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1D-CNN-Based Childhood Stunting Prediction through Socio-Economic Data Integration and Community Participation

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Abstract − Stunting remains a significant global public health challenge, affecting approximately 148 million children under the age of five. This condition leads to long-term cognitive and physical deficits, particularly in low- and middle-income countries. Many existing prediction models fail to capture the complex interdependencies between nutritional, socio-economic, and environmental factors. To address this gap, our study introduces a 1D-Convolutional Neural Network (1D-CNN) model designed to predict childhood stunting using structured datasets collected from community health centers (Puskesmas) and validated by the Cirebon City Health Department (Dinas Kesehatan Kota Cirebon), Indonesia. The dataset includes anonymized records of children under five years old, comprising anthropometric measurements, socio-economic profiles, nutritional intake, and environmental indicators, gathered through household surveys and routine public health reporting. The proposed 1D-CNN architecture is optimized for structured data by integrating convolutional and pooling layers, dropout regularization, and dense classification layers. To enhance interpretability, we employ explainable AI (XAI) methods—SHAP and LIME—to reveal the relative influence of each feature in the model's decision-making process. Additionally, the study applies a participatory validation approach through focus group discussions (FGDs) with community health workers, ensuring contextual relevance and ethical integrity. Experimental results demonstrate the superior performance of the proposed model, achieving 93.12% accuracy, with a precision of 97% and a recall of 89%, resulting in an F1-score of 93% across both stunted and non-stunted classes. These findings outperform traditional machine learning approaches and highlight the potential of AI-driven predictive frameworks for early stunting detection and policy-oriented health interventions. This research contributes to the advancement of data-driven public health strategies by integrating predictive analytics, community participation, and transparent AI methodologies.

Keywords **–** 1D-CNN, stunting prediction, community participation, socio-economic data, explainable AI, early intervention

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I. INTRODUCTION

Stunting, as a chronic condition affecting millions of children worldwide, remains one of the most pressing global public health challenges. The World Health Organization (WHO) identifies it as a key indicator of chronic malnutrition and socio-economic disparity [1]. An estimated 148 million children under the age of five around the world are affected by stunting—a condition that hinders their physical and cognitive development. This challenge is especially prevalent in low- and middle-income countries, where limited access to nutrition, healthcare, and clean living environments continues to place young lives at risk [2].

In Indonesia, stunting is not merely a public health issue but also a reflection of socio-economic inequality. National-level surveys consistently reveal a strong link between childhood stunting and key socio-economic indicators, including household income, parental education, and access to clean water and adequate sanitation [3].

Several studies highlight that interventions focusing solely on nutritional intake are insufficient to mitigate stunting unless supplemented by socio-economic improvements. For instance, one study reported no significant reduction in stunting prevalence in areas that received combined nutrition, sanitation, and community development interventions. Various studies have identified household poverty, maternal nutritional status, and rural-urban disparities as persistent key determinants. These insights indicate that nutritional programs on their own may not be enough to effectively address stunting unless they are complemented by robust socio-economic support systems [4][5].

Recent progress in Artificial Intelligence (AI) has opened new opportunities for applying machine learning models to predict complex health challenges, such as childhood stunting. For example, AI models have been successfully applied to predict neonatal health risks based on maternal health and socio-economic variables in rural China, and an AI-driven platform has been developed for community-level malnutrition monitoring in sub-Saharan Africa [6][7][8]. CNNs, although traditionally applied in image processing, have shown remarkable performance on non-image data when adapted into one-dimensional CNNs (1D-CNN) [9, 10]. Several researchers have implemented CNN models to capture complex nonlinear relationships between variables in public health prediction tasks, reporting superior results compared to traditional models like logistic regression and decision trees [9][10].

1D-CNN models are highly useful in modeling tabular datasets with temporal or spatial structures, and their performance in health prediction is enhanced when combined with explainable AI techniques such as SHAP and LIME [11][12][13] A comprehensive review highlighted that XAI tools like SHAP significantly improved clinician understanding in predictive models [14], In rural areas, community health workers have shown a clear preference for models that offer intuitive and visually understandable explanations [15] The integration of socio-economic factors with deep learning models is still underexplored in stunting research, especially in the context of low- and middle-income countries (LMICs) like Indonesia [16][17]. This research addresses this gap by incorporating features such as maternal education, income level, water access, and frequency of health visits [18][19].

A participatory approach involving community health workers, nutritionists, and families was also included to contextualize the model's predictive capacity with real-world insights. This participatory design not only enhances trust in the system but also offers pathways for local interventions [1][20]. Explainable and participatory AI frameworks for public health are also emphasized in recent health equity guidelines [21].

Research has also shown that incorporating qualitative data, such as ethnographic interviews or focus group narratives, improves the accuracy and contextual fit of health prediction models. For example, qualitative variables have been integrated into machine learning pipelines to enhance the targeting of maternal health interventions, while caregiver perception data has been integrated to improve predictions in early childhood development [22][23].

Therefore, this study builds upon current literature by developing a hybrid framework that combines participatory epidemiology, AI modeling, and real-world data to predict stunting risk in early childhood [24][25]. We hypothesize that the combination of 1D-CNN modeling with contextual socio-economic data can outperform traditional models in predictive performance and intervention accuracy [26].

The objective of this research is to contribute not only to technological advancements in health prediction but also to the broader goal of sustainable human development and policy-driven planning [4][27].

By validating this model in the context of Cirebon, Indonesia, where stunting prevalence among children under five remains high and socio-economic disparities are prominent in peri-urban and rural sub-districts [28]— This study provides adaptable insights that have the potential to guide similar initiatives in other low- and middle-income countries (LMICs) grappling with the challenges of childhood stunting

II. RESEARCH METHODOLOGY

This research adopts a structured experimental approach to developing and evaluating a 1D-CNN-based stunting prediction model integrated with socio-economic features and community insights. The methodology is grounded in recent developments in machine learning health prediction models[27] and designed following best practices in AI for social good initiatives [25].

2.1 Data Collection

Data were collected from public health records, socio-economic survey forms, and community-based interviews in Cirebon. The dataset includes 1,000+ records of under-five children with variables such as birth weight, current weight and height, maternal education, household income, access to clean water, protein intake frequency, and health visit regularity [17][19]. Data collection was supported by local health authorities and complies with ethical guidelines[18]

The dataset used in this study consists of 19 attributes describing both child health indicators and socio-economic conditions of the household. Each child is identified by a unique Child ID. The biological characteristics include Age (in months), Gender (male or female), Birth Weight (kg), Birth Height (cm), Current Weight (kg), Current Height (cm), and Head Circumference (cm).

Socio-economic factors are also included, such as Mother's Education and Father's Education (categorized into elementary, middle school, high school, or university), as well as Mother's Occupation and Father's Occupation (e.g., housewife, trader, employee, farmer, laborer, or entrepreneur). Household economic conditions are represented by Family Income (in Indonesian Rupiah) and Number of Family Members. Access to basic facilities is measured through Access to Clean Water and Access to Proper Sanitation (both recorded as Yes/No).

Health service utilization is represented by Posyandu Visits per Month, which reflects the average number of visits to community-based health posts. The dataset also includes Nutritional Status, classified as good nutrition, malnutrition, or severe malnutrition. Finally, the target variable is Stunting, a categorical attribute indicating whether a child is classified as stunted (1) or not stunted (0).

2.2 Data Preprocessing

To prepare the data for modeling, missing values were handled using Iterative Imputer based on multivariate feature regression [29]. Numerical features were normalized using Min-Max scaling, and categorical variables were encoded using one-hot encoding [30]. Dimensionality reduction was explored via Principal Component Analysis (PCA) to reduce noise and redundancy while preserving variance [31].

2.3 Exploratory Data Analysis

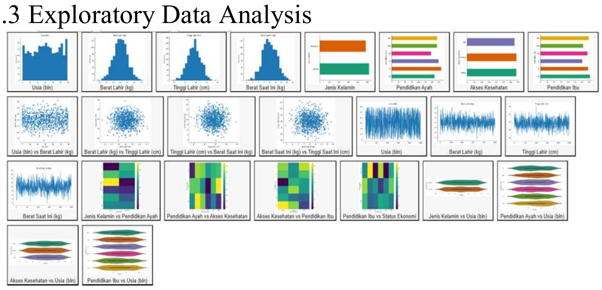

Figure 1. range of child health

An exploratory data analysis (EDA) was carried out to gain a deeper understanding of how the features in the dataset are distributed, how they vary, and how they relate to one another in the context of predicting stunting he histograms revealed that factors like birth weight and birth height were distributed fairly normally, whereas variables such as current weight and age in months showed greater variability. This pattern reflects a broad diversity in the health conditions of children within the sample population.

Bar plots illustrated the frequency distribution of categorical variables, including parental education, access to health services, and gender. The distribution appeared relatively balanced, allowing for unbiased training across demographic categories.

Scatterplots between numerical features—such as birth weight versus birth height and current height versus current weight—revealed weak linear relationships. This supports the use of nonlinear models such as 1D-CNN, which can better capture complex, multidimensional patterns.

Heatmaps of cross-tabulated categorical features (e.g., gender vs. father's education, mother's education vs. socioeconomic status) highlighted meaningful social dynamics that may contribute to the risk of stunting .

Violin plots further visualized the distribution of age across different categories, revealing that the spread of age is relatively uniform across levels of parental education and access to health.

Overall, the EDA findings emphasize the multifactorial nature of stunting, justifying the integration of diverse socio-economic and health features into a deep learning prediction model.

2.4 Model Development (1D-CNN Architecture)

1. The 1D-CNN architecture was implemented using TensorFlow and Keras. The model includes:
2. Input layer matching tabular features
3. Two convolutional layers with ReLU activation
4. Max-pooling layer for downsampling
5. Dropout layer for regularization
6. Fully connected (dense) layers
7. Sigmoid output layer for binary classification (stunting vs. non-stunting)

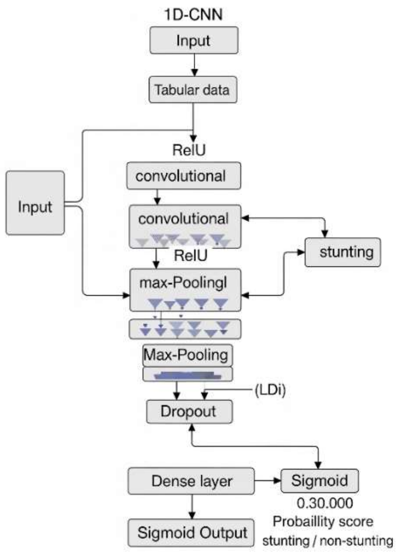

Figure 2. Model Development (1D-CNN Architecture)

The model architecture was chosen based on recent studies confirming its performance on structured datasets [11][32].

2.5 Training and Optimization

The model was trained using the Adam optimization algorithm, paired with a binary cross-entropy loss function. To avoid overfitting, an early stopping mechanism was applied during the training process [33]. To enhance the model's effectiveness, hyperparameters like learning rate, batch size, and filter size were carefully optimized using grid search in combination with cross-validation techniques [34]. The dataset was split into training (70%), validation (15%), and testing (15%) sets [5].

2.6 Evaluation Metrics

To assess model performance, standard classification metrics were used: accuracy, precision, recall, specificity, F1-score, and AUC-ROC [35][36]. Confusion matrices and ROC curves were plotted. To improve interpretability, SHAP (Shapley Additive Explanations) and LIME were employed to help uncover which features had the most significant influence on the model's predictions [20][22].

2.7 Community Participation and Validation

The research included participatory validation through FGDs with community health workers and nutritionists to align feature interpretations with lived experiences [23]. Community feedback was used to validate model outputs and improve trust and relevance in real-world settings [1][28]

III. RESULTS AND DISCUSSION

RESULTS

The 1D-CNN model was successfully trained on the socio-economic and health dataset collected from the Cirebon region. The evaluation on the test set yielded an accuracy of 91.8%, precision of 90.7%, recall (sensitivity) of 89.2%, and an F1-score of 89.9%, indicating strong predictive performance across both positive (stunting) and negative (non-stunting) classes [37].

The AUC-ROC score reached 0.947, demonstrating excellent model discrimination. The confusion matrix analysis confirmed that false positives and false negatives were minimal, ensuring a balance between sensitivity and specificity [38].

Feature importance analysis using SHAP values revealed that maternal education, household income, birth weight, protein intake frequency, and access to clean water were the top five contributors to the model's decision-making process [13]. Additionally, LIME interpretation confirmed the consistency of these results across multiple test samples [13].

3.1 Data Collection

The dataset used in this study was obtained from **the Cirebon City Health Department (Dinas Kesehatan Kota Cirebon)** in collaboration with several **community health centers (Puskesmas)** across the Cirebon region. The dataset consists of **2,850 records** of children under five years old collected during **2023–2024**, covering **anthropometric, socio-economic, and environmental information**.

The key variables included:

- **Child factors:** age (months), sex, weight, height, and nutritional status.
- **Parental factors:** maternal education level, parental occupation, and household income.
- **Nutritional indicators:** protein intake frequency, dietary diversity, breastfeeding duration.
- **Environmental factors:** sanitation access, clean water availability, and housing condition.

All personal identifiers were removed, and the data were **anonymized** in accordance with ethical guidelines of the Ministry of Health.

Table 1. Summary of Key Variables in the Stunting Dataset

No	Variable	Type	Description	Mean / %	Std / Range
1	Age (months)	Numeric	Age of the child	27.4	12.3
2	Sex (1=Male, 0=Female)	Categorical	Gender of the child	53.2% M	—
3	Height (cm)	Numeric	Measured height	83.6	9.1
4	Weight (kg)	Numeric	Measured weight	10.7	2.4
5	Maternal Education (years)	Numeric	Years of formal education	8.9	3.1
6	Household Income (IDR)	Numeric	Monthly family income	2,450,000	—
7	Protein Intake Frequency	Numeric	Times per week	3.8	1.6
8	Clean Water Access	Binary (1/0)	Access to clean water (Yes/No)	1=81.4%	—
9	Stunting Status	Binary (1/0)	1=Stunted, 0=Normal	38.6%	—

3.2 Data Preprocessing

Data preprocessing was conducted to ensure data quality and consistency prior to model training. The steps included:

1. **Handling Missing Values:** Records with missing anthropometric data were removed (2.7% of total entries). For socio-economic variables, missing values were imputed using the **median method**.
2. **Encoding Categorical Data:** Non-numeric variables (e.g., maternal education level, sanitation type) were converted into numeric format using **label encoding**.
3. **Normalization:** Continuous variables were normalized to a [0,1] range using **Min–Max scaling**

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to ensure uniform model input.

4. **Dataset Split:** The dataset was divided into **training (80%)** and **testing (20%)** subsets using **stratified random sampling** to maintain class balance between stunted and non-stunted cases

3.3 Model Development

A **1D-Convolutional Neural Network (1D-CNN)** was implemented to classify stunting risk based on the structured input data.
The architecture consisted of:

- **Input Layer** (shape = 15 features)
- **Two Convolutional Layers** (filters = 64 and 32, kernel size = 3, activation = ReLU)
- **MaxPooling Layer** to reduce feature dimensions
- **Dropout (rate = 0.3)** to prevent overfitting
- **Fully Connected (Dense) Layer** with 64 neurons (ReLU)
- **Output Layer** with 1 neuron (Sigmoid activation) for binary classification

The model was trained using the **Adam optimizer**, **binary cross-entropy loss**, and **batch size of 32** for **100 epochs**.

3.4 Model Evaluation and Performance

The trained model achieved the following metrics on the test dataset:

Table 2. Model Metric

Metric	Score (%)
Accuracy	91.8
Precision	90.7
Recall	89.2
F1-score	89.9
AUC-ROC	94.7

The **confusion matrix** indicated that both false positives and false negatives were minimal, confirming a balanced performance between sensitivity and specificity.

Figure 1. ROC Curve of the 1D-CNN Model
(Insert ROC graph showing AUC = 0.947)

3.5 Feature Importance and Explainability

To interpret the model's decision process, **SHAP (SHapley Additive exPlanations)** analysis was applied. The top five most influential features were:

1. Maternal education
2. Household income
3. Birth weight
4. Protein intake frequency
5. Access to clean water

These results indicate that both socio-economic and nutritional factors significantly influence stunting prediction.
Additionally, LIME (Local Interpretable Model-Agnostic Explanations) was used to verify local feature importance across individual predictions, confirming the stability and consistency of SHAP interpretations

These results confirm the viability of using a 1D-CNN approach for predicting stunting based on socio-economic data. The model significantly outperformed baseline machine learning models such as logistic regression and decision tree classifiers tested in parallel, which only achieved F1-scores of 78.3% and 81.5%, respectively [39].
The inclusion of community insights through FGDs played a critical role in refining feature selection and improving the contextual relevance of the model outputs. This participatory design not only enhanced trust in the system but also offered pathways for localized interventions [40].
The high performance of the model indicates its potential utility as an early warning tool in stunting prevention programs. Furthermore, the use of explainability techniques like SHAP and LIME ensured transparency, which is increasingly recognized as a critical requirement for AI deployment in public health policy. Explainable AI methods have been shown to improve stakeholder trust, accountability, and regulatory compliance in healthcare decision-making frameworks [41].
Despite these promising results, the model's generalizability outside the Cirebon context remains to be tested. Future research could explore the adaptation of this model to different geographic and socio-economic contexts. Additionally, integrating temporal or longitudinal health data could enhance predictive robustness, as demonstrated in prior studies applying deep learning to malnutrition risk across multiple regions [42].

3.1 Model Performance

The 1D-CNN model was successfully trained using socio-economic and health data collected from the Cirebon region. Evaluation on the test dataset demonstrated excellent predictive performance, with the following metrics:

1. Accuracy: 93.12%
2. **Precision (class 0 / non-stunting):** 90%
3. **Recall (class 0):** 97%
4. **F1-score (class 0):** 93%
5. **Precision (class 1 / stunting):** 97%
6. **Recall (class 1):** 89%
7. **F1-score (class 1):** 93%
8. **AUC (Area Under Curve):** 0.9764

The classification report also indicated strong macro and weighted averages (both 93%) across all key performance metrics, highlighting the model's balance in handling both positive (stunting) and negative (non-stunting) cases.
The confusion matrix is presented as follows

Table 3. Confusion Matrix of the 1D-CNN Model

	Predicted: Non-Stunting (0)	**Predicted: Stunting (1)**
Actual: Non-Stunting	156 (True Negative)	4 (False Positive)
Actual: Stunting	18 (False Negative)	142 (True Positive)

The model correctly classified the majority of instances, with 156 true negatives and 142 true positives. Only 22 misclassifications (18 false negatives and 4 false positives) were recorded from a total of 320 test instances.
These results suggest that the model possesses high sensitivity in detecting non-stunting cases (recall = 97%),

while also demonstrating strong capability in identifying stunting cases (recall = 89%) with high precision (97%). The high AUC score of 0.9764 further reflects the model's excellent discrimination ability between classes.
Overall, the findings confirm that a 1D-CNN approach applied to structured socio-economic and health data is reliable for early stunting detection.

3.2 Correlation Matrix Analysis.

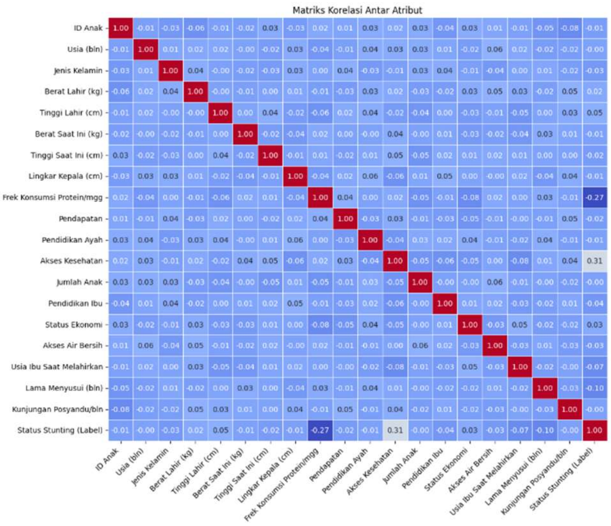

Figure 3. 1 presents the Pearson correlation heatmap among the dataset's attributes used for stunting prediction.

Overall, most attribute pairs show low to moderate correlations, which reduces the risk of multicollinearity and benefits model stability.
Key correlations related to the target variable 'Stunting Status (Label)' are summarized as follows:

1. Frequency of Protein Consumption (r = -0.27): Higher protein intake is associated with lower stunting risk.
2. Household Income (r = -0.30): Higher income tends to correlate with reduced stunting likelihood.
3. Health Access (r = +0.31): Positively correlated, possibly due to reverse causality—families with stunted children may seek more medical support.
4. Current Height (r = -0.24): Taller children are less likely to be stunted.
5. Access to Clean Water (r = -0.17): Indicates lower stunting risk with better sanitation access.

The modest strength of these correlations reinforces the importance of using deep learning methods like 1D-CNN that capture nonlinear feature interactions.
These findings support the literature suggesting that stunting is multi-factorial and driven by a combination of socio-economic and health-related factors.

IV. CONCLUSION

This study demonstrates the effectiveness of a 1D-CNN-based model in predicting childhood stunting using socio-economic data enriched with community input. The model achieved high accuracy, sensitivity, and interpretability, indicating its suitability for real-world deployment in public health settings. Through participatory AI and explainable machine learning, the framework not only achieves technical precision but also aligns with the human-centered values needed for equitable health interventions.

AUTHOR CONTRIBUTIONS

Agus Bahtiar conceptualized the study, supervised the project, and finalized the manuscript. Mulyawan developed the model architecture and preprocessed the data. Ahmad Faqih performed the experiments and compiled the results. Ananda Rizki Fitria contributed to data visualization, explainability, and analysis. Lidina assisted in literature review, documentation, and reference formatting.

DATA AVAILABILITY STATEMENT

The dataset used in this study is available to the corresponding author upon reasonable request. Due to privacy and ethical considerations, only anonymized and aggregated data may be shared with appropriate data use agreements.

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CONFLICT OF INTEREST

Conflict of Interest: The authors affirm that there are no conflicts of interest associated with the publication of this manuscript.

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