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BEYOND ALGORITHMS: AN INTEGRATED APPROACH TO FAKE NEWS DETECTION USING MACHINE LEARNING TECHNIQUES

Bimantyoso Hamdikatama[1*]

Faculty of Communication and Informatics[1],
Universitas Muhammadiyah Surakarta, Surakarta, Indonesia[1]
www.ums.ac.id[1]
bh972@ums.ac.id[1*]

(*) Corresponding Author
(Responsible for the Quality of Paper Content)

Abstract— *The internet has become a major source of information, but it also facilitates the rapid spread of fake news, which can significantly influence public opinion and social decisions. While various techniques have been developed for detecting fake news, many studies focus on individual algorithms, which often result in suboptimal performance. This study addresses this gap by comparing machine learning models, including Support Vector Classification (SVC), XGBoost, and a Stacking Ensemble that combines both SVC and XGBoost, to determine the most effective approach for fake news detection. Text preprocessing was performed using IndoBERT, which provides context-aware and semantically rich text representations specifically for the Indonesian language. The evaluation results demonstrate that the Stacking Ensemble outperforms the individual models, achieving an accuracy of 82%, compared to 79% for XGBoost and 78% for SVC. This superior performance is attributed to the complementary strengths of the base models: SVC excels in handling high-dimensional data, while XGBoost effectively manages imbalanced datasets and captures complex feature interactions. The use of IndoBERT further enhances model performance by improving text representation through contextual embeddings. These findings highlight the effectiveness of ensemble learning in enhancing predictive performance and robustness for fake news detection, demonstrating the potential of combining different machine learning techniques with advanced preprocessing methods to achieve more reliable results.*

Keywords: *BERT, ensemble learning, SVC, XGBoost.*

Intisari— *Internet telah menjadi sumber informasi utama, tetapi juga memfasilitasi penyebaran berita palsu secara cepat, yang dapat memengaruhi opini publik dan pengambilan keputusan sosial secara signifikan. Meskipun berbagai teknik telah dikembangkan untuk mendeteksi berita palsu, banyak penelitian yang hanya berfokus pada algoritma individu, yang sering kali menghasilkan kinerja yang kurang optimal. Penelitian ini mengatasi kesenjangan tersebut dengan membandingkan model pembelajaran mesin, termasuk Support Vector Classification (SVC), XGBoost, dan Stacking Ensemble yang menggabungkan SVC dan XGBoost, untuk menentukan pendekatan paling efektif dalam mendeteksi berita palsu. Pemrosesan teks dilakukan menggunakan IndoBERT, yang menyediakan representasi teks yang kaya secara semantik dan kontekstual khusus untuk bahasa Indonesia. Hasil evaluasi menunjukkan bahwa Stacking Ensemble memiliki kinerja lebih baik dibandingkan model individu lainnya, dengan akurasi mencapai 82%, dibandingkan dengan 79% untuk XGBoost dan 78% untuk SVC. Kinerja unggul ini disebabkan oleh kekuatan komplementer dari model dasar: SVC unggul dalam menangani data berdimensi tinggi, sementara XGBoost efektif dalam mengelola dataset tidak seimbang dan menangkap interaksi fitur yang kompleks. Penggunaan IndoBERT semakin meningkatkan kinerja model dengan memperbaiki representasi teks melalui embedding kontekstual. Temuan ini menegaskan efektivitas pembelajaran ensemble dalam meningkatkan kinerja prediktif dan ketahanan sistem untuk deteksi berita palsu, serta menunjukkan potensi penggabungan berbagai teknik pembelajaran mesin dengan metode pra-pemrosesan lanjutan untuk mencapai hasil yang lebih andal.*

Kata Kunci: *BERT, pembelajaran ensemble, SVC, XGBoost.*

INTRODUCTION

In the digital era, social media and online platforms have transformed news dissemination, while also fueling the spread of fake news. Fake news, often designed to mislead or promote specific agendas, significantly impacts public opinion, election outcomes, and trust in legitimate news sources [1].

Social media is integral to life in Indonesia, with 185.3 million out of 278.7 million people using the internet. As of January 2024, 49.9% of the population (about 139 million) have social media accounts, and 75% of internet users are active on at least one platform [2].

Detecting fake news is challenging due to the vast volume and variety of content. Addressing this requires both technological tools and human judgment. The spread of political misinformation on platforms like Twitter underscores its social impact, even affecting reliable sources like Wikipedia [3] [4].

Fake news spreads rapidly and has significant social consequences, with political misinformation on platforms like Twitter often gaining wider reach through frequent retweets [5][6]. Even trusted sources like Wikipedia are vulnerable to false information. Addressing this issue, integrating social media data with machine learning has proven effective [7].

Machine learning, particularly Natural Language Processing (NLP), enables automated analysis of large datasets to detect patterns in fake news dissemination. By analyzing language, sentiment, and structure, NLP identifies markers distinguishing false content from legitimate news, offering a faster, more efficient alternative to traditional fact-checking methods [8][9][10][11].

This study compares SVC, XGBoost, and a Stacking Ensemble combining SVC and XGBoost to identify the most effective method for fake news detection. Each algorithm was chosen based on its distinct strengths: SVC excels in handling high-dimensional data commonly found in text classification tasks, while XGBoost is renowned for its ability to address imbalanced datasets and deliver high accuracy through advanced boosting techniques [12] [13].

The decision to compare these algorithms stems from the need to empirically validate their performance in the specific context of fake news detection in Indonesia, rather than relying solely on theoretical claims or previous studies. This experimental approach ensures that the selected methods are rigorously tested against real-world challenges, such as varying dataset characteristics, imbalanced class distributions, and model adaptability [14][15]. The criteria for selecting these algorithms include their demonstrated success in text classification tasks, flexibility in adapting to diverse dataset conditions, and computational efficiency, which makes them suitable for large-scale data processing[16]. By incorporating a stacking ensemble, this study leverages the complementary strengths of SVC and XGBoost, aiming to enhance overall model performance and robustness. Through this comparison, the study provides a thorough evaluation of the strengths and limitations of these methods, offering insights into their applicability in fake news detection [17][18].

Previous research has explored various methods for fake news detection, but each has limitations. One study, examined fake news across social and traditional media using features like news sources, spatial patterns, and political bias, employing K-nearest Neighbor for classification. While effective, it struggled with false positives and lacked generalization across platforms.

Another study [13], used Naive Bayes for detecting fake news on Facebook, but its reliance on a single model proved inflexible and inadequate for complex data. A third study integrated sentiment as a key feature for fake news detection, but relying on sentiment alone failed to capture the full complexity of fake news, and it did not compare with a wide range of modern methods.

This research makes a key contribution by using a current and relevant dataset, covering news from 2019 to 2024. It includes both fake and real news in Indonesian, collected from hoax-reporting sites and trusted portals. Headlines are paraphrased to align with hoax claims and verified using Bing API and OpenAI LLM, with facts labeled by tone and topic and validated by human review.

Moreover, this study contributes by utilizing context-aware preprocessing with indoBERT, enhancing feature extraction beyond traditional TF-IDF. Additionally, it employs ensemble learning stacking of SVC and XGBoost, combining their strengths for improved accuracy and generalization in fake news detection, offering a more robust solution than previous single-model approaches [19].

MATERIALS AND METHODS

This research employs several methods to compare the accuracy levels of various machine learning models.

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Data Collection

The dataset selection process for this study was carefully designed to meet specific criteria, ensuring its relevance and reliability for fake news detection.

1. Relevance to Fake News Detection, the dataset must contain both fake (hoax) and real news, with clear labeling to facilitate classification tasks.
2. Language Specificity, the dataset is required to be in Indonesian, reflecting the language and cultural context of the target audience.
3. Recent and Up-to-Date, The dataset should cover news from 2019 to 2024 to ensure it is current and relevant to the latest trends in fake news dissemination.
4. The data is sourced from both hoax-reporting sites (e.g., Mafindo) and reputable Indonesian news portals, ensuring a diverse range of news sources.
5. Validation and Fact-Checking, All claims in the dataset have been verified using tools like the Bing API and OpenAI LLM to ensure accuracy, with each claim being reviewed and labeled by humans.

The systematic selection process involved compiling news headlines from both hoax-reporting sites and trusted news portals, ensuring a balanced representation of fake and real news. Headlines from news portals were paraphrased to align with the characteristics of claims found in hoax data, maintaining consistency in format and structure. To ensure the reliability of the dataset, each claim underwent fact-checking through automated tools, followed by human validation. This thorough process ensures that the dataset is suitable for addressing the challenges of fake news detection in the Indonesian context.

A sample headline from the dataset: ”Belum genap sebulan, dua produk terbaru Apple, iPhone 6 dan iPhone 6 Plus sudah diragukan kekuatannya.” labeled as fake news based on verification. And “Menteri Keuangan Sri Mulyani Indrawati menegaskan belum ada pembahasan struktur gaji pegawai negeri sipil (PNS)” labeled as real news.

Research Contributions

This study makes several unique contributions to the advancement of fake news detection methods, particularly by leveraging IndoBERT for preprocessing data:

1. Innovative Use of IndoBERT for Preprocessing

This research introduces the use of IndoBERT, a transformer-based language model specifically trained on Indonesian texts, as a preprocessing step. IndoBERT is utilized to generate contextual embeddings that enhance the representation of Indonesian-language text data. This approach is novel in the domain of fake news detection for the Indonesian language, where traditional preprocessing techniques like TF-IDF or word embeddings are more commonly used.

2. Evaluation of IndoBERT-Enhanced Models on Indonesia Datasets

The research evaluates the effectiveness of IndoBERT-enhanced preprocessing in combination with machine learning models such as SVC, XGBoost, and a Stacking Ensemble. The findings demonstrate that IndoBERT preprocessing improves model accuracy and F1-scores, especially on balanced datasets, compared to traditional methods.

3. Filling the Gap in Indonesian Fake News Detection Research

This study addresses the lack of research focusing on advanced NLP techniques like transformer models for preprocessing in fake news detection within the Indonesian context. By incorporating IndoBERT, this research paves the way for future studies to explore transformer-based models in similar tasks.

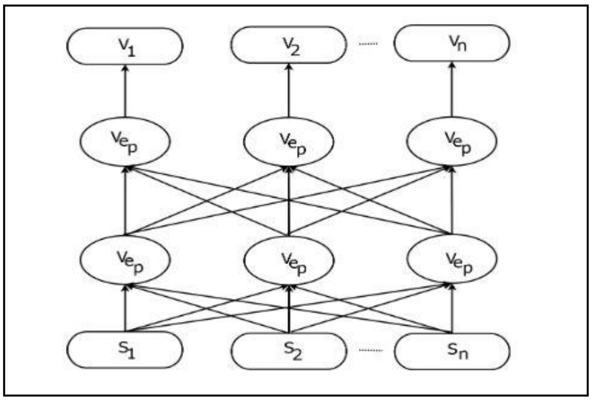
IndoBERT

The preprocessing in this study utilizes indoBERT (Indonesia Bidirectional Encoder Representations from Transformers) to enhance the dataset's contextual understanding for fake news detection. IndoBERT is a pre-trained language model specifically designed for processing the Indonesian language, based on the Bidirectional Encoder Representations from Transformers (BERT) architecture[20]. It is developed to handle the unique linguistic features of Indonesian, such as its rich morphology, diverse word order, and extensive use of affixes.

By being pre-trained on a large corpus of Indonesian text, IndoBERT effectively captures contextual word representations, making it highly effective for various natural language processing (NLP) tasks such as text classification, sentiment analysis, named entity recognition, and machine translation[21]. The model leverages BERT’s bidirectional training approach, enabling it to understand words in the context of the surrounding text rather than just in sequence, which is crucial for capturing the subtleties of Indonesian grammar and semantics.

The systematic process begins with text cleaning using regular expressions to remove unwanted characters and patterns. Instead of traditional methods like stemming and stopword removal, indoBERT processes the raw text as input, preserving linguistic nuances and context[22].

Next, the text is tokenized using indoBERT's WordPiece tokenizer, which breaks text into subword units, enabling better handling of rare or complex words. The tokenized text is then converted into embeddings by indoBERT, capturing both semantic and syntactic information. These embeddings serve as input features for the classification models, providing a rich, context-aware representation of the text. This advanced preprocessing ensures a deeper understanding of linguistic patterns, significantly enhancing the accuracy and reliability of fake news detection[23].



Source: (Alzaidi, 2024) [23]
Figure 1. BERT network model

In Figure 1, S_n represents the encoded form of each word, V_{ep} is the transformer architecture, and V_n is the word's vectorized representation after training. BERT uses a multi-layer bidirectional transformer to process the entire text sequence, integrating contextual information at each layer. The model input combines Token, Segmentation, and Position Embeddings for pre-training and next-sentence prediction. Word meanings depend on their context and position, as specified by the transformer's relative or absolute position embeddings.
It is calculated using the formula:

$$TPE(W_{loc}, 2_{p+1}) = cos(W_{loc}/1000^{\frac{2p}{d_{model}}}) \quad (1)$$

$$TPE(W_{loc}, 2_p) = sin(W_{loc}/1000^{\frac{2p}{d_{model}}}) \quad (2)$$

Where the word position in the text is W_{loc}, p symbolizes the dimension of input word window, and the dimension of encoding vector is d_{model}. The cosine function is the encoded representation of odd position. The sine function is the encoded representation of even position.

Data Exploration

The data exploration phase involved analyzing the dataset to understand its structure and key features. Descriptive statistics and visualizations, such as bar charts and word clouds, were used to examine the distribution of fake and real news, identify common terms, and detect any outliers. This step provided valuable insights into the dataset, helping guide further preprocessing and feature selection for building effective machine learning models.

Data Analysis

The data analysis phase focused on evaluating the performance of various machine learning models, including Naive Bayes, SVC, Logistic Regression, and XGBoost. After preprocessing, the models were trained and tested using techniques like cross-validation. Performance metrics such as accuracy, Precision, Recall, F1 score, and ROC AUC were used to compare the models and identify the one that delivered the best accuracy for fake news detection.

Hyper tuning parameter

Hyper tuning using cross-validation was applied during the model training process to optimize the parameters of each machine learning model. This technique was used to systematically test different parameter values, ensuring that the models achieve the best possible performance without overfitting.

$$CV_{Score} = \frac{1}{k}\sum_{i=1}^{k} score_i \quad (3)$$

The overall cross-validation score, CV_{score}, is determined by averaging the performance scores, $Score_i$, of a model across k folds, where k represents the number of splits in the dataset. This method evaluates the model's accuracy or F1 score for each fold, ensuring a robust assessment of its ability to generalize to unseen data by mitigating reliance on a single train-test split.

The cross-validation process divides the dataset into multiple folds, training and validating the model on different subsets, which helps in selecting the optimal parameters for Naive Bayes, SVC, Logistic Regression, and XGBoost models. This

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process maximizes accuracy and model generalization.

Algorithm Application

The algorithms employed in this study include Support Vector Classification (SVC), XGBoost, and Ensemble Learning.

Rather than developing a new algorithm, this study focuses on evaluating the performance of existing models that are well-suited for text classification tasks. The chosen algorithms represent a spectrum of machine learning approaches, from linear classifiers (SVC) to ensemble methods (XGBoost and Stacking). This allows for a systematic comparison of their capabilities, addressing critical factors such as accuracy, computational efficiency, and robustness in handling imbalanced datasets.

The comparative approach ensures practical applicability, as it identifies the most effective solution for deployment in real-world scenarios without requiring extensive computational resources or complex model training pipelines.

Support Vector Classification (SVC) is a robust machine learning algorithm that excels in classifying high-dimensional data, making it ideal for fake news detection[24]. Its ability to find optimal hyperplanes allows for effective separation of real and fake news articles. Additionally, SVC is resilient to overfitting, enabling reliable predictions even when the number of features is high, which is common in text classification tasks.

$$f(x) = \omega^T x + b \tag{4}$$

Here, ω denotes the weight vector that determines the orientation of the decision boundary, while x is the feature vector representing the input data. The term b represents the bias, which allows the decision boundary to be shifted away from the origin.

XGBoost is an advanced machine learning algorithm based on gradient boosting, well-suited for fake news detection. It excels in handling large datasets and offers high accuracy through its ensemble learning approach, combining multiple weak learners to produce a strong predictor[25][26]. Its efficiency and ability to prevent overfitting make it a powerful choice for improving classification performance.

$$\hat{y} = \sum_{k=1}^{k} f_k(x) \tag{5}$$

- $\hat{y}$: final prediction
- $f_k(x)$: k-th model
- k : number of model

Ensemble learning is a powerful machine learning approach that combines the predictions of multiple base models to enhance overall accuracy and generalization. By aggregating the strengths of diverse algorithms, it mitigates individual model weaknesses and reduces errors. Among its techniques, stacking is particularly notable for its two-layer structure: base models independently predict outcomes, while a meta-model integrates these predictions to make the final decision[19].

For instance, in combining Support Vector Classifier (SVC) and XGBoost, the base models generate predictions, which are then passed to a meta-model, such as Logistic Regression, to optimize the final output. This method is highly effective due to its ability to leverage SVC's strength in handling high-dimensional data and XGBoost's robustness with imbalanced datasets. Stacking ensures a flexible yet systematic approach to improving model performance, making it an essential tool in complex predictive tasks. The formula for stacking ensemble can be represented as:

$$\hat{y}_i = g(f_1(x), f_2(x), \dots f_n(x)) \tag{6}$$

- x : input features
- y : True labels
- $f_1, f_2, .. f_n$: base models
- g : meta model

Evaluation Methods

Evaluation methods for classification are used. Accuracy, Precision, Recall, and F1 scores proved useful for confusion matrices[27].

$$Accuracy = TP + \left(\frac{TN}{TP}\right) FP + FN + TN \tag{7}$$

$$Precision = \frac{TP}{TP} + FP \tag{8}$$

$$Recall = \frac{TP}{TP} + FN \tag{9}$$

$$F1 = 2 * \frac{precision * Recall}{Precision + Recall} \tag{10}$$

TP shows a positive result, FP shows a false positive result, TN shows a negative result, and FN shows a false negative result.

The Receiver Operating Characteristic (ROC) curve is a graphical representation that illustrates the performance of a binary classification model at various threshold settings[28]. The area under the ROC curve (AUC) quantifies the model's ability to

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distinguish between the positive and negative classes.

$$TPR = \frac{TP}{TP+FN} \tag{11}$$

$$FPR = \frac{FP}{FP+TN} \tag{12}$$

ROC Curve is plot TPR (y-axis) against FPR (x-axis) and AUC The area under the ROC curve can be calculated using numerical integration methods (such as the trapezoidal rule) or by using specific algorithms that estimate the area based on the TPR and FPR values.

Calibrated probabilities refer to predicted probabilities that accurately reflect the true likelihood of an event. In machine learning, raw probability outputs from models like SVM or tree-based methods can be biased or poorly aligned with real-world outcomes. Calibration techniques adjust these probabilities to ensure they are interpretable and reliable. This process is crucial for applications requiring probabilistic confidence, such as medical diagnosis or risk assessment, as it enhances the decision-making capability of predictive models.
Formula :

$$P(y = 1|x) = f(x) \tag{13}$$

Where $f(x)$ is a monotonic function fitted to map predicted probabilities to the true probability distribution, learned by minimizing:

$$\sum_{i=1}^{n} w_i (y_i - f(x_i))^2 \tag{14}$$

- w_i : weight for each sample
- $f(x)$: A monotonic function

RESULTS AND DISCUSSION

By utilizing available data sources, the analysis and prediction of fake news detection can be performed using data exploration and machine learning techniques with Python libraries, focusing on a comparison of the Naive Bayes, SVC, Logistic Regression, and XGBoost algorithms.

Dataset

The dataset used has a balanced distribution between real and fake news, with no null values. However, there are still issues such as inconsistencies in uppercase and lowercase letters, the presence of URLs, symbols, inappropriate characters like emails, numbers, and punctuation that need to be cleaned for better processing. Figure 2 shows a snapshot of Sample Dataset.

The dataset consists of two columns: news and tagging.The tagging column is used to indicate the classification of the news, where a value of hoax represents fake news, and valid represents real news. Based on the wordcloud graph obtained, the common words that appear from each data for valid news and hoax news are shown in Figure 3.

The primary objective of creating the word cloud is to visually represent the most frequent and significant terms in the dataset, thereby aiding in the exploration and understanding of textual patterns in both fake and real news. Word clouds are useful for highlighting key themes or topics that emerge from the data, making it easier to identify important keywords and terms that could be indicative of fake news characteristics.

The process of generating the word cloud involves several systematic steps, beginning with the preprocessing phase, where the text data undergoes a context-aware transformation using BERT (Bidirectional Encoder Representations from Transformers)[29]. Unlike traditional methods such

news	tagging
Dalam sesuap daging ikan lele, terkandung 3.000 sel kanker. Judul artikel tersebut beberapa hari terakhir menjadi pembicaraan hangat di media sosi...	valid
Anggota BANSER di kudus jawa tengah di keroyok sama emak-emak penjual nasi udukAnggota BANSER di kudus jawa tengah di keroyok sama emak-emak penju...	hoax
Seorang Kanibal Berkeliaran Di Baubau Sulawesi TenggaraSekilas info. Kalau ada yang tok tok atau ketemu dijalan sama orang aneh. Ciri cirinya poko...	hoax
Spanduk Warga Nahdliyin Rindu Khilafah Milik NUSpanduk yang bertuliskan "WARGA NAHDLIYIN RINDU KHILAFAH" dan logo NU.\n \n "Nemu foto thn 2003 seb...	hoax
Petugas KPPS Bandung Meninggal DiracunDitemukan zat kimia C11H16NO2PS dalam tubuh korban KPPS, efek dari Racun....VX (nama IUPAC: O-ethyl S-[2- (dii...	hoax
Kementerian Keuangan menegaskan kabar yang menyebut tentang kenaikan gaji Presiden Joko Widodo (Jokowi) hingga Rp 553 juta per bulan merupakan dat...	valid
Ketika Anies-Sandi Menang Dengan Kekuatan Kaum Radikal IndonesiaKetika Anies-Sandi menang dengan kekuatan kaum radikal Indonesia	valid
AWAN HITAM MENYEDOT AIR LAUTAstagfirullah\n Apakah ini tanda tanda akhir zaman semakin dekatt\n waallahualam\n Kejadian langka AWAN HITAM MENYEDOT...	valid
Anda mungkin pernah mendengar istilah bendgate. Ya, tahun lalu, setelah peluncuran iPhone 6 Plus, skandal besar yang dijuluki bendgate ini mencuat...	valid
Razia Besar-besaran Karena Kerabat Begal Akan Balas DendamPihak kepolisian akan melakukan Razia besar2an di semua titik. Razia dilakukn dgn Gabung...	hoax

Source: (Research Results, 2024)

Figure 2 . Sample of Dataset

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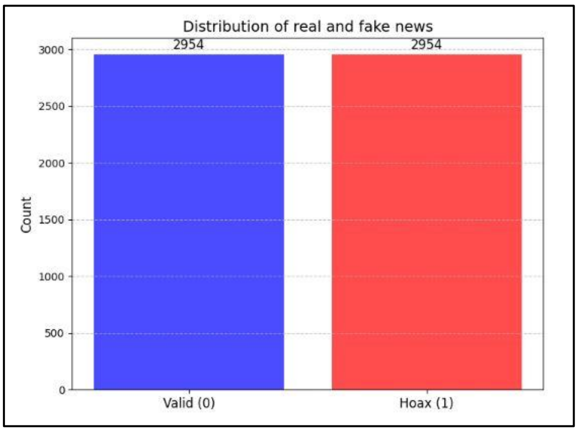
Source: (Research Results, 2024)

Figure 3. Word cloud of Real News and Fake News

as TF-IDF, which rely on word frequency and document occurrence, BERT enables the creation of more meaningful and semantically rich representations of the text by capturing contextual relationships within the language. This preprocessing step is essential to improve the model's understanding of word associations and nuances.

Figure 3 compares the most prominent terms in real and fake news within the Indonesian dataset. In real news, words like "Ikan Lele," "Media Sosial," and "Iphone 6" dominate, reflecting topics related to local culture, social media, and technology. In fake news, terms such as "Indonesia," "Jokowi," and "foto" are more frequent, indicating a focus on political figures and generalized claims, often used to mislead or evoke emotional responses.



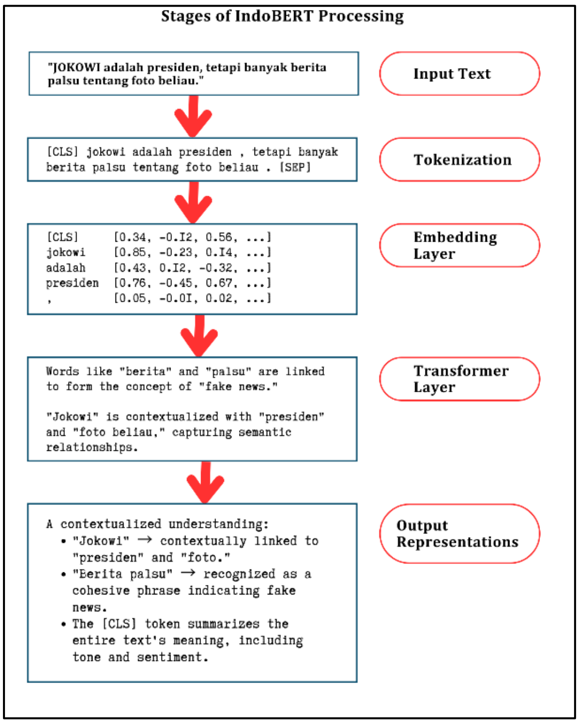
Source: (Research Results, 2024)

Figure 4. Distribute of Real and Fake News

Figure 4 has shown the dataset is balanced, with 2,954 real and 2,954 fake news samples, ensuring that the machine learning models remain unbiased, resulting in more accurate predictions for both categories.

IndoBERT

The first step in using indoBERT is preparing the data to be fed into the model. This involves several tasks to make raw text suitable for training. Workflow of IndoBERT processing, illustrating the stages from tokenization of raw text to contextualized output representations for downstream tasks in Figure 5.



Source: (Research Results, 2024)

Figure 5. Stages of indoBERT preocessing

Cross Validation

The allocation of training and testing samples is separated for each dataset as Figure 6.

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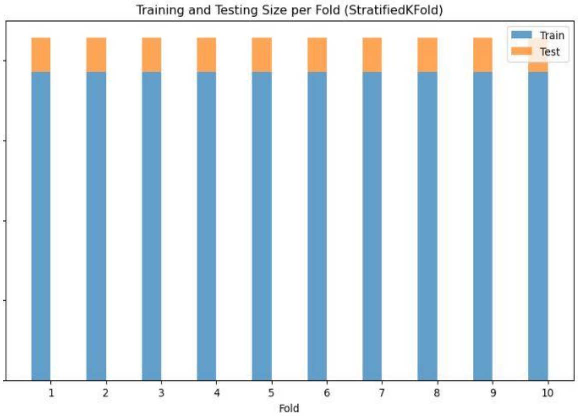
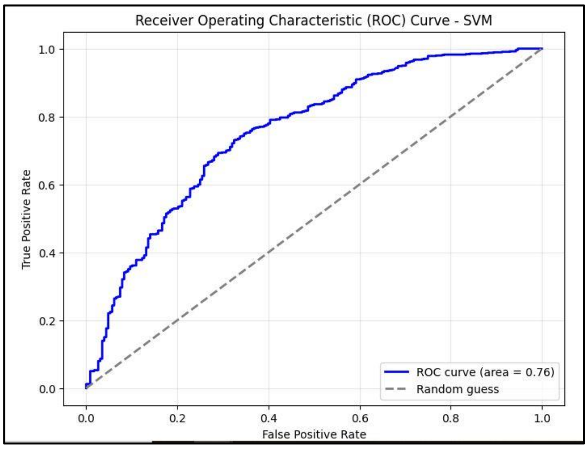


Source: (Research Results, 2024)
Figure 6. Training and testing size per fold (Stratified K-Fold)

Figure 6 illustrates how the training and testing samples are distributed across each fold. The samples are split using a random state based on the specified number of folds. A 10-fold cross-validation approach is applied.

Support Vector Classifier

The Support Vector Classifier (SVC) method is used to build a model for each dataset, which includes both fake news and real news. SVC is advantageous because of its ability to effectively handle high-dimensional data and perform well in cases where the decision boundary is not linear. It uses support vectors to create a hyperplane that best separates the classes, making it particularly powerful for complex classification tasks. Additionally, SVC is robust against overfitting, especially in scenarios with a clear margin of separation between classes, making it an effective tool for text classification problems.

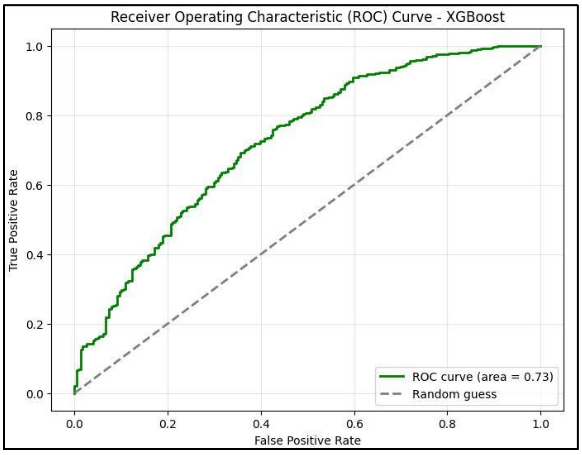


Source: (Research Results, 2024)
Figure 7. ROC curve SVC

Figure 7 shows vector Classifier (SVC) model with an AUC value of 0.76. This high AUC score signifies that the model excels at differentiating between real and fake news. The closer the AUC is to 1, the stronger the model's performance, indicating its effectiveness in distinguishing positive from negative classes. This result highlights the SVC model's high level of reliability and precision in predicting whether news is real or fake.

Extreme Gradient Boosting

The XGBoost classification method is used to develop a model for each dataset, which includes both fake news and real news. XGBoost offers several advantages, including its ability to handle large datasets efficiently and its strong performance on complex, non-linear relationships. It uses an ensemble of decision trees, making it highly effective at capturing intricate patterns in the data. Additionally, XGBoost is known for its speed, scalability, and built-in regularization, which helps prevent overfitting, making it particularly powerful for both classification and regression tasks.



Source: (Research Results, 2024)
Figure 8. ROC curve XG Boost

Figure 8 displays the ROC curve for the XGBoost model, with an AUC value of 0.73. This high AUC score indicates that the model has a strong ability to distinguish between real and fake news. This result emphasizes the reliability of the XGBoost model in accurately predicting whether news is real or fake with a high degree of precision.

Ensemble Learning with Stacking Using SVC and XGBoost

The architecture of the Stacking Classifier, as shown in Figure 9, combines the strengths of Support Vector Classification (SVC) and XGBoost (XGB) to enhance fake news detection. In this model, SVC and XGB serve as base learners, capturing

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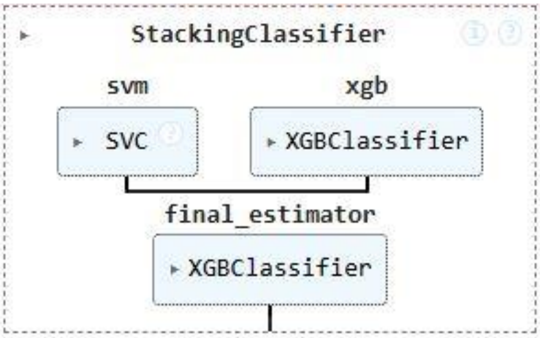
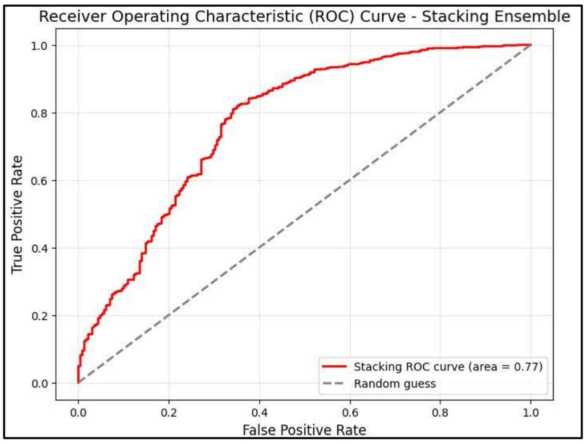
different aspects of the dataset, while XGB acts as the final estimator, leveraging the outputs of both base models to improve classification accuracy. This ensemble approach optimally integrates the advantages of each algorithm, where SVC handles high-dimensional data effectively, and XGB excels in managing imbalanced datasets and complex feature interactions, resulting in a more robust and accurate prediction system.



Source: (Arjun et al., 2018) [30]

Figure 9. Stacking Classifier

SVC excels in handling high-dimensional data and creating precise decision boundaries, while XGBoost is effective with imbalanced datasets and captures complex patterns through gradient boosting. The stacking approach integrates predictions from both base models, leveraging their complementary strengths to improve overall performance. Evaluation using metrics like accuracy, F1-score, and ROC AUC confirms that the stacking model outperforms individual algorithms, demonstrating superior accuracy and generalization in detecting fake news.



Source: (Research Reslults, 2024)

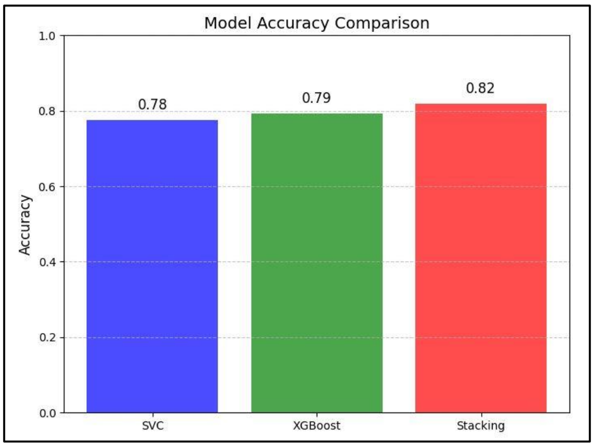
Figure 10. ROC curve Ensemble

Figure 10 illustrates the architecture of the stacking ensemble, where SVC and XGBoost contribute to a unified prediction model, showcasing the synergistic effect of combining these algorithms for improved fake news detection.

Figure 10 shows the ROC curve for the Ensemble Learning model, with an impressive AUC value of 0.77. This high AUC score signifies that the model excels at differentiating between real and fake news. The closer the AUC is to 1, the stronger the model's performance, indicating its effectiveness in distinguishing positive from negative classes. This result highlights the SVC model's high level of reliability and precision in predicting whether news is real or fake.

Evaluation

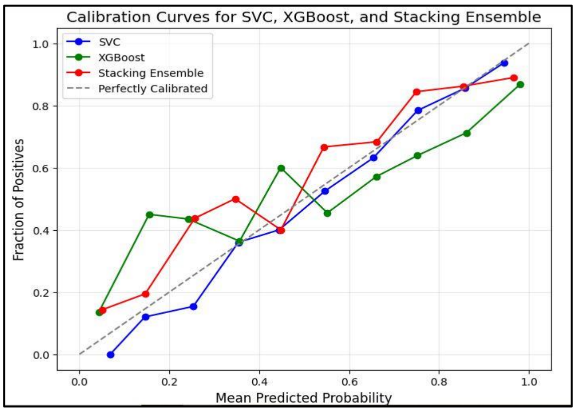
A comparison between the SVC, XGBoost and Ensemble Learning methods was performed to predict fake news. The comparison is based on the model's ability to differentiate between real and fake news, with accuracy scores for each technique assessed over multiple folds. This approach ensures that the models' performance is robust and generalizable across various data subsets, offering insights into the most effective technique for fake news detection.



Source: (Research Results, 2024)

Figure 11. Comparison accuracy curve for SVC, XG Boost, and Stacking

Figure 11 shows the accuracy curves for the models reveal significant performance variations. For the SVC model, the highest accuracy reached 0.78. In comparison, the XGBoost model demonstrated better performance, with a maximum accuracy of 0.79. The best-performing model, Ensemble Stacking, achieved the highest accuracy of 0.82, indicating its superior performance in this analysis.



Source: (Research Results, 2024)
Figure 12. Calibration curve for SVC, XGBoost, and Stacking

Figure 12 shows the calibration results reveal the average predicted probabilities for each model, with Stacking providing the highest average predicted probability of 0.5062, followed closely by XGBoost at 0.5032, and SVC at 0.5010. These values indicate that the predicted probabilities from all three models are relatively close to each other, with Stacking showing a slight advantage in terms of probability estimation. While the differences are minimal, this suggests that the Stacking ensemble model has a marginally better ability to calibrate its predictions compared to the individual models, making it potentially more reliable in scenarios where accurate probability estimates are crucial. This subtle distinction highlights the potential benefit of using a combination of models, as Stacking may leverage the strengths of both SVC and XGBoost to produce more reliable and consistent probability predictions.

Source: (Research Results, 2024)
Figure 13. Model Training Time Comparison

Figure 13 illustrate the comparison of model training times reveals notable differences in computational efficiency among the three approaches. XGBoost emerged as the fastest model, with a training time of 4.39 seconds, demonstrating its capability to efficiently process large datasets and capture complex feature interactions. This efficiency is further enhanced by its parallel processing capabilities and optimized gradient boosting mechanism. SVC, on the other hand, required a moderate training time of 11.05 seconds, indicative of the computational effort needed to construct optimal hyperplanes in high-dimensional spaces. In contrast, the Stacking Ensemble exhibited the longest training time at 63.72 seconds due to its multi-layered architecture, which involves training two base models (SVC and XGBoost) and an additional meta-model for prediction aggregation. Despite its higher computational cost, the Stacking Ensemble offers a trade-off by potentially improving classification performance.

When evaluated on a balanced dataset, the Stacking Ensemble consistently delivered the best performance, achieving the highest accuracy (82%) and strong F1-scores for both classes, particularly excelling in class 0 (F1-score: 0.75). The balanced dataset enabled the ensemble to leverage the complementary strengths of SVC and XGBoost more effectively, as each model contributed to a more equitable classification of both positive and negative instances.

XGBoost also performed well on the balanced dataset, achieving a recall of 0.87 for class 1 and an improved F1-score of 0.65 for class 0 compared to its performance on an imbalanced dataset. This suggests that balancing the dataset significantly mitigates the tendency of boosting algorithms to favor the majority class. However, while XGBoost excelled at identifying instances of class 1, its overall performance was still outperformed by the ensemble approach.

SVC, known for its robustness in high-dimensional data, maintained consistent performance across both classes. On the balanced dataset, SVC achieved F1-scores of 0.70 and 0.68 for class 0 and class 1, respectively, indicating a reliable yet slightly lower performance compared to Stacking. The balanced dataset allowed SVC to distribute its classification power more evenly, reducing its reliance on adjustments such as class weights or oversampling techniques.

The results can be seen in Table 2 of the Model Report, emphasize the importance of using balanced datasets in machine learning tasks, particularly for classification problems where minority class performance is critical. The Stacking Ensemble demonstrates that combining models can enhance robustness and adaptability, especially in balanced

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scenarios. However, the choice of the algorithm should also consider computational efficiency, making XGBoost a viable alternative for applications with strict time constraints.

Table 1. The Model Report

Model	Accuracy		Precision	Recall	F1-score
BERT + SVC	0.78	0	0.53	0.43	0.48
		1	0.83	0.88	0.86
BERT + XGBoost	0.79	0	0.64	0.29	0.39
		1	0.81	0.95	0.88
BERT + Stacking	0.82	0	0.66	0.48	0.55
		1	0.85	0.92	0.89

Source: (Research Results, 2024)

Analysis of Factors Affecting Model Performance

The superior performance of the Stacking Ensemble model, as evidenced by its highest accuracy (82%) and ROC AUC (0.77), can be attributed to several key factors that leverage the complementary strengths of its base models—Support Vector Classification (SVC) and XGBoost.

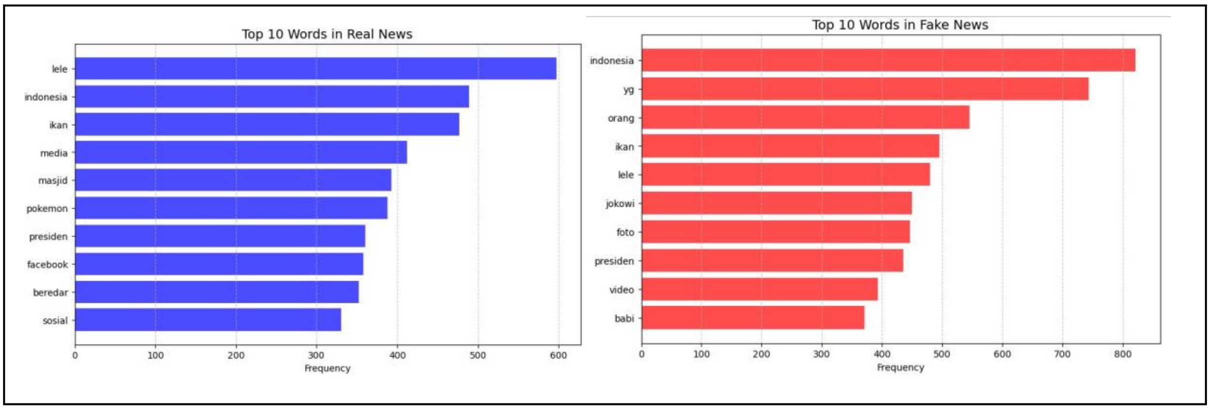
1. The Synergistic Effect of Stacking Ensemble
The Stacking Ensemble model excels due to its ability to combine the unique advantages of SVC and XGBoost. SVC is known for its effectiveness in handling high-dimensional data, making it suitable for complex text classification tasks. On the other hand, XGBoost is particularly adept at managing imbalanced datasets and capturing intricate patterns through gradient boosting. By integrating these models, the Stacking Ensemble mitigates the individual limitations of each, resulting in enhanced generalization and robustness in fake news detection.

2. Impact of Preprocessing with IndoBERT
The preprocessing step using IndoBERT significantly contributes to the improved performance of all models, particularly the Stacking Ensemble. IndoBERT provides context-aware embeddings that capture semantic nuances in the Indonesian language, enhancing the models' ability to differentiate between subtle textual cues in fake and real news.

3. Comparative Limitations of SVC and XGBoost
While both SVC and XGBoost perform well individually, their limitations become apparent when compared to the ensemble approach:

- SVC: Although SVC achieves a respectable AUC of 0.76, its performance is constrained by its sensitivity to parameter tuning and less effective handling of non-linear relationships in the data.
- XGBoost: Despite its strong performance (AUC 0.73), XGBoost can be prone to overfitting, especially when dealing with high-dimensional sparse data typical in text classification.

In summary, the integration of SVC and XGBoost in a stacking ensemble leads to a balanced trade-off between bias and variance, improving predictive accuracy. IndoBERT's advanced preprocessing enhances the feature space, allowing models to capture complex linguistic patterns more effectively. Moreover, understanding the causal factors behind model performance provides insights for future improvements, such as optimizing model parameters and exploring additional ensemble techniques.



Source: (Research Results, 2024)
Figure 14. Top 10 Word in Dataset

In Figure 14, which shows the top 10 most frequent words found in the fake news detection dataset, there is a noticeable difference between the dominant words in real and fake news. For real news, words like Lele, Indonesia, Ikan, Media, and Masjid are frequently mentioned, indicating that the content is related to local and cultural topics in Indonesia, as well as daily life. On the other hand, in fake news, words like Indonesia, yg (short for yang), orang, ikan, and lele appear often, suggesting a more general and sometimes poorly structured language use. The presence of the word yg (a shorthand for yang) in fake news, for example, may point to imprecise language use, which is common in news that is less verified or produced quickly without attention to writing quality. These differences can serve as important indicators in distinguishing between credible and potentially fake news.

Practical and Academic Implications of Algorithm Comparison

This study not only presents the performance metrics of Support Vector Classification (SVC), XGBoost, and the Stacking Ensemble but also emphasizes their practical and academic implications. Understanding these aspects is crucial for both practitioners seeking efficient deployment strategies and researchers aiming to advance algorithm development.

The comparison highlights that the Stacking Ensemble model achieves the highest accuracy (82%) and ROC AUC (0.77), making it a strong candidate for real-world fake news detection systems. Practitioners can rely on these results to select models based on specific operational needs:

- Deployment Efficiency: XGBoost, with its faster training time (4.39 seconds), is ideal for real-time applications where computational efficiency is critical.
- Accuracy Prioritization: For applications where detection accuracy is paramount, such as content moderation on social media platforms, the Stacking Ensemble offers superior performance by leveraging the complementary strengths of both SVC and XGBoost.
- Resource Constraints: SVC, despite its slightly lower accuracy (78%), provides robust performance with moderate computational resources, making it suitable for environments with limited hardware capabilities.

From an academic perspective, this comparison provides valuable insights into the performance dynamics of different algorithms in the context of Indonesian-language fake news detection:

- Algorithm Improvement: The observed performance gaps suggest potential areas for enhancing existing models. For instance, SVC's sensitivity to high-dimensional data could be mitigated by integrating advanced feature selection techniques or kernel optimization.
- Ensemble Effectiveness: The study demonstrates how ensemble methods, particularly stacking, can significantly improve classification outcomes. This finding encourages further exploration into hybrid models that combine traditional machine learning with emerging deep learning techniques.
- Future Research Directions: The results highlight the need for adaptive algorithms capable of handling diverse and evolving datasets. Researchers can build on these findings to develop more generalized models, possibly incorporating temporal dynamics through recurrent neural networks (RNNs) or transformer-based architectures.

Through this dual focus on practical applicability and academic advancement, the study contributes not only to immediate implementation strategies but also to the broader discourse on algorithm development for fake news detection.

CONCLUSION

This research focuses on advancing fake news detection using a dataset in the Indonesian language, incorporating IndoBERT for enhanced preprocessing and applying machine learning models, including SVC, XGBoost, and a Stacking Ensemble. A key contribution of this study is the innovative use of IndoBERT for preprocessing Indonesian text, which improves text representation by leveraging contextual embeddings, thus enhancing the accuracy of subsequent machine learning models.

The study's findings demonstrate that the Stacking Ensemble approach outperforms individual models, achieving the highest accuracy (82%) and ROC AUC (0.77) scores. This superior performance can be attributed to the synergistic integration of SVC and XGBoost within the ensemble framework. SVC's strength lies in handling high-dimensional data and constructing optimal hyperplanes for text classification tasks,

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while XGBoost excels in managing imbalanced datasets and capturing complex feature interactions through gradient boosting techniques. The combination of these complementary capabilities results in improved predictive performance, robustness, and generalization in fake news detection.

Moreover, the use of IndoBERT as a preprocessing step significantly enhances model performance by providing context-aware embeddings that capture semantic nuances in the Indonesian language. This advanced text representation allows models to better differentiate between subtle linguistic patterns present in real and fake news, contributing to the overall effectiveness of the ensemble model.

While this research establishes the effectiveness of ensemble methods, future research should explore more advanced deep learning architectures such as LSTM, GRU, or ABiLSTM. These models, designed to capture temporal dependencies and contextual relationships in text, could offer deeper insights into linguistic structures, enabling more precise identification of fake news. Integrating such deep learning techniques with ensemble methods, or leveraging pre-trained models fine-tuned for the Indonesian language, could further improve detection performance.

Finally, expanding the dataset to include more diverse sources and languages would allow for the testing of model generalizability across various contexts. This expansion could lead to the development of a more globally applicable fake news detection system that handles multilingual and cross-cultural news content. By adopting these advanced techniques and broadening the dataset, future work has the potential to significantly improve the accuracy, reliability, and applicability of fake news detection, offering a powerful tool in the fight against misinformation.

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