Journal of Artificial Intelligence and Engineering Applications

Website: https://ioinformatic.org/

15th October 2025. Vol. 5. No. 1; e-ISSN: 2808-4519

Integration of the Naive Bayes Algorithm in Website-Based Detection of Hoaxes Related to Nutritious Food Health Information

Khairul Reza Bakara[1*], Didi Febrian[2], Yulita Molliq Rangkuti[3], Zulfahmi Indra[4], Kana Saputra S[5]

[1,3,4,5]Ilmu Komputer, Universitas Negeri Medan,
[2]Matematika, Universitas Negeri Medan
khairulrezabakara@gmail.com[1*], febrian.didi@unimed.ac.id[2], molliq22rangkuti@gmail.com[3]
zulfahmi.indra@unimed.ac.id[4], kanasaputras@unimed.ac.id[5]

Abstract

There is an intelligent solution for automatic detection due to the increasing number of health-related hoaxes, especially those concerning nutritious food. The aim of this study is to integrate the Multinomial Naive Bayes algorithm into a hoax detection system that focuses on health information about nutritious food found on the internet. A quantitative method was employed, using the Multinomial Naive Bayes algorithm and the Term Frequency-Inverse Document Frequency (TF-IDF) feature extraction technique. The dataset used consists of 1,000 Indonesian-language news articles collected from five platforms: TurnBackHoax for hoaxes, and Detik, Kompas, Tempo, and the Ministry of Health for valid news. The data was divided into 800 training samples and 200 testing samples. The results of this study show a Precision of 0.9717, Recall of 0.9712, and F1-Score of 0.9712, as indicated by the Weighted Average, which accounts for the number of instances in each class. The overall model accuracy is 0.97125, based on the proportion of correctly classified data. These findings demonstrate that the system is capable of identifying distinctive linguistic patterns that differentiate between valid and invalid information. This indicates that probabilistic statistical techniques such as Naive Bayes are highly suitable for use in text-based fake information detection, particularly in the domain of health-related nutritious food information.

Keywords: *Naive Bayes, TF-IDF, Hoax Detection, Health News, Text Classification, Website.*

1. Introduction

Hoaxes, or what are commonly known as false news, have become a sensational phenomenon in Indonesia, growing increasingly widespread in today's digital era. With the rapid advancement of information technology, people now have easier access to various sources of information. However, this also accelerates the spread of inaccurate and misleading information. Hoaxes can influence public perception, create distrust, and even trigger serious social conflicts. The spread of hoax news, particularly in the context of health information, has become a significant challenge in Indonesia. With the rise of internet access and media usage, inaccurate information can spread rapidly, often without proper verification. Therefore, it is essential to have an effective news filtering system capable of detecting and classifying hoax content, especially in the field of health.

According to the Indonesian Ministry of Communication and Information (Kominfo), the majority of hoax issues are related to the health sector, amounting to 2,256 cases since 2018. In addition, there are numerous misleading pieces of information related to medicines and health products (CNN Indonesia, 2024). The most common health-related hoaxes include alternative treatments, prohibitions against certain practices, and warnings about consuming specific foods or drinks together (Haikal, 2020).

Nutritional food in Indonesia has received increasing attention, particularly as public awareness of healthy lifestyles continues to grow. Various programs and studies have demonstrated that consuming nutritious foods plays a crucial role in improving nutritional status and overall public health. Hoaxes related to health, including information about nutritious food, are highly concerning as they can lead to increased mortality rates and stunting caused by poor dietary choices. The main issue addressed in this study is to minimize the spread of false health-related information—particularly regarding nutritious food—since it can confuse the public and pose serious health risks. This is especially concerning among older adults, who are often more susceptible to believing health-related misinformation, potentially leading to fatal consequences.

This awareness encourages individuals to make more thoughtful food choices, aiming to foster a healthier and more productive generation. For instance, a recent viral video on YouTube claimed that the "free school lunch program" served spoiled and rotten food that caused students to vomit. According to Komdigi (2025), this video, uploaded on January 10, 2025, and viewed over 8,000 times on social media, was proven false. It nevertheless sparked public concern, especially among parents, regarding President Prabowo Subianto's free nutritious meal program.

There are still many unverified hoax news stories that mislead the public, and identifying their original sources remains difficult due to the complexity of the verification process. Under the Indonesian Criminal Code, Article 14 paragraph (1), individuals who intentionally spread false news or hoaxes may face imprisonment for up to ten years (Mufid & Hariandja, 2019). Consequently, new hoaxes continue to emerge, often unfiltered and driven by personal or financial interests, especially in the health sector, targeting uninformed groups such as the elderly.

Today, anyone with internet access can disseminate information or news. Every individual has the opportunity to play a role in sharing content—whether through social media, blogs, or other online platforms. While this expands the reach of information, it also increases the risk of spreading fake or inaccurate news. Therefore, it is crucial for internet users to possess strong media literacy skills so they can evaluate the reliability of information sources and understand the consequences of sharing false information. Collective awareness of responsible information sharing can help create a healthier and more trustworthy information ecosystem (Tambusai et al., 2021).

Online news sites—intended to be reliable sources of information—often become entangled in the spread of hoaxes. People who rely on these outlets for health-related decisions may thus be exposed to misleading information. This issue has become more critical in the digital era, where information can be accessed anytime and anywhere. Studies show that low levels of media literacy among the public contribute to the spread of hoaxes, making individuals more vulnerable to misinformation.

On the internet, hoaxes have become a global issue, disrupting social order and affecting the stability of democracy, culture, politics, and the economy. To address this problem, the use of technology to detect hoax news is increasingly relevant. Various tools and algorithms can be developed to analyze and verify information before it is disseminated. Moreover, public education on recognizing inaccurate information is vital so that individuals can think critically when consuming news and engage in constructive discussions.

With the right approach, the negative impacts of hoaxes can be minimized. One effective method for this purpose is the Naive Bayes classification algorithm, which is based on Bayes' theorem. In this study, it is applied to detect fake news on the internet. The Naive Bayes algorithm is a probabilistic text classification technique widely used in natural language processing. It works by calculating the probability that a piece of news belongs to a particular category—such as hoax or valid—based on features like specific keywords and phrases. Its main advantages lie in its ability to efficiently handle large datasets and its accuracy in identifying linguistic patterns within news content.

2. Research Method

This research consists of several processes as illustrated in the following figure.

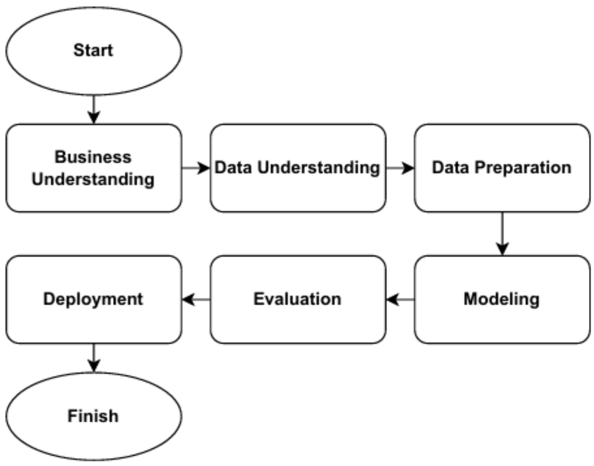

Fig. 1: Research Workflow

2.1. Business Understanding

Business Understanding is the research stage aimed at identifying the main problem that serves as the foundation of the study. In this research, the issue lies in the increasing spread of hoax news related to health information and the ease with which the public can access invalid or misleading news that may endanger health. Based on this identified problem, it is necessary to develop a news detection model that can classify information to determine its authenticity whether it is a hoax or not so that reliable and beneficial information can be produced

2.2. Data Understanding

Data Understanding is the stage in which the researcher examines and ensures that the data used in the study aligns with the research requirements. The data is converted into a CSV format to prevent errors during the classification process in machine learning. The collected health news data consists of news articles labeled as hoax and valid, ensuring accuracy and reliability in the final results.

2.3. Data Preparation

In the Data Preparation stage, the researcher processes the data before it is used by performing case folding, stopword removal, and tokenizing. Afterward, the Modeling stage is carried out to generate the final results.

2.4. Modeling

Modeling is the next stage following preprocessing, where the researcher applies the Multinomial Naïve Bayes algorithm. This algorithm is well-suited for text mining, as it analyzes word frequencies and trains the model using preprocessed training data converted into a vectorized representation. The data is transformed into a geometric vector form that can be resized without losing quality. This vectorization process refers to a technique that optimizes data processing execution to enhance performance.

2.5. Evaluation

Evaluation is the next stage, where researchers assess the performance of the model using metrics such as accuracy, precision, recall, and the F1-score to determine the accuracy and effectiveness of the previous stages.

2.6. Deployment

In this stage, the researcher implements the model deployment process by integrating it into a website-based platform, making it easier for users to detect hoax news directly through the system**.**

3. Result and Discussion

All paragraphs must be justified alignment. With justified alignment, both sides of the paragraph are straight.

3.1. Business Understanding

The author identifies the main problem in this research as addressing false news and preventing the public from accepting misleading information, as people today often find it difficult to distinguish between hoax news and valid news. This phenomenon requires serious attention due to its negative impact. Therefore, the author emphasizes the importance of developing a classification model capable of distinguishing between hoax and valid news. This model is expected to serve as an effective tool in reducing the adverse effects of hoax news dissemination. Further research is needed to explore how machine learning algorithms can be optimized to improve the accuracy of news classification and to understand the factors that influence public perception of the information they receive.

3.2. Data Understanding

Indonesian Language : the dataset used to develop the classification model must consist of text in the Indonesian language. It is essential to ensure that the model can accurately understand and generate predictions related to news written in this language.

News Data Scraping : The scraping technique is used to collect news information available in Indonesia. In this context, websites such as detik.com, kompas.com, kemkes.go.id, and tempo.co serve as the primary sources for gathering reliable news. The use of this technique enables efficient data collection, facilitating accurate news information analysis.

Valid News Sources : Valid news is labeled as (0) in the dataset and sourced from the four platforms — detik.com, kompas.com, kemkes.go.id, and tempo.co. Each entry includes the title, date, news link, and news description to ensure data completeness and reliability.

Hoax News Sources : Hoax news is labeled as (1) in the dataset and obtained from the turnbackhoax.id platform. Each record includes the title, date, news link, and news description as supporting details for analysis.

News Data Identification : The data obtained through the scraping technique is stored in CSV format, allowing researchers to manage and analyze the data efficiently using various analytical tools.

Hoax and Valid Labels : The dataset must contain clear labels for each news entry, indicating whether the news is hoax (1) or valid (0). This dataset format plays a crucial role in the classification process, making it easier for researchers to distinguish between valid and hoax news.

Tab. 1: Valid Data Example

Title	Ini Alasan Orang Masih Ngidam Makanan Manis Meski Sudah Kenyang
Date	16 Mar 2025
Link	https://food.detik.com/info-sehat/d-7824599/ini-alasan-orang-masih-ngidam-makanan-manis-meski-sudah-kenyang
Description	Banyak orang ingin makan makanan manis bahkan setelah makan utama membuat mereka kenyang. Bentuk ngidam makanan ini ternyata memiliki jawaban ilmiah. Ini adalah penjelasannya.Jika makanan manis tidak "ditutup" dengan makanan utama, sebagian besar orang akan menganggapnya tidak lengkap. Karena itu, meskipun mereka sudah kenyang, mereka tetap mencari makanan manis.Kondisi ini tampaknya tidak muncul begitu saja…
Label	0

Tab. 2: Hoax Data Example

Title	Resep Ustaz Abdul Somad: Obat Prostatitis Pakai Telur dan Cola

Date	January 14, 2025
Link	https://turnbackhoax.id/2025/01/14/penipuan-resep-ustaz-abdul-somad-obat-prostatitis-pakai-telur-dan-cola/
Description	Setelah itu, TurnBackHoax mengunggah video akun Facebook berjudul "Heart" ke alat deteksi moderasi AI Hive. Hasil analisis menunjukkan bahwa konten tersebut merupakan rekayasa AI dengan kemungkinan 99,9 persen…
Label	1

3.3. Data Preparation

One of the main objectives of the case folding process is to convert all letters in the text into lowercase. This step is crucial to reduce variations in text formatting that could lead to irrelevant analysis results. This technique is applied to the news titles, with the first step being to identify the text element to be transformed—specifically, the "Description" column in the data_train DataFrame. Next, the **Lowercasing** function (text.lower()) is used to convert all letters into lowercase, resulting in consistent and more easily analyzable text. The **Cleansing** process is then performed to remove non-alphabetic characters such as numbers, punctuation marks, and symbols.

Tab. 3: Cleansing Results

Description	hoax	clean
Seminggu ber-uap: Menurut dokter, ini…	1	seminggu ber uap menurut dokter ini
Ada makhluk hidup di dalam vaksin itu…	1	ada makhluk hidup di dalam vaksin itu
Meminum air dalam jumlah banyak dapat…	1	meminum air dalam jumlah banyak dapat
Tahukah Kamu! Meminum terlalu banyak	1	tahukah kamu meminum terlalu banyak
Ternyata Biaya utk Cuci Ginjal ku…..	1	ternyata biaya utk cuci ginjal ku

The purpose of the stopword removal process is to eliminate common words such as *"ini" (this)*, *"yang" (that)*, and *"dan" (and)*. The first step is to identify words categorized as stopwords and then use NLTK to remove them from the text. This process produces cleaner data, making it more suitable for the next stage of analysis.

Finally, the tokenizing process divides the text into separate components, including words, punctuation marks, and symbols. At this stage, the tokenization function is applied to each element in the "Description" column of the data_train DataFrame using the pandas apply() method. The result is a "Title" column that has been split into word tokens, making further analysis easier.

Additionally, to improve the quality of the text being analyzed, researchers should perform more thorough data cleaning procedures, which include removing punctuation, numbers, and irrelevant characters. To ensure that the classification model functions properly, these preprocessing enhancements must also be incorporated.

Tab. 4: Tokenizing Results

Description	hoax	token
Seminggu ber-uap: Menurut dokter, ini…	1	['seminggu', 'ber', 'uap', 'menurut', 'dokter', …
Ada makhluk hidup di dalam vaksin. Itu…	1	['ada', 'makhluk', 'hidup', 'di', 'dalam', 'vaksin', 'itu', …
Meminum air dalam jumlah banyak dapat…	1	['meminum', 'air', 'dalam', 'jumlah', 'banyak', 'dapat', …
Tahukah Kamu! Meminum terlalu banyak…	1	'tahukah', 'kamu', 'meminum', 'terlalu', 'banyak', …
Ternyata Biaya utk Cuci Ginjal ku…	1	'ternyata', 'biaya', 'utk', 'cuci', 'ginjal', …

3.4. Modeling

In the modeling stage, the data is divided into two parts: training data and testing data. This division uses the TF-IDF (Term Frequency–Inverse Document Frequency**)** method, which aims to measure the importance of words within a document. This technique allows for a more effective evaluation of the model's ability to recognize patterns in previously unseen data, as it enhances text representation quality and emphasizes relevant words—resulting in improved classification accuracy and effectiveness.To begin, the dataset is split into two portions: eighty percent (80%) for training data and twenty percent (20%) for testing data**.** The training data is used to train the model, while the testing data evaluates the model's performance after training.To ensure that the category distribution within the dataset remains balanced, future research may explore various data splitting techniques, such as stratified sampling. This approach is crucial for improving the model's generalization capability and minimizing the risk of producing biased outcomes.

In text processing, feature extraction is an essential process that transforms news text into a numerical representation that can be used by classification algorithms. The frequency of words appearing in each document is measured using TF-IDF (Term Frequency–Inverse Document Frequency), one of the most commonly used feature extraction methods. This technique assigns weights to important words, producing a more meaningful representation of the text and enhancing the performance of classification algorithms in identifying patterns and extracting relevant information.

With the **TF** and **IDF** values already calculated, the **TF-IDF** can be determined using the following formula:

$$TF - IDF = TF \times IDF$$

For the document:

$$TF - IDF\ (Dokumen) = 0.55\ \times 1.077 \approx 0.5924$$

FinalResult:

$$\text{Dokumen}\ : TF - IDF \approx 0.5924$$

This calculation produces the TF-IDF value for the word “Otak” (Brain) in the relevant document, indicating the significance of that word within the text. For further text classification analysis, this method helps determine the weighting of important words, thereby improving the accuracy and effectiveness of the model.

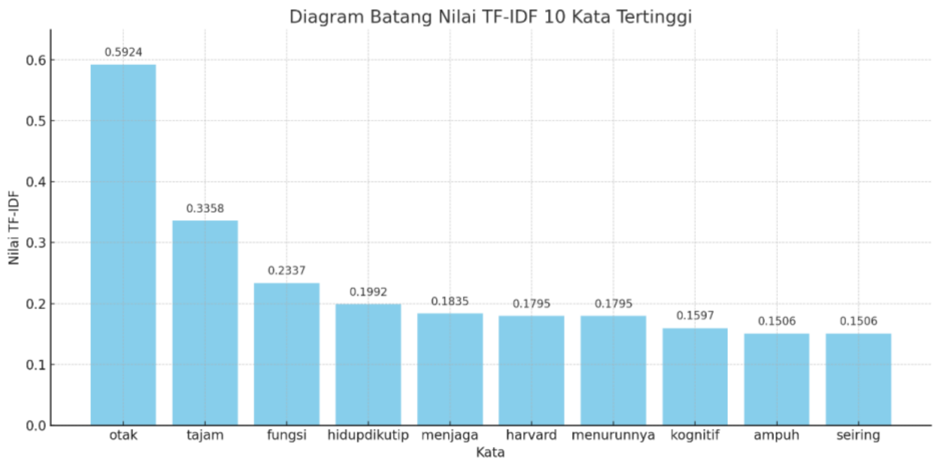

Fig. 2: TF-IDF Value Diagram of Top 10 Words Based on System

The Multinomial Naive Bayes model is used to classify text based on its representation after the TF-IDF (Term Frequency–Inverse Document Frequency) process, which converts the text into a numerical format reflecting the importance of words within a document. This model classifies data with discrete features, including text represented using TF-IDF values.

In its approach, Multinomial Naive Bayes assumes that each feature (word) contributes independently to the existing class (Hoax or Valid) and employs a multinomial distribution to model the probability of word combinations within each class. This enables the model to effectively analyze and classify textual data based on the likelihood of word occurrences.

Calculating Probabilities for Hoax Classes

The prior probability for the **Valid** class is calculated using the formula:

$$P(w_i \mid c) = \frac{\text{Count}(w_i \text{ in class } c) + 1}{\text{Total words in class} + \mid V \mid}$$

(where $\mid V \mid$is the vocabulary size).

ComputerLog-Likelihood
We compute the logarithm of the probability for each word in the **Valid** class:

$$\text{Log-Likelihood} + \text{Log-Prior for each class}$$

Use the natural logarithm (base e).

Example of smoothing applied to the Hoax class:

$$\text{Total words (Hoax)} + \text{Smoothing: } 87 + 10 = 97$$

Tab. 5 : Calculation of Probability and Likelihood of Hoax

Kata	**Freq(Hoax)**	$P(w\|Hoax)$	$In(P(w\|Hoax))$
Otak	33	$\frac{34}{97} \approx 0.3505$	-1.048
Tajam	9	$\frac{10}{97} \approx 0.1030$	-2.273
Fungsi	8	$\frac{9}{97} \approx 0.0928$	-2.374
Hidupdikutip	5	$\frac{6}{97} \approx 0.0618$	-2.778
Menjaga	6	$\frac{7}{97} \approx 0.0722$	-2.639
Harvard	3	$\frac{4}{97} \approx 0.0412$	-3.178
Menurunnya	11	$\frac{12}{97} \approx 0.1237$	-2.079
Kognitif	4	$\frac{5}{97} \approx 0.0515$	-2.973
Ampuh	4	$\frac{5}{97} \approx 0.0515$	-2.973
Seiring	4	$\frac{5}{97} \approx 0.0515$	-2.973

The total contribution of the log-likelihood from each word is calculated and then added together with the prior probability.

ExampleCalculation:
The total log-probability can be calculated as:

$$\text{Log}(P(\text{Hoax} \mid \text{document})) = \text{Log}(0.495) \approx -0.703$$

The total log-likelihood from all words is computed as:

$$= -1.048 - 2.273 - 2.374 - 2.778 - 2.639 - 3.178 - 2.079 - 2.973 - 2.973 - 2.973 = -25.288$$

Final Calculation:

$$\text{Log}(P(\text{Hoax} \mid \text{document})) = \text{Log}(P(\text{Hoax})) + \sum(\text{log-likelihood for each word})$$
$$= -25.288 + (-0.703) = -25.991$$

Thus, the total log-probability for the Hoax class is -25.991, representing the overall likelihood of the document being classified as hoax.

Calculating Probability for Valid Classes

Total hoax words + Smoothing: 62 + 10 = 72

Tab. 6 : Valid Probability and Likelihood Calculation

Kata	**Freq(Valid)**	$P(w\|Valid)$	$In(P(w\|Valid))$
Otak	7	$\frac{8}{72} \approx 0.1111$	-2.197
Tajam	13	$\frac{14}{72} \approx 0.1944$	-1.834
Fungsi	4	$\frac{5}{72} \approx 0.0694$	-2.970
Hidupdikutip	6	$\frac{7}{72} \approx 0.0972$	-2.351
Menjaga	5	$\frac{6}{72} \approx 0.0833$	-2.485
Harvard	7	$\frac{8}{72} \approx 0.1111$	-2.197
Menurunnya	4	$\frac{5}{72} \approx 0.0694$	-2.970

Kognitif	6	$\frac{7}{72} \approx 0.0972$	-2.351
Ampuh	5	$\frac{6}{72} \approx 0.0833$	-2.485
Seiring	5	$\frac{6}{72} \approx 0.0833$	-2.485

Calculating Total Log-Likelihood and Log-Prior for the Valid Class

The total contribution of the log-likelihood from each word is calculated and summed using the prior probability:

ExampleCalculation:
The total log-probability can be calculated as:

$$\text{Log}(P(\text{Valid} \mid \text{document})) = \text{Log}(0.505) \approx -0.683$$

The total log-likelihood can be calculated as:

$$= -2.197 - 1.834 - 2.970 - 2.351 - 2.485 - 2.197 - 2.970 - 2.351 - 2.485 - 2.485 = -24.335$$

Final Calculation:

$$\text{Log}(P(\text{Valid} \mid \text{document})) = \text{Log}(P(\text{Valid})) + \sum(\text{log-likelihood for each word})$$
$$-24.335 + (-0.683) = -25.018$$

This shows the total log-probability for the **Valid** class after combining the prior probability and the log-likelihood contributions of all words.

Conversion of Log Posterior to Probability Using Softmax

The **Softmax function** is used to convert the log-posterior results into interpretable probability values:

$$P(\text{Hoax}) = \frac{e^{-25.991}}{e^{-25.991} + e^{-25.018}}$$
$$P(\text{Valid}) = \frac{e^{-25.018}}{e^{-25.991} + e^{-25.018}}$$

Step 1: Exponential Calculation

$$e^{-25.991} \approx 5.233 \times 10^{-12}$$
$$e^{-25.018} \approx 2.672 \times 10^{-11}$$

Step 2: Calculate the Denominator

$$e^{-25.991} + e^{-25.018} = 5.233 \times 10^{-12} + 2.672 \times 10^{-11} = 3.1953 \times 10^{-11}$$

Step 3: Compute the Probability for Each Class

$$P(\text{Hoax}) = \frac{5.233 \times 10^{-12}}{3.1953 \times 10^{-11}} \approx 0.1637$$
$$P(\text{Valid}) = \frac{2.672 \times 10^{-11}}{3.1953 \times 10^{-11}} \approx 0.8363$$

Adjustment of system results and manual calculations

Tab. 7 : Comparison results of manual calculations and system results

Kelas	Log Posterior	Probabilitas
Hoax	-25.991	16.37%
Valid	-25.018	83.63%

If the log-probability value is positive, the document is more likely to be classified into the *Valid* category. Conversely, if the value is negative, it is most likely classified into another category (e.g., *Hoax*).

3.5. Evaluation

In this section, the author evaluates the performance of the classification model using metrics such as Accuracy**,** Precision**,** Recall, and the F1-Score. These metrics provide a comprehensive understanding of how well the model classifies the data. Accuracy measures the proportion of correct predictions out of all predictions, while Precision evaluates how many of the positive predictions made by the model are actually correct. On the other hand, Recall measures the model's ability to identify all relevant instances within the dataset.When assessing a classification model, it is essential to consider the balance between precision and recall, especially when dealing with imbalanced datasets, where one class may have significantly more samples than the other.To make these metrics easier to interpret and analyze, the author visualizes the evaluation results using graphs. These results also serve as the foundation for future model improvements aimed at enhancing the model's accuracy and effectiveness in real-world applications.The code used in this stage calculates and presents the evaluation results of the Multinomial Naive Bayes model based on the training and testing datasets. It performs classification on both datasets and computes performance metrics such as accuracy**,** precision**,** recall**,** and the F1-score. Additionally, the code generates and displays a confusion matrix, which illustrates how the model performs on the training set. For visualization purposes, the Seaborn library is utilized, showing the number of correct and incorrect predictions for each class **(**Valid and Hoax**).**

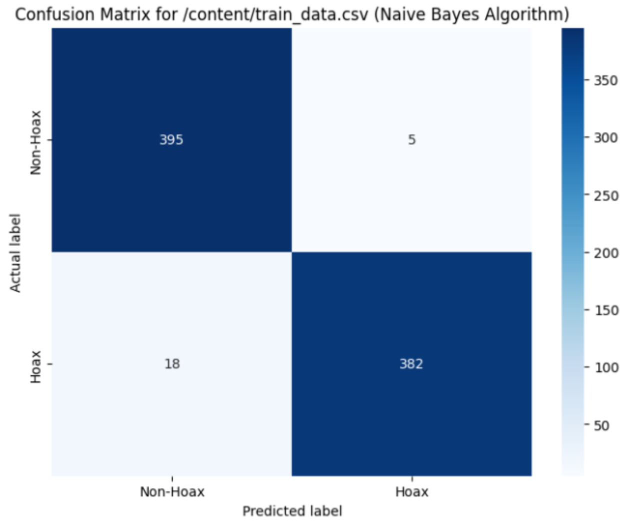

Fig. 3: Classification Form For Train data

The table above presents the evaluation metrics for the classification model used to distinguish between Hoax and Non-Hoax classes. The accuracy metric for the Non-Hoax class is 0.9564, indicating that the model achieved 95.64% accuracy in predicting this class. Meanwhile, the accuracy for the Hoax class is 0.9871, demonstrating an exceptionally high accuracy rate of 98.71%.In terms of Recall, the model successfully identified 98.75% of all actual Non-Hoax instances, while achieving a 95.5% success rate for Hoax instances. The F1-Score, which represents the harmonic mean of Recall and Precision, is 0.9717 for Non-Hoax and 0.9708 for Hoax, indicating strong and balanced performance across both classes.The dataset contains 400 instances for each class, and the model achieved an overall accuracy of 97.13%, representing the proportion of correct predictions among all predictions made. The Macro Average provides the unweighted average of metrics across all classes, with Precision = 0.9717, Recall = 0.9712, and F1-Score = 0.9712, without taking class distribution into account.Meanwhile, the Weighted Average—which considers the number of instances in each class—also shows Precision = 0.9717, Recall = 0.9712, and F1-Score = 0.9712. Overall, these results indicate that the model performs excellently in text classification, making it well-suited for information verification and hoax detection applications.

3.6. Deployment

The analysis results derived from the confusion matrix and comparison table indicate that the model's performance is highly satisfactory. In the next stage, the author will proceed with the implementation of the model using the Python-based Flask framework. The trained model will be stored in a pickle or joblib format for deployment purposes.The use of frameworks such as Flask enables the development of a more responsive web application that can automatically detect hoax-related information. Furthermore, conducting additional testing and performance evaluations in a real-world environment is essential to ensure the model's reliability and effectiveness when applied in broader, practical contexts.

Interface Display Implementation

Fig. 4: Hoax News Detection interface display

The initial homepage interface appears when the website is first opened. On this page, there are input fields for the news title, news date, news link, and news description that will be analyzed. Additionally, there is a "Predict News" button that allows users to test and determine whether the submitted news is classified as hoax or factual.

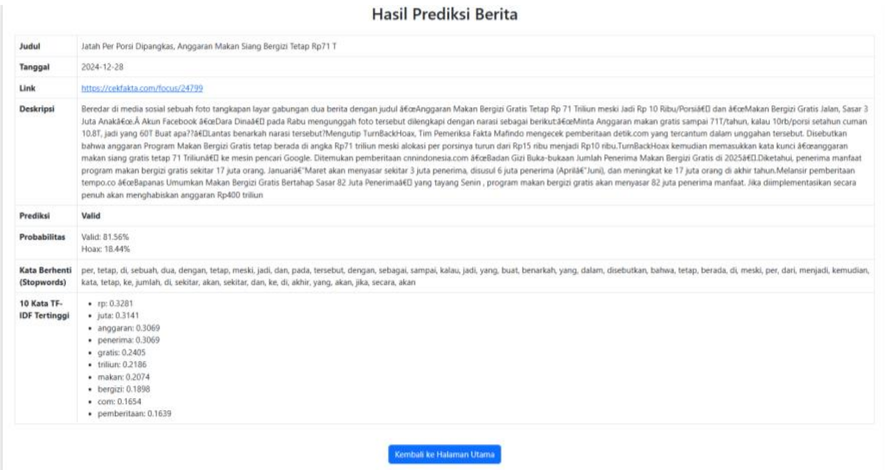

Fig. 5: Display of news detection system results

This page displays the prediction results when the news is classified as valid, including the probability values for both *hoax* and *valid* categories. If the valid probability value is higher, the news is determined to be factual. Additionally, in the prediction results section, the system presents the top 10 TF-IDF values, representing the most significant words identified by the prediction model.

4. Conclusion

This study demonstrates that the Multinomial Naive Bayes algorithm, when combined with the Term Frequency–Inverse Document Frequency (TF-IDF) feature extraction method, can effectively classify valid and hoax news. Based on a dataset of 800 entries (396 hoax and 404 valid), the model achieved strong results, with Precision = 0.9717, Recall = 0.9712, and F1-Score = 0.9712, as shown by the Weighted Average, which accounts for the number of instances in each class. The model's overall accuracy was 0.97125**,** indicating a high level of correctness in predictions. These findings suggest that the system can effectively recognize distinctive linguistic patterns that differentiate valid information from false information. This highlights that probabilistic statistical techniques, such as Naive Bayes, are highly suitable for text-based fake news detection, particularly in the context of health-related and nutritious food information**.**

The web-based detection system allows individuals to independently verify the authenticity of health-related information. Through this digital platform, users can access real-time classification services, promoting greater awareness of the importance of digital literacy and information verification**.** Furthermore, the system can be further enhanced by expanding the dataset, improving Natural Language

Processing (NLP) techniques, and integrating advanced machine learning methods to achieve higher accuracy and broader coverage in hoax detection across various topics.

Acknowledgement

The author would like to express profound gratitude to all parties who have provided support, guidance, and assistance throughout the research process. Special appreciation is extended to the supervisors, colleagues, and family for their continuous motivation and prayers, which greatly contributed to the successful completion of this research.

References

[1] Agustina, N., Adrian, A., & Hermawati, M. (2022). *Implementasi Algoritma Naïve Bayes Classifier untuk Mendeteksi Berita Palsu pada Sosial Media.* Faktor Exacta, 14(4), 206. https://doi.org/10.30998/faktorexacta.v14i4.11259
[2] Aisyah, S., Dika, M. F. Z., Yasmin, A., Hanifah, T. P., & Pradana, F. B. A. (2022). *Hoax News and Future Threats: A Study of the Constitution, Pancasila, and the Law* (Vol. 1). https://doi.org/10.15294/ijpgc.v1i1.56881
[3] Albab, M. U., Karuniawati P, Y., & Fawaiq, M. N. (2023). *Optimization of the Stemming Technique on Text Preprocessing President 3 Periods Topic.* Jurnal TRANSFORMATIKA, 20(2), 1–10. https://doi.org/10.26623/transformatika.v20i2.5374
[4] Pangesti, I. A., Zen, N. A., & Kurnianto, D. (2023). *Evaluasi Kinerja Algoritma Naïve Bayes pada Sistem Deteksi Berita Hoax.* Journal of Informatics and Communications Technology, 5(2), 103–110. https://doi.org/10.52661
[5] Kasingku, J. D. (2023). *Peran Makanan Sehat Dalam Meningkatkan Kesehatan Fisik dan Kerohanian Pelajar.* http://ejournal.mandalanursa.org/index.php/JUPE/index
[6] Fajriana, S. (2022). *Machine Learning.*
[7] Haikal, H. (2020). *Persepsi Masyarakat terhadap Hoax Bidang Kesehatan.* Jurnal Manajemen Informasi dan Administrasi Kesehatan (JMIAK), 3(2). https://doi.org/10.32585/jmiak.v3i2.836
[8] Halim, J., & Lasut, D. (2024). *Document Plagiarism Detection Application Using Web-Based TF-IDF and Cosine Similarity Methods.* Bit-Tech, 7(2), 202–213. https://doi.org/10.32877/bt.v7i2.1697
[9] Khairani, U., Mutiawani, V., & Ahmadian, H. (2024). *Pengaruh Tahapan Preprocessing Terhadap Model Indobert dan Indobertweet Untuk Mendeteksi Emosi Pada Komentar Akun Berita Instagram.* Jurnal Teknologi Informasi dan Ilmu Komputer, 11(4), 887–894. https://doi.org/10.25126/jtiik.1148315
[10] Martantoh, E., & Yanih, N. (2022). *Implementasi Metode Naïve Bayes Untuk Klasifikasi Karakteristik Kepribadian Siswa di Sekolah MTS Darussa'adah Menggunakan PHP MySQL.* Jurnal Teknologi Sistem Informasi, 3(2), 166–175. https://doi.org/10.35957/jtsi.v3i2.2896
[11] Prasanti, D., & Media Informasi Kesehatan Bagi Masyarakat, P. (2017). *The Portrait of Media Health Information for Urban Community in the Digital Era.* (Vol. 19, Issue 2).
[12] Mufid, F. L., & Hariandja, T. R. (2019). *Efektivitas Pasal 28 Ayat (1) UU ITE tentang Penyebaran Berita Bohong (Hoax).* Jurnal Rechtens, 8(2), 179–198. https://doi.org/10.36835/rechtens.v8i2.533
[13] Mustofa, H., & Mahfudh, A. A. (2019). *Klasifikasi Berita Hoax dengan Menggunakan Metode Naive Bayes.* Walisongo Journal of Information Technology, 1(1), 1. https://doi.org/10.21580/wjit.2019.1.1.3915
[14] Dewi, N. K. (2023). *Identifikasi Berita Hoax dengan Menerapkan Algoritma Text Mining.* Journal of Informatics, Electrical and Electronics Engineering, 2(3), 65–74. https://doi.org/10.47065/jieee.v2i3.888
[15] Tamba, S. P., Laia, A., Butar Butar, Y. K., & Faculty of Science and Technology. (2023). *Penerapan Data Mining untuk Klasifikasi Berita Hoax Menggunakan Algoritma Naive Bayes.* Jurnal TEKINKOM, 6(2), 2023. https://doi.org/10.37600/tekinkom.v6i2.922
[16] Permatasari, A., & Suhendi, S. (2020). *Rancang Bangun Sistem Informasi Pengelolaan Talent Film berbasis Aplikasi Web.* Jurnal Informatika Terpadu, 6(1), 29–37. https://doi.org/10.54914/jit.v6i1.255
[17] Athifahputih, P. Y. R. (2022). *Penegakan Hukum terhadap Penyebaran Berita Hoax dilihat dari Tinjauan Hukum.* Jurnal Hukum dan Pembangunan Ekonomi, 10(1), 2022.
[18] Rahutomo, F., Pratiwi, I. Y. R., & Ramadhani, D. M. (2019). *Eksperimen Naïve Bayes pada Deteksi Berita Hoax Berbahasa Indonesia.* Jurnal Penelitian Komunikasi dan Opini Publik, 23(1). https://doi.org/10.33299/jpkop.23.1.1805
[19] Manthovani, R. (2023). *Dampak Berita Hoax terhadap Keamanan Negara dalam Perspektif Cyberlaw Bela Negara.* Jurnal Magister Ilmu Hukum, 8(2), 14. https://doi.org/10.36722/jmih.v8i2.2305
[20] Alfarizi, M. R. S., Al-farish, M. Z., Taufiqurrahman, M., Ardiansah, G., & Elgar, M. (2023). *Penggunaan Python sebagai Bahasa Pemrograman untuk Machine Learning dan Deep Learning.* In *Karimah Tauhid* (Vol. 2, Issue 1).
[21] Putri, S. A. A. (2024). *Deteksi Hoax pada Berita Kesehatan Berbahasa Indonesia Menggunakan Algoritma Multinomial Naïve Bayes.* Program Studi Teknik Informatika, Fakultas Sains dan Teknologi, Universitas Islam Negeri Maulana Malik Ibrahim Malang.
[22] Septiani, D., & Isabela, I. (2023). *Analisis Term Frequency–Inverse Document Frequency (TF-IDF) dalam Temu Kembali Informasi pada Dokumen Teks.* SINTESIA: Jurnal Sistem dan Teknologi Informasi Indonesia.
[23] Sriyano, C. S., & Setiawan, E. B. (2021). *Pendeteksian Berita Hoax Menggunakan Naive Bayes Multinomial pada Twitter dengan Fitur Pembobotan TF-IDF.*
[24] Tambusai, J. P., Aditia, I. M., Dewi, D. A., & Furnamasari, Y. F. (2021). *Runtuhnya Nilai-Nilai Persatuan dan Kesatuan Bangsa Bernegara Akibat Merajarelanya Hoax.*
[25] Wirth, N. (1971). *Program Development by Stepwise Refinement.* Communications of the ACM, 14(4), 221–227. https://doi.org/10.1145/362575.36257