Building of Informatics, Technology and Science (BITS)
Volume 7, No 2, September 2025 Page: 1186−1192
ISSN 2684-8910 (media cetak)
ISSN 2685-3310 (media online)
DOI 10.47065/bits.v7i2.7871

Fake News Detection with Hybrid CNN-SVM on Data AI and Technology

Aditya Lesmana*, Yuliant Sibaroni, Sri Suryani Prasetyowati

Faculty of Informatics, Bachelor of Informatics, Telkom University, Bandung, Indonesia
Email: [1,*]adittcn18@gmail.com, [2]yuliant@telkomuniversity.ac.id, [3]srisuryani@telkomuniversity.ac.id
Correspondence Author Email: adittcn18@gmail.com
Submitted: **03/07/2025**; Accepted: **01/09/2025**; Published**: 04/09/2025**

Abstract−The spread of fake news or *hoaxes* in this digital era, especially related to the issue of intelligence (AI) and Technology, is increasingly unsettling because it can trigger public misunderstanding and reduce trust in technological developments. News such as the claim that AI will lead to mass unemployment is a clear example of the spread of misleading information. Therefore, a system that can accurately detect fake news is needed. The purpose of this research is to develop a fake news detection system that is able to accurately identify hoaxes on topics related to AI and Technology. This study proposes a hybrid deep learning method that combines Convolutional Neural Network (CNN) and Support Vector Machine to improve the accuracy of hoax news detection. CNN is used to extract complex news text features, whereas SVM is used as a classifier because of its advantage of being able to separate classes within optimal margins. The selection of this method is based on the results of previous research which shows that each method has good performance, but has certain limitations. By combining the two, it is hoped that more optimal results can be obtained in detecting fake news, especially the topic of AI and Technology. The evaluation was carried out using news datasets related to AI and Technology that have gone through a process of preprocessing, feature extraction with TF – IDF, and feature expansion using Glove Embedding. The results obtained showed that the CNN-SVM hybrid model provided increased accuracy compared to using a single method.

Keywords: Hoax Detection; CNN; SVM; Deep Learning; Fake News; AI; Technology

1. INTRODUCTION

The rapid development of information technology has brought significant changes in the way people access and disseminate information. Social media and online news sites are now the main channels for people to obtain information quickly and easily [1]. However, behind this convenience, there is a big challenge in the form of the rampant spread of fake news (*hoax*), especially in emerging technology topics, such as *artificial intelligence* (AI). Fake news that circulates without verification can cause panic, wrong decision-making, and even reduce public trust in the development of digital technology [2].In dealing with these problems, an accurate and adaptive *hoax* detection system is needed . One potential solution is to utilize *deep learning* approaches, which are able to recognize complex patterns and characteristics of text that are not recognizable with traditional approaches. This research focuses on the development of fake news detection systems on AI and technology topics by utilizing the hybrid methods of Convolutional Neural Network (CNN) and Support Vector Machine (SVM). CNN is known to be effective in extracting spatial features from text data, while SVM excels as a classifier in class separation by optimal margins [3][4].

The combination between CNN and SVM, otherwise known as the CNN-SVM hybrid approach, has been widely used in several studies because it is able to combine the advantages of both algorithms, CNN's strength in extracting features and SVM's capabilities in the classification of high-dimensional data. Even so, until now there are still few studies that specifically apply the CNN-SVM hybrid approach to detect *hoax* news on the topic of AI and technology. Several previous studies have examined *hoax* detection using the CNN, SVM, or a combination of the two approaches. The Hoax *Detection on Social Media with CNN and SVM* study showed that the CNN–SVM hybrid approach was able to achieve an accuracy of up to 95.79%, slightly better than CNN (95.11%) and SVM (95.95%) individually [5]. Meanwhile, the *Hoax Detection of Covid-19 News using CNN and SVM study* recorded an accuracy of 75.8% for CNN and 77.9% for SVM, which suggests that the topic and quality of the data greatly affect the model's performance [6]. The study *Detecting Fake News on Social Media Combined with the CNN Methods* shows that CNN can achieve a high accuracy of 98.57% in detecting fake news on social media [7]. On the other hand, *the study The Effect of Information Gain Feature Selection for Hoax Identification in Twitter Using SVM* used the SVM method with the selection of *the Information Gain* feature and succeeded in obtaining an accuracy of 96.55% [8].Of the four studies, none have explicitly examined the application of hybrid CNN-SVM specifically to AI- and technology-themed hoax news, as well as integrating the representation of semantic features from GloVe and statistical features from TF-IDF, as well as using data balancing methods such as *smote*. This gap is the basis for the research gap that is to be filled in this research, considering the high spread of *hoaxes* on the topic of AI and technology which is often conveyed in technical terms and convincing information packaging.

Based on this background, this study aims to develop an accurate fake news detection system using CNN-SVM's *hybrid deep learning* approach on news data related to AI and technology. The system is built through data collection, *text preprocessing*, feature extraction and expansion (TF-IDF and GloVe), CNN and SVM model training, and hybrid model merging. Evaluation was carried out using classification matrices such as accuracy, precision, recall, F1-score, and AUC. The results of this research are expected to make a scientific contribution to the development *of*

Building of Informatics, Technology and Science (BITS)
Volume 7, No 2, September 2025 Page: 1186−1192
ISSN 2684-8910 (media cetak)
ISSN 2685-3310 (media online)
DOI 10.47065/bits.v7i2.7871

a better hoax detection system as well as a practical contribution in supporting disinformation mitigation efforts in the digital era.

2. RESEARCH METHODOLOGY

2.1 System Design Procedure

This research aims to develop *a hoax* detection system on artificial intelligence (AI) and technology topics with a hybrid deep learning approach that combines *Convolutional Neural Network* (CNN) and *Support Vector Machine (SVM)***.** The flow of the research stages is described as follows.

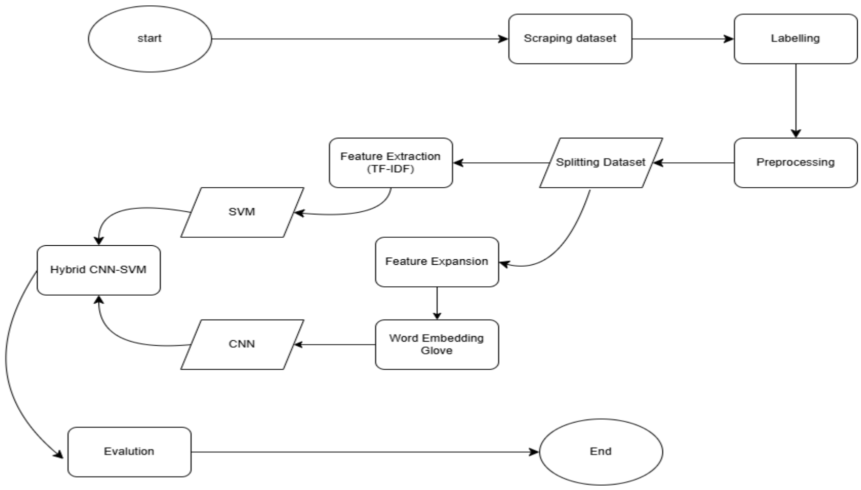


Figure 1. CNN-SVM Hybrid system stage flow

2.2 Scrapping Dataset

Data collection was carried out through a web *scraping* process from the Twitter (X) platform, using *the Python* programming language and *tweet-harvest* library version 2.6.1. The *scraping* process is aimed at gathering public opinion and viral news related to AI and technology topics, especially those that have the potential to contain *hoaxes* or misinformation. The details of the scraping results are shown in Table 1.

Table 1. Scraping Results

No	KataKunci Scraping	Dataset File Name	Language
1.	beritaviral	AI_Hoax_1.csv	Indonesia
2	video viral AI robot	AI_Hoax_2.csv	Indonesia
3	AI news viral artificial intelligence	AI_Hoax_3.csv	English
4	Chat GPT viral heboh	AI_Hoax_4.csv	Indonesia
5	Astonishing robotviral	AI_Hoax_5.csv	Indonesia
6	deep fake viral video AI	AI_Hoax_6.csv	English
7	AIbreakthrough amazing technology	AI_Hoax_7.csv	English

The entire file is combined into one main dataset *AI_hoax_dataset.csv with 936 tweets and 17 attributes. Full-text columns* are used as the main feature for text analysis, while *source queries* are the basis for labeling.

2.3 Labelling

The data labeling process is carried out to determine whether a tweet falls into the category *of hoaxes* or non-hoaxes. In this study, labeling was carried out manually by considering the source of the query from the tweet *source query* that was previously determined during the *scraping process*. Label determination is carried out with the following approach:

a. Label 1 for *hoaxes*
b. Label 0 for *non hoax*

Table 2 summarizes the division of labels by category.

Table 2. Label Distribution Results

No	Category	Source Query	Label
1.	beritaviralAI	AI_Hoax_1.csv	0
2	video viral AI robot	AI_Hoax_2.csv	1

Building of Informatics, Technology and Science (BITS)
Volume 7, No 2, September 2025 Page: 1186−1192
ISSN 2684-8910 (media cetak)
ISSN 2685-3310 (media online)
DOI 10.47065/bits.v7i2.7871

No	Category	Source Query	Label
3	AI news viral artificial intelligence	AI_Hoax_3.csv	1
4	ChatGPT viral heboh	AI_Hoax_4.csv	0
5	Astonishing robotviral	AI_Hoax_5.csv	0
6	deep fake viral video AI	AI_Hoax_6.csv	1
7	AIbreakthrough amazing technology	AI_Hoax_7.csv	0

The labeling results of a total of 936 tweet data are as follows:

a. 724 data *hoax* (label 1)
b. 212 data *non hoax* (label 0)
c. Rasio *hoax* 77,35 %

2.4 Preprocessing

The Preprocessing process is done to clean the text of irrelevant elements, such as URLs, mentions, hashtags, HTML symbols, punctuation, and excess spaces. Text is also converted to lowercase. Data that is too short (≤15 characters) is deleted. The result is saved in the *clean_text column*, while the original text remains in the *full_text column*. The final data count is 935 lines.

2.5 Splitting Dataset

The dataset was divided into training data (748 lines) and test data (187 lines) with an 80:20 ratio using stratified split to keep the *proportion of hoaxes* balanced. The proportion of *hoaxes* in the training data was 77.27%, and in the test data was 77.54%. This division ensures that the model is trained and tested fairly against the class distribution.

2.6 Feature Extraction (TF-IDF)

Feature extraction is performed on text data using the TF-IDF *(Term Frequency-Inverse Document Frequency)* method for use in SVM models. Configuration:

a. ngram_range = (1,4) → Captures context from unigrams to 4-grams
b. max_features = 8000 → Limit the most relevant features
c. English stopword removal

Because the data was unbalanced, the smote (*Synthetic Minority Over-sampling Technique*) **technique** was used to balance the class before model training.

2.7 Model SVM

The Support Vector Machine *(*SVM) model uses the RBF *(Radial Base Function*) kernel. The model was trained on TF-IDF results that had been balanced using SMOTE.

a. c = 15
b. *Classification threshold* : 0.3
c. Class *weight* adjustments to handle data inequality

This model is able to detect patterns explicitly based on the distribution of numerical features of the text.

2.8 Feature Expansion (Glove)

For the CNN model, *a GloVe (Global Vectors for Word Representation) based semantic representation is used:*

a. Each word is converted into a 100-dimensional vector.
b. Padding is applied so that all contexts are fixed in size of 120 tokens.
c. Of the total 3,946 words, 74.7% were successfully mapped to *Glove.*

This embedding helps the model understand the meaning and interconnectedness between words in the context of AI and Technology.

2.9 Model CNN

The Convolutinal Neural Network *(*CNN) model is used for Glove's embedding-based text classification. CNN's architecture includes:

a. Three *layers of Conv1d* with kernels 3, 4 and 5.
b. *MaxPooling* dan *GlobalMaxPooling*
c. Three layers of Dense (256, 128, 64) with *ReLU activation*
d. *Layer output* using *sigmoid*

Optimization using *Adam*, the *loss binary crossentropy function*, and the classification *threshold* are set at 0.4.

2.10 Hybrid CNN-SVM

The CNN–SVM *hybrid* model was developed to combine CNN's advantages in extracting semantic features and SVM's strength in classification. The process begins by taking features from the CNN model (*dense* layer before

Building of Informatics, Technology and Science (BITS)
Volume 7, No 2, September 2025 Page: 1186−1192
ISSN 2684-8910 (media cetak)
ISSN 2685-3310 (media online)
DOI 10.47065/bits.v7i2.7871

dropout), which represents semantic information from *GloVe's embedding-based* text. In parallel, the TF-IDF feature of the text data is also set up. These two feature types are then normalized using *the StandardScaler* and merged into a single combined feature vector. This vector is used as an input to an SVM model with an RBF kernel and a C=20 parameter, which is trained to separate *hoax* and *non-hoax* classes. The system uses *a weighted ensemble of* three models, namely:

a. CNN (weight 0.3)
b. SVM (bobot 0.3)
c. Hybrid CNN-SVM (bobot 0.4)

Voting is carried out based on the *probability* of the output of each model, with *a final classification threshold* of 0.35. The complete scheme of the architecture is shown in Figure 2.

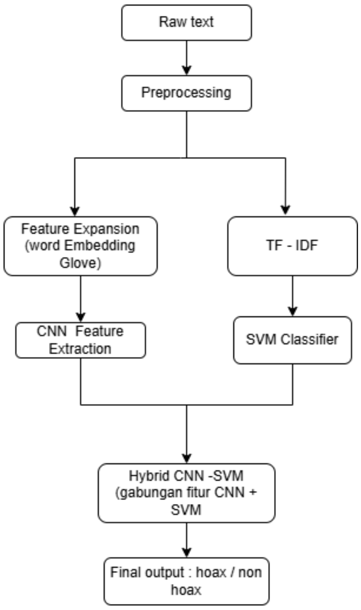


Figure 2. CNN-SVM Hybrid Architecture

2.11 Relevance of Research Concepts to Keywords

This research is built on a number of core concepts that are reflected in the main keywords, namely *Hoax Detection*, *Convolutional Neural Network (CNN), Support Vector Machine (SVM), Deep Learning*, *Fake News*, *Artificial Intelligence (AI),* and *Technology*. All of these elements are the foundation in system design, data selection, and modeling and evaluation. The elaboration of the relevance of each concept is explained as follows:

a. Deteksi *Hoax*
The main goal of this research is to develop an automated system to identify false information (*hoaxes*) in news and public opinion, especially those spread through social media. The focus is directed at news that contains potential misinformation related to AI and technology.

b. *Convolutional Neural Network(CNN).*
CNN is leveraged as part of a *deep learning* approach to extract semantic features from text. The CNNs in this study were trained using *GloVe embedding*, and were designed to recognize contextual linguistic patterns of text representations in vector form.

c. *SupportVectorMachine*(SVM)
SVM is used as a classification model that has a high ability to distinguish two classes explicitly based on numerical features. In this study, SVM functioned both independently and in a hybrid model with CNN.

d. *CNN deep learning*
as part of *the deep learning* family plays a crucial role in capturing the structure and representation of complex text data. The use of this approach allows the model to understand the hidden meanings of hoax texts in more depth.

e. *Fake News*.
The data analyzed in the study was in the form of tweets that were categorized as fake news or non-hoax. The information contained in fake news is often misleading, and has the potential to have a negative impact on public perception of AI and technology issues.

f. *Artificial Intelligence (AI)*
It is the content domain of the news analyzed, covering topics such as ChatGPT, AI robots, and deepfakes. This content was chosen because of the high intensity of the spread of hoaxes in the name of AI technology on digital platforms.

Building of Informatics, Technology and Science (BITS)
Volume 7, No 2, September 2025 Page: 1186−1192
ISSN 2684-8910 (media cetak)
ISSN 2685-3310 (media online)
DOI 10.47065/bits.v7i2.7871

g. TechnologyRefers to digital developments and innovations that are the context of the news collected. Technology topics are used as a basis for compiling scraping keywords, as well as a thematic scope in modeling hoax detection

The integration of all the above elements shows that this research is not only built on a technical approach, but also rooted in relevant social and thematic contexts. This makes the urgency and contribution of research in facing the challenges of spreading *hoaxes* in the rapidly growing era of information technology.

3. RESULTS AND DISCUSSION

3.1 Model Test Results

a. This study conducted three experiments to evaluate the performance of CNN, SVM, and *hybrid* CNN–SVM models. The purpose of this experiment was to observe the impact of the use of data *balancing* methods (*smote*), cross-validation, and feature extraction methods on classification performance.
b. The details of the experiment are as follows:
   1. Experiment 1: Initial baseline without *random splitting* and without *smote* on CNN
   2. Experiment 2: Adding *smote* to the CNN model to address class imbalances.
   3. Experiment 3: Using *random splitting* and *cross-validation* on CNN and SVM with *smote.*

   Table 3 is the test results of each model and *the CNN-SVM* Hybrid

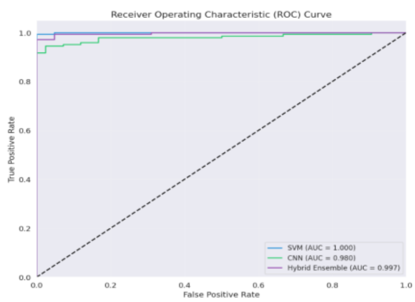
Table 3. Test results of each model and CNN-SVM Hybrid

Mode	Experiment to	Accuracy (%)	Precision	Recall	F1-Score	ROC-AUC
CNN (Embedding)	1	70.05	0.81	0.70	0.72	0.850
	2	88.77	0.89	0.89	0.89	0.860
	3	93.05	0.95	0.93	0.93	0.980
	Average	83.96	0.88	0.84	0.85	0.897
SVM (TF-IDF)	1	95.72	0.96	0.96	0.96	0.993
	2	95.72	0.96	0.96	0.96	0.993
	3	96.90	0.97	0.97	0.97	0.997
	Average	96.11	0.96	0.96	0.96	0.994
Hybrid (CNN-SVM)	1	91.44	0.91	0.91	0.91	0.983
	2	91.98	0.92	0.92	0.92	0.985
	3	97.86	0.98	0.98	0.98	0.997
	Average	93.76	0.94	0.94	0.94	0.988

Based on Table 3, the CNN-SVM Hybrid model shows the best performance across all evaluation matrices. In the third experiment, the model achieved the highest accuracy of 97.86% and an AUC of 0.997.l. Significant improvements were also seen in the CNN model, from 70.05% in the first experiment to 93.05% in the third experiment after using *smote* and *random splitting*. This shows that data balancing and cross-validation techniques have a big impact on performance. The SVM model also shows stable performance with an average accuracy of 96.11% and an AUC of 0.994. However, *the hybrid model* still excels because it manages to combine the advantages of textual and spatial features.

3.1.1 Analysis of Test Results

a. The CNN model experienced a significant increase from 70.05% (experiment 1) to 93.05% (experiment 3), proving the effectiveness of *smote* and *random splitting* techniques in improving *deep learning performance*.
b. The SVM model shows very stable and high performance, with an average accuracy of 96.11% and an AUC of 0.994. This demonstrates the reliability of SVM in TF-IDF-based text classification.
c. The CNN–SVM hybrid model outperforms the two previous approaches with the highest accuracy, f1-score, and near-perfect AUC. The combination of features from GloVe (CNN) and TF-IDF (SVM) results in richer and more effective data representations.



Gambar 3. Roc Curve

Building of Informatics, Technology and Science (BITS)
Volume 7, No 2, September 2025 Page: 1186−1192
ISSN 2684-8910 (media cetak)
ISSN 2685-3310 (media online)
DOI 10.47065/bits.v7i2.7871

The ROC Curve image shows the performance of the three models in distinguishing between *hoax* and *non-hoax classes* based on the classification threshold value. The ROC curve plots the value *of the True Positive Rate* (TPR) against *the False Positive Rate* (FPR). Interpretation:

1. The closer the curve is to the upper left corner, the better the model will be
2. AUC values are used key indicators:
   a) SVM =1000 (excellent).
   b) CNN = 0.980 (very good).
   c) Hybrid CNN-SVM = 0.997 (almost perfect).

3.2 Implementation

Implementation is carried out by building a Python-based classification pipeline that includes data scraping, text preprocessing, CNN, SVM, and hybrid CNN–SVM model training, and evaluation of results. The model is applied to classify news from platform X (Twitter) as a hoax or not. The system also generates automatic predictions based on user input text, with the display of results in the form of labels and classification probability values. The entire system is tested and validated using prepared test data, and produces high performance that can be used to automatically detect hoaxes in AI and technology news.

3.3 Comparison with Previous Research

This study is compared with four previous studies that used the CNN, SVM, and a combination of the two approaches in detecting hoaxes on social media. Table 4 summarizes the accuracy results of each study and the methods used.

Table 4. Comparison Results with Previous Research

No	Research Title	Method	Accuracy (%)
1	Detection Hoax on Media Social with CNN and SVM	CNN, SVM, CNN–SVM	95.95 (SVM), 95.11 (CNN), 95.79 (Hybrid)
2	Hoax Detection of Covid-19 News using CNN and SVM	CNN, SVM	75.8 (CNN), 77.9 (SVM)
3	Detecting Fake News on Social Media Combined with the CNN Methods	CNN	98.57
4	The Effect of Information Gain Feature Selection for Hoax Identification in Twitter Using SVM	SVM + IG Feature Selection	96.55

Based on the results in Table 4, the approach using pure CNN was shown to be able to produce very high accuracy, as shown in the third study which reached 98.57% [7]. These results show the effectiveness of spatial representations in processing contextual information in social media texts. The CNN–SVM hybrid approach also showed competitive performance with an accuracy of up to 95.79% [8], better than the single CNN model in the same study (95.11%). This indicates that the incorporation of spatial and textual features is capable of providing a significant increase in accuracy. Meanwhile, a second study using Covid-19 news data showed lower accuracy, which was 75.8% for CNN and 77.9% for SVM [9]. This can be due to the complexity of the topic and the high variability in Covid-19 data which makes it difficult for models to accurately distinguish between *hoaxes* and facts. The fourth study applied feature selection using *the Information Gain* technique to improve SVM performance. As a result, the model's accuracy reached 96.55% [10], which suggests that feature optimization has a significant influence on classification performance. When compared to this study, the CNN–SVM hybrid model developed was able to achieve an accuracy of up to 97.86% with an AUC of 0.997, exceeding most of the results reported in previous studies. This advantage is believed to be obtained through the integration of textual (TF-IDF) and semantic (*GloVe*) **feature** representations, the use of *smote* for class balancing, and the application of *ensemble voting strategies* between CNN, SVM, and hybrid models. These results reinforce that a hybrid approach with the integration of the power *of deep learning* and *machine learning* provides a more optimal solution in the classification of *hoax news*, especially in dynamic domains such as artificial intelligence and technology.

4. CONCLUSION

This research was conducted to answer the problem of the spread of *hoax news* that is increasingly rampant, especially in the topic of artificial intelligence (AI) and technology. By utilizing *a hybrid* approach between *Convolutional Neural Network* (CNN) and *Support Vector Machine* (SVM), this study succeeded in building a more accurate *hoax* detection system . CNN is used to extract semantic features from news text using *GloVe embedding*, while SVM is utilized for classification based on TF-IDF features. The combination of these two approaches is reinforced with *smote* techniques to overcome data imbalances and *ensemble voting* strategies to combine the strengths of the models used. The test results show that the CNN–SVM hybrid model is able to provide the best performance compared to the single model, with the highest accuracy reaching 97.86% and an AUC of 0.997. This proves that the integration of *deep learning* and *machine learning* methods can complement each other and result in a more reliable classification system,

Building of Informatics, Technology and Science (BITS)
Volume 7, No 2, September 2025 Page: 1186−1192
ISSN 2684-8910 (media cetak)
ISSN 2685-3310 (media online)
DOI 10.47065/bits.v7i2.7871

especially in the context of news with complex language such as AI and technology topics. In conclusion, this hybrid approach is not only technically effective, but also has great potential to be implemented as a tool to ward off the spread of *hoaxes* in the current digital era, both for social media platforms, online media, and the general public.

REFERENCES

[1] O. Ajao, D. Bhowmik, and S. Zargari, “Fake news identification on Twitter with hybrid CNN and RNN models,” *ACM Int. Conf. Proceeding Ser.*, no. July, pp. 226–230, 2018, doi: 10.1145/3217804.3217917.

[2] S. Ahlawat and A. Choudhary, “Hybrid CNN-SVM Classifier for Handwritten Digit Recognition,” *Procedia Comput. Sci.*, vol. 167, no. 2019, pp. 2554–2560, 2020, doi: 10.1016/j.procs.2020.03.309.

[3] N. N. Prachi, M. Habibullah, M. E. H. Rafi, E. Alam, and R. Khan, “Detection of Fake News Using Machine Learning and Natural Language Processing Algorithms,” *J. Adv. Inf. Technol.*, vol. 13, no. 6, pp. 652–661, 2022, doi: 10.12720/jait.13.6.652-661.

[4] M. Krichen, “Convolutional Neural Networks: A Survey,” *Computers*, vol. 12, no. 8, pp. 1–41, 2023, doi: 10.3390/computers12080151.

[5] M. S. Asramanggala, S. S. Prasetyowati, and Y. Sibaroni, “Optimal Number Data Trains in Hoax News Detection of Indonesian using SVM and Word2Vec,” *Build. Informatics, Technol. Sci.*, vol. 5, no. 1, pp. 21–28, 2023, doi: 10.47065/bits.v5i1.3516.

[6] D. P. Putra and E. B. Setiawan, “Hoax Detection Using Long Short-Term Memory (LSTM) and Gate Recurrent Unit (GRU) on Social Media,” *Build. Informatics, Technol. Sci.*, vol. 4, no. 4, pp. 1815–1820, 2023, doi: 10.47065/bits.v4i4.3084.

[7] A. R. I. Fauzy and Erwin Budi Setiawan, "Detecting Fake News on Social Media Combined with the CNN Methods," *J. RESTI (Engineering Sist. and Teknol. Information)*, vol. 7, no. 2, pp. 271–277, 2023, doi: 10.29207/resti.v7i2.4889.

[8] F. R. Tama and Y. Sibaroni, “Fake News (Hoaxes) Detection on Twitter Social Media Content through Convolutional Neural Network (CNN) Method,” *JINAV J. Inf. Vis.*, vol. 4, no. 1, pp. 70–78, 2023, doi: 10.35877/454ri.jinav1525.

[9] S. W. Nurdin and I. F. Nugraha, "Deepfake Threats and AI-Based Disinformation: Implications for Cybersecurity and Indonesia's National Stability," *JIMR: Journal of International Multidisciplinary Research*, vol. 4, no. 1, pp. 73–92, 2025, doi: 10.62668/jimr.v4i01.1551.

[10] M. Benedict and E. B. Setiawan, “Hoax Detection on Social Media with Convolutional Neural Network (CNN) and Support Vector Machine (SVM),” *2023 11th Int. Conf. Inf. Commun. Technol. ICoICT 2023*, vol. 2023-Augus, no. April, pp. 361–366, 2023, doi: 10.1109/ICoICT58202.2023.10262433.

[11] R. D. Natasya, "The Implementation of Artificial Intelligence (AI) in Modern Technology," *Journal of Computer and Science Technology*, vol. 2, no. 1, pp. 22–24, 2023.

[12] A. Sathiya Priya and T. Manisha, “CNN and RNN using Deepfake detection,” *Int. J. Sci. Res. Arch.*, vol. 11, no. 2, pp. 613–618, 2024, doi: 10.30574/ijsra.2024.11.2.0460.

[13] M. Sudhakar and K. P. Kaliyamurthie, “Detection of fake news from social media using support vector machine learning algorithms,” *Meas. Sensors*, vol. 32, no. July 2023, p. 101028, 2024, doi: 10.1016/j.measen.2024.101028.

[14] F. W. R. Tokpa, B. H. Kamagaté, V. Monsan, and S. Oumtanaga, “Fake News Detection in Social Media: Hybrid Deep Learning Approaches,” *J. Adv. Inf. Technol.*, vol. 14, no. 3, pp. 606–615, 2023, doi: 10.12720/JAIT.14.3.606-615.

[15] J. Mallet, L. Pryor, R. Dave, and M. Vanamala, “Deepfake Detection Analyzing Hybrid Dataset Utilizing CNN and SVM,” *ACM Int. Conf. Proceeding Ser.*, pp. 7–11, 2023, doi: 10.1145/3596947.3596954.

[16] N. E. Febriyanty, M. A. Hariyadi, and C. Crysdian, “Hoax Detection News Using Naïve Bayes and Support Vector Machine Algorithm,” vol. 4, no. 2, pp. 191–200, 2023, doi: 10.25008/ijadis.v4i2.1306.

[17] C. Juditha, “Artificial Intelligence and Hoaxes: Disruptive Challenges to Digital Literacy in Online Communities and Government’s Anticipatory Efforts,” *Jurnal Ilmiah Manajemen Informasi dan Komunikasi*, vol. 9, no. 1, pp. 28–38, Jun. 2025, doi: 10.56873/jimik.v9i1.531.

[18] I. G. Hosea, V. O. Waziri, I. Ismaila, J. Ojeniyi, M. Olalere, and O. Adebayo, “A Machine Learning Approach to Fake News Detection Using Support Vector Machine (SVM) and Unsupervised Learning Model,” *Adv. Multidiscip. Sci. Res. J. Publ.*, vol. 11, no. 1, pp. 11–18, 2023, doi: 10.22624/aims/csean-smart2023p1.

[19] M. R. Shoaib, Z. Wang, M. T. Ahvanooey, and J. Zhao, “Deepfakes, Misinformation, and Disinformation in the Era of Frontier AI, Generative AI, and Large AI Models,” *arXiv preprint*, arXiv:2311.17394, 2023, doi: 10.48550/arXiv.2311.17394.

[20] A. D. Cahyani, A. K. Ramdani, and Y. Sibaroni, *“Hoax Detection of Covid-19 News using Convolutional Neural Network and Support Vector Machine,”* International Journal on Informatics and Communication Technology (IJoICT), vol. 9, no. 2, pp. 177–185, Dec. 2023, doi: 10.21108/ijoict.v9i2.872.

[21] R. Fatimah, D. Zakaria, et al., *“AI-Generated Misinformation: A Literature Review,”* International Journal of Artificial Intelligence and Data Mining (IJAIDM), vol. 7, no. 2, pp. 241–254, 2024, doi: 10.24014/ijaidm.v7i2.26455.