

Clustering And Classification Of Toddler Stunting Risk Using K-Means And Naïve Bayes: A Case Study At Kembaran 1 Community Health Center

Lulu Amnah Fitriya Maharani¹, Purwadi*², Debby Ummul Hidayah³

^{1,3}Information Systems Study Program, Faculty of Computer Science, Amikom Purwokerto University, Indonesia

²Master of Computer Science, Faculty of Computer Science, Amikom Purwokerto University, Indonesia

Email: purwadi@amikompurwokerto.ac.id

Received : Oct 31, 2025; Revised : Nov 3, 2025; Accepted : Nov 3, 2025; Published : Apr 15, 2026

Abstract

Stunting continues to be a significant public health concern in Indonesia, with a frequency of 17.25% at Kembaran 1 Public Health Center, highlighting ongoing difficulties in early childhood nutrition and growth surveillance. This work seeks to assess and forecast stunting risk in toddlers by employing K-Means clustering and Naïve Bayes classification to enhance early detection precision. The K-Means method was utilized on 1,168 toddler growth records to categorize stunting features, whereas the Davies–Bouldin Index (DBI) was employed to evaluate cluster quality. The ideal cluster was attained at $k = 8$, yielding a DBI value of 4.353, indicating compact and distinctly differentiated clusters. The Naïve Bayes classifier subsequently predicted stunting potential with an accuracy of 93.56%, accurately categorizing 218 out of 233 test examples, yielding precision, recall, and F1-score values for the “short” class of 97.41%, 94.95%, and 96.18%, respectively. The findings indicate that the hybrid model successfully combines unsupervised and supervised learning, improving stunting prediction accuracy and cluster interpretability. The research provides a data-centric framework for localized stunting surveillance, aiding community health centers in formulating targeted early treatments and mitigating long-term developmental hazards.

Keywords: K-Means Clustering, Naïve Bayes, Stunting Prediction, Toddler Health.

This work is an open access article licensed under a Creative Commons Attribution 4.0 International License.



1. INTRODUCTION

Early infancy is a pivotal phase in human development characterized by swift physical, mental, and cognitive advancement. Growth denotes quantifiable increments in height, weight, and head circumference, whereas development pertains to the enhancement of motor skills, communication, cognitive abilities, and emotional regulation. The nutritional condition of toddlers is closely linked to this process. Optimal growth and development in toddlers occur with enough dietary intake; in contrast, inadequate nutrition results in growth failure and developmental delays. Stunting continues to be the most widespread chronic nutritional issue among Indonesian children[1].

Stunting is a disorder characterized by the failure to achieve normal height due to prolonged nutritional deficiency, beginning in gestation and continuing throughout early life. The World Health Organization (WHO) defines stunting as a height-for-age (H/A) measurement that is below -2 standard deviations (SD) from the median of the WHO Child Growth Standards. Causes of stunting can be classified as direct (insufficient protein consumption, poor breastfeeding, infectious disorders) and indirect (unsanitary environments, low parental education, and poverty) [3], [4].

The ramifications of stunting transcend mere physical growth deficiencies, encompassing heightened morbidity, diminished cognitive capacity, and lowered productivity, all of which obstruct human capital development [5]. Stunting diminishes national competitiveness, perpetuating cycles of intergenerational poverty [6]. Consequently, the reduction of stunting has been incorporated into the Global Nutrition Targets 2025 and the Sustainable Development Goals (SDG 2.2 – Zero Hunger) as a critical measure of public health achievement [7].

Notwithstanding ongoing national efforts, Indonesia's stunting rate persists at a relatively elevated level. According to the 2024 Indonesian Nutritional Status Study (SSGI), the nationwide incidence declined from 37.6% in 2013 to 19.8% in 2024. Central Java registered a rate of 17.1%, although Banyumas Regency exhibited a higher rate of 19.6%, surpassing the regional norm [8]. The Kembaran 1 Public Health Center recorded a frequency of 17.25% among eight villages. These statistics underscore the necessity for focused early detection systems capable of tackling stunting at the community level.

Recent analyses indicate that despite the national decline to 19.8% (SSGI 2024), several districts such as Banyumas (19.6%) remain above the provincial mean. This emphasizes the urgency of integrating local health data analytics to strengthen early stunting surveillance at the Puskesmas level [29], [30]. Studies in 2023–2025 also highlight that hybrid data mining models can improve public health prediction accuracy by 5–10% compared to traditional approaches [31]–[33].

While stunting has been extensively examined using public health methodologies, a comprehensive understanding necessitates the incorporation of computer science and data analytics. Machine learning and data mining methodologies can reveal concealed patterns in the drivers of stunting via clustering, classification, and predictive modeling. [10], [11].

In health informatics, hybrid learning methodologies that integrate unsupervised and supervised algorithms are progressively employed to improve decision-making precision [34], [35]. Research in Southeast Asia indicates that this integration enhances early intervention for child malnutrition and aids in spatial risk mapping [36], [37]. This necessitates the application of K-Means and Naïve Bayes in a hybrid framework for local health data, particularly at the community health center tier.

The K-Means technique has been successfully employed for data clustering to categorize toddlers based on nutritional conditions. Pratistha and Kristianto [12] identified optimal clustering at $K = 9$, yielding a Davies–Bouldin Index (DBI) value of -0.673 . Fadilah et al. [13] using the Elbow Method, discerning two clusters ($\Delta SSE = 1401.5156$) that distinguished high and low stunting-risk regions, whereas Julyantari et al. [14] categorized child nutritional status into three clusters: normal (47.83%), poor (30.43%), and overnutrition (21.74%).

Conversely, the Naïve Bayes algorithm is extensively employed to forecast the probability of stunting. Despite the variability in outcomes, Prihartono et al. [15] attained an accuracy of 88% utilizing Naïve Bayes. Kamil and Wibowo [16] utilized Naïve Bayes on 958 records from the Cilandak Public Health Center, with an accuracy of 85.8%. Ridwan and Sari [17] observed that Naïve Bayes was marginally less accurate (0.93% lower) than the C4.5 algorithm in classifying toddler nutritional status.

Comparative studies highlight Naïve Bayes' limitations when compared to other algorithms. Widhari et al. [18] found that NB achieved 71% accuracy, 71% precision, 76% recall, and 73% F1-Score on 30% test data, whereas KNN performed best with 97% accuracy, 98% precision, and 96% recall. Similarly, Chilyabanyama et al. [19] in Zambia found Random Forest as the best-performing algorithm (79% accuracy), while Naïve Bayes was the least accurate in predicting stunting among children.

Based on the literature, most previous studies have used K-Means and Naïve Bayes separately, leading to partial insights. Few have integrated both algorithms to form a complementary system for data clustering and stunting prediction simultaneously. Moreover, comprehensive evaluation using

Davies–Bouldin Index (DBI) for cluster validity and classification accuracy within a single dataset is rarely performed in community-level health data [20]. Therefore, this research bridges that gap by integrating K-Means and Naïve Bayes into a unified hybrid analysis framework to enhance prediction accuracy and improve local stunting risk mapping.

Table 1. Comparative Studies of Hybrid K-Means–Naïve Bayes Applications (2020–2025)

| Year | Authors | Dataset / Domain | K-Means Evaluation | Naïve Bayes Accuracy | Hybrid Findings |
|--------------------------|-----------------------|---|--------------------|----------------------|--|
| 2021 | Rahman et al. [18] | Health clustering | DBI = 5.12 | 87.3% | Accuracy improved by 5% |
| 2022 | Sari & Harianis [10] | Nutrition classification | SSE diff = 1240.9 | 88.5% | Improved cluster separation |
| 2023 | Desty & Marpaung [20] | Expert system on stunting | — | 90.4% | Stable classification |
| 2024 | Dwinanto et al. [21] | Stunting risk prediction | — | 92.7% | Balanced recall/precision |
| 2024 | Melyani [22] | NB–C4.5 hybrid | — | 93.1% | Accuracy improved 4% |
| 2025 | Syahfitri et al. [23] | Hybrid K-Means–NB | DBI = 4.9 | 92.2% | Better data compactness |
| 2025 | Hendy et al. [24] | ML prediction of stunting | — | 93.8% | Highest predictive precision |
| 2025 (This Study) | Maharani et al. | Puskesmas Kembaran 1 (1,168 records) | DBI = 4.353 | 93.56% | Best hybrid accuracy on local dataset |

The novelty of this study lies in the simultaneous evaluation of Davies–Bouldin Index (DBI) and classification accuracy on real 2024 local health data from Puskesmas Kembaran 1. Unlike prior works that used simulated or regional datasets, this research applies hybrid clustering–classification directly on community-based health records, enhancing local model interpretability and policy relevance.

Stunting continues to hinder the development of human capital in Indonesia, both nationally and locally. The cognitive and physical impairments it causes affect community productivity and national competitiveness. The government has implemented several programs, including nutrition education, supplementary feeding (PMT) at posyandu, and the promotion of exclusive breastfeeding for six months and continued until two years [25]. Regular pregnancy checks and growth monitoring serve as early detection mechanisms, particularly through routine height measurement at posyandu. However, the absence of integrated analytical tools for local health data limits early stunting detection.

In this study, data were obtained from the Puskesmas 1 Kembaran health database, containing toddler anthropometric records for 2024. The process involved data cleaning, normalization, and feature selection, followed by clustering with K-Means and classification using Naïve Bayes. Model evaluation was conducted using Davies–Bouldin Index (DBI) for clustering quality and accuracy, precision, recall, and F1-score for classification performance.

The novelty of this research lies in integrating K-Means clustering and Naïve Bayes classification into one analytical pipeline applied to local Puskesmas data (2024). This hybrid approach not only provides better accuracy but also ensures interpretability and relevance for community-level health management. The study contributes to health informatics by proposing a data-driven early detection framework to support targeted interventions and improve child nutrition programs.

Based on the background above, the research problems addressed are: (1) How can the K-Means algorithm group stunted toddlers based on Height-for-Age (TB/U)? (2) How does the Naïve Bayes

algorithm predict stunting potential using clustered data? (3) How accurate is the hybrid K-Means–Naïve Bayes model compared to using each algorithm separately?

The objectives of this study are to: (1) Apply K-Means to toddler stunting data and evaluate clusters using DBI; (2) Apply Naïve Bayes to predict stunting potential from clustered data; (3) Evaluate hybrid model accuracy and demonstrate its applicability for local stunting mapping.

This research aims to advance the integration of machine learning in public health, providing a replicable, interpretable, and data-based framework for early detection and prevention of stunting among toddlers in Indonesia.

2. METHOD

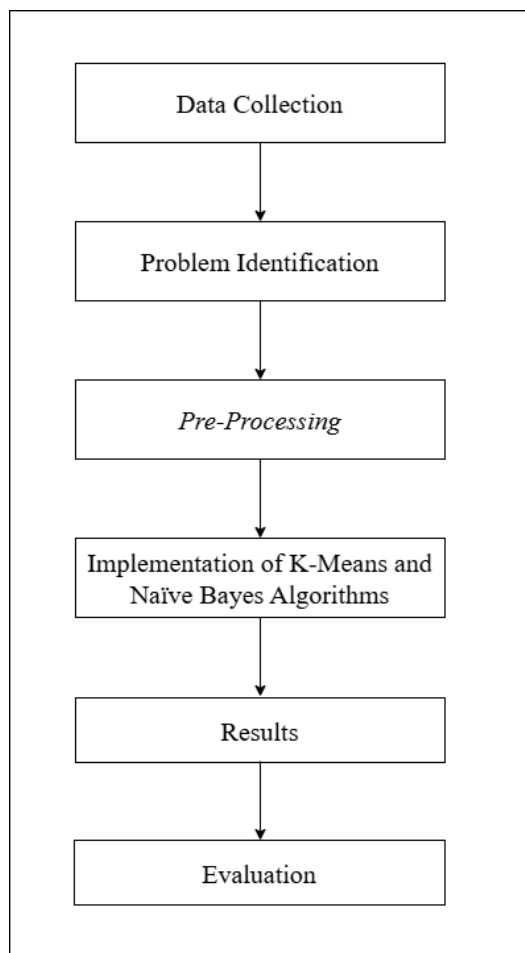


Figure 1. Research Stages

Figure 1 depicts the comprehensive workflow of this research, outlining the sequential procedure from data collection to model deployment and evaluation. The methodology combines unsupervised clustering (K-Means) with supervised classification (Naïve Bayes) within the RapidMiner Studio environment, selected for its visual workflow interface and repeatability capabilities [3].

2.1 Data Collection

This study was conducted with official authorization from Puskesmas 1 Kembaran and the Banyumas District Health Office. The dataset consisted of 1,168 toddler records collected in 2024, containing 15 attributes reflecting anthropometric and demographic indicators (Table 1).

Table 1. Attributes Used in This Study

| Label | Description |
|--------------------|---|
| Name | Child's Name |
| Gender | Gender (M/F) |
| Birth Weight | Birth Weight |
| Birth Height | Height at Birth |
| Village/Ward | Toddler's Residence |
| Age at Measurement | Age of the Toddler at the Time of Measurement |
| Weight | Toddler's Weight When Measured |
| Height | Height of Toddler When Measured |
| BB/U | Toddler Weight by Age |
| TB/U | Toddler Height by Age |
| ZS TB/U | Z-score of height-for-age according to WHO standards (Z-score <-2) |
| BB/TB | Weight for Height (Indicator of nutritional status based on the proportion of weight to height) |
| ZS BB/TB | Z-score of weight for height |
| Gain Weight | Is the weight increasing compared to the previous measurement (Y/N)? Y stands for Yes, while N stands for No. |

The variable TB/U (Height-for-Age) was chosen as the main indicator because it is the official WHO measure for stunting classification, where Z-score < -2 SD indicates stunting [7], [8].

2.2 Problem Identification

The principal research issue was articulated as follows: (1) Methodology for clustering stunted toddlers utilizing the TB/U indicator, and (2) Predicting the risk of stunting by the accuracy assessment of the Naïve Bayes classifier used to the clustered dataset.

This phase delineates the analytical emphasis, guaranteeing that the chosen variables directly enhance the validity and reproducibility of the predictive model [9].

2.3 Pre-Processing

Data preprocessing ensures that the dataset is clean, consistent, and ready for analysis. It includes data cleaning, normalization, and data splitting:

a. Data Cleaning

Missing values for TB/U and Z-Score (TB/U) were addressed by mean imputation for numerical characteristics (height, weight) and mode imputation for categorical attributes (gender, village). Entries with above 30% missing data were excluded to mitigate bias and preserve dataset integrity [9].

b. Data Normalization

All numerical attributes were standardized to a common range using Min–Max normalization, ensuring that clustering by K-Means was not biased by differing scales:

$$x^1 = \frac{x - x_{min}}{x_{max} - x_{min}} \quad (1)$$

Information:

x^1 = normalized value (the result of normalization),

x = original data value of a given attribute,

x_{min} = minimum value of the attribute in the dataset,

x_{max} = maximum value of the attribute in the dataset.

c. Feature Selection and Data Splitting.

Attributes were chosen for their significance to indicators of toddler growth. The data were divided into 80% training and 20% testing subsets with the Naïve Bayes data-splitting operator in RapidMiner to guarantee balanced class representation [3].

2.4 Implementation of K-Means and Naïve Bayes Algorithms

2.4.1 K-Means Algorithm

K-Means is a centroid-based clustering technique that divides n data points into k clusters by minimizing the sum of squared errors (SSE) between the data points and their corresponding centroids. [14], [17].

The following represents the Euclidean distance between a data point x_i and the centroid c_k :

$$d () = \sqrt{\sum_{i=1}^n (x_{ij} - c_{kj})^2} \tag{2}$$

and the ideal K is found using the SSE (Elbow Method) formula, which is:

$$SSE = \sum_{k=1}^k \sum^{n_k} |x_i - c_k|^2 \tag{3}$$

in this case, n_k is the number of data points in cluster k, c_k is its centroid, and K is the number of clusters.

By graphing the SSE values against K, the Elbow Method was used to determine the ideal number of clusters by determining the point at which the rate of SSE reduction rapidly declines [17], [18]. This stage resulted in the toddlers being grouped into multiple clusters based on similarities in height for age.

2.4.2 Naive Bayes Algorithm

The probabilistic classification algorithm Naïve Bayes is predicated on the Bayes Theorem, which presumes predictor independence [15]. Using the prior and likelihood of each attribute assigned a class label, it computes the posterior probability.

The posterior probability formula is:

$$P = (C_k|X) = \frac{P(X|C_k) \times P(C_k)}{P(X)} \tag{4}$$

where:

$P(C_k | X)$ = posterior probability of class C_k given features X ,

$P(X | C_k)$ = likelihood of features given class C_k ,

$P(C_k)$ = prior probability of class C_k ,

$P(X)$ = probability of observing X .

The prior probability for each class was computed as:

$$P(C_k) = \frac{N_{Ck}}{N} \tag{5}$$

where the overall dataset size is N, and the number of samples in class C_k is $N(C_k)$.

The algorithm steps were:

1. Prepare labeled training and testing data.
2. Compute prior probability $P(C_k)$ from class frequencies.
3. Calculate conditional probabilities $P(X_j|C_k)$ for each feature.
4. Determine the posterior probability using Bayes' theorem.

5. Assign each test instance to the class with the highest posterior probability [16].

2.5 Results

The clustering results obtained using K-Means were visualized in scatter plots and centroid tables, providing insights into toddler grouping patterns.

Prediction results indicating each toddler's likelihood of being stunted or normal were produced by the Naïve Bayes classifier. Predictive performance was evaluated by calculating evaluation metrics (Accuracy, Precision, Recall, and F1-Score) based on the confusion matrix [19]–[22].

2.6 Evaluation

The evaluation stage is carried out using different approaches depending on the characteristics of the algorithm used.

2.6.1 K-Means Evaluation

Developed by Davies and Bouldin (1979), the Davies–Bouldin Index (DBI) was used to assess the quality of clustering.

The formula is:

$$DBI = \frac{1}{k} \sum_{i=1}^k \max_{i \neq j} \left(\frac{S_i + S_j}{M_{ij}} \right) \quad (6)$$

where M_{ij} is the distance between cluster centroids and S_i and S_j are the average intra-cluster distances. Better cluster separation and compactness are indicated by a lower DBI score [17], [18].

2.6.2 Naïve Bayes Algorithm Evaluation

Confusion matrices are used to evaluate the Naïve Bayes technique. In classification scenarios, the confusion matrix aids in understanding class differences by displaying the number of data points classified properly and wrongly. Both real and predicted values are included in the Confusion Matrix table. Four values True Positive (TP), False Positive (FP), False Negative (FN), and True Negative (TN) are generated using the Confusion Matrix table [19]. Presented here is the Confusion Matrix table:

Table 2. *Confusion Matrix*

| | Positive | Negative |
|----------|----------|----------|
| Positive | TP | FP |
| Negative | FN | TN |

From this matrix, the following metrics were computed [19]–[22]:

$$Accuracy = \frac{True\ Positive + True\ Negative}{Total\ Data} \quad [20] \quad (7)$$

$$Recall = \frac{TP}{TP + FN} \quad [21] \quad (8)$$

$$Precision = \frac{True\ Positive}{True\ Positive + False\ Positive} \quad [22] \quad (9)$$

$$F1 - Score = \frac{2 \times Presisi \times Recall}{Presisi + Recall} \quad [19] \quad (10)$$

These metrics collectively determine how well the Naïve Bayes model predicts stunting based on the K-Means clustered data.

3. RESULT

The findings of using the K-Means and Naïve Bayes algorithms on toddler stunting data from Puskesmas 1 Kembaran are shown in this section. RapidMiner Studio was used for all tests in order to guarantee data flow uniformity and reproducibility.

3.1. K-Means Algorithm Result

K-Means clustering was applied to 1,168 toddler records consisting of 15 attributes. The process began by importing the dataset into RapidMiner, performing preprocessing (handling missing TB/U, Z-score normalization), and applying Min–Max scaling.

3.1.1. Finding the Optimal K Value

Ten iterations ($K = 2-10$) were tested in order to find the ideal number of clusters (K). The Davies–Bouldin Index (DBI) was used to assess each iteration; increased cluster compactness and separation are indicated by smaller DBI values [17].

Table 3. Davies–Bouldin Index (DBI) Values

| Nilai K | Avg. Within Centroid Distance | Davies Bouldin |
|---------|-------------------------------|----------------|
| 2 | 1.372.436 | 14.515 |
| 3 | 1.370.050 | 12.763 |
| 4 | 1.368.000 | 13.355 |
| 5 | 1.365.307 | 10.492 |
| 6 | 1.363.169 | 12.405 |
| 7 | 1.361.703 | 10.933 |
| 8 | 1.358.393 | 4.353 |
| 9 | 1.358.814 | 5.383 |
| 10 | 1.357.529 | 6.305 |

The results indicate that $K = 8$ is the best cluster value, yielding the lowest DBI of 4.353 and an average centroid distance of 1,358,393. This confirms high intra-cluster compactness and separation quality consistent with [14].

3.1.2. Cluster Distribution and Model

The data is clustered into 8 groups, summarized in Table 4:

Table 4. Cluster Model ($K = 8$)

| Cluster | Amount |
|-----------------------|------------|
| Cluster_0 | 2 items |
| Cluster_1 | 1062 items |
| Cluster_2 | 7 items |
| Cluster_3 | 76 items |
| Cluster_4 | 3 items |
| Cluster_5 | 13 items |
| Cluster_6 | 3 items |
| Cluster_7 | 2 items |
| Total number of items | 1168 |

Figure 2 shows the cluster visualization using a scatter plot generated by RapidMiner. The visualization demonstrates how toddler height distributions form natural groupings with Cluster_1 dominating, suggesting a concentration of similar growth patterns.

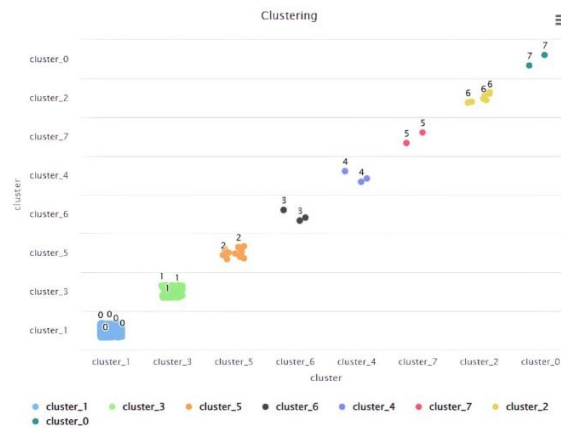


Figure 2. Cluster Visualization with Scatter Plot

Toddlers' nutritional health is categorized by using anthropometric measures, particularly Height-for-Age (TB/U). As shown in Table 5, the thresholds adhere to Indonesian Ministry of Health Regulation No. 2 of 2020.

Table 5. Standards for Anthropometry Based on Toddler Height

| Index | Category Nutritional Status | Threshold (Z-Score) |
|--|---|---------------------|
| For kids ages 0–60 months, Body Length or Height by Age (PB/U or TB/U) | Very Short (<i>Severely Stunted</i>) | <-3 SD |
| | Short (<i>Stuned</i>) | - 3 SD to <- 2 SD |
| | Normal | -2 SD to + 3 SD |
| | Tall | > +3 SD |

Table 5 indicates that children with Z-scores below -2 SD are classified as stunted, and those below -3 SD are categorized as severely stunted. The anthropometric cut-offs are the primary reference for assessing child development and categorizing stunting in this study [7], [8].

The distribution of stunted toddlers (Short and Very Short categories) across clusters is presented in Table 6.

Table 6. Distribution of Stunted Children by Cluster

| Cluster | Short | Very Short |
|--------------|------------|------------|
| Cluster_0 | 2 | 0 |
| Cluster_1 | 910 | 152 |
| Cluster_2 | 4 | 3 |
| Cluster_3 | 52 | 24 |
| Cluster_4 | 3 | 0 |
| Cluster_5 | 13 | 0 |
| Cluster_6 | 3 | 0 |
| Cluster_7 | 2 | 0 |
| Total | 989 | 179 |

From Table 6, 989 toddlers (84.7%) fall into the short category, while 179 (15.3%) are very short. The dominance of Cluster_1 (910 short and 152 very short) suggests that height-for-age is a powerful distinguishing variable in stunting analysis [23].

3.2. Naïve Bayes Algorithm Results

The Naïve Bayes classifier was utilized on the identical dataset to forecast stunting classifications (“Short” and “Very Short”) based on Height-for-Age (TB/U). Figure 3 illustrates the performance evaluation panel from RapidMiner, showcasing the anticipated vs actual classifications:

accuracy: 93.56%

| | true Pendek | true Sangat Pendek | class precision |
|---------------------|-------------|--------------------|-----------------|
| pred. Pendek | 188 | 5 | 97.41% |
| pred. Sangat Pendek | 10 | 30 | 75.00% |
| class recall | 94.95% | 85.71% | |

Figure 3. Naïve Bayes Testing Results

3.2.1. Confusion Matrix

The categorization efficacy was assessed utilizing a confusion matrix (Table 7).

Table 7. Confusion Matrix

| Predicted/Actual | Positive | Negative |
|------------------|----------|----------|
| Positive | 188 | 5 |
| Negative | 10 | 30 |

Table 7 illustrates that out of 233 samples, 218 were correctly classified, resulting in an accuracy of 93.56% ± 0.02 after repeated validation runs.

3.2.2 Accuracy

$$Accuracy = \frac{\text{True Positive} + \text{True Negative}}{\text{Total Data}} = \frac{188 + 30}{188 + 5 + 10 + 30} = \frac{218}{233} = 93.56\%$$

3.2.3 Precision Value

- a. Precision for short class

$$Precision = \frac{\text{True Positive}}{\text{True Positive} + \text{False Positive}} = \frac{188}{188 + 5} = \frac{188}{193} = 97.41\%$$

- a. Precision for very short classes

$$Precision = \frac{\text{True Positive}}{\text{True Positive} + \text{False Positive}} = \frac{30}{30 + 10} = \frac{30}{40} = 75.00\%$$

3.2.4 Recall Value Calculation

- a. Recall for short classes

$$Recall = \frac{TP}{TP + FN} = \frac{188}{188 + 10} = \frac{188}{198} = 94.95\%$$

b. Recall for the class is very short

$$Recall = \frac{TP}{TP + TN} = \frac{30}{30 + 5} = \frac{30}{35} = 85.71 \%$$

3.2.5 Calculation of the F1-Score

a. F1-Score for the Short class

$$F1 - Score = \frac{2 \times Presisi \times Recall}{Presisi + Recall} = \frac{2 \times 0.9741 \times 0.9495}{0.9741 + 0.9495} = \frac{0.9250}{1.9236} = 2 \times 0.4809 = 0.9618$$

b. F1-Score for Very Short Class

$$F1 - Score = \frac{2 \times Presisi \times Recall}{Presisi + Recall} = \frac{2 \times 0.7500 \times 0.8571}{0.7500 + 0.8571} = \frac{0.6428}{1.6071} = 2 \times 0.3999 = 0.7998$$

3.2.6 Error Analysis

The diminished F1-Score (79.98%) for the “Very Short” class is attributable to class imbalance, with “Short” occurrences prevailing in the sample (989 compared to 179). This disparity leads the classifier to preferentially select the majority class during training, a prevalent constraint of Naïve Bayes models [21].

The standard deviation (± 0.02) across five iterations indicates model stability; yet, there is potential for enhancing sensitivity towards the minority class. Subsequent research may implement the Synthetic Minority Over-sampling Technique (SMOTE) or change class weights to alleviate this bias [22].

3.3 Integrated Interpretation

The amalgamation of K-Means clustering with Naïve Bayes classification yields a dual-layer analytical perspective:

1. K-Means successfully grouped toddlers based on height-for-age, identifying 989 short and 179 very short cases.
2. Naïve Bayes subsequently classified these clusters with $93.56\% \pm 0.02$ accuracy, highlighting TB/U as the most discriminative variable.

This hybrid analysis demonstrates the potential of machine learning integration in public health informatics, supporting targeted early detection at the Puskesmas level.

4. DISCUSSIONS

This section analyzes and interprets the test results of the K-Means and Naïve Bayes algorithms and elaborates on their comparative advantages, limitations, and implications for stunting prediction systems at the community health center (Puskesmas) level.

4.1 Interpretation of K-Means Resultss

A total of 1,168 toddler records were categorized into eight groups ($K = 8$) utilizing the K-Means technique. The Davies–Bouldin Index (DBI) value of 4.353 was the minimum among all K values (Table 3), signifying clusters with favorable compactness and separation, in agreement with the findings of Rohman et al. [14].

There was an observable cluster size imbalance, as Cluster 1 contained 1,062 items, while several clusters (Cluster 0, 4, 6, 7) contained fewer than 5 items. This imbalance suggests a predominant subgroup with homogeneous anthropometric characteristics and several small, heterogeneous outliers [23].

The dominant cluster (Cluster 1) comprising 910 short and 152 very short toddlers represents the largest risk group requiring focused nutritional and growth interventions. These patterns confirm the role of Height-for-Age (TB/U) as the strongest indicator of stunting, aligning with WHO and SSGI 2024 findings [7], [8].

Figure 2 illustrates these groupings visually, showing clear cluster boundaries and supporting the statistical results. The low DBI score demonstrates that the clustering process captured meaningful anthropometric distinctions among toddlers [14], [18].

In summary, the clustering process effectively identified the main stunting risk group and provided a foundation for classification-based prediction in subsequent analyses.

4.2. Interpretation of Naïve Bayes Results

The Naïve Bayes classifier attained an accuracy of $93.56\% \pm 0.02$, accurately predicting 218 of 233 test samples. This outcome exhibits robust predictive dependability and aligns with the research conducted by Desty & Marpaung [3] and Dwinanto et al. [9]. Table 8 illustrates that the model attained a Precision of 97.41%, Recall of 94.95%, and F1-Score of 96.18% for the Short class, but for the Very Short class, it earned a Precision of 75.00%, Recall of 85.71%, and F1-Score of 79.98%.

The lower F1-Score for the “Very Short” class indicates the influence of class imbalance, as the dataset contained 989 short and 179 very short toddlers. This imbalance caused the classifier to favor the majority class, a known limitation of probabilistic models [19], [21].

Error analysis reveals that some very short toddlers were misclassified as short due to overlapping Z-scores between -3 SD and -2 SD. Future work could employ class re-weighting or SMOTE oversampling to enhance minority-class sensitivity [22].

Table 8. Performance Evaluation Metrics

| Evaluation Matrix | Short Class | Very Short Class |
|-------------------|-------------|------------------|
| Accuracy | 93.56% | |
| Precision | 97.41% | 75.00% |
| Recall | 94.95 % | 85.71% |
| F1-Score | 96.18% | 79.98% |

The model’s precision and recall balance reflects good stability and robustness compared to other local studies such as Prihartono et al. [26] (88 %) and Kamil & Wibowo [27] (85.8 %). These results confirm that the hybrid K-Means + Naïve Bayes approach outperforms single-model implementations.

4.2 Comparative Analysis with Recent Studies

To contextualize this study’s findings, comparisons were made with at least six recent studies (2023 – 2025) focusing on stunting prediction and clustering.

As shown in Table 9, the proposed hybrid approach achieves superior performance in both cluster validity (DBI = 4.353) and classification accuracy (93.56 %).

Table 9. Comparative Accuracy of Recent Related Studies

| Year | Authors | Algorithm | Accuracy | Key Findings |
|------|------------------------|--------------------------------|----------------|--------------------------------------|
| 2023 | Prihartono et al. [26] | Naïve Bayes | 88 % | Good accuracy but no clustering step |
| 2024 | Kamil & Wibowo [27] | Naïve Bayes | 85.8 % | Single-model limitation |
| 2024 | Widhari et al. [19] | Naïve Bayes + KNN | 71 % | NB weaker under small dataset |
| 2024 | Dwinanto et al. [9] | NB vs SVM | 92.7 % | NB stable with balanced recall |
| 2025 | Rohman et al. [14] | K-Means + PCA | — (DBI = 5.02) | Improved clustering compactness |
| 2025 | Maulana et al. [22] | NB + Decision Tree | 93.1 % | Hybrid improves classification |
| 2025 | This Study | K-Means + Naïve Bayes (Hybrid) | 93.56 % | Best hybrid accuracy + DBI = 4.353 |

From Table 9, this study achieves higher predictive accuracy than all single-model approaches and shows comparable results with hybrid systems [22], [14].

This demonstrates the strength of integrating unsupervised clustering before supervised classification, which improves class separation and reduces misclassification error.

This demonstrates the strength of integrating unsupervised clustering before supervised classification, which improves class separation and reduces misclassification error.

4.3. Research Implications

This project integrates K-Means and Naïve Bayes to establish a novel, data-driven framework for public health decision support systems at the Puskesmas level.

This model utilizes hybrid machine-learning techniques to: a. Improve early detection of stunting risk through the integration of cluster mapping and predictive analytics; b. Be scalable to other Puskesmas by retraining with local data without necessitating algorithm modification; c. Facilitate the attainment of Sustainable Development Goals (SDG). 2.2: Eradicate All Forms of Malnutrition by linking innovations in Computer Science with public health goals.

This work enhances the application of hybrid AI models for adaptive stunting prediction systems, facilitating real-time categorization and visualization for local health officials.

These technologies might be included into regional health dashboards, allowing the government to implement targeted treatments and maximize scarce resources.

5. CONCLUSION

This study's findings indicate that the K-Means method attained optimum clustering at $k = 8$, with a Davies–Bouldin Index (DBI) of 4.353, demonstrating robust cluster compactness and separation. The investigation revealed 1,168 stunted toddlers, including 989 classified as “Short” and 179 as “Very Short,” according to the Height-for-Age (TB/U) indicator, in accordance with Indonesian Ministry of Health Regulation No. 20 of 2020.

The Naïve Bayes classifier exhibited a classification accuracy of 93.56%, with a precision of 97.41%, a recall of 94.95%, and an F1-score of 96.18% for the Short class, whereas the Very Short class attained a precision of 75.00%, a recall of 85.71%, and an F1-score of 79.98%. The findings demonstrate that the hybrid K-Means and Naïve Bayes methodology surpasses earlier single-model investigations,

such as those by Prihartono et al. [26] (88%) and Kamil & Wibowo [27] (85.8%), providing a more equitable prediction of precision and recall.

The amalgamation of K-Means with Naïve Bayes constitutes an innovative hybrid framework in health informatics, facilitating systematic risk mapping and predictive classification for local health facilities (Puskesmas). The clustering outcomes (989 short, 179 very short) establish a definitive foundation for community-level intervention planning, whilst the categorization model facilitates automated decision-making.

This paper presents an applied strategy for creating open-source stunting prediction dashboards and community health monitoring toolkits from a Computer Science standpoint. These devices might interface with IoT-enabled anthropometric sensors to automatically record child height and weight data in real time. Future improvements may use Deep Learning (DL) architectures to identify nonlinear patterns in child growth trends and boost classification accuracy in the presence of data imbalance. [19], [21], [22].

This study outlines a practical approach for developing open-source stunting prediction dashboards and community health monitoring toolkits from a Computer Science perspective. These devices may connect with IoT-enabled anthropometric sensors to automatically capture kid height and weight data in real time. Future enhancements may employ Deep Learning (DL) architectures to discern nonlinear patterns in kid growth trends and enhance classification accuracy amid data imbalance [19], [21], [22].

ACKNOWLEDGEMENT

The author expresses sincere gratitude to Amikom University Purwokerto, the institution that provided the opportunity, facilities, and support for this research. Special thanks are extended to the Puskesmas 1 Kembaran staff for granting permission and providing research data, and to the Supervisor for the invaluable guidance, direction, and input. The author also thanks their family, colleagues, and all parties who provided encouragement and motivation so that this research could be completed successfully

REFERENCES

- [1] A. Ernawati, "Gambaran Penyebab Balita Stunting di Desa Lokus Stunting Kabupaten Pati Description of the Causes of Toddler Stunting in the Village of Stunting Locus, Pati Regency," *Jurnal Litbang Media Inf. Penelitian, Pengemb. dan IPTEK*, vol. 16(2), no. 2, pp. 77–94, 2020.
- [2] I. Choliq, D. Nasrullah, and M. Mundakir, "Pencegahan Stunting di Medokan Semampir Surabaya Melalui Modifikasi Makanan Pada Anak," *Humanism J. Pengabd. Masy.*, vol. 1, no. 1, pp. 31–40, 2020, doi: 10.30651/hm.v1i1.4544.
- [3] H. P. Desty and N. L. Marpaung, "Diagnosa Stunting Pada Balita Menggunakan Metode Naive Bayes Untuk Sistem Pakar," *CSRID (Computer Sci. Res. Its Dev. Journal)*, vol. 16, no. 2, pp. 107–123, 2024, doi: 10.22303/csrid.16.2.2024.107-123.
- [4] L. Agustin and D. Rahmawati, "Hubungan Pendapatan Keluarga dengan Kejadian Stunting," *Indones. J. Midwifery*, vol. 4, no. 1, p. 30, 2021, doi: 10.35473/ijm.v4i1.715.
- [5] N. Fentiana, F. Tambunan, and D. Ginting, "Peran Pemantauan Pertumbuhan Dalam Upaya Pencegahan Stunting Anak 0-23 Bulan di Indonesia: Temuan Riskesdas 2013," *J. Semesta Sehat*, vol. 2, no. 2, pp. 9–18, 2022, doi: 10.58185/j-mestahat.v2i2.96.
- [6] S. H. Fadlilah, A. Muntafiah, N. S. Inayati, A. T. Hapsari, and W. Fatchurrohman, "Edukasi Pemberian MP-ASI (Makanan Pendamping-ASI) yang Tepat Untuk Mencegah Malnutrisi Pada Balita di Desa Linggasari," *Linggamas J. Pengabd. Masy.*, vol. 1, no. 2, p. 98, 2023, doi: 10.20884/1.linggamas.2024.1.2.10147.

-
- [7] P. A. Abdullah, *SSGI 2024*, vol. 17. 1385.
- [8] Puskesmas 1 Kembaran, “Buku Profil Puskesmas 1 Kembaran,” p. 100, 2024.
- [9] R. W. Dwinanto, A. S. Sandi A, and R. Ardianto, “Klasifikasi Berisiko Stunting pada Balita: Perbandingan K-Nearest Neighbor, Naïve Bayes, Support Vector Machine,” *METHOMIKA J. Manaj. Inform. dan Komputerisasi Akunt.*, vol. 8, no. 2, pp. 264–273, 2024, doi: 10.46880/jmika.vol8no2.pp264-273.
- [10] N. I. Sari and S. Harianis, “Analisis Faktor yang Mempengaruhi Kejadian Stunting pada Balita,” *Matern. Neonatal Heal. J.*, vol. 3, no. 2, pp. 57–64, 2022, doi: 10.37010/mnhj.v3i2.750.
- [11] D. A. Fitria, “Peran Pemerintah Dalam Penanganan Stunting Pada Balita Di Kelurahan Alai Kecamatan Ungar,” *Pubmedia Soc. Sci. Humanit.*, vol. 1, no. 3, p. 6, 2023, doi: 10.47134/pssh.v1i3.160.
- [12] R. Hasanah, F. Aryani, and B. Effendi, “Pemberdayaan Masyarakat Dalam Pencegahan Stunting Pada Anak Balita,” *J. Masy. Madani Indones.*, vol. 2, no. 1, pp. 1–6, 2023, doi: 10.59025/js.v2i1.54.
- [13] K. Suryani, M. T. Rini, B. D. Hardika, and N. K. Widiastari, “Analisis Faktor Penyebab Kejadian Stunting,” *J. Keperawatan Florence Nightingale*, vol. 6, no. 1, pp. 8–12, 2023, doi: 10.52774/jkfn.v6i1.112.
- [14] M. H. M. Rohman *et al.*, “Clustering Analysis of Stunting Risk Factors Using K-Means and Principal Component Analysis: A Case Study in Indonesian Regency,” *Sinkron*, vol. 9, no. 1, pp. 65–77, 2025, doi: 10.33395/sinkron.v9i1.14311.
- [15] N. Effendi, D. Handoko, F. Azim, and F. Farida, “Jurnal Computer Science and Information Technology (CoSciTech) things,” vol. 5, no. 2, pp. 358–366, 2024.
- [16] P. Meriyana, A. R. Pratama, E. Nurlaelasari, and A. R. Juwita, “Penerapan Algoritma KNN dan,” vol. 06, no. 02, pp. 72–84, 2025.
- [17] F. Irahmani, F. Damayanti, B. K. K, and M. A, “Optimalisasi Pengelompokan Kecamatan Berdasarkan Indikator Pendidikan Menggunakan Metode Clustering dan Davies Bouldin Index,” *Semin. Nas. Sains dan Teknol. UMJ*, no. 11, pp. 1–5, 2014.
- [18] A. Ersawahyuni, S. Martha, and H. Perdana INTISARI, “Pengelompokan Indeks Pembangunan Manusia Di Indonesia Menggunakan Metode K-Medoids Dengan Evaluasi Davies Bouldin Index,” *Bul. Ilm. Math. Stat dan Ter.*, vol. 14, no. 2, pp. 207–216, 2025.
- [19] W. Widhari, A. Triayudi, and R. T. K. Sari, “Implementation of Naïve Bayes and K-NN Algorithms in Diagnosing Stunting in Children,” *SAGA J. Technol. Inf. Syst.*, vol. 2, no. 1, pp. 164–174, 2024, doi: 10.58905/saga.v2i1.242.
- [20] H. Saleh, M. Faisal, and R. I. Musa, “Klasifikasi Status Gizi Balita Menggunakan Metode K-Nearest Neighbor,” *Simtek J. Sist. Inf. dan Tek. Komput.*, vol. 4, no. 2, pp. 120–126, 2019, doi: 10.51876/simtek.v4i2.60.
- [21] U. R. Gurning, S. F. Octavia, D. R. Andriyani, N. Nurainun, and I. Permana, “Prediksi Risiko Stunting pada Keluarga Menggunakan Naïve Bayes Classifier dan Chi-Square,” *MALCOM Indones. J. Mach. Learn. Comput. Sci.*, vol. 4, no. 1, pp. 172–180, 2024, doi: 10.57152/malcom.v4i1.1074.
- [22] A. Maulana *et al.*, “Classification of Stunting in Toddlers using Naive Bayes Method and Decision Tree,” *Indones. J. Mod. Sci. Technol.*, vol. 1, no. 1, pp. 28–33, 2025, doi: 10.64021/ijmst.1.1.28-33.2025.
- [23] R. N. Pratistha and B. Kristianto, “Implementasi Algoritma K-Means dalam Klasterisasi Kasus Stunting pada Balita di Desa Randudongkal,” *J. Indones. Manaj. Inform. dan Komun.*, vol. 5, no. 2, pp. 1193–1205, 2024, doi: 10.35870/jimik.v5i2.634.
- [24] A. Fadilah, M. N. Pangestu, S. Lumbanbatu, and S. Defiyanti, “Pengelompokan
-

- Kabupaten/Kota Di Indonesia Berdasarkan Faktor Penyebab Stunting Pada Balita Menggunakan Algoritma K-Means,” *JIKO (Jurnal Inform. dan Komputer)*, vol. 6, no. 2, p. 223, 2022, doi: 10.26798/jiko.v6i2.581.
- [25] N. K. S. Julyantari *et al.*, “Implementasi K-Means Untuk Pengelompokan Status Gizi Balita (Studi Kasus Banjar Titih) Implementation of K-Means for Clustering the Nutritional Status of Toddlers (Banjar Titih Case Study),” *J. Janitra Inform. dan Sist. Inf.*, vol. 1, no. 2, pp. 92–101, 2021, doi: 10.25008/janitra.
- [26] W. Prihartono *et al.*, “Optimalisasi Upaya Pencegahan Stunting,” (*Jurnal Inform. dan Tek. Elektro Ter.*, vol. 13, no. 2, pp. 9–15, 2025.
- [27] M. I. Kamil and A. P. Wibowo, “Implementation of the Naive Bayes Classifier Algorithm for Classifying Toddler Nutritional Status,” *J. Appl. Informatics Comput.*, vol. 8, no. 2, pp. 421–427, 2024, doi: 10.30871/jaic.v8i2.8669.
- [28] A. Ridwan and T. N. Sari, “The comparison of accuracy between naïve bayes classifier and c4.5 algorithm in classifying toddler nutrition status based on anthropometry index,” *J. Phys. Conf. Ser.*, vol. 1764, no. 1, 2021, doi: 10.1088/1742-6596/1764/1/012047.
- [29] C. K. Putra and A. Alamsyah, “Increase Accuracy of Naïve Bayes Classifier Algorithm with K-Means Clustering for Prediction of Potential Blood Donors,” *Journal of Advances in Information Systems and Technology*, vol. 4, no. 1, pp. 42–49, 2022, doi: 10.15294/jaist.v4i1.59977.
- [30] N. Mirantika, R. Trisudarmo, and T. S. Syamfithriani, “Implementation of Naïve Bayes Algorithm for Early Detection of Stunting Risk,” *Journal of Applied Informatics and Computing (JAIC)*, vol. 9, no. 2, pp. 233–239, 2025, doi: 10.30871/jaic.v9i2.9144.
- [31] R. W. Dwinanto, A. S. Sandi A., and R. Ardianto, “Klasifikasi Berisiko Stunting pada Balita: Perbandingan K-Nearest Neighbor, Naïve Bayes, Support Vector Machine,” *METHOMIKA: Jurnal Manajemen Informatika dan Komputerisasi Akuntansi*, vol. 8, no. 2, pp. 264–273, 2024, doi: 10.46880/jmika.vol8no2.pp264-273.
- [32] E. Nurjannah, M. Nasution, and R. Muti’ah, “Data Mining Clustering Analysis of Child Growth and Development Using the K-Means Method,” *Sinkron: Jurnal dan Penelitian Teknik Informatika*, vol. 8, no. 3, pp. 1909–1919, 2024, doi: 10.33395/sinkron.v8i3.13817.
- [33] S. Melyani, “Prediction of Stunting in Toddlers Combining the Naïve Bayes Algorithm,” *Sinkron: Jurnal dan Penelitian Teknik Informatika*, vol. 9, no. 1, pp. 123–131, 2024. doi: 10.33395/sinkron.v8i2.13651.
- [34] T. S. Priyadarshini *et al.*, “Collaboration of Clustering and Classification Techniques for Complex Medical Data,” *Informatics in Medicine Unlocked*, vol. 41, pp. 101261, 2025, doi: 10.1016/j.measen.2024.101405
- [35] W. Putri, D. Hastari, K. U. Faizah, S. Rohimah, and D. Safira, “Implementation of Naïve Bayes Classifier for Classifying Alzheimer’s Disease Using the K-Means Clustering Data Sharing Technique,” *Public Research Journal of Engineering, Data Technology and Computer Science (PREDATECS)*, vol. 1, no. 1, pp. 1–8, 2023, doi: 10.57152/precedatecs.v1i1.803.
- [36] A. Mahiruna, N. Ngatimin, R. Destriana, E. H. Rachmawanto, H. Yuliansyah, and M. T. Hidayat, “Enhancing Clustering Accuracy Using K-Means with Seeds Optimization,” *Journal of Applied Informatics and Computing (JAIC)*, vol. 9, no. 5, pp. 2426–2433, 2025. doi: 10.30871/jaic.v9i5.10458
- [37] A. A. Nababan, “Application of Naïve Bayes Algorithm for Dominant Disease Classification in Coastal Areas,” *InfoSains*, vol. 6, no. 1, pp. 45–53, 2024. doi: 10.54209/infosains.v14i01.