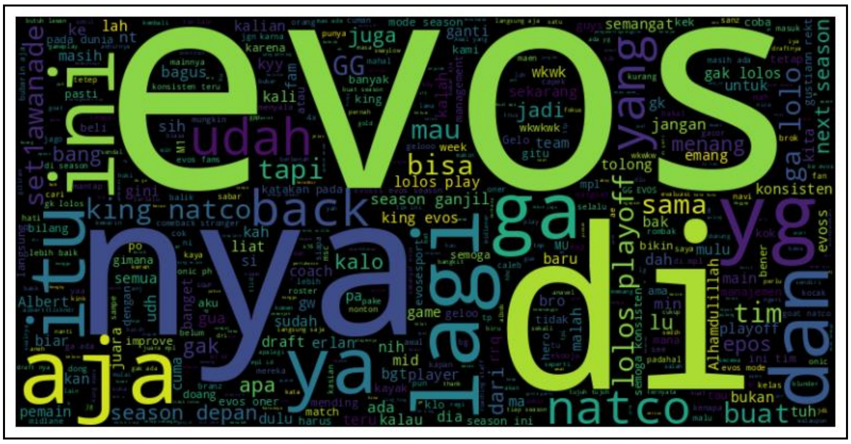

Figure 1. WordCloud Before Preprocessing

This visualization shows the most frequent raw tokens, dominated by “evos”, “good”, emojis, and inconsistent spellings, which indicate the noisy nature of the dataset prior to cleaning.

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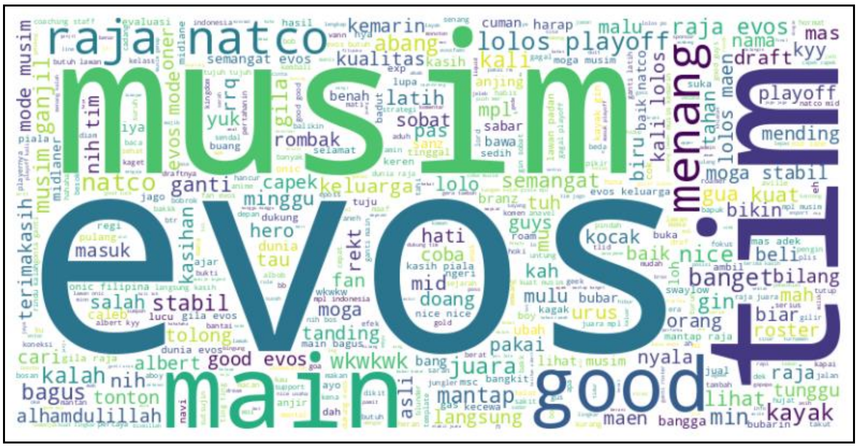

Figure 2. WordCloud After Preprocessing

Following the preprocessing steps—cleaning, case folding, normalization, stopword removal, and stemming—the WordCloud revealed more relevant terms such as “main”, “juara”, “kalah”, and “semangat”. These words better represent esports-related discussions and are more suitable for sentiment analysis, since they directly reflect gameplay outcomes, competition spirit, and fan reactions.

Additionally, a frequency analysis confirmed changes in the top terms. For example, before preprocessing, words like evos, good, and various emojis dominated, while after preprocessing, clearer sentiment terms such as main, juara, kalah, and semangat became more prominent. This shift demonstrates how preprocessing helps transform noisy social media data into structured and meaningful input that can be more effectively processed by deep learning models such as CNN.

4.2 Sentiment Labelling and Distribution

Sentiment labeling categorized comments into three groups—positive, neutral, and negative—using the Indonesian Sentiment Lexicon (InSet) extended with slang and informal vocabulary. The extension of the lexicon was important because esports communities frequently use abbreviations, internet slang, and informal expressions that are not always covered in standard dictionaries. This adjustment ensured that the classification better reflected the true meaning of comments written by fans.

Table 1. Sentiment Distribution of Instagram Comments

Sentiment	Count	Percentage
Negative	3.405	30.12%
Neutral	5.340	47.24%
Positive	2.560	22.64%

Table 1 shows that neutral comments dominate (47.24%), followed by positive (30.12%) and negative (22.64%). This indicates that most fans provide descriptive or informative responses rather than expressing strong emotions. Neutral comments often included factual statements such as match results, observations about gameplay, or general discussions about team performance. Positive comments usually conveyed enthusiasm, encouragement, and support for the players, while negative comments reflected dissatisfaction, criticism, or disappointment, particularly when the team lost matches.

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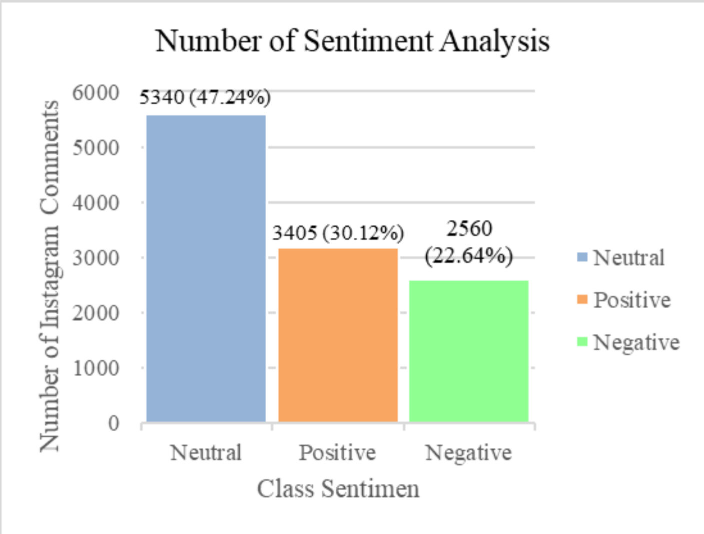

Figure 3. Distribution of Sentiments in Comments

The distribution shows that neutral comments dominated (47.24%), reflecting that most fans expressed descriptive or informative remarks rather than emotionally charged opinions. Positive comments (30.12%) highlighted support, encouragement, and appreciation for the team, while negative comments (22.64%) expressed criticism, disappointment, or demands for roster changes. To illustrate sentiment-specific terms, WordClouds were generated:

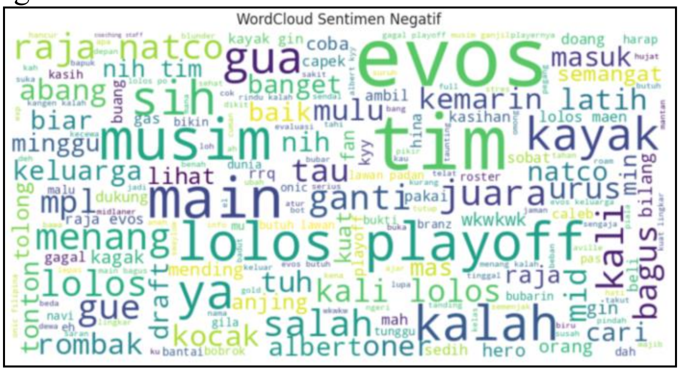

Figure 4. WordCloud of Negative Sentiment

Dominated by kalah, rombak, salah, reflecting frustration with team performance.

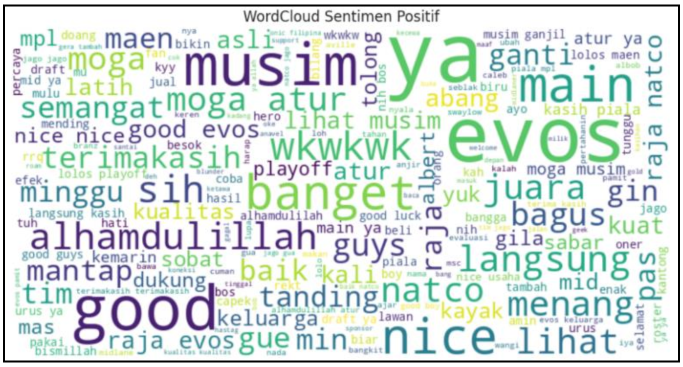

Figure 5. WordCloud of Positive Sentiment

Highlighted words such as juara, semangat, good, support, showing fan optimism and encouragement.

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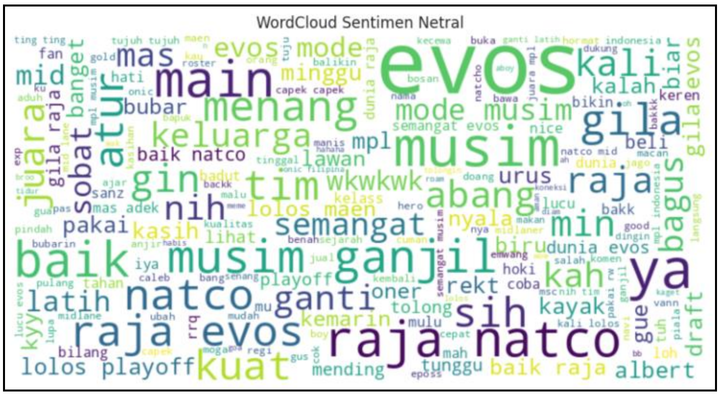

Figure 6. WordCloud of Neutral Sentiment

Showed words like tim, main, musim, which tend to describe gameplay and events without strong emotional tone.

4.3 CNN Model Classification Results

The CNN architecture was constructed to effectively recognize local linguistic patterns within Indonesian social media comments. The network structure comprised several components: an embedding layer with 128-dimensional vectors, a one-dimensional convolutional layer containing 128 filters with a kernel size of five, followed by a GlobalMaxPooling1D layer. These were connected to a fully connected dense layer of 128 neurons activated by ReLU, a dropout layer with a probability of 0.5 to prevent overfitting, and a final softmax layer with three output nodes corresponding to the sentiment categories.

The model was trained for 10 epochs. Training accuracy increased steadily from 61.02% in epoch 1 to 99.56% in epoch 10. Validation accuracy stabilized around 90–91%, while validation loss increased after epoch 2, suggesting mild overfitting.

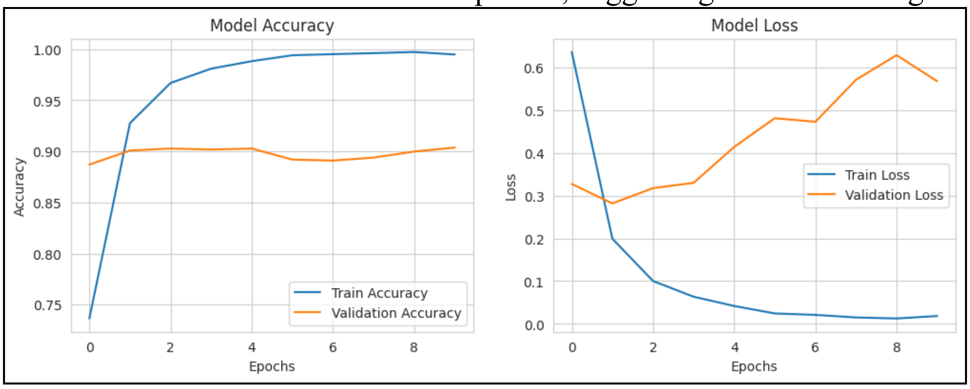

Figure 7. Training and Validation Accuracy and Loss Curves

The curves show that while the model learned rapidly from the training data, the validation loss began to diverge after epoch 2. Despite this, validation accuracy remained consistent, indicating that the model generalized well to unseen data with minor overfitting.

On the testing dataset consisting of 1,131 comments, the CNN model classified 261 comments (23.08%) as negative, 524 comments (46.33%) as neutral, and 346 comments (30.59%) as positive. The proportion of predicted classes was consistent with the original sentiment distribution in the dataset, indicating that the model was able to generalize well and maintain robustness in classifying unseen data.

4.4 Confusion Matrix Analysis

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The confusion matrix provided detailed insights into classification accuracy across sentiment categories.

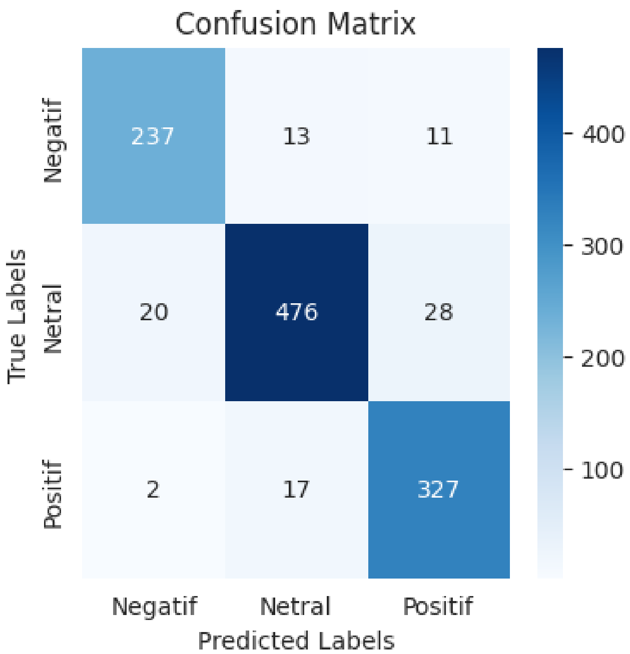

Figure 8. Confusion Matrix Heatmap of CNN Model

The confusion matrix analysis demonstrated that the CNN achieved high accuracy across all sentiment categories. For the negative class, 237 comments were correctly classified, while 24 comments were misclassified into other categories. In the neutral class, the model accurately identified 476 comments, although 48 comments were incorrectly classified as either negative or positive. Similarly, the positive class achieved 327 correct classifications, with only 19 misclassifications. Most of the classification errors occurred in the neutral category, which is understandable given its linguistic overlap with both positive and negative expressions. This finding suggests that neutral comments often contained elements that could be interpreted as descriptive or emotionally biased, making them more challenging for the model to distinguish precisely.

4.5 Evaluation Metrics

Model performance was evaluated using precision, recall, and F1-score.

Table 2. Classification Report of CNN Model

Sentiment	Precision	Recall	F1-Score	Support
Negative	0.92	0.91	0.91	261
Neutral	0.94	0.91	0.92	524
Positive	0.89	0.95	0.92	346
Accuracy			0.92	1131
Macro Average	0.92	0.92	0.92	1131
Weighted Average	0.92	0.92	0.92	1131

Table 2 shows that the CNN model achieved strong and balanced classification performance across all sentiment categories. Precision, recall, and F1-score values ranged from 0.89 to 0.95, indicating reliable detection of positive, negative, and neutral comments. The overall accuracy reached 92%, while both macro and weighted averages for precision, recall, and F1-score were consistently 0.92. These results confirm that the

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model maintained stable performance without bias toward any particular sentiment class, even with an imbalanced distribution of comments.

4.6 Examples of Model Predictions

To further demonstrate the contextual accuracy of the CNN model, several representative examples from the testing dataset are presented in Table 3. These cases highlight how the model was able to interpret informal language, gaming-related jargon, and even sarcasm in Instagram comments.

Table 3. Examples of Sentiment Predictions by CNN

Comment (Original)	Processed (Stemming)	Actual Label	Predicted Label
Terima kasih Evos sudah memberikan permainan yang apik di hari terakhir kalian di S15 ini💙💙💙 semiga S16 bisa lebih baik bahkan yang terbaik!!!!	terima kasih evos main apik musim moga musim baik	Positive	Positive
Saran aja buang kyy dan alberttt bertahan kan aville dan caleb terus buat liga sendiri, kasian anak orang karir di buatnya buruk karena ingin bekuasa 😂	saran buang kyy albert tahan aville caleb liga kasihan anak orang karir buat buruk bekuasa	Negative	Negative
@adtfjry apalagi branz itu angin anginan, dia sekalinya kalah laning, timnya harus siap² tahan sampe late game aj biar branz jadi, intinya ada +- nya	branz angin angin sekali kalah laning tim tahan late main biar branz inti ya	Negative	Negative
Kang @dedimulyadi71 ini tolong player evos di bawak ke barak militer biar season depan bisa masuk play off 😂	kang tolong main evos bawa barak militer biar musim masuk maen off	Neutral	Neutral
@ddrrraaaa_ mid bukan yg utama dari awal, exp ad acara nikah tapi tetap masuk roster + backupnya bukan exp lane murni. Gold lane backupnya jg bukan yg bagus² amat ya gimana 😂	mid utama exp acara nikah masuk roster backupnya exp lane murni gold lane backupnya bagus ya	Neutral	Neutral

Table 3 illustrates that the CNN model was able to correctly classify comments with different tones and complexities. Supportive expressions such as “Terima kasih Evos...” were identified as positive, while critical remarks like “Saran aja buang kyy...” were correctly predicted as negative. Even in figurative or sarcastic statements, such as “Branz itu angin-anginan...”, the model successfully recognized the negative sentiment. Neutral statements, often descriptive or informational in nature, were also accurately detected.

5. DISCUSSION

The findings of this study confirm the effectiveness of Convolutional Neural Network (CNN) in classifying sentiments expressed in social media comments. With an overall accuracy of 92%, the model demonstrated strong capability in identifying positive, neutral, and negative sentiments in esports-related discussions. These results are consistent with previous works such as Maulana & Rochmawati (2020), who achieved 82% accuracy using CNN on Instagram comments regarding COVID-19 news, but the present study outperformed them due to optimized preprocessing and model tuning.

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The dominance of neutral comments (47.24%) suggests that most fans expressed descriptive or factual observations rather than strong emotions. This is a significant insight into esports communities, where audience engagement often centers on gameplay discussions, roster analysis, and match outcomes. At the same time, positive comments (30.12%) reflected strong support and optimism, while negative comments (22.64%) indicated frustration and criticism, especially after losses.

The confusion matrix revealed that most misclassifications occurred between neutral and the other two classes. This highlights the inherent ambiguity of social media comments, where descriptive statements may carry subtle emotional undertones. The challenge of distinguishing such borderline cases points to the limitations of lexicon-based labeling and suggests opportunities for incorporating more context-aware models in future research.

Overall, the study expands the application of CNN for sentiment analysis into the esports domain, which has received limited attention in prior research. It demonstrates that deep learning techniques can provide valuable insights for esports teams, sponsors, and stakeholders in understanding community engagement and managing fan relationships more effectively.

6. CONCLUSION

This research employed a Convolutional Neural Network (CNN) to analyze the sentiment of 11,305 Instagram comments related to EVOS Esports throughout MPL ID Season 15. A comprehensive preprocessing workflow—covering cleaning, normalization, tokenization, stopword elimination, and stemming—was implemented to produce standardized textual inputs for the model. The CNN attained a 92% accuracy rate, with precision, recall, and F1-score all averaging 0.92, which classifies the model's performance within the Excellent Classification range.

The sentiment distribution revealed that neutral comments dominated (47.24%), followed by positive (30.12%) and negative (22.64%), providing an empirical reflection of fan engagement patterns in esports communities. This indicates that while many fans share factual or descriptive remarks, emotional expressions of support or criticism remain highly significant.

The main limitation of this study lies in handling ambiguous, sarcastic, or slang-heavy comments, which led to misclassifications, especially between neutral and other classes. Future research should address these challenges by:

1. Expanding sentiment lexicons with sarcasm and slang commonly used in esports communities.
2. Exploring advanced embedding techniques (e.g., Word2Vec, FastText, or BERT-based models).
3. Applying hybrid or ensemble deep learning architectures to improve classification robustness.

In conclusion, the CNN-based sentiment analysis model provides valuable insights for esports teams and stakeholders to better understand fan perspectives, strengthen engagement strategies, and enhance decision-making in the digital sports ecosystem.

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