Classification of Real and Fake News Using the Artificial Neural Network Method

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***Abstract*—The rapid spread of fake news through digital platforms poses a significant challenge in the current era, as misinformation can quickly influence public perception and disrupt social stability. This research focuses on the development and implementation of an Artificial Neural Network (ANN) model to classify news articles as either real or fake. The study utilizes news data collected from the past year, which is processed through several stages including data preprocessing, feature extraction, model training, and evaluation. The ANN model is designed to recognize complex patterns in news text, enabling it to distinguish between authentic and fabricated information with high accuracy. Experimental results indicate that the proposed ANN approach achieves an accuracy rate of 98% in classifying news articles. The findings also reveal annual fluctuations in the distribution of fake and real news, with a notable decline in fake news observed in 2025, which may reflect increased public awareness and improved verification practices. The study highlights the ongoing risks posed by digital misinformation and underscores the importance of integrating ANN-based solutions into information systems to enhance digital literacy and support more reliable news dissemination. This contribution is expected to assist stakeholders in mitigating the negative impacts of fake news and fostering a more trustworthy digital information environment.**

***Keywords*— Artificial Neural Network (ANN), Classification, Digital Literacy, Digital Platforms, Fake News, News Verification.**

I. INTRODUCTION

Rapid developments in information and communication technology (ICT) have fundamentally changed many facets of daily life, including how individuals communicate, work, and access information [1]. The ease of access to information through the internet enables society to acquire various data and knowledge quickly and efficiently, enhancing opportunities for learning, decision-making, and innovation [2]. Additionally, this technology supports more effective communication in business, education, and social life. However, despite its benefits, ICT also poses negative impacts that must be carefully addressed. One of the main challenges is the threat to security and privacy. The increasing use of digital technology creates opportunities for cybercrimes such as hacking, identity theft, and malware distribution, which can jeopardize personal and organizational data integrity [3]. Additionally, the digital divide persists, with unequal access to technology resulting in disparities in how information is used. This gap can hinder educational opportunities, economic advancement, and social inclusion, emphasizing the need for policies that promote equitable access to digital resources [4].

In particular, the phenomenon of fake news propagation has emerged as a critical challenge in the digital age, especially within the Indonesian context. Social impact is also a concern, particularly in terms of dependency on technology. Excessive use of social media can reduce direct social interactions and potentially affect mental health [5]. Moreover, the spread of false information or hoaxes through digital platforms has become increasingly widespread, potentially misleading and harming society. Therefore, digital literacy is a crucial aspect in addressing this challenge, enabling people to filter information more wisely and avoid the negative impacts of information and communication technology [6][7]. The massive spread of hoaxes in the digital era has become a serious threat to social, political, and democratic stability in Indonesia. [8]. The ease of access to information through social media and digital platforms facilitates the rapid spread of hoaxes, allowing them to shape public opinion and influence society's perception of certain events or issues [9]. This not only creates confusion and distrust toward official institutions but also hinders essential activities, such as elections, which heavily rely on public confidence in circulating information. One tangible impact of hoax dissemination is the rising social and political tensions, leading to polarization within society [10]. During the 2017 Jakarta gubernatorial election, for example, the widespread circulation of false information triggered social conflicts and deepened divisions among supporter groups [11]. Moreover, hoaxes can also influence election outcomes by manipulating public opinion and political decisions, thereby threatening the democratic process, which should operate fairly and transparently. The spread of misinformation not only misleads voters but can also distort political discourse, ultimately undermining trust in electoral institutions and democratic governance.

Not only does hoax information impact political aspects, but it can also lead to financial losses, damage

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reputations, and even threaten public safety if the misleading information pertains to health or security issues [12]. The challenge of fake news is not unique to Indonesia; globally, researchers have highlighted the rapid and wide-reaching spread of misinformation and its adverse effects on public trust and societal stability [21], [22]. This context underscores the urgency of developing reliable, automated systems for fake news detection, especially in languages with limited resources.

The latest progress in artificial intelligence and natural language processing technologies has created new opportunities for the automatic identification of fake news [23]. Deep learning architectures—including Convolutional Neural Networks (CNN), Long Short-Term Memory (LSTM), and Bidirectional Encoder Representations from Transformers (BERT)—have demonstrated strong capabilities in detecting intricate patterns within news text [13]. Several previous studies have introduced various deep learning models to tackle this challenge. For instance, Singhania et al. (2023) proposed the 3HAN model, a deep neural network with three hierarchical attention levels, which achieved an accuracy of 96.77% in fake news detection by assigning different attention weights to words, sentences, and headlines [14]. The implementation of such models demonstrates significant potential for practical application in combating the spread of false information and improving the credibility of news dissemination [13].

Furthermore, the integration of Artificial Neural Network (ANN) in news classification can also be extended to multilingual news analysis, enabling the system to detect misinformation across different languages and regions. By leveraging deep learning techniques, ANN-based models can continuously improve their accuracy through real-time data updates and adaptive learning mechanisms. Additionally, combining ANN with Natural Language Processing (NLP) methods improves the system's capability to understand context, sentiment, and subtle linguistic nuances, further strengthening the detection of fake news. This advancement not only contributes to combating misinformation but also fosters a more informed society, empowering individuals with reliable and credible sources of information. As technology continues to evolve, ANN-based news classification systems have the potential to integrate with social media platforms and digital news aggregators, offering proactive solutions to prevent misinformation before it spreads widely [7], [23].

The widespread dissemination of false information poses significant threats to social cohesion, democratic processes, and public trust in institutions [22]. In Indonesia, the impact of hoax dissemination has been particularly evident during critical political events, where misinformation has contributed to social polarization and undermined electoral integrity. The consequences extend beyond political spheres, affecting public health decisions, economic stability, and community relationships, thereby highlighting the urgent need for effective countermeasures. The importance of digital literacy and public awareness is thus increasingly recognized as a vital component in the fight against misinformation [7].

This study aims to develop and implement a news classification model based on Artificial Neural Network (ANN) that can effectively distinguish between real and fake news, thereby assisting the public in filtering the information they receive [6]. This system is expected to foster greater public awareness so that information is not accepted at face value, and to encourage wiser information management [7]. The proposed model achieved 98% accuracy in distinguishing between authentic and fabricated news content, marking a notable advancement compared to conventional machine learning techniques [23]. This research offers an effective solution for early-stage fake news detection that relies primarily on content analysis rather than propagation patterns, making it suitable for immediate deployment upon content publication. Furthermore, the results of this study indicate fluctuations in fake news distribution across different years, with a decline observed in 2025, suggesting increased public awareness and improved verification strategies. The findings of this study support the advancement of smart information systems that enhance public awareness and mitigate the adverse effects of fake news, ultimately supporting a more informed and trustworthy digital ecosystem [21], [22], [23].

A. *Writing Format*

News is a form of information delivered to the public via multiple channels, such as printed publications, electronic media, and online platforms [15]. The primary purpose of news is to provide knowledge, notifications, or updates about current events and issues relevant to society's daily life [16]. The development of information technology has brought significant changes to the production, distribution, and consumption of news. This transformation allows news to spread more quickly and reach a wider audience without geographical limitations [17]. However, the ease of access and rapid distribution of information also present new challenges, particularly regarding the verification of its accuracy. The abundance of news sources that are not always reliable requires society to be more critical in receiving and filtering the information they consume.

B. *Artificial Neural Network (ANN)*

Artificial Neural Networks (ANN) are computational systems modeled after the way biological neural networks operate in the human brain. It is designed to process information through a series of interconnected processing units [18]. This network consists of three primary layers: the input layer, which takes in raw data; one or more hidden layers, which execute complex mathematical computations; and the output layer, which produces the final classification or prediction result [19]. Each artificial neuron is linked to others via weighted connections, where the weights determine how strongly input features influence the output. The hidden layers utilize nonlinear activation functions, such as sigmoid or hyperbolic tangent, which introduce non-linearity into the model [20]. This function enables Artificial Neural Networks (ANN) to learn complex patterns in data that cannot be represented by simple linear relationships. While various hybrid and deep learning models like IndoBERT, BiLSTM, CNN, and LSTM have shown strong performance in fake news detection, this research specifically focuses on the implementation of the Artificial Neural Network (ANN) method due to its proven adaptability and effectiveness for text classification tasks in the Indonesian context [24], [25].

II. METHOD

The research method for classifying fake news or real news using the Artificial Neural Network approach consists of several stages, as illustrated in Figure 1 below.

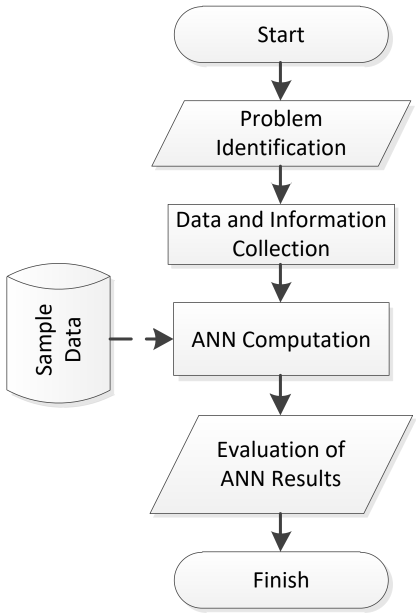

Figure 1 ANN Method Research Workflow

A. Problem Identification

The main issue identified is the widespread dissemination of fake news (hoaxes), which can lead to social and political harm. Therefore, a system capable of automatically and accurately classifying news into two categories real news and fake news is needed. The challenge lies in processing complex and diverse textual news data so that the classification model can recognize patterns distinguishing real from fake news with a low error rate.

B. Data and Information Collection

To support the implementation of this research, data and information related to both real and fake news need to be collected and processed to generate an accurate classification. The news data used in the study is sourced from news archives over the past year to enhance the data processing and boost classification accuracy. The selection of this time period aims to enable the model to recognize current patterns in information dissemination, allowing the system to effectively detect fake news circulating in society.

C. ANN Computation

*T*o support the implementation of this research, data and information related to both real and fake news need to be collected and processed via ANN Computation to generate an accurate classification. The news data used in the study is sourced from news archives over the past year to enhance the data processing and boost classification accuracy. The selection of this time period aims to enable the model to recognize current patterns in information dissemination, allowing the system to effectively detect fake news circulating in society.

The ANN computation process involves several mathematical operations that mimic the functioning of biological neural networks. Each artificial neuron processes input signals through a series of computational steps, including weighted summation, activation function application, and error propagation during the learning phase. The following stages describe the detailed mathematical framework underlying the ANN implementation [26]:

1) Weighted Sum: The first computational step involves calculating the total input value received by each neuron from the previous layer. This process, known as weighted summation, represents the core mathematical operation in neural networks [27], [28]. The weighted sum aggregates all incoming signals according to their relative importance, as determined by the connection weights [27].

Calculate the total input value of each previous neuron using the formula 1.

$$z = \sum_{i=1}^{n} (\mathrm{xi}.\,\mathrm{wi}) + \mathrm{b} \tag{1}$$

Description:

- *xi* : i-th input signal from the previous layer
- *wi* : i-th weight representing the connection strength between neurons
- *b* : *neuron bias,* which acts as an intercept term that allows the activation function to shift
- *z* : *output* before activation (pre-activation value)

The bias term (b) is crucial as it provides the neuron with additional flexibility to model complex patterns by allowing the activation function to be shifted horizontally, similar to the intercept in linear regression [28]. Weights (wi) determine how strongly each input affects the neuron's output, positive values amplify the input’s effect, while negative values diminish it.

2) Determining the Activation Function: After computing the weighted sum (z), the result is processed by an activation function, which adds non-linearity to the model. This step is crucial as it allows the ANN to capture and model intricate patterns that simple linear models cannot represent. The activation function determines whether and to what extent a neuron should be activated based on its input [29].

Common activation functions include the following:

- Sigmoid: $\boldsymbol{f(z) = \frac{1}{1+e^{-z}}}$ (2)

  The sigmoid activation transforms any real number input into a value between of 0 and 1, making it ideal for use in binary classification scenarios. It provides smooth gradients and was historically popular in early neural network implementations.
- ReLU (Rectified Linear Unit): $\boldsymbol{f(z) = max(0, z)}$ (3)

  ReLU is currently the most widely used activation function because of its computational simplicity and its effectiveness in addressing the vanishing gradient issue; it returns zero for negative values and outputs the input unchanged if it's positive.
- Tanh: $\boldsymbol{f(z) = \frac{e^{z}-e^{-z}}{e^{z}-e^{-z}}}$ (4)

  The hyperbolic tangent function provides zero-centered outputs ranging from -1 to 1, often resulting in faster convergence during training compared to sigmoid.

1) Loss Function

A loss function measures how much the model's predictions deviate from the actual target values, providing a measure of prediction accuracy [30]. For this fake news classification task, Mean Squared Error (MSE) is used to assess the model's performance during training [31].

$$z=\frac{1}{n}\sum_{i=1}^{n}(yi-yi')^2 \quad (5)$$

- yi : Actual target value (ground truth label)
- yi' : Predicted value generated by the ANN model
- n : Total number of training samples

MSE is particularly effective for regression tasks and binary classification as it penalizes larger errors more heavily due to the squaring operation [30], [31]. This characteristic encourages the model to minimize significant prediction errors, leading to more robust classification performance. Research has shown that MSE can be effectively used in neural networks for both regression and classification problems, especially when dealing with datasets containing noise and outliers [32].

2) Backward Pass (Backpropagation)

Following the error calculation, the backpropagation algorithm propagates the error signal backward through the network to compute gradients with respect to each weight and bias. This process enables the network to learn by adjusting its parameters to minimize the loss function [33].

The gradient calculation uses the chain rule of calculus:

$$\frac{\partial E}{\partial w} = \frac{\partial E}{\partial y'} \cdot \frac{\partial y'}{\partial z} \cdot \frac{\partial z}{\partial w} \quad (6)$$

Description:

- $\frac{\partial E}{\partial w}$: Gradient of error with respect to weight w
- $\frac{\partial E}{\partial y'}$: Gradient of error with respect to predicted output
- $\frac{\partial y'}{\partial z}$: Gradient of activation function
- $\frac{\partial z}{\partial w}$: Gradient of weighted sum with respect to weight

Backpropagation efficiently computes these gradients by working backward from the output layer back through the network toward the input layer, allowing the network to determine how each weight contributes to the overall error [33], [34]. The algorithm leverages the composite structure of neural networks to efficiently calculate gradients, making the computational complexity independent of the number of layers [33].

3) Weight Update

After computing the gradients, the weights are updated using gradient descent optimization to minimize the loss function [35]. Repeating this process incrementally enhances the model's ability to classify news articles accurately [36].

$$\boldsymbol{w_{new} = w_{old} - \eta \frac{\partial E}{\partial w}} \quad (7)$$

Description:

$\boldsymbol{\eta}$: Learning rate which controls the step size during weight updates

$\frac{\partial E}{\partial w}$: Weight gradient computed during backpropagation

The learning rate (η) is a key hyperparameter influencing how quickly and steadily the model converges during training. If set too high, the model might skip over the optimal point, while a value that is too low can slow down learning or cause the model to get stuck in suboptimal solutions. Research has demonstrated that appropriate selection of learning rate can significantly impact neural network performance, with optimal values typically ranging between 0.1 to 0.8 depending on the specific problem domain [37].

D. Evaluation of ANN Results

The results of the calculation process using Artificial Neural Network will be a classification of data into two categories: real news and fake news. Based on this classification, an analysis will be conducted to determine the number of real news and fake news present in each year. The conclusion will be drawn based on the quantitative comparison of these two types of news over the observed time period.

III. RESULTS AND DISCUSSION

A comprehensive dataset comprising 1000 news articles was utilized for the ANN computational process, with a representative sample of 20 entries presented in the analysis.

The dataset includes various features such as character count in headlines, character count in article content, publication year, word count from the news content, frequency of negative terms within the content, and credibility scores from verified news sources, which is shown in Table 1 as follows.

TABLE 1
NEWS DATA

Title Lenght	Text Lenght	Year	Word Count	Negative Word Count	Trusted Score
23	1434	2023	216	0	1
35	1588	2022	238	0	0
28	1472	2022	222	0	1
20	1659	2023	247	0	1
36	1441	2023	215	0	1
48	1764	2023	268	0	1
18	1748	2022	263	0	1
31	1650	2024	258	0	1
42	1904	2022	291	0	0
39	1316	2022	206	0	0
39	1417	2024	219	0	0
34	1514	2025	229	0	0
42	1403	2022	218	0	0
46	1738	2023	265	0	1
41	1314	2025	206	0	0
28	1760	2023	261	0	1
22	1705	2024	262	0	1
27	1729	2024	266	0	0
19	1411	2024	213	0	0
39	1417	2024	219	0	0

From Table 1, the Z value is then calculated to determine the classification of fake news or real news shown in table 2 as follows.

TABLE 2
NEWS PREDICTION CALCULATION RESULT

Number	Score	Prediction
1	2	real
2	0	fake
3	2	real
4	2	real
5	2	real
6	2	real
7	2	real
8	2	real
9	0	fake
10	0	fake
11	0	fake
12	0	fake
13	0	fake
14	2	real
15	0	fake
16	2	real
17	2	real
18	0	fake
19	0	fake
20	2	real

The output of the Artificial Neural Network (ANN) model is a probability value between 0 and 1, representing the likelihood that a news article is classified as real or fake. To convert this probability into a discrete class label, a classification threshold is applied. In this study, a threshold value of 0.5 is used, meaning that if the output probability is greater than or equal to 0.5, the news is classified as "real" (encoded as 2); otherwise, it is classified as "fake" (encoded as 0). This thresholding approach is widely used in binary classification tasks and allows for a clear decision boundary between the two classes [38], [39]. The choice of label encoding (2 for real, 0 for fake) is a convention adopted in this research to facilitate data processing and result interpretation [40].

The classification results based on each year for the types of fake and real news are shown in Table 3 as follows.

TABLE 3
NEWS SUMMARY CLASSIFICATION RESULT BY YEAR

Year	Fake News	Real News
2022	121	116
2023	192	157
2024	177	133
2025	58	45

The classification results using the Artificial Neural Network (ANN) model show yearly fluctuations in the distribution of fake and real news. As presented in Table 3, the highest number of fake news articles was recorded in 2023 (192 articles), while the lowest was in 2022 (121 articles). In contrast, the amount of real news followed a similar trend, with the lowest in 2022 (116 articles) and a projected decrease in 2025 (45 articles).

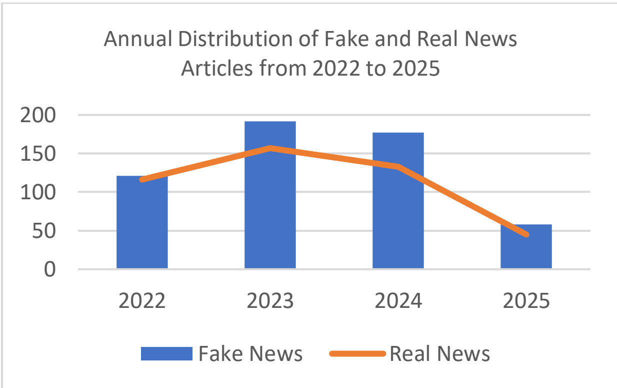

Figure 2 News Summary Classification Result

Figure 2 illustrates the annual distribution of fake and real news articles from 2022 to 2025. The observed decline in fake news in 2025, although based on incomplete data, may indicate the effectiveness of digital literacy campaigns and stricter platform policies in combating misinformation.

The ANN model achieved an overall classification accuracy of 98%, with high precision and recall values for both classes. This performance is consistent with previous studies that reported high accuracy for ANN-based fake news detection models. For example, Amanda et al. (2025) achieved 93% accuracy using a Multilayer Perceptron, while Singhania et al. (2023) reported 96.77% accuracy with a hierarchical attention network. Our results demonstrate that even a relatively simple ANN architecture can deliver robust performance in distinguishing real and fake news.

Critical Interpretation: The downward trend in fake news cases, especially in 2025, may be attributed to increased public awareness, improved content moderation by digital platforms, and the implementation of stricter regulations. However, the persistence of fake news, albeit at lower levels, underscores the ongoing challenge of combating misinformation. The high accuracy of the ANN model suggests its practical applicability in real-time fake news detection systems, but further validation across multiple data sources and longer periods is recommended.

Limitations: The main limitation of this study is the incomplete data for 2025, which may affect the reliability of the observed trend. Additionally, the model primarily relies on textual features and does not incorporate social context or multimedia data, which are increasingly relevant in fake news dissemination. Future research should explore multi-modal approaches and broader data collection to enhance detection performance.

IV. CONCLUSION

This study reveals that the spread of fake news fluctuates from year to year, with the highest number recorded in 2023 at 192 news items. Conversely, the lowest amount of fake news was noted in 2022, totaling 121 items. Preliminary data for 2025 indicates a decrease in fake news to 58 items, although this data has not yet been fully recorded through the end of December. Similarly, the volume of genuine news follows a comparable trend, with the lowest count in 2022 at 116 items and an estimated lower number in 2025, amounting to 45 items. From these findings, it can be concluded that the pattern of fake news dissemination exhibits fluctuations likely influenced by various factors such as digital media user behavior, social media platform policies, and increased public awareness regarding information verification. The decline in fake news in 2025, although provisional, may indicate the effectiveness of strategies implemented to counter disinformation and enhance digital literacy. These findings suggest that the public is becoming more conscious of the dangers posed by fake news and the importance of verifying information before sharing it. However, challenges remain, particularly as hoax dissemination techniques become increasingly sophisticated and capable of infiltrating various digital platforms. Therefore, ongoing efforts to improve digital literacy education and enforce stricter regulations are necessary to strengthen defenses against fake news. This study has several limitations, including incomplete data collection for 2025, which renders the results preliminary. Additionally, the methodology focuses primarily on Artificial Neural Network-based approaches, which, despite high accuracy in quantitative analysis, have limitations in capturing the social and psychological aspects of information spread. The generalizability of the findings should also be considered carefully, as the data may not encompass all digital platforms where fake news circulates. To address these limitations, future research could integrate quantitative and qualitative approaches by analyzing fake news dissemination patterns from social and psychological perspectives. Moreover, broader data collection covering multiple digital platforms is needed to obtain more representative results. Further studies could also explore the roles of government policies and technology companies in mitigating fake news spread and developing more effective strategies. The implications of this research are highly relevant for various stakeholders, including government bodies, digital media platforms, and the general public. The findings underscore the critical need to enhance digital literacy and implement stricter regulations to combat disinformation. For academics and researchers, this study opens avenues for further investigation into fake news dissemination patterns and the effectiveness of countermeasures. With continued research and development, more effective preventive measures can be established to reduce the negative impact of fake news in the future.

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