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Performance Analysis of SVM and BERT in Predicting the Availability of Stunting Prevention Services in Indonesia

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Abstract – Stunting, defined as being too short for one's age with a Height-for-Age Z-score (HAZ) below –2 SD according to WHO, remains a serious public health problem in Indonesia. This study predicts the availability of stunting prevention services at the village level using machine learning. Data from 25,800 villages were categorized into Complete (9,245), Partial (13,609), and Not Available (2,946), showing class imbalance. Two algorithms were evaluated: Support Vector Machine (SVM) with TF-IDF and SMOTE for class balancing, and Bidirectional Encoder Representations from Transformers (BERT) using IndoBERT with class-weighted loss. Evaluation metrics included accuracy, precision, recall, F1-score, and computation time. Results show BERT achieved 92% accuracy with consistent performance across classes (cross-validation 91.55%, SD 0.0024), effectively capturing contextual meaning in narrative text. SVM reached 83% test accuracy with fast computation (±1 min 42 s) and remained robust for imbalanced data. Both models performed well, but minority-class recognition remains challenging. These findings highlight the complementary strengths of SVM and BERT, providing data-driven insights to support policy decisions and improve targeting of stunting prevention services at the village level.

Keywords: Stunting; SVM; machine learning; BERT; stunting prevention.

I. INTRODUCTION

Stunting remains a serious public health challenge in Indonesia, mainly due to prolonged malnutrition and recurrent infections during the first 1,000 days of life, a critical period for children's growth and development [1], [2]. It is defined by the WHO as a height-for-age (HAZ) below −2 standard deviations from the growth standard [3], and addressing it is crucial for achieving the SDGs on hunger and malnutrition [4]. Given the multifactorial determinants of stunting, UNICEF emphasizes the importance of a multisectoral approach and data-driven mapping of the availability of stunting prevention services as a prerequisite for effective intervention planning [5,6]. Accordingly, this study is framed as a computational investigation of village-level service availability rather than an epidemiological analysis of stunting prevalence.

Despite advances in epidemiological research and policy frameworks, computational approaches for analyzing village-level narrative administrative reports to predict stunting prevention service availability remain limited, particularly those leveraging advanced natural language processing techniques. Using a national dataset of 75,265 villages, this study provides a comprehensive computational analysis by comparing classical machine learning and deep learning approaches on narrative constraint reports. This local-level infrastructure assessment is crucial for effective stunting prevention convergence programs and evidence-based decision-making. The urgency is underscored by Indonesia's 2022 stunting prevalence of 21.6%, which exceeds both WHO thresholds and the 2024 national target [7,8]. Most previous studies focus on regional prevalence using structured variables, leaving national-scale narrative-based computational analyses largely unexplored. To address this gap, we apply a comparative modeling approach—SVM using TF-IDF representations and BERT using contextual embeddings—advancing computational assessment of village-level service provision through administrative narrative interpretation.

From a computational perspective, machine learning methods offer great potential for analyzing the complexity of public health data. Support Vector Machines (SVMs) are known for their strong generalization capabilities, resistance to overfitting, and effectiveness in handling high-dimensional data through the principle of structural risk minimization [9]. A number of studies have applied SVM in the context of stunting and reported high performance, particularly with the use of optimized Radial Basis Function (RBF) kernels [10,11]. Study [12] demonstrates that SVM can achieve perfect accuracy in classifying stunting in toddlers with appropriate parameters. However, these studies generally focus on structured variables and regional prevalence. In contrast, our study predicts village-level service availability at the national scale and integrates narrative data for richer insights.

On the other hand, developments in deep learning have introduced Bidirectional Encoder Representations from Transformers (BERT) as a cutting-edge model in natural language processing that is capable of capturing contextual and semantic information in depth. BERT has demonstrated superior performance in various text-based classification tasks, including scientific article classification and social media-based mental health issue detection, often surpassing classical machine learning methods such as SVM [13,14]. By leveraging BERT on narrative village-level reports, this study provides actionable insights to guide resource allocation and targeted interventions at the local level. However, applying BERT to interpret narrative data in the context of village-level public health services, as well as its performance evaluation through direct comparison with classical machine learning models, has rarely been studied.

Referring to previous studies that proved both methods to be successful, to date there has been no study that explicitly compares SVM and BERT for analyzing village-level narrative administrative reports to predict stunting prevention service availability at national scale. This study fills this gap through a comparative modeling approach where both classical machine learning (TF-IDF-based SVM) and deep learning (transformer-based BERT) are systematically evaluated on the same narrative dataset. The uniqueness of this research lies in the direct algorithmic comparison between classical and deep learning approaches for interpreting qualitative administrative narratives in public health contexts, thereby providing methodological contributions for text-based service prediction as well as practical implications for the formulation of stunting prevention policies and the strengthening of data-based convergence programs in Indonesia.

II. METHOD

The initial stage of the research began with a literature review on stunting, prevention efforts in Indonesia, and the application of machine learning, particularly Support Vector Machine (SVM) and BERT in health data classification. This literature review aimed to understand the context of the problem, identify research gaps, and design a relevant methodology. This analysis provides a comprehensive overview of the causes, long-term impacts, and intervention strategies that have been implemented, while also serving as the basis for formulating a research methodology that has been visualized in the form of research stages in Fig. 1.

A. Data Collection

This research data is sourced from the official Indonesian One Data website and includes numerical, categorical, and narrative text data from 75,265 villages in Indonesia. The dataset is stored in CSV format to facilitate processing using the Python programming language with the pandas library. The main column analyzed is 'Challenge_Faced_(Explain)', which contains narrative descriptions. Although this dataset is nationally representative due to its official administrative coverage, several limitations remain: some narrative comments are incomplete, the "Challenge_Faced_(Explain)" column is often empty, and villages with stronger reporting systems may be overrepresented. These factors may introduce biases including reporting bias—well-resourced villages may provide more detailed narratives, missing data bias—66% data loss after cleaning may exclude under-resourced villages, and keyword-based labeling may oversimplify complex scenarios. These limitations emphasize careful interpretation when generalizing findings.

B. Data Preprocessing

Data preprocessing is a series of systematic steps designed to transform raw data into a cleaner and more structured format, ready for use in machine learning modeling processes. The main purpose of data preprocessing is to improve data quality, address any issues that may exist, and ensure that the data is ready for use in training model.

1) Data Cleaning: The data cleaning stage was carried out to remove empty values (NaN) and "0" in the "Challenge_Faced_(Explain)" column. This process used the dropna() function and string filters so that only data containing valid narrative constraints was retained. After data cleaning, the amount of data decreased from 75,265 to 25,800. This step aimed to improve the quality of the dataset so that the machine learning model could be trained more accurately without interference from irrelevant data.

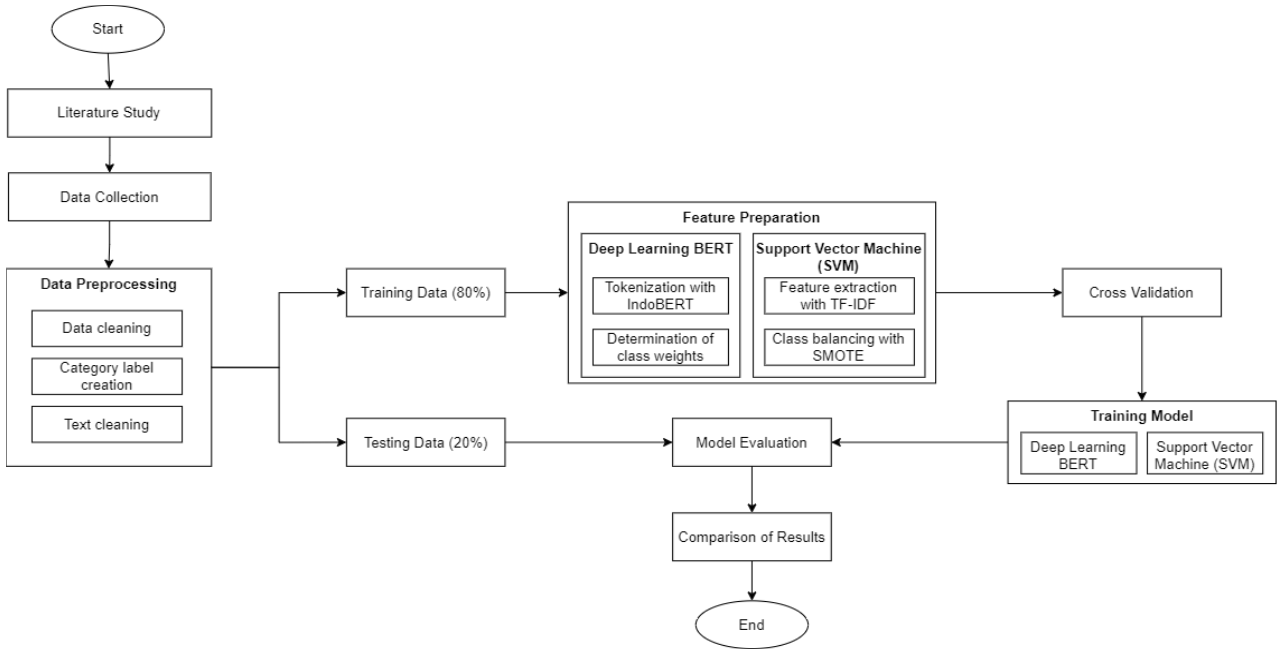

Fig 1. Research flow

2) Category Label Creation: Narrative data related to stunting prevention service constraints are categorized into three levels of service availability: Complete (9,245 villages), Partial (13,609 villages), and Not Available (2,946 villages). These categories are determined using keyword-based logic to ensure an objective and consistent labeling process. Next, these categories are converted into numerical labels 0, 1, and 2, which are stored in a new column as target variables.

3) Text Cleaning: The narrative text of stunting service constraints was cleaned through case folding (lowercase letters), removal of links, numbers, and punctuation marks, tokenization into words, stemming using Sastrawi, and stopword removal to eliminate common words. The result was clean, ready to be represented in vector form for the feature formation stage.

C. Data Splitting

After preprocessing is complete, the dataset is divided into two subsets using the train_test_split function from the scikit-learn library, with a ratio of 80% for training data and 20% for test data. This division is to test the model's generalization ability on new data. Training data is used to recognize patterns, while test data serves to measure the model's adaptability. The division is performed using label stratification (stratify=y, random_state=42) so that the proportion of each category in both subsets remains balanced, allowing the model to learn evenly from all classes.

D. Feature Preparation

The feature preparation stage between the SVM and BERT models differs, as they use different text representation approaches. SVM requires manual feature extraction, while BERT generates automatic representations based on semantic context.

1) Features for SVM: For the SVM model, text data is converted into numerical vectors using TF-IDF with max_features=3,000 and n-gram range (1,2) to balance information coverage and computational efficiency. The dataset contains 70 numerical columns, but this study focuses exclusively on textual analysis of 'Challenges_Faced_(Explain)', using only TF-IDF vectors. Class balancing was performed using SMOTE, selected for its compatibility with LinearSVC and proven effectiveness in handling imbalanced text classification tasks. After augmentation, the three classes (Complete, Partial, and Not Available) had the same number of data points, 13,609 each.

2) Features for BERT: In the BERT approach, text is converted into tokens using the IndoBERT tokenizer to form contextual representations. The maximum token length is set to 128, which is a standard configuration for BERT-based models processing short-form administrative text. This choice balances computational efficiency with adequate context capture, as village-level administrative constraint reports are typically concise, structured narratives rather than lengthy documents.

Class imbalance is addressed through weighted CrossEntropyLoss computed via class_weight('balanced'). Alternative strategies (SMOTE, text augmentation, focal loss) were not used as they risk altering semantic meaning or administrative terminology of the narratives, while class weighting preserves text authenticity.

E. Cross Validation

To evaluate the stability and generalizability of the model, cross-validation was performed on both algorithms using a random state of 42, allowing model performance to be objectively assessed against data variations.

1) SVM Cross-Validation: In the SVM model, five-fold stratified K-fold cross-validation was performed. Each iteration used four subsets for training and one for validation, with random_state=42. Performance stability was evaluated using average accuracy and standard deviation across all folds. A comparison of cross-validation accuracy with test set accuracy will show whether the model is overfitting or not.

2) BERT Cross-Validation: K-Fold Cross Validation with three folds and data randomization (random_state=42) was performed on the BERT model. Each fold is trained and validated independently using a new model, with the text converted into tokens by the IndoBERT tokenizer. The average accuracy and standard deviation are used to assess consistency: std $\leqslant$ 0.05 indicates a stable model, while std > 0.05 indicates potential overfitting.

F. Training Model

This study compares two modeling approaches, namely Support Vector Machine (SVM) and Deep Learning BERT, each of which is run separately as in the preprocessing stage.

1) Support Vector Machine (SVM): SVM is a classification model that uses hyperplanes as intermediaries to distinguish between different categories. In this study, SVM was trained using a linear kernel with TF-IDF feature vectors as input. SVM is calculated by following equationequation (1) where ns is the number of support vectors, α_i is the weight of each support vector, y_i is the data class, x_i is the support vector variable, x_d is the data to be classified, and b is the error value. This formula calculates the linear combination of all support vectors to determine the prediction class from the positive or negative results.

$$f(x_d) = \sum_{i=1}^{ns} \alpha_i \; y_i x_i x_d + b \qquad (1)$$

The Support Vector Machine (SVM) model in this study was trained using LinearSVC with parameters C=1.0, class_weight='balanced' to address residual class imbalance, max_iter=5000 to achieve convergence, and random_state=42 for reproducibility. The training data, which had been resampled with SMOTE, was used to train the model so that the minority class was more balanced.

2) Deep Learning BERT: Bidirectional Encoder Representations from Transformers, or BERT for short, is a deep learning technology based on artificial neural networks that can perform unsupervised pre-training on large-scale corpora to generate high-quality language representations [15]. Compared to previous NLP architectures, BERT stands out for its simplicity of concept but extraordinary empirical power. This strength makes BERT superior, with its main advantages in performance lying in two key aspects. First, BERT relies on two innovative initial training approaches, namely Masked Language Model (MLM) and Next Sentence Prediction (NSP). Second, this model utilizes abundant resources, including large data volumes and high computational capabilities for training [16].

The BERT model uses IndoBERT (indobenchmark/indobert-base-p1) for three-class classification. Training was performed using the Hugging Face Transformers library with a weighted loss function. The training hyperparameters were explicitly set as follows learning_rate=2e-5, per_device_train_batch_size=8, per_device_eval_batch_size=8, num_train_epochs=3, weight_decay=0.01, and random_seed=42. All experiments were conducted using the Google Colab cloud environment with NVIDIA Tesla T4 GPU to support both SVM computation and BERT training.

G. Model Evaluation

Model evaluation is important to ensure that the model can make accurate predictions on new data and does not simply memorize the training data [17]. Model evaluation can be performed by examining the Confusion Matrix, which consists of four parts: True Positive (TP), True Negative (TN), False Positive (FP), and False Negative (FN). Using these four values, various model evaluation metrics such as Accuracy, Precision, Recall, and F1 Score can be calculated [18]. Accuracy is calculated using equation (2), which calculates the ratio between True Positive and True Negative and the total number of predictions of True Positive, True Negative, False Positive, and False Negative. Thus, this equation measures the overall accuracy of the model's predictions from the entire data set.

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} \quad (2)$$

Precision and Recall are used to understand how the model handles positive and negative errors. Precision is calculated according to equation (3), where the ratio between True Positive and the total number of True Positive predictions plus False Positive is calculated to measure the true positive prediction value of all parts claimed to be positive values. Meanwhile, based on equation (4), Recall is obtained by calculating the ratio between True Positive and the total number of actual positive cases (True Positive plus False Negative).

$$Precision = \frac{\mathrm{TP}}{\mathrm{TP+FP}} \quad (3)$$

$$Recall = \frac{\mathrm{TP}}{\mathrm{TP+FN}} \quad (4)$$

$$F1\ Score = 2\ x\ \frac{\mathrm{Precision\ x\ Recall}}{\mathrm{Precision+Recall}} \quad (5)$$

The F1-score is a metric that combines precision and recall into a single number, which is the harmonic mean of the two scores [19]. Based on equation (5), the F1 Score is calculated based on the Precision and Recall values, which are first multiplied to obtain the numerator, then the two values are added together as the denominator, and the result of the division is multiplied by 2.

III. RESULT AND DISCUSSION

A. Comparison of Support Vector Machine and Deep Learning BERT Performance

This study compares Support Vector Machine (SVM) and Deep Learning BERT (IndoBERT-base-p1) in predicting village-level stunting prevention service availability in Indonesia. The stunting1.csv dataset contains narrative text on service obstacles, preprocessed via normalization, stemming, and stopword removal to produce the clean_kendala column. Data were labeled into three categories—Complete, Partial, and Not Available—and split 80:20 stratified. SVM used TF-IDF features and SMOTE for class balance, while BERT applied class weighting. Both models were evaluated using accuracy, precision, recall, F1-score, and computation time.

B. Data Preprocessing Stages

To ensure data quality, the Kendala_yang_dihadapi_(Jelaskan) column was cleaned through normalization and noise removal.. Stemming (Sastrawi) and stopword removal (NLTK) produced clean_kendala. Labels were mapped numerically: Not Available (0), Partial (1), Complete (2). The next stage applied model-specific preprocessing, differing between SVM and BERT in feature representation and handling of class imbalance.

Preprocessing SVM: The cleaned text was transformed into numerical features using a TF-IDF Vectorizer (maximum 3,000 features, bigram range 1–2). Data were split into 80% training and 20% testing using stratified sampling. Label distribution showed class imbalance, with Partial as the majority and Not Available as the minority class (Fig. 2), which could bias model learning.

To address this, the Synthetic Minority Over-sampling Technique (SMOTE) was applied only to the training data. SMOTE generates new synthetic samples for minority classes based on feature-space similarity rather than duplication. After applying SMOTE, the dataset became balanced across all three label categories, as shown in Fig. 3.

Fig 2. Distribution of label categories before SMOTE (training data)

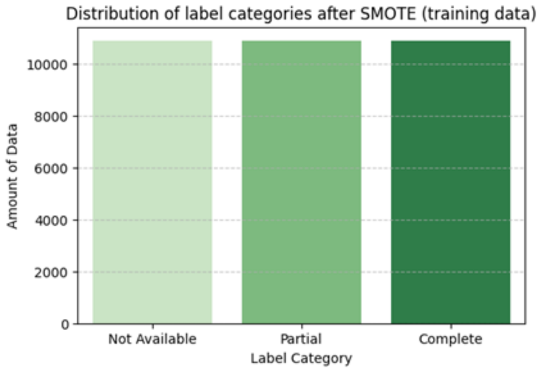

Fig 3. Distribution of label categories after SMOTE (training data)

The balanced dataset improved model generalization and ensured equal learning across categories. Performing SMOTE only on training data also prevented data leakage, maintaining the reliability of model evaluation. This step allowed the SVM model to classify narrative data more accurately and robustly across all service-availability categories.

1) BERT preprocessing: The clean_kendala text was tokenized using the IndoBERT-base-p1 tokenizer with a maximum sequence length of 128 tokens, generating input IDs and attention masks. The dataset was split into 80% training and 20% testing using stratified sampling. Class imbalance was observed prior to class weighting, with Partial as the majority class and Not Available as the minority (Fig. 4).

2) To address this, class weights were computed automatically based on label frequency and applied to the loss function during model training. The resulting weights are shown in Fig. 5, where higher weights were assigned to minority classes to balance learning.

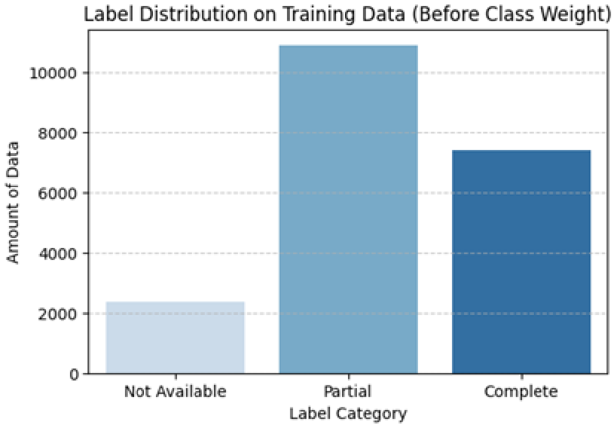

Fig 4. Label distribution in training data before class weighting

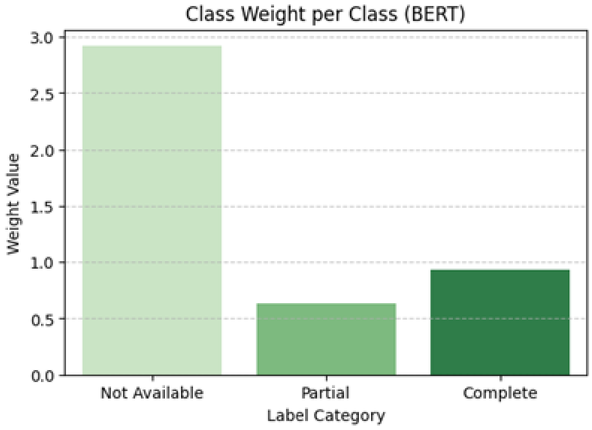

Fig 5. Class weight values per label category (BERT)

This approach eliminated the need for data duplication like SMOTE and ensured that the IndoBERT model treated all classes proportionally during fine-tuning.

C. Model Processing Stages

1) SVM Processing: The SVM model was trained using TF-IDF features with stratified 80:20 train–test splitting. Class imbalance was addressed by applying SMOTE to the training data. Using LinearSVC with class weighting, the model achieved a cross-validation accuracy of 89.5% (SD = 0.003) and a test accuracy of 83.0%, indicating stable generalization and good computational efficiency.

2) BERT Processing: The BERT model fine-tuned IndoBERT-base-p1 using tokenized inputs (max length 128) and class-weighted loss to mitigate class imbalance. After three training epochs, the model achieved 92% accuracy, outperforming SVM by more effectively capturing contextual information in Indonesian narrative text.

D. Model Evaluation Result

Evaluation is carried out on two models, namely Support Vector Machine (SVM) and Bidirectional Encoder Representations from Transformers (BERT) with datasets that have gone through the preprocessing stage. The evaluation results are presented through the metrics of accuracy, precision, recall, F1-score, and visualization using confusion matrix.

1) SVM Model: Evaluation of the SVM model showed good performance, achieving an accuracy of 83.0%. Misclassification of villages with partial or unavailable services is particularly concerning from a public health perspective, as these areas may be overlooked despite having fragmented or insufficient stunting prevention programs. Technically, the confusion matrix (Fig. 6) shows that SVM classified Complete and Partial categories well, while the Not Available class remained more difficult to distinguish due to limited samples.

The matrix shows that misclassification mainly occurs between the Partial and Complete categories. From a public health perspective, this error is critical because villages with fragmented or inconsistently implemented stunting prevention services may be incorrectly classified as having complete coverage and therefore deprioritized for follow-up interventions.

The evaluation metrics in Table I show that the Complete class achieved the highest F1 score (0.90), followed by Partial (0.83), while Not Available received a lower F1 score (0.62). This indicates strong performance in identifying villages with fully available stunting prevention services, but lower sensitivity to partial and unavailable coverage. Classification errors in these categories—especially Partial—pose a critical public health risk, as villages with inconsistently implemented programs may be misprioritized, leading to suboptimal targeting and persistent gaps in stunting prevention interventions.

To ensure reliability and generalization, a 5-fold cross-validation was conducted on the resampled training data. The mean accuracy (89.5%, SD = 0.003) closely matched the test accuracy (83%), indicating good generalization and no overfitting. These results confirm that SVM efficiently classifies service categories but remains slightly biased toward majority classes. In a public health context, such misclassification—particularly of villages with partial or unavailable services—may cause under-targeted interventions and leave high-risk areas insufficiently supported.

2) BERT Model: The BERT model achieved superior performance with an accuracy of 92%, outperforming SVM by effectively capturing contextual information in Indonesian narrative text. As shown in Fig. 7, BERT demonstrated balanced classification across all categories, including stable recognition of villages with limited service availability. This balanced performance is critical for public health analysis, as it improves the identification of villages with partial or unavailable services that require follow-up assessment or intervention.

As shown in Table II, the Complete class achieved the highest performance with an F1-score of 0.94, followed by Partial (0.93), while Not Available obtained an F1-score of 0.80, resulting in a macro average F1-score of 0.89. This balanced performance across categories enhances the accurate identification of villages with partial or unavailable stunting prevention services, thereby reducing the risk of misallocation of public health interventions and supporting more precise prioritization for follow-up actions.

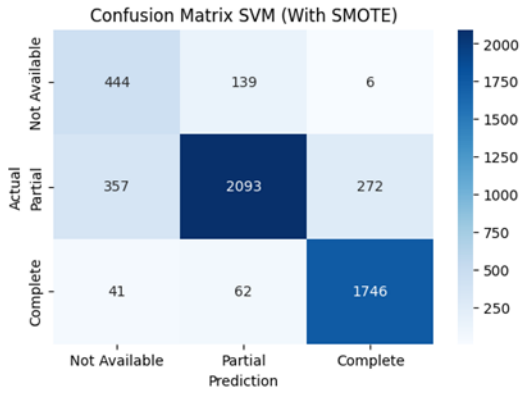

Fig 6. Confusion Matrix - SVM

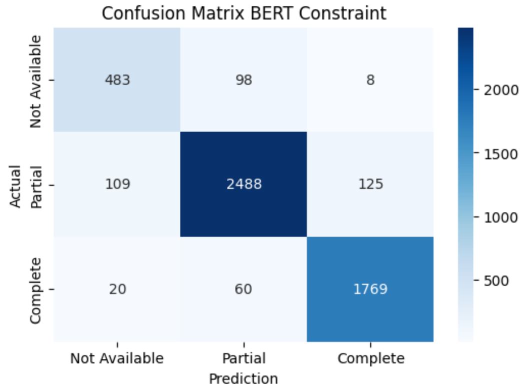

Fig 7. Confusion Matrix - BERT

TABLE I
SVM MODEL EVALUATION RESULT

	Precision	**Recall**	**F1-Score**	**Support**
Not Available	0.53	0.75	0.62	589
Partial	0.91	0.77	0.83	2722
Complete	0.86	0.94	0.90	1849
Accuracy			0.83	5160
Macro avg	0.77	0.82	0.79	5160
Weighted avg	0.85	0.83	0.83	5160

TABLE II
BERT MODEL EVALUATION RESULT

	Precision	**Recall**	**F1-Score**	**Support**
Not Available	0.79	0.82	0.80	589
Partial	0.94	0.91	0.93	2722
Complete	0.93	0.96	0.94	1849
Accuracy			0.92	5160
Macro avg	0.89	0.90	0.89	5160
Weighted avg	0.92	0.92	0.92	5160

These results show that the BERT model successfully captures contextual and semantic relationships within sentences, allowing for more accurate classification of service-availability categories. In the context of public health and stunting prevention, this high accuracy is crucial for identifying areas with insufficient or incomplete services. Thus, BERT can support data-driven policy decisions and help ensure that health interventions are directed effectively to the villages most in need. For comparison, a 3-fold cross-validation was also performed on the BERT model to evaluate its stability. The average accuracy of 91.55% (SD 0.0024) confirmed consistent performance across folds, indicating no overfitting.

E. Comparison of SVM & BERT Algorithm Model Result

The purpose of comparing the SVM and BERT models is to highlight their strengths and limitations based on accuracy, ability to handle minority classes, computation time, and overall modeling performance, in order to determine the most appropriate algorithm for text classification in this study. Both models were trained and evaluated using the same preprocessed dataset described previously.

The results show that BERT achieved higher accuracy (92%) than SVM (83%), at the cost of substantially longer computation time (approximately 30 minutes versus less than 2 minutes). This highlights the trade-off between performance and computational efficiency, where deep learning models offer superior contextual understanding of narrative data, while SVM remains suitable for resource-limited settings.

From a public health perspective, misclassification of villages with partial service availability represents a critical risk, as these areas often have formally existing but inconsistently implemented stunting prevention programs. When misclassified as having complete coverage, such villages may be excluded from follow-up assessments or program strengthening, allowing service gaps to persist. Therefore, model outputs should be used as early screening tools to prioritize field verification of Partial and Not Available villages rather than as direct determinants of resource allocation. It is also essential to distinguish between service availability, utilization, and child health outcomes, as the presence of services does not necessarily translate into effective use or improved nutritional status.

Failure to detect villages with partial service coverage is particularly critical, as these areas often represent intervention-ready settings where timely strengthening of service quality and utilization could prevent further deterioration of child nutrition outcomes.

IV. CONCLUSION

This study compared SVM and BERT (IndoBERT-base-p1) for classifying the availability of stunting prevention services at the village level in Indonesia. While BERT achieved higher accuracy and SVM remained efficient for resource-limited settings, both models showed limitations in identifying minority classes. Therefore, the results should be interpreted as indicative screening outputs rather than definitive evidence for policy decisions. Future research should prioritize expanding and balancing datasets, applying cost-sensitive SVM to reduce misclassification of villages with partial or unavailable services, and refining BERT through domain-adaptive pretraining or ensemble approaches. In addition, integrating multi-source or multimodal data—such as administrative records, geographic indicators, and field surveys—would enable a more comprehensive assessment of service capacity and strengthen the use of machine learning to support evidence-informed stunting prevention policies.

TABLE III
COMPARISON OF SVM AND BERT MODELS

Metode	**Accuracy (%)**	**Time (second)**	**Advantages**	**Weaknesses**
SVM	83.00	102	Fast processing, efficient for structured text data, performs well with limited resources.	Limited understanding of deep contextual meaning; moderate difficulty in recognizing minority classes.
BERT	92.00	1.796	Excellent contextual understanding, capable of processing long and complex sentences with high accuracy.	Requires significant computational resources and longer training time.

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