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Development of Robot Feature for Stunting Analysis Using Long-Short Term Memory (LSTM) Algorithm

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Abstract - Stunting prevalence in Indonesia persists as a significant challenge, necessitating concerted efforts from all stakeholders. We developed a robot for stunting analysis using a deep learning algorithm. It aligns with the Sustainable Development Goal (SDG) agenda, specifically targeting SDG 3, which focuses on ensuring good health and well-being for all. Long Short-Term Memory (LSTM) is a type of Recurrent Neural Network (RNN) developed to address the issue of vanishing gradient in RNNs. In general, either LSTM can be used in analysis. This study aims to classify stunting based on age and height using LSTM. The LSTM model was trained with 50 epochs using datasets collected from the health office and robots. The evaluation results show a training accuracy of 96.65% and training validation of 96.61%, with precision, recall, and f1-score varying in relevance to the f1-score and support value. This research illustrates the potential for using data classification methods in stunting diagnosis. However, it is necessary to adjust parameters and augment the training dataset to enhance model performance. With good convergence at epoch 50, these results show the model's ability to classify stunting based on age and height. However, further validation and testing on larger datasets is needed to thoroughly test the reliability and generalization of the model. This research can contribute to the development of deep learning regarding robots as a means of testing stunting. This research provides initial evidence of the potential of stunting classification methods using robots. However, parameter adjustments and increasing the amount of training data need to be done to improve the overall model performance.

Keywords—Long short-term memory, LSTM, Stunting, Robot, Deep learning, Classification

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1. INTRODUCTION

The toddler stage is a critical phase in a child's growth and development journey, as it lays the foundation for their cognitive abilities to blossom in alignment with their age-related milestones. Nutritional deficiencies during this pivotal period can severely impede a toddler's growth trajectory, leading to frequent illness and, if left unaddressed, potential mortality[1]. Addressing malnutrition remains a top priority for the government, with particular emphasis

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on combating stunting—a condition characterized by growth impairment, where a child's height fails to align with their age due to prolonged inadequate nutritional intake. Stunting prevalence in Indonesia persists as a significant challenge necessitating concerted efforts from all stakeholders. Recognizing its gravity, the Indonesian government has designated stunting management as a national priority program, mandating comprehensive strategies to curb its escalating incidence [2]. The bad impact of stunting is a decrease in academic achievement, increasing the risk of obesity, being more susceptible to non-communicable diseases, and increasing the risk of degenerative diseases (which is a process of gradual reduction in nerve cell function for no known reason). There are two negative impacts that stunting can have, namely short term and long term. In the short term, it affects brain development, where if nutrition is not appropriate, brain development is reduced, on the other hand, motor brain development is delayed, In the long term, the adverse effects that may occur include impaired cognitive abilities and learning achievements, weakened immunity making one more susceptible to illnesses, and an increased risk of developing diabetes, obesity, cardiovascular diseases, cancer, stroke, and disabilities in later life [3].

According to the Ministry of Health in Indonesia, the latest findings from the Indonesian Nutritional Status Survey (SSGI) indicate a positive trend: the prevalence of stunting declined from 24.4% to 21.6% in 2022 [4]. While this is encouraging progress, it's important to note that the World Health Organization (WHO) recommends a stunting prevalence of less than 20%. In Semarang, one of Indonesia's cities, the stunting prevalence stood at 21.3% in 2021 [5]. Researchers have highlighted that stunting is most prevalent among toddlers from low socio-economic backgrounds [6]. Additionally, parental education levels play a significant role in shaping parental knowledge about nutrition and childcare practices. Inappropriate parenting patterns can elevate the risk of stunting among children[7]. The development of robots for stunting detection has been gaining significant attention. An anthropometric system equipped with multisensory detection was developed to enable non-contact measurement. This system utilizes a variety of sensors, including load, distance, and temperature sensors. Specifically, load cells and infrared sensors are employed to measure body mass, height, and head circumference [8]. Additionally, an Arduino microcontroller-based system utilizes ultrasonic and load cell sensors to measure the length and weight of children. The data gathered from these sensors are processed by a microcontroller for early stunting detection [9]. However, a fully integrated robotic system with multisensory capabilities for early stunting detection has yet to be developed.

Aligning with SDG program, our recent development, Lintang (meaning 'star' in Javanese) robot, represents a significant contribution in the realm of toddler education within Semarang city as can be seen in Figure 1. Accessible through https://robotlintang.id/, Lintang serves as an innovative tool aimed at enlightening parents on the critical importance of fostering a healthy and hygienic environment for their toddlers. Under the ownership of the Semarang City Government, Central Java, Indonesia, Lintang is poised to become an integral resource for disseminating information and education about stunting, a prevalent concern among children in the region. There are three main advantages of the robot, namely: early detection of stunting, child-friendly design, and cost-effective solution. Lintang stands as a versatile device capable of accurately measuring the weight and height of toddlers up to children under 5 years old, in strict accordance with the regulations outlined in Indonesia's stunting prevention program. Leveraging the ESP32 Microcontroller, which facilitates internet connectivity, and a connected load cell, Lintang can seamlessly transmit measurement data to a secure private database server. This data serves as a foundational resource for analyzing the possibility of stunting in children, enabling proactive intervention and support. Moreover, the integration of Robot Lintang's measurement results with the data of children registered as patients at the Semarang City Health Office, managed through the website information system https://sim.sayanganak.semarangkota.go.id/, ensures the creation of comprehensive medical records.

Figure 1. Lintang, Equipped With IoT And AI For Early Stunting Detection And Text-to-Speech Integration

2. LITERATURE REVIEW

In the field of stunting identification using machine learning and deep learning techniques, several methods have been investigated. For example, the Random Forest method attains an accuracy of 79%, whereas the Artificial Neural Network method achieves an accuracy of 72% [10],[11]. Despite these promising results, the landscape of stunting classification methods encompasses a myriad of alternatives, necessitating the pursuit of a reliable approach that optimizes accuracy and reduces data dimensionality, especially when dealing with extensive feature sets[12]. Deep learning methodologies emerge as compelling candidates for stunting classification due to their demonstrated efficacy in achieving high performance and accuracy levels. Notably, LSTM method has garnered attention for its adeptness in handling sequential data, a characteristic particularly advantageous for stunting analysis [13]. Unlike traditional algorithms, LSTM is highly effective at capturing long-term dependencies in sequential data, thus enhancing the interpretability of stunting trends [14],[15]. Motivated by these considerations, this study employs the LSTM method for stunting classification, leveraging its capabilities to integrate and analyze sequential stunting data. In light of the foregoing discussion, this research undertakes the classification of stunting utilizing the LSTM method, drawing upon integrated stunting data. This approach is particularly pertinent given the nature of stunting data, wherein variables such as body weight are not merely measured at a single instance but are instead analyzed sequentially to discern developmental trends. By harnessing the power of LSTM and sequential data analysis. This research aims to provide new perspectives on categorization and understanding of stunting phenomena.

3. RESEARCH METHODOLOGY

The methodology outlined in this research is an attempt to develop a robot designed to detect stunting early through the use of deep learning techniques. This framework integrates dataset from healthcare institution, i.e., Dinkes data, and IoT to tackle this pressing issue. It comprises seven interconnected components, including the acquisition of health institution data and the utilization of IoT technology for real-time data collection. By merging health institution data with IoT-generated data, the framework enables comprehensive analyses of stunting risk factors. Preprocessing, augmentation, and balancing of the dataset are essential steps to ensure data quality and model robustness. Splitting the dataset into training and validation sets facilitates model development and evaluation. The utilization of LSTM networks, renowned for their capacity to model time-based relationships, is central to the framework's methodology. The stunting detection model undergoes thorough testing to gauge its effectiveness and accuracy. Through comprehensive evaluation metrics and validation procedures, the framework seeks to ensure the reliability and utility of the developed system.

Figure 2 shows the research methodology. This study only discusses the evaluation stage and will not proceed to the deployment stage.

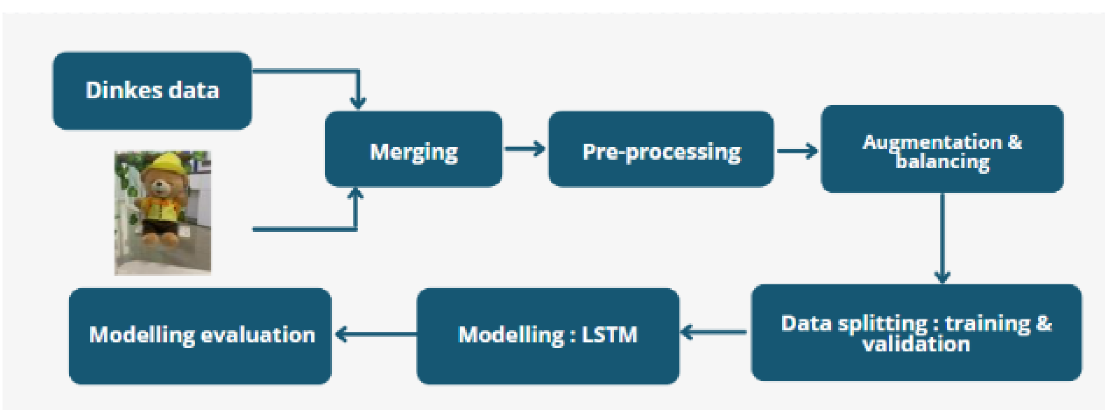


Figure 2. Research Methodology Focusing On The Evaluation Stage

The research integrates two distinct datasets: one sourced from healthcare institutions, specifically Dinkes data, and another obtained from IoT sensors embedded within the robot. This amalgamation of data sources enriches the research dataset, providing a comprehensive foundation for stunting analysis. Upon merging the datasets, a rigorous preprocessing phase ensues. This involves thorough data cleaning procedures to eliminate inconsistencies and errors, ensuring that the combined dataset is coherent and readily interpretable. Such meticulous preprocessing enhances the efficacy of subsequent data analyses.

Following data cleaning, the augmented dataset undergoes a process of augmentation and balancing. This step aims to enhance the dataset's richness and diversity while addressing any potential biases or imbalances inherent in the original data sources. By augmenting and balancing the dataset, the research endeavors to improve the robustness and generalizability of the subsequent models. Subsequently, the augmented and balanced dataset is partitioned into distinct subsets for training and validation purposes. This partitioning facilitates effective model development and evaluation, ensuring that the developed models are both trained on sufficient data and validated on independent samples. The core of the methodology revolves around the utilization of LSTM networks. These specialized recurrent neural networks excel at modeling the temporal dependencies within sequential data, rendering them particularly well-suited for analyzing time-series data such as that encountered in stunting research. By employing LSTM algorithms, the research aims to extract meaningful insights from the combined dataset, effectively converting raw data into actionable information.

Finally, the developed models undergo comprehensive evaluation using rigorous modeling evaluation techniques. This evaluation process is designed to assess the performance and efficacy of the stunting detection models, with a particular emphasis on minimizing error rates and maximizing predictive accuracy. Through meticulous evaluation metrics and validation procedures, the research endeavors to ensure the reliability and utility of the developed stunting detection system.

3.1. LSTM Algorithm

The LSTM algorithm constitutes a notable advancement within the domain of recurrent neural networks (RNNs). Designed to mitigate the challenges associated with long-term dependency problems, such as the vanishing gradient issue, LSTM offers a capability to capture and retain information over extended sequences. This unique feature sets it apart from traditional methods, making it particularly well-suited for tasks requiring the processing of lengthy temporal data. At the heart of the LSTM architecture lies its ability to maintain long-term memory through specialized memory cells. Comprising an input layer, hidden layer, and output layer, LSTM structures itself to effectively process sequential data over extended durations. Visualizing the LSTM architecture elucidates its intricate processing mechanism. Each LSTM cell generates two output results: the actual output transmitted to subsequent cells, and the formation of the output cell. Within this architecture, neural network layers containing parameters and biases are represented by boxes, while elemental operations such as vector element addition or multiplication are denoted by circles. The interconnection of matrices or vectors is visually depicted by joined lines, illustrating information flow, while diverging lines signify distinct pathways for data processing [16]. By encapsulating these fundamental principles, the LSTM architecture empowers researchers and practitioners to tackle complex temporal data analysis tasks with unprecedented efficacy and precision, thereby advancing the frontiers of machine learning and artificial intelligence [17]. Figure 3 depicts the architecture of LSTM method.

The main components of LSTM are as follow.

3.1.1. Forget Gate

The pivotal stage in LSTM processing involves discerning the pertinent information to retain within the cell state and identifying data that warrants discarding. This critical decision-making process is facilitated by a sigmoid layer referred to as the "Forget Gate Layer." Operating within a range of 0 to 1, the forget gate assigns values to determine the significance of incoming information. A value of 1 signifies that the data is deemed crucial and should be preserved within the cell state, whereas a value of 0 indicates that the information is deemed non-essential and consequently purged from memory. This meticulous gating mechanism enables LSTM networks to selectively retain salient information while discarding extraneous data, thereby enhancing their ability to capture and preserve essential temporal dependencies effectively.

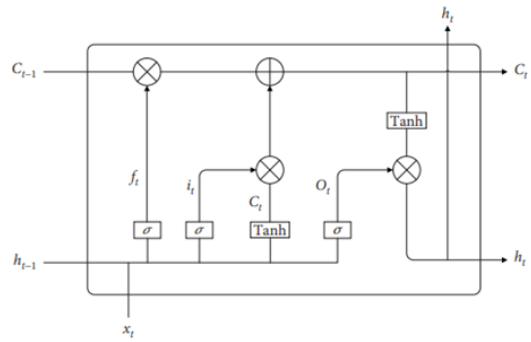


Figure 3. The Architecture Of LSTM Method

$$\text{Forget Gate } ft = \sigma(Wf\ .[\ ht{-}1, Xt\ ] + bf) \tag{1}$$

Where:

ft	: Forget Gate
σ	: Sigmoid activation function
Wf	: Weight of forget gate
$ht{-}1$	: hidden State in time step
Xt	: Data input

3.1.2 Input Gate

The subsequent phase in LSTM processing involves determining the assimilation of new information from the input (Xt) into the cell state, thereby facilitating the updating of the cell state. This pivotal task is orchestrated by the input gate, which encompasses two primary operations. Initially, a sigmoid layer, denoted as the "Input Gate Layer," is employed to compute the value of it, thereby determining the relevance of incoming data for updating. Subsequently, the tanh layer contributes to the process by generating a new candidate value for the cell state (Ct), further refining the information assimilation process. This intricate interplay between the input gate's constituent layers enables LSTM networks to selectively incorporate pertinent new information into the cell state, thereby ensuring the continual refinement and enhancement of model performance.

$$\text{Input Gate } it = \sigma(Wi\ .[\ ht{-}1,\ Xt\ ] + bi) \tag{2}$$

Where

σ	: activation function
Wi	: input gate weight i
ht-1	: Hidden state on timestep before
bi	: input gate bias

The subsequent stage involves the determination of which fresh input information (Xt) will be assimilated into the cell state, thus facilitating its update. This pivotal operation is orchestrated by the input gate, comprising two primary operations. Firstly, a sigmoid layer, referred to as the "input gate layer," computes the value of it, thereby discerning the relevance of incoming data for updating. Subsequently, the tanh layer contributes to this process by generating a new candidate value for the cell state (Ct). This dual-operation mechanism within the input gate ensures the selective integration of pertinent new information into the cell state, thereby perpetuating the refinement and optimization of LSTM model performance.

3.1.3 Update Cell State

During the cell state update phase, the previous cell state undergoes transformation to yield the current cell state. This critical stage serves to discern newly relevant information while expunging extraneous data. The formulation of this update process stems from the integration of inputs from both the gate and forget gate mechanisms. By amalgamating these inputs, the LSTM model achieves a refined cell state representation, thereby enhancing its capacity to capture and retain salient temporal dependencies while discarding irrelevant information.

$$Ct = ft * Ct{-}1 + it * Ct \tag{3}$$

Where

Ft	: foregate gate
Ct-1	: cell state on time before
It	: input gate
Ct	: cell state

3.1.4 Output Gate

The computation of the current cell state (Ct) involves several key steps. Firstly, the prior cell state ($Ct{-}1$), in conjuction with the current input (xt) and the previous hidden state ($ht{-}1$), is utilized to generate an intermediate value. This value is then subjected to parameter multiplication, akin to previous stages, but exclusively focused on the output gate. Subsequently, the resulting product undergoes transformation through a sigmoid function to constrain the output gate value (Ot) within the range of 0 to 1. Following this, the current cell state (Ct) is modulated using hyperbolic tangent activation (tanh) to confine its value between -1 and 1. Finally, the output gate value (Ot) serves as a weighting factor, dictating the contribution of the transformed cell state to the calculation of the current hidden state (ht). This meticulously orchestrated process ensures the precise modulation of information flow within the LSTM architecture, thereby facilitating effective learning and prediction tasks.

$$Ot = \sigma\, (Wo * [\ \mathrm{O}\ ht{-}1, Xt\ ] + bo\ ) \tag{4}$$

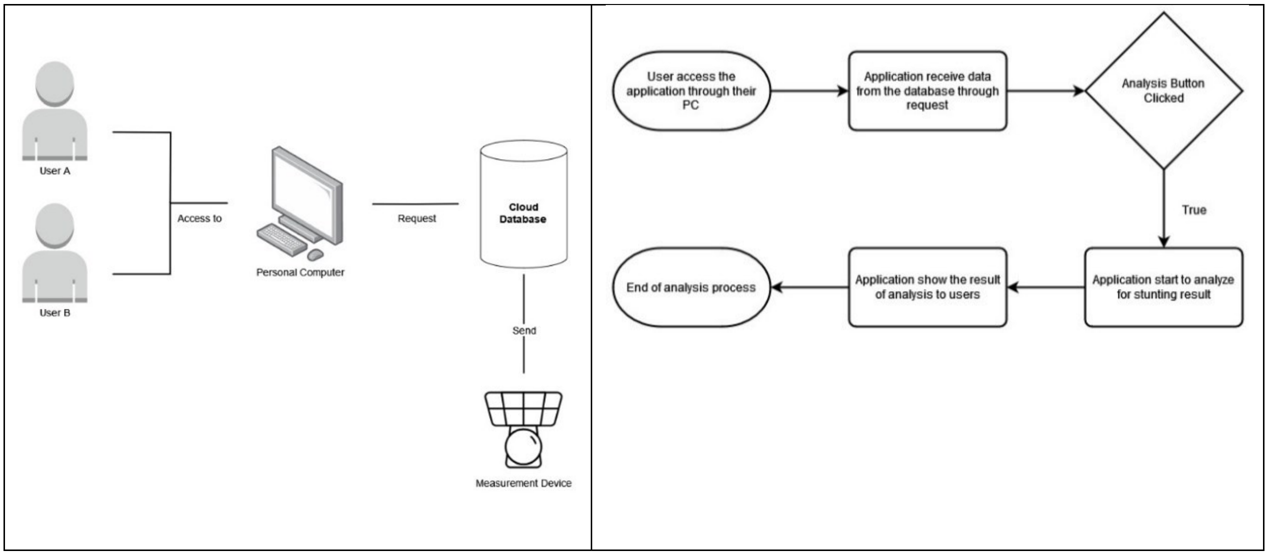
Where:

Ot	: output gate
Bo	: bias output

3.2 Integration Of Classification To Application

In the current study, we focus on the development of web application, which is pivotal in modern software ecosystems. It is a Website Application developed using the Laravel framework, leveraging the PHP programming language in its latest version 8.0. Laravel was chosen due to its user-friendly nature and the inclusion of its own Eloquent Model, streamlining database processes. The developed application encompasses essential components including a landing page, serving as the initial point of interaction for users, dashboards providing a comprehensive overview of measurement results obtained from the associated device, and detailed pages offering in-depth analysis of data pertaining to infants or children under 5 years old. This multi-faceted approach ensures that users have access to pertinent information and functionalities essential for effective monitoring and analysis within the specified domain.

As depicted in Figure 4, consider the scenario where two distinct types of users access the application via their Personal Computers (PCs), each connected to the internet to retrieve data from the database. Upon retrieval, the data is displayed within the application interface and undergoes acceptance to enable subsequent analysis within the system. Simultaneously, the database continually receives data from devices tasked with measuring infants or children under 5 years old, ensuring a consistent influx of information for analysis. While the application must cater to diverse user needs, it doesn't necessitate the implementation of separate systems. The system's process flow can be succinctly outlined through three sequential processes and a decision point. Upon user access, individuals can review records and measurement history encompassing variables such as weight, height, and Gross Motor Skills. Subsequently, these variables are parsed into the parameters required for the subsequent analysis process. Upon the user's request for analysis, the data is processed through this analysis module, yielding results that are then presented within the application interface. This process encapsulates the third step in the system's process flow, as illustrated in the flowchart diagra depicted in Figure 2.



(a) (b)

Figure 4. (a) Web Application's Usage Scenario, (b) Chart

3.3 Application Program Interface (API) And Request Method

In accordance with the preceding flowchart, the application interacts with the database via a request mechanism facilitated by an Application Programming Interface (API). These methods, often referred to as HTTP verbs, include GET, POST, UPDATE, and DELETE. Of these methods, the GET method is commonly utilized within the API context. It serves dual purposes: retrieving measurement data from the database and transmitting measurement data from the measurement device. The data transmitted by the device typically encompasses four attributes: Device ID, Height, Weight, and Measurement Position. Subsequently, this data is requisitioned by the application to facilitate stunting analysis and is persistently stored within the corresponding infant or child records. A comprehensive depiction of the API's operational flow can be observed in Figure 5, illustrating the seamless transfer of data between the application and the database through the intermediary of the API. This orchestrated exchange ensures the efficient retrieval, processing, and storage of critical measurement data, thereby facilitating the analysis and monitoring of stunting indicators within the specified domain.

4. RESULTS AND DISCUSSIONS

4.1 Dataset

The toddler data used was 9738 based on calculation of Z-Score TB/U. The dataset will be partitioned into training and testing subsets. The training subset will comprise 70% of the total data, while the testing subset will constitute the remaining 30%. The stunting dataset encompasses four attributes: gender, age, height, and weight, along with the stunting classification as shown in Table 1.

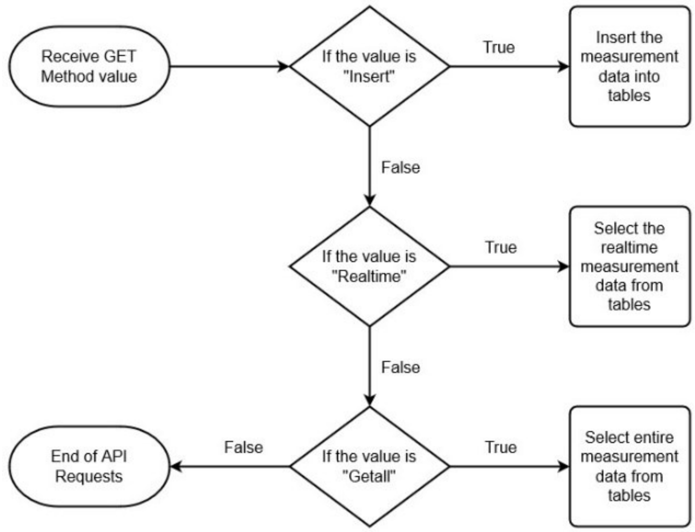


Figure 5. API Request Flowchart Diagram Methods

Table 1. Toddler Sample Data

No	Jenis_Kelamin	Umur	Tb	Bb	Stunting
1	L	43	92.0	12.15	ya
2	P	37	84.0	10.45	tidak
3	L	58	95.7	13.85	ya
4	L	18	74.0	8.00	tidak
5	L	17	78.3	8.45	tidak

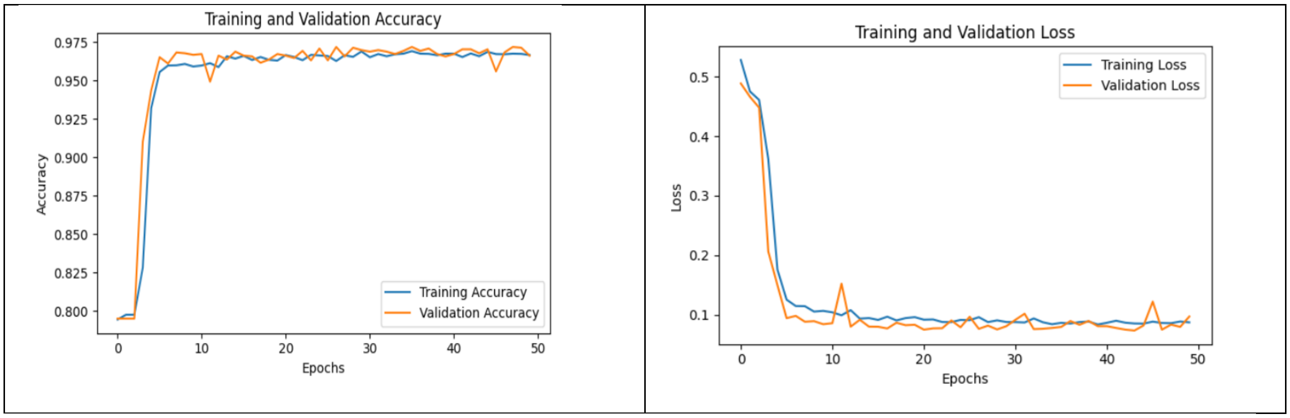
Where attribute:

Jenis_kelamin (gender): contains categorical data that has values Male(L) and Female(P)
Umur (Age): numerical data that shows the age of toddler based on month
Tb (Height): numerical data that shows body height in centimeter
Bb (weight): numerical data that shows body weight in kilogram
Stunting: the categorical value of the status of stunting

4.2 Modeling and Testing

Model evaluation is crucial in identifying the most effective architectural parameters. Prior to testing, preprocessed data undergoes a pivotal step known as data split, where it is partitioned into distinct subsets. This separation yields two subsets: training data and validation data, with a conventional ratio of 80% for training and 20% for validation. In this study, parameter experimentation focused on varying the number of neurons within the LSTM layer. Specifically, the test involved evaluating the performance of the LSTM layer with 64 neurons across 50 epochs. The outcomes of these tests are illustrated in Figures 6 (a) and (b), providing insights into the model's performance under different configurations. This rigorous testing regime enables researchers to identify the most suitable model architecture, ultimately facilitating the development of robust and effective stunting detection systems.

Figure 6 (a) illustrates the accuracy values obtained from both the training and validation datasets. In the training data, a commendable accuracy of 96.65% was achieved, exhibiting a consistent stability throughout the 50 epochs. Conversely, the validation data showcased a slightly lower accuracy of 96.61%, albeit with a notable improvement observed towards the 50th epoch.



(a) (b)

Figure 6. The Accuracy And Loss Of The Approach

Turning to Figure 6 (b) , the loss values for both the training and validation datasets are depicted. The training data yielded a minimal loss value of 0.0873, while the validation data exhibited a slightly higher loss value of 0.0972. Notably, the training data showcased a steady decline in loss values over the epochs, indicative of effective learning. Conversely, the validation data displayed a slight increase in loss values around the 10th epoch; however, this trend was subsequently reversed, with a notable decrease observed post the 12th epoch. These findings underscore the robustness of the model training process, with both accuracy and loss metrics indicating favorable outcomes. The minor fluctuations observed in the validation data suggest potential areas for further refinement; however, overall, the results signify the efficacy of the developed stunting detection model. Table 2 presents precision, recall and F1-Score of the approach.

Table 2. Precision, Recall And F1-Score Performance

Precision	**Recall**	**F1-Score**
0.97	0.86	0.91

5. CONCLUSION

The classification evaluation employing LSTM, trained over 50 epochs, yielded a commendable accuracy rate of 96.61%. This noteworthy result underscores the model's proficiency in correctly classifying instances, signifying its efficacy in stunting analysis. While this accuracy level is promising, there remains ample opportunity for enhancing model performance through meticulous parameter adjustments and augmenting the volume of training data. Such refinements hold the potential to further elevate the model's predictive accuracy and robustness, thereby enhancing its utility in real-world applications. Furthermore, an insightful analysis of the accuracy trends across epochs reveals compelling insights into the model's convergence behavior. Notably, at epoch 50, the model demonstrates signs of convergence, indicative of its adeptness in learning and generalizing from the training data. This convergence milestone serves as a testament to the model's efficacy in mastering the underlying patterns inherent in the dataset, thereby bolstering its classification capabilities. Moving forward, continued efforts to optimize model parameters and augment training data hold the promise of further enhancing the model's performance and resilience. Through iterative refinement and validation, the developed LSTM-based classification model stands poised to make meaningful contributions to the early detection and intervention of stunting, ultimately improving healthcare outcomes for vulnerable populations.

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AUTHOR CONTRIBUTIONS

Muhammad Rahadian Abdurrahman - Draft Preparation, Writing - Editing;
Halim Al-Aziz - Data Acquisition – Preprocesing, Writing;
Farras Adhani Zayn - Modeling – Writing.
Muhammad Agus Purnomo: Data Acquisition - Preprocessing, Writing;
Heru Agus Santoso: Conceptualization, Methodology, Supervision, Review - Editing;

CONFLICT OF INTERESTS

No conflict of interests were disclosed.

ETHICS STATEMENTS

Our publication ethics follow The Committee of Publication Ethics (COPE) guideline.

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