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# Optimizing Convolutional Neural Networks with Particle Swarm Optimization for Enhanced Hoax News Detection

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***Abstract***

**Background:** The global spreading of hoax news is causing significant challenges, by misleading the public and undermining public trust in media and institutions. This issue is worsened by the rapid spreading of misinformation which is facilitated by digital platforms, triggering social unrest and threatening national security. To overcome this problem, reliable and robust method is essential to adapt to the evolving tactics of misleading information spreading.
**Objective:** This study aimed to improve the accuracy of hoax news detection tools by evaluating the effectiveness of Deep Learning methods enhanced with Convolutional Neural Networks (CNNs) using Particle Swarm Optimization (PSO).
**Methods:** The dataset was processed by tokenization, stopword removal, and stemming. CNNs were trained with default parameters, due to their potential as one of the effective methods for text classification. Furthermore, PSO was used to optimize the main parameters such as filters, kernel sizes, and learning rate, which was refined iteratively based on validation accuracy.
**Results:** The optimized CNNs+PSO was further tested by data training to show its effectiveness in detecting hoax news and misleading articles. The result showed that the optimized CNNs+PSO model had high effectiveness, by achieving accuracy rate of 92.06%, precision 91.6%, and recall 96.19%. These values validated the model's ability to classify hoax news in Indonesian accurately.
**Conclusion:** This study showed that the optimized CNNs+PSO method was highly effective in detecting hoax news and misleading articles by achieving impressive accuracy, precision, and recall rate. The integration showed the potential of CNNs+PSO to mitigate the impacts of hoax news, enhance public awareness, and promote people to critically believe the news

***Keywords:*** Convolutional Neural Networks, Deep Learning, Hoax, Particle Swarm Optimization, Text Mining

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## I. INTRODUCTION

The use of internet is continuously increasing, with April 2023 data showing a significant annual global growth of approximately 5.18 billion users [1]. Due to the rapid growth of digital platform, hoax news is now easily accessed by people globally, which increases the negative impacts [2]. This phenomenon has caused a rise in textual data significantly, driven by the increasing availability of news and the consumption of online information. Along with the increasing available news, the challenge to distinguish between accurate, reliable, and misleading information, such as hoax news, is also arising [3]. This rapid and pervasive spreading of hoax news causes serious challenges, such as undermining social trust in the institution, disrupting social cohesion, and affecting public safety. To overcome the risks, there is a need for the development of sophisticated and dependable tools that can accurately detect and effectively limit the proliferation of misinformation.

The spreading of hoax news and misleading articles has become a common phenomenon, occurring for centuries [4], [5]. Hoax news spreading, including misleading information is aimed at diminishing the people's trust in any entities, products, services, or individuals [6], deceiving the public by providing unverified, worse, or hoax news [7], [8]. This kind of explosive growth of hoax news has disrupted public trust, destroying social cohesion, and continuously increasing alongside the high accessibility of the global internet [9], [10]. To overcome this issue, advanced learning methods are highly needed, specifically Convolutional Neural Networks (CNNs) to classify news and identify hoax. This method emphasizes the importance of developing models capable of early and effectively identifying any misinformation or trends that have earned significant attention from the public in recent years [11], [12].

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Due to the increasing need for advanced machine learning methods for misinformation detection, CNNs have been identified as a specialized deep learning architecture designed to learn directly from data. As a regularized variant of Multi-Layer Perceptron (MLP) in deep feed-forward Artificial Neural Networks [13], CNNs use convolution operations to generate output that significantly enhances training performance [14]. Despite the traditional association with image processing, CNNs have proven effective for textual data application [15], showing potential as versatile tools for various domains. This capacity and ability to capture complex patterns serves as a foundational model in deep learning, which excels in various tasks, including object classification, detection, and segmentation [16]. Furthermore, CNNs have shown a significant ability to effectively detect hoax news, including in Indonesian textual contents, by leveraging their ability to distinguish various textual features [17]. These advancements underscore the potential of CNNs as robust tools in combating misinformation, particularly when integrated with optimized methods to further enhance performance.

Several studies had explored innovative methods to enhance the performance of CNNs for text-based applications in detecting hoax news. Kim and Ko [8] proposed the combination of graphic method and summary to enhance the accuracy of hoax news detection by using CNNs, which had proven to boost performance significantly compared to other models. Jain et al [17] showed the application of CNNs to identify hoax news by analyzing both the content and metadata, enhancing the detection system's robustness. More importantly, Nayoga et al. [18] applied CNNs to classify Indonesian news articles, showing the effectiveness in handling language-specific nuances and achieving high detection accuracy. These studies collectively show that CNNs excel in traditional computer vision applications and significantly outperform other algorithms in hoax news detection, thereby validating their superiority in accurately identifying and classifying misinformation.

Despite the unique potential, traditional machine learning methods have not provided significant performance for detecting hoax news. In comparison, deep learning is more efficient in extracting hoax news detection features than regular machine learning due to the ability to extract both high and low levels. Therefore, optimization is required to search for optimal parameters in model operation [12]. Several methods can be used to increase the accuracy of this algorithm, such as optimizing accuracy using Particle Swarm Optimization (PSO) by adjusting specific parameters. PSO has been applied in numerous domains to optimize the parameters of neural network models [11]. Experimental results show that PSO is able to increase the accuracy of Naive Bayes Classifier (NBC) algorithm by 23.38%. This can be achieved by optimizing the parameter values for population size and maximum number of generations, although longer computing time is required [19].

According to Abdallah [20], PSO method was proposed for summarizing single Arabic documents. The suggested method outperformed evolutionary strategies such as Genetic Algorithms (GA) and Harmony Search (HS) regarding F-measure results. This superiority is attributed to the use of TF-IDF weights as an innovative heuristic feature for computing informative scores. In comparison, PSO only requires 100 iterations, while HS needs 100,000 iterations. Janani and Pranolo et al. [21], [22] have also shown the effectiveness of PSO in optimizing complex models, further validating the potential to enhance deep learning model performance by achieving better convergence rates and minimizing computational costs. Although CNNs have been widely applied in hoax news detection, one of the persistent challenges is the optimization of hyperparameters, which significantly influence model performance. In conventional CNNs-based text classification, hyperparameter tuning is often conducted manually through grid or random search, which are computationally expensive and do not promise the best possible configuration. The absence of an efficient and adaptive optimization strategy can limit feature extraction and reduce classification accuracy.

In this context, PSO was introduced as an efficient computational method to optimize CNNs hyperparameter. PSO has shown its effectiveness in optimizing neural network structures in other domains, particularly to enhance convergence level and generalization capabilities. Therefore, this study aimed to improve the accuracy of hoax news detection tools by evaluating the effectiveness of deep learning methods enhanced with CNNs using PSO. By automating hyperparameter tuning, PSO had the potential to enhance CNNs classification performance and reduce computational overhead, serving as a suitable method for detecting hoax news efficiently.

## II. LITERATURE REVIEW

The task of hoax news detection has been excessively explored in the past few years using various methods to overcome the challenges arising in identifying and mitigating the spreading of hoax news. Neural networks, and intense learning models such as CNNs, have shown significant results in this domain. Additionally, CNNs were shown to effectively capture local patterns in test data, distinguishing between legitimate and hoax news. Among various studies, Nasir et al. [13] used a hybrid model that combined CNNs with Recurrent Neural Networks (RNNs) to enhance its detection effectivity. Vishwakarma et al. [14] also explored CNNs to detect hoax news, showing its effectiveness in handling large-scale textual data. Farid et al. [15] developed hoax news detection model using CNNs and TF-IDF weighting method, which achieved high accuracy by integrating the feature for information acquisition. Noor et al. [16] contributed significantly to combining augmentation data methods to enhance CNNs overall performance, which showed an accuracy of 82,81% in detecting hoax news in Indonesian.

The optimization algorithms were practically essential for enhancing the performance of neural network models. In this context, PSO had been inspired by the social behavior of birds, serving as a popular option in optimizing neural network parameters due to the ability to find global optimal in complex study spaces. According to Salem [23], an optimized PSO algorithm improved the predictive power of learning machine models by identifying the best hyperparameters to provide the highest accuracy. The integration of the hybrid CNNs with RNNs using PSO had been performed by Adwan [24] to prove and perform a deep learning strategy for detecting deepfake video. The result achieved an average accuracy of 97.26% and 94.2% on Celeb-DF and DFC, respectively. Another comparative study was conducted by Airlangga [25], where PSO outperformed other optimization methods, emphasizing its suitability to optimize complex neural network architectures. This suggested that the combination of CNNs and PSO represented a promising method to develop a robust and accurate detection system, as well as overcome the dynamics of misinformation. Similarly, Khotimah et al [15] reported significant hoax news detection accuracy using optimized CNNs with a feature selection method.

The most current method to hoax news detection leverages advanced machine learning to achieve high accuracy and robustness. CNNs were found to be highly effective in handling text-based data and extracting relevant features for classification, as reported by Nasir et al. [13] and Vishwakarma et al. [14]. Optimization methods like PSO enhance model performance by improving hyperparameter and network structure, leading to high accuracy and generalization, as shown by Ajao et al. [26] and Qolomany et al. [27]. According to Noor et al. [16], data augmentation methods refine model performance by increasing the diversity and quantity of the training data. This combination consisted of CNNs, PSO, and augmentation, which represented the cutting edge in hoax news detection, providing a robust framework to withstand misinformation across various linguistic and contextual settings.

Traditional methods such as grid and random search are widely used but require extensive computational resources without optimal results. In this context, PSO as a nature-inspired optimization algorithm, has been successfully used in optimizing deep learning architectures across various domains due to the ability to efficiently search for optimal hyperparameter configurations. Despite its effectiveness, PSO has not been extensively explored in the context of hoax news detection, particularly for optimizing CNNs models. This study hypothesizes that integrating PSO into CNNs-based hoax detection models can provide a systematic and adaptive method for hyperparameter tuning, improving classification accuracy while maintaining computational efficiency.

Previous studies on hoax news detection have explored various deep learning methods, including hybrid models by combining CNNs with RNNs or transformation-based architecture. Although this method had performed significant improvements in classification, the rising challenge was in the manual selection of hyperparameters, which affected the ability to generalize effectively across different datasets. Hyperparameter tuning was critical since improper configurations could cause overfitting or underfitting, degrading the accuracy of classification.

## III. METHODS

### A. Framework

The algorithm selection and validation were crucial for achieving accurate text classification, as shown in the framework presented in Fig. 1. The flowchart covered the entire process, starting from data input to deployment. Text preprocessing was carried out in modeling stage, which included sorting and preparing the data need, as shown in Fig. 2. Subsequently, the preprocessing text was used to train CNNs algorithm, which was optimized by using PSO.

By the following modeling stage, the evaluation included testing the processed data and validation process to CNNs+PSO model by calculating accuracy, precision, and recall values. These particular values were applied to validate the model's performance using Confusion Matrix (CM). The result of CNNs+PSO model was compared with a single CNNs model to determine the effectiveness of the optimization. The final stage was deployment, where the selected algorithm was applied to new data. After the deployment stage, the selected algorithm was applied and evaluated to ensure its performance with new data input. Moreover, the flowchart in Fig. 3 provides a detailed visualization of the algorithm selection and validation steps. It also emphasized the importance of preprocessing, model training, optimization, and rigorous evaluation to achieve reliable and accurate text classification.

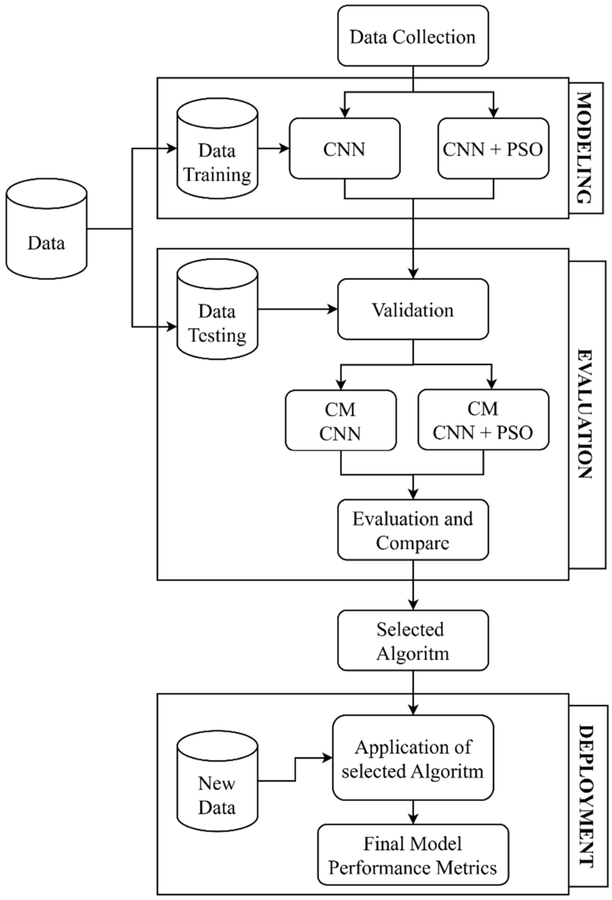


Fig. 1 Study Methodology

*B. Data Collection*

The dataset used in this study was titled “Indonesian Political News Facts and Hoaxes”, which was obtained from Kaggle [28]. Compilation of the dataset was performed through web-scrapping from various reputable Indonesian news platforms, such as CNNs, Kompas, Tempo, and Turnbackhoax. The dataset was pre-labeled with hoax news labels, verified, and published by Experts at Tunbackhoax, ensuring accuracy and reliability. Every hoax news article included in this study had been rigorously validated and published on Turnbackhoax website. Consequently, no additional labeling stage was required, allowing immediate use of the dataset. Detailed information about the sources of datasets and publication dates is provided in Table 1.

TABLE 1
DATASET INFORMATION USED

| Source | Date | | Total of News |
|---|---|---|---|
| | Beginning | End | |
| CNNs | 01 June 2021 | 21 February 2023 | 9.630 |
| Kompas | 20 April 2017 | 21 February 2023 | 4.750 |
| Tempo | 01 January 2021 | 04 February 2023 | 6.592 |
| Turnbackhoax | 08 September 2015 | 28 February 2023 | 10.381 |

*C. Text Preprocessing*

This stage transforms unstructured data into structured according to the requirements. The objective of text preprocessing is to transform documents into data prepared for subsequent processing. In this stage, the text is converted into term indices to create a set of term indices that can effectively represent the documents. Fig. 2 shows the flowchart when text preprocessing is conducted.

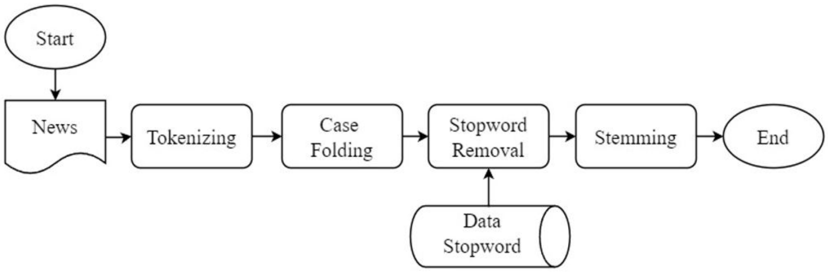


Fig. 2 Flowchart Text Preprocessing

The text preprocessing stage comprises tokenizing that focuses on splitting a text into meaningful units [29], including words or phrases, known as tokens. One sort of text segmentation called tokenization typically focuses on determining which alphabetic or alphanumeric characters are separated from non-alphanumeric characters like spaces and punctuation marks [30]. Case folding is performed to convert all capital letters in the document to lowercase. This is followed by stopword removal to discard words that have no meaningful contribution, for example, "yang," "apa," and "dengan". However, some words may be retained when considered essential for the data used in calculations [31]. Finally, stemming is performed to extract word stems or root forms, which may not entirely represent semantic meaning [32].

*D. Convolutional Neural Networks (CNNs)*

CNNs are a development of Multilayer Perceptrons (MLPs) [33], which is included in the type of feed-forward (nonrepetitive) LSTM-Recurrent neural network by Bahad [34]. These CNNs are specifically designed to process data in two dimensions [35]. In text classification and Natural Language Processing (NLP), one-dimensional convolutional neural network (Conv1D) is often used [36]. CNNs can be categorized as a type of deep neural network due to their high depth and wide application in image data processing, image analysis, detection, and recognition of objects in images. Generally, CNNs resemble ordinary neural networks, consisting of neurons with weights, biases, and activation functions [37].

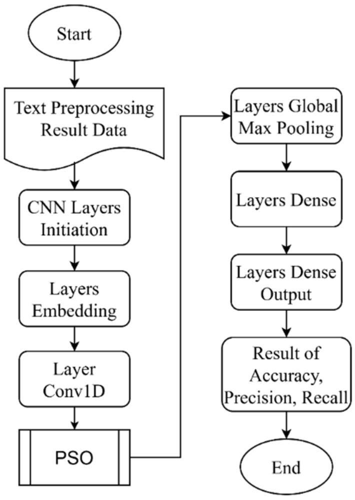


Fig. 3 Flowchart Optimize CNNs Using PSO

The flowchart of CNNs algorithm in this study is shown in Fig. 3. The first stage includes text preprocessing, where the text is cleaned by removing punctuation marks, tokenizing, stopword, and performing other relevant functions to prepare the data for further processing. The second stage is CNNs layer initialization, which includes configuration by determining the number of filters, kernel size, activation function, and other parameters needed to form layers. After the initialization is complete, the embedding layers are created in CNNs to transform the representation of words in the text into a denser numerical model. These pre-trained integrations, generated through training on a substantial amount of text data, are input into deep neural networks and applied to various text classification tasks [38]. Following the embedding layers, ConvID layer is applied, by using one-dimensional convolution operation on the embedded data to extract essential features from the text. After this process, PSO method is applied to optimized CNNs parameters. These PSO-optimized parameters are used to reconfigure CNNs for further training and evaluation. Furthermore, global max pooling later is activated to identify and select the maximum value from each feature generated by convolution layer [39]. Dense layers are also added to achieve smoother dimensionality reduction, ensuring that all essential features used for classification are retained [38]. These dense (fully connected) layers are incorporated after the pooling layers to combine the features generated by the convolution and pooling layers before passing to the subsequent layer. Finally, the fully connected layers are used as the output of CNNs, generating predictions based on the features received. The last stage includes evaluating the model performance using accuracy, precision, and recall metrics, which indicate how effectively the model can classify text.

### *E. Particle Swarm Optimization (PSO)*

PSO is a simple and efficient optimization method that has gained significant attention across different disciplines [40]. Furthermore, it obtains inspiration from the collective movement of various animals [41], mainly during essential activities such as foraging for food. These animals influence one another in their group, achieving individual and collective objectives more easily. Based on Kennedy and Eberhart created PSO algorithm, which first introduced in 1995 [42]. In the algorithm, there are two main concepts, namely speed and coordinates. Each particle has coordinates and initial velocity in the solution space. As the algorithm progresses, the particles move towards the best-coordinated solution [43]. The process of PSO includes initializing a swarm of particles, evaluating their fitness, and iteratively updating positions and velocities based on local as well as global best solutions to find the optimal parameters (Figure 4). The advantages include the simplicity of implementation, more efficient use of memory, and the lack of special operators. Due to these simple properties, PSO is a fast and effective algorithm. However, there are some drawbacks such as early convergence and becoming trapped in local optima when addressing intricate multimodal issues [44]. To overcome this issue, various PSO certifications have been developed using several operators since the first version was published.

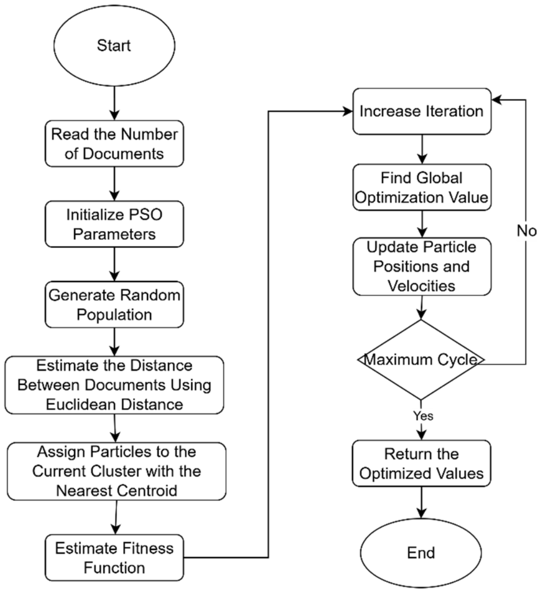


Fig. 4 Particle Swarm Optimization

### *F. Confusion Matrix*

In confusion matrix, every row and column serve specific roles, corresponding to the actual classes in the instances, and predicted types, respectively. Generally, confusion matrix is used to assess the performance and characteristics of classification models. In the confusion matrix, four key measurements are present, namely true positives (TP), true negatives (TN), false positives (FP), and false negatives (FN). TP occurs when the predicted and actual results are positive. TN occurs when both the expected and actual results are negative. FP occurs when the predicted result is positive, but the actual result is negative. FN occurs when the expected result is negative, while the actual result is positive [45], [46]. Confusion Matrix has several matrices, namely accuracy, precision, and recall [47].

*1) Accuracy*

Accuracy is calculated as the ratio of correctly classified instances to the total number of instances, as shown in Equation 1 [48], [49]. This metric is widely used to evaluate the overall performance of classification models.

$$accuracy = \frac{(TP+TN)}{(TP+FP+TN+FN)} \quad (1)$$

*2) Precision*

Precision is calculated as the ratio of true positive predictions to the total number of positive predictions made by the model, as shown in Equation 2 [49]. This metric is particularly important in scenarios where minimizing false positives is crucial, such as identifying hoax news with high confidence to prevent wrongful labeling.

$$precision = \frac{TP}{(TP+FP)} \quad (2)$$

*3) Recall*

Recall, also referred to as sensitivity or TP rate, is calculated as the ratio of true positive predictions to the total number of actual positive cases, as shown in Equation 3 [49]. This metric is critical since identifying all positive cases is essential, such as ensuring that all hoax news is detected to prevent its spread [49]. Recall formula can be defined as follows.

$$recall = \frac{TP}{(TP+FN)} \quad (3)$$

To evaluate the performance of CNNs+PSO model, confusion matrix was used to compute accuracy, precision, and recall for three data splits (60:40, 70:30, and 80:20) to ensure robust validation. Accuracy level was used to measure the overall model. Meanwhile, precision evaluated the proportion of positive predictions to minimize the rate of false positive in the data. Recall assessed the identifying ability of model for all actual positive cases, ensuring comprehensive detection of hoax news. This matrix was further averaged across the data splits to provide holistic assessment of model performance. The results from this evaluation compared the performance of CNNs+PSO model with CNNs baseline to show the impact of optimization.

## IV. RESULTS

The 29,643 news in the dataset was divided into three training and testing processes with data percentages of 60%:40%, 70%:30%, and 80%:20%. This comparison was used to conduct experiments on the refined CNNs model by PSO on hoax news detection. The more data training, the more precise the test results [49]. From training and testing results for each data comparison, accuracy, precision, and recall values were obtained, respectively, as shown in Table 3 for CNNs and Tables 4-5 for CNNs+PSO.

TABLE 2
RESULT FOR CNNS ARCHITECTURAL MODEL

| | | | Predicted | |
|---|---|---|---|---|
| | | | Valid (+) | Hoax (-) |
| 60:40 | Actual | Valid (+) | TP: 17.924 | FN: 563 |
| | | Hoax (-) | FP: 2.206 | TN:8.932 |
| 70:30 | Actual | Valid (+) | TP: 17.874 | FN: 631 |
| | | Hoax (-) | FP: 1.586 | TN: 9.552 |
| 80: 20 | Actual | Valid (+) | TP: 17.867 | FN: 638 |
| | | Hoax (-) | FP: 1.550 | TN: 9.588 |

Table 2 provides the data necessary to compute accuracy, precision, and recall using TP, FN, FP, and TN outcomes. Furthermore, Table 3 shows the results of news classification achieved through CNNs. From 29,643 news data, the percentage comparison between training and testing was taken as 60:40, 70:30, and 80:20, respectively.

TABLE 3
CNNS ACCURACY, PRECISION, AND RECALL CALC RESULT

| Proportions | Accuracy (%) | Precision (%) | Recall (%) |
|---|---|---|---|
| 60 : 40 | 90.65 | 89.04 | 96.95 |
| 70 : 30 | 92.52 | 91.85 | 96.59 |
| 80 : 20 | 92.62 | 92.02 | 96.55 |
| Average | 91.93 | 90.97 | 96.70 |

The accuracy values were 90.65%, 92.52%, and 92.62%, indicating that CNNs model classified Indonesian news with an average accuracy of 91.93%. The precision values obtained were 89.04%, 91.85%, and 92.02% for the same data splits, resulting in an average of 90.97%. Similarly, recall values were 96.95%, 96.59%, and 96.55%, with an average of 96.70%. As presented in Table 3, these values showed the effectiveness of CNNs method in classifying Indonesian news data accurately.

TABLE 4
RESULT FOR CNNS+PSO ARCHITECTURAL MODEL

| | | | Predicted | |
|---|---|---|---|---|
| | | | Valid (+) | Hoax (-) |
| 60:40 | Actual | Valid (+) | TP: 17.993 | FN: 512 |
| | | Hoax (-) | FP: 2.165 | TN: 8.973 |
| 70 :30 | Actual | Valid (+) | TP: 17.320 | FN: 1.185 |
| | | Hoax (-) | FP: 1.096 | TN: 10.042 |
| 80: 20 | Actual | Valid (+) | TP: 18.088 | FN: 417 |
| | | Hoax (-) | FP: 1.684 | TN: 9.454 |

Table 4 provides the essential data to compute accuracy, precision, and recall by using TP, FN, FP, and TN outcomes. Meanwhile, Table 5 shows the results of news classification achieved through CNNs method. From 29,643 news data, the percentage comparison between training and test data was taken as 60:40, 70:30, and 80:20, respectively.

TABLE 5
CNNS+PSO ACCURACY, PRECISION, AND RECALL CALC RESULT

| Proportions | Accuracy (%) | Precision (%) | Recall (%) |
|---|---|---|---|
| 60 : 40 | 90.97 | 89.26 | 97.23 |
| 70 : 30 | 92.31 | 94.05 | 93.60 |
| 80 : 20 | 92.91 | 91.48 | 97.75 |
| Average | 92.06 | 91.60 | 96.19 |

The accuracy values were 90.97%, 92.31%, and 92.91%, indicating that the refined CNNs model by PSO could classify Indonesian news with an average accuracy of 92.06%. Precision values obtained were 89.26%, 94.05%, and 91.48% for the same data splits, with an average of 91.60%. Similarly, recall values were 97.23%, 93.60%, and 97.75%, with an average of 96.19%. These values show the effectiveness of the refined CNNs model by PSO in classifying Indonesian news data accurately.

## V. DISCUSSION

The results show that the integration of PSO with CNNs leads to improvements in classification accuracy, precision, and recall. However, rather than framing this as a novelty solely due to the lack of previous applications, the primary contribution of this study is in addressing the challenge of hyperparameter selection in deep learning-based hoax detection. Since the performance of CNNs model in text classification tasks is significantly dependent on hyperparameter configurations such as the number of filters, kernel size, and learning rate, inefficient tuning can lead to suboptimal feature extraction and reduced classification accuracy. To overcome the limitation, this study introduces PSO as an optimization method that systematically fine-tunes CNNs hyperparameters, ensuring improved performance and reducing computational inefficiencies. The experimental results indicate that CNNs+PSO achieves marginally better accuracy than a standard CNNs model, validating the potential of adaptive optimization method in hoax detection. Although the improvements are not significant, the efficiency of PSO is shown in automating parameter selection, minimizing manual intervention, and enhancing CNNs capability to extract meaningful textual patterns.

Based on the results, there is a need to compare the proposed method with previous studies on hoax news detection. Shu et al. (2020) [50] conducted a study on PolitiFact and GossipCop FakeNewsNet Repository data using several methods, namely support vector machines, logistic regression, Naive Bayes, CNNs, and social article fusion (SAF). The results showed that SAF performed better in accuracy by 69.1% and 68.9%. Qin Li et al [51] proposed multi-level CNNs for the weight of sensitive words (MCNNs-TFW) hoax news detection system. This was based on MCNNs combined to perform hoax news detection, where MCNNs extracted article representation and TFW calculated the weight of sensitive words. The method was tested on Weibo and NewsFN news datasets, and the evaluation results showed that MCNNs-TFW had an accuracy of 88.82% and 90.10%, outperforming several methods such as LIWC (Linguistic Inquiry and Word Count), CNNs, and RST. Furthermore, Noor et al [16] carried out synonym-based data augmentation for hoax detection using CNNs and Easy Data Augmentation (EDA) method. The results showed the potential to detect hoax news in Indonesian language articles with accuracy results of 82.81%. In this study, a similar analysis was carried out to find hoax news in Indonesian articles, by comparing two methods, namely standard and CNNs optimized model using PSO. The investigation leverages dataset exceeding 29,643 news articles and assesses the models' performance across various training and testing data splits. Both the base and the refined CNNs model by PSO achieved impressive accuracy in classifying real and hoax news. The average accuracy exceeded 90% for all data splits. Specifically, CNNs+PSO model showed marginal improvement in terms of accuracy and precision compared to the baseline CNNs. This result suggested that PSO had the potential to refine the performance of CNNs for hoax news detection tasks. Regarding the optimization effectiveness, the improvement obtained from PSO optimization was relatively modest due to suboptimal parameter selection or exploitation of insufficient capabilities. To address the limitation, further studies should focus on fine-tuning PSO parameters and conducting a more in-depth analysis of their influence on model performance.

TABLE 6
COMPARISON OF CNNS WITH CNNS+PSO

| Confusion Matrix | | | |
|---|---|---|---|
| Method | Accuracy (%) | Precision (%) | Recall (%) |
| CNNs | 91.93 | 90.97 | 96.70 |
| CNNs+PSO | 92.06 | 91.60 | 96.19 |

The evaluation of the optimization process using confusion matrix, as presented in Table 6, shows that PSO optimization effectively improves the accuracy and precision of CNNs algorithm. However, the improvements are marginal, which can be attributed to suboptimal combination of parameter values, population size, and maximum use [24]. Compared to other studies, as shown in Table 7, CNNs+PSO model shows superior accuracy, indicating the advantage of integrating PSO for hyperparameter tuning in CNNs architectures, particularly for Indonesian-language datasets. These results underscore the value of PSO in enhancing CNNs performance, particularly in complex text classification tasks.

TABLE 7
COMPARISON OF CNNS+PSO MODEL PERFORMANCE WITH OTHER STUDIES

| Study | Method | Accuracy (%) | Dataset Language |
|---|---|---|---|
| Shu et al. [52] | SAF | 69.10 | English |
| Qin Li et al. [53] | MCNNs-TFW | 88.82 | English |
| Noor et al. [16] | CNNs+EDA | 82.81 | Indonesia |
| This Study | CNNs+PSO | 92.06 | Indonesia |

The comparison of the proposed CNNs+PSO model with previous study is based solely on reported accuracy values from respective studies due to the lack of access to the original datasets. Consequently, a direct re-experiment was not carried out using their methods on our dataset, making the comparison literature-based rather than experimental. This limitation underscores the need for caution in interpreting the superiority of the model in this study compared to previous methods. Although the results indicate that CNNs+PSO achieves higher accuracy than previous methods, the results remain theoretical rather than empirically verified. To address this, future studies should focus on re-implementing previous methods using the same dataset to ensure a more rigorous comparative analysis as well as establish a fair and conclusive evaluation of model performance. Furthermore, examining how these models handled ambiguous or borderline news cases would be a key aspect for any future studies that may be held, as certain types of hoax news might raise specific classification challenges.

Another important consideration was the computational cost, which was essential in real-life applications. PSO provided a promising optimization, exploring other alternative or hybrid methods, such as Genetic Algorithms or Hybrid PSO variants, could further enhance CNNs performance in hoax news detection. This study showed the potential of CNNs to identify hoax news in Indonesia. Furthermore, additional studies should be performed to maximize their impact. By addressing the considerations, future studies were expected to contribute to the development of robust and accurate methods to combat misinformation effectively.

## VI. CONCLUSIONS

In conclusion, this study showed the efficiency of optimizing CNNs with PSO for detecting hoax news in Indonesian datasets. The proposed method achieved significant results, with an accuracy of 92.06% precision of 91.60%, and recall of 96.19%, outperforming CNNs baseline model. It further confirmed that the integration of PSO enhanced CNNs hyperparameter tuning, leading to more precise text classification.

This study underscored the potential of CNNs+PSO framework in combating misinformation, particularly for linguistic nuances present in Indonesian texts. The results also showed the model's scalability and adaptability in multilingual and cross-context applications. For further investigation, studies could explore further refinements of PSO parameters, integration with other optimization methods, and application framework in various language and contextual settings. By addressing the directions, this study served as a reference for more robust and efficient solutions to mitigate the pervasive issue of hoax news dissemination.

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**Data Availability:** The dataset used in this research, titled Indonesian Political News Facts and Hoaxes, is publicly available on Kaggle at https://bit.ly/4eLhTNs. The dataset consists of 29,643 news articles from sources such as CNN, Kompas, Tempo, and Turnbackhoax, with hoax labels verified by Turnbackhoax experts. This ensures the data validity for hoax detection research.

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