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A Vision-Based Deep Learning System Using Convolutional Neural Networks for Automated Recognition of Infant Complementary Foods

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ABSTRACT (10PT)

Automatic recognition of complementary foods (MPASI) plays an important role in supporting the objective and efficient monitoring of early childhood nutrition. However, the highly homogeneous visual characteristics of complementary foods in terms of colour, texture, and shape pose a significant challenge to computer vision-based recognition systems. This study proposes a Convolutional Neural Network (CNN)-based system for automatic classification of complementary food images using the ComFoodID21 dataset, a new dataset developed specifically to represent the variety of complementary foods. Three CNN architectures, namely EfficientNetB0, ResNet50, and MobileNetV2, were tested to evaluate the performance of complementary food image recognition. Experimental results show that ResNet50 provides the best balance between accuracy and computational time efficiency, achieving 98.28% accuracy, 99.14% precision, 98.28% recall, and 98.28% F1-score in about 4.5 minutes of training time. EfficientNetB0 achieved similar accuracy (98.28%) but required longer computation time (about 12.2 minutes), while MobileNetV2 obtained 93.10% accuracy with better memory efficiency. These findings suggest that CNN architectures with deep feature extraction capabilities such as ResNet50, are superior for homogeneous image domains such as complementary foods. Further research can be focused on the development of CNN-Transformer hybrid models and automatic nutrition estimation to support artificial intelligence-based nutrition monitoring systems.

1. Introduction

Complementary feeding is essential for children aged 6 to 24 months during the transition from exclusive breastfeeding to a more varied diet. These foods help fulfil nutritional needs that breastmilk alone can no longer fulfil after the first six months[1]–[3]. Appropriate complementary feeding practices are essential for optimal growth, development, and health outcomes in children 6-24 months of age [4].

Currently, monitoring the nutritional composition of complementary foods is largely manual and subjective. [5]–[7]. This can lead to inconsistencies and potential nutritional disparities, especially in regions with diverse weaning practices and limited resources[2], [8], [9]. In addition, the lack of comprehensive standardised guidelines and weak regulatory oversight of complementary feeding products increases the risk of nutritional gaps in early childhood [9]. Research shows that there is considerable variability in the nutritional content of complementary foods, which may affect the reliability of nutritional assessments. [5], [10], [11].

Automated food recognition systems, powered by artificial intelligence (AI), offer a promising solution to this challenge [12]–[14]. AI technologies, such as computer vision and machine learning, can facilitate more objective and accurate tracking of the nutritional content of complementary foods [15]–[17]. This technology can automate the identification and categorisation of food ingredients, making the process more efficient and reducing the risk of human error. [18]–[24].

Complementary foods usually have a soft texture, such as porridge, making it difficult to distinguish between different types of food based on texture alone [25]–[27]. The colour of complementary foods is often monotonous, usually shades of pale yellow, beige or orange. This lack of colour variation can lead to confusion in visually identifying different foods. [28]–[30]. There is often a gap between caregivers' knowledge and practices regarding complementary feeding, which can affect the consistency and quality of complementary feeding [31], [32].

Most computer vision-based food recognition research focuses on common foods or adult foods. [33]–[39]. Some popular datasets for food recognition include Food-101[40] and UEC FOOD 256[41], which includes many categories and general imagery, as well as Nutrition5k [42] which provides dishes with nutritional annotations, videos, and depth imagery. Other datasets, such as TurkishFoods-15 [33], AIFood [43], UEC FOOD 100/256 [41], Food2K[44], ISIA Food-500 [45], MyFoodRepo-273 [46], MedGRFood [47], and THFOOD-100 [48], offers various sizes, categories, and additional information such as segmentation or focus on specific cuisines. While covering a wide range of food types and culinary cultures, all of these datasets focus on general or adult foods, and none are specific to complementary foods.

Food recognition systems are essential for diet monitoring, calorie estimation, and management of health conditions. These systems can automatically identify foods and calculate their nutritional content, thus aiding better dietary management [49][50]. Convolutional Neural Networks (CNN) are widely used for food image recognition due to their high accuracy. [51]–[56]. For example, Inception-v4 achieved 95.2% accuracy on Indonesian food [57], while YOLOv5 and Faster R-CNN also showed promising results in detection and recognition. [41].

Although Convolutional Neural Networks (CNN) have achieved tremendous success in food recognition in general, some challenges remain unresolved. The quality and representativeness of existing datasets is one of the most critical issues, as most benchmarks such as Food-101 and UEC FOOD 256 were developed for adult foods and do not yet represent the characteristics of complementary foods. [51], [57]. Variations in backgrounds, lighting, and viewing angles also complicate the task of recognition [58]–[60]. c In addition, CNN models often face limitations in real-time performance and generalization, especially in dealing with high intra-class similarity and inter-class variability [61], [62]. Although transfer learning and data augmentation techniques have been used to improve resilience, these approaches are not always sufficient for domain-specific challenges [59], [60], [63]–[65].

Recent advances, including ensemble learning and knowledge distillation combining CNNs and Vision Transformers, have shown potential in improving classification accuracy and feature extraction[61]. Hierarchical classification, food localization, and new architectures such as ASTFF-

Net have also been introduced to handle multi-object scenes and complex lighting [60][62]. However, no research has specifically examined CNN-based recognition for complementary foods. The lack of domain-specific datasets and systematic evaluation highlights a significant research gap, motivating this study to explore CNN-based recognition as an initial benchmark for complementary food image analysis.

This research proposes a vision-based system using Convolutional Neural Network (CNN) for automatic recognition of complementary foods. This system is designed to identify various types of complementary food from food images with a high level of accuracy, so that it can support the process of monitoring child nutrition more objectively, quickly, and efficiently. By automating the identification process, this system is expected to contribute to the development of intelligent monitoring systems in the field of child nutrition and expand the application of vision-based control systems in the context of intelligent automation.

The novelty of this research lies in the application and evaluation of a CNN model optimized specifically for the visual characteristics of complementary foods, which have a high degree of colour and texture homogeneity. In addition, this research also developed a representative complementary food dataset to support model training, overcoming the limitations of common datasets that generally focus on adult food and do not take into account the visual peculiarities of baby food.

The main contributions of this research can be summarised in three ways.

- Design and develop a computer vision-based complementary feeding recognition system using Convolutional Neural Network (CNN) architecture with high accuracy, capable of classifying complementary feeding images automatically and efficiently.
- Build a special complementary food dataset (ComFoodID21) containing images of complementary foods with homogeneous visual characteristics, so that it can be used as an initial benchmark for deep learning-based baby food recognition research.
- Demonstrating the potential of applying CNN models within the framework of intelligent nutrition monitoring systems, as a first step towards the development of computer vision-based automated systems for classification and nutritional analysis of complementary foods.

2. Method

To achieve accurate and efficient classification of complementary food images, this study proposes a deep learning-based framework that integrates conventional and transfer learning approaches. This methodology is designed to systematically compare three convolutional artificial neural network (CNN) architectures: MobileNetV2, EfficientNetB0, and ResNet50.

The overall process starts with the collection of annotated food images followed by preprocessing steps such as resizing, normalization and data augmentation to improve generalizability. The dataset was then divided into training, validation, and testing subsets with proportions of 70%, 20%, and 10% respectively. Each model is trained on the same dataset configuration to ensure consistent comparison.

During the training phase, the model is optimized using the Adam's optimizer with categorical cross entropy as the loss function, while early stopping and learning rate reduction techniques are applied to prevent overfitting. Once the model is trained, performance is evaluated using accuracy, precision, recall, and F1 score metrics. The complete flow of the proposed methodology is illustrated in Fig. 1, which shows the flow from data collection to model evaluation

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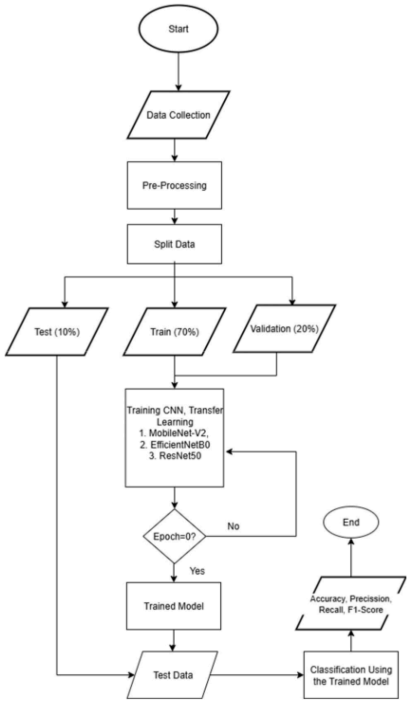

Fig. 1. The proposed method

3. Results and Discussion

This section presents the experimental results and discussion of the proposed computer vision-based complementary food recognition system. Experiments were conducted to evaluate the performance of three Convolutional Neural Network (CNN) architectures, namely MobileNetV2, EfficientNetB0, and ResNet50, in performing automatic classification of complementary food images using the ComFoodID21 dataset.

The main objective of this test is to assess the ability of each model to recognize complementary food images that have very homogeneous visual characteristics, in terms of color, texture and shape. Evaluation was conducted using accuracy, precision, recall and F1-score metrics, along with training time analysis and confusion matrix visualization to see the classification distribution of each class.

3.1. Data Collection and Preparation

The dataset used in this study, named ComFoodID21, was specifically developed to represent complementary foods for infants aged 6-24 months. The construction of the dataset began with the development of complementary food menus that followed the nutritional and health standards recommended by the Ministry of Health of the Republic of Indonesia's complementary food recipe book, as well as through expert validation and nutrisurvey. Overall, ComFoodID21 contains 1,378 complementary food images divided into 21 complementary food category classes with a total of 71 ingredient classes that represent typical Indonesian complementary foods. Each category has a minimum of 5 ingredient categories covering a wide range of food items such as rice, vegetables, fruits, animal proteins, and legumes to ensure nutritional diversity and real-world relevance.

After food preparation, each complementary food dish underwent nutrient composition analysis to document its macro and micronutrient content. This data was recorded as part of the research documentation prior to shooting. The image capture process was then carried out under controlled conditions to ensure uniformity and reproducibility. Images were taken using a digital camera at three different distances (10 cm, 20 cm, and 30 cm) with an aspect ratio of 1:1 to maintain proportional consistency across samples. To optimise natural lighting, all shooting sessions were conducted outdoors between 9am and 11am, when sunlight provides stable and diffuse lighting. These steps are systematically applied to ensure high-quality images suitable for computer vision analysis. Fig.2 is an example of the ComFoodID21 dataset

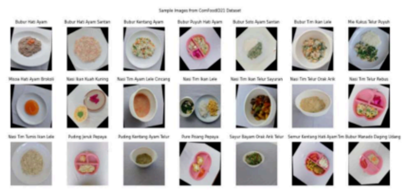

Fig. 2. Sample Images from ComFoodID21 Dataset

Initially, the collected images were annotated in YOLO format for the purpose of object detection. To support classification-based deep learning, the dataset was converted into a structured image classification format, with each class directory containing all images of a particular complementary food category. The data was divided into training (≈70%), validation (≈20%), and testing (≈10%) subsets to ensure a balanced representation across all 21 classes. The integrity of the dataset was validated by checking for missing or empty class folders, and the class distribution was visualised to ensure balance across divisions. Fig.3 shows the class-wise distribution graph of the dataset.

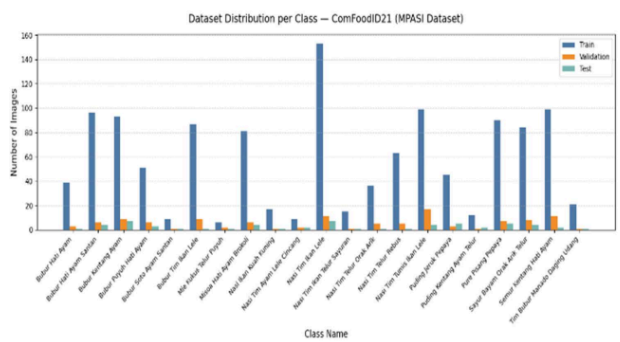

Fig. 3. Dataset Distribution per Class- ComFoodID21 Dataset

3.2. EfficienetB0 Model Results

The EfficientNetB0 model is used in this study to classify complementary food images based on 21 classes in the ComFoodID21 dataset. This architecture was chosen for its ability to balance network complexity and computational efficiency through a compound scaling approach that proportionally adjusts the depth, width and resolution of the network.

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Based on Fig. 4, it can be seen that the training process for 30 epochs shows a consistent trend of increasing accuracy and a steady decrease in loss value. In the early phase (epoch 0-5), the accuracy curve increases sharply in both training and validation data, indicating that the feature learning process is effective. After entering the 10th epoch, the validation accuracy is close to 0.95, then slowly increases until it reaches 98.28% at the end of training.

Meanwhile, the training loss and validation loss graphs show a consistent exponentially decreasing pattern until approaching convergence below the value of 0.1. There is no significant indication of overfitting, as the difference between the training and validation curves is relatively small. This shows that the model is able to generalise well to untrained data. The stable performance also reflects the superiority of the EfficientNetB0 architecture in handling highly homogeneous datasets such as complementary foods, where the differences between classes are often subtle and can only be distinguished through texture and micro-colour features.

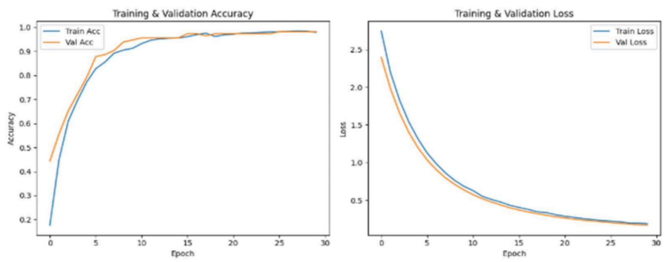

Fig. 4. EfficientNetB0-Training & Validation Accuracy and Loss

The confusion matrix shown in Fig. 5 illustrates the classification performance of the model against 21 classes of food images. Most of the main diagonal elements show high values, indicating that most of the classes can be correctly recognised by the model. For example, classes such as "Chicken Potato Porridge", "Broccoli Chicken Liver Miso", "Vegetable Egg Fish Team Rice", and "Scrambled Egg Team Rice" show a perfect number of true positives, each reaching 7 images on its diagonal. Only a small number of misclassifications occurred, for example, in the class "Chicken Liver Porridge" which was sometimes classified as "Coconut Milk Chicken Liver Porridge", as well as "Egg Chicken Potato Pudding" which slightly overlapped with "Papaya Banana Puree". This error is natural given the high visual similarity between the classes, both in terms of colour and surface texture.

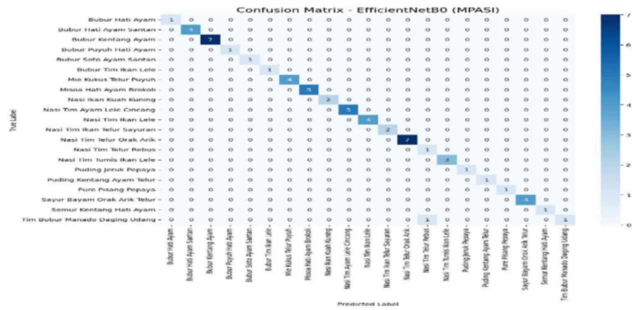

Fig. 5. Confusion Matrix- EfficientNetB0

3.3. MobileNetV2 Model Results

The MobileNetV2 model performed well in the complementary food image classification task, with an overall accuracy of 93.10%, precision of 89.68%, recall of 90.87%, and F1-score of 88.21%. Although the value is slightly lower than EfficientNetB0 and ResNet50, this result still shows that lightweight architectures such as MobileNetV2 are capable of classifying complementary food images with high accuracy in complex and homogeneous domains. Grafik *Training & Validation Accuracy* pada Fig. 6 shows that the accuracy increases sharply until around the 10th epoch, then stabilises near the maximum value with no indication of overfitting. Similarly, the loss graph shows a consistent downward trend between training and validation data, signalling the stability of the learning process.

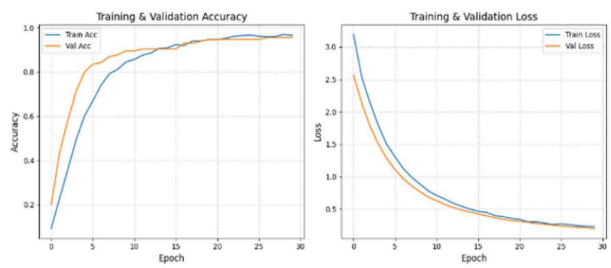

Fig. 6. MobileNetV2-Training & Validation Accuracy and Loss

The confusion matrix results in Fig. 7 show that most of the complementary food classes can be well recognised by the model, especially classes with quite distinctive visual features such as "Chicken Potato Porridge", "Catfish Team Rice", and "Broccoli Chicken Liver Mythos", which have a high number of correct predictions. However, there were some misclassifications in classes with very similar visual appearance, such as "Coconut Milk Chicken Liver Porridge" and "Catfish Team Porridge", which is most likely due to the homogeneity of color and texture in baby food. This phenomenon confirms that although MobileNetV2 is computationally efficient, its ability to extract fine features is still limited compared to deeper architectures such as ResNet50.

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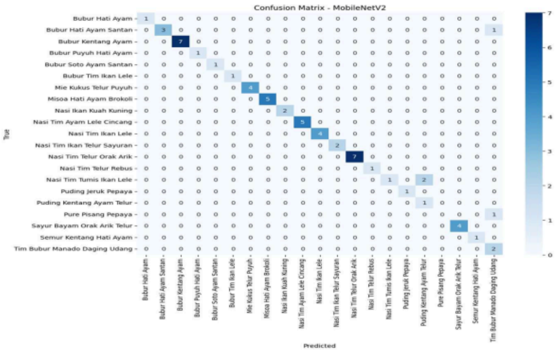

Fig. 7. MobileNetV2-Confusion Matrix

3.4. Results of the ResNet50 model

The training results using the ResNet50 architecture show excellent and stable performance in the classification process of complementary food images. Based on the Training & Validation Accuracy graph in Fig. 8, the model experienced a rapid increase in accuracy in the first 10 epochs, and stabilized around 98-99% in the 20th epoch until the end of the training. The difference between training accuracy and validation accuracy is very small, indicating that the model does not suffer from overfitting and is able to generalise well to the validation data. This is reinforced by the loss graph, which decreases consistently until it converges below 0.1, indicating an efficient and stable optimization process during training.

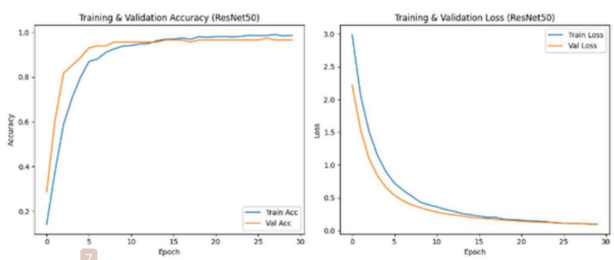

Fig. 8. ResNet50-Training & Validation Accuracy and Loss

The visualization of the confusion matrix in Fig. 9 shows that most of the complementary food classes are correctly classified, indicated by the dominance of high diagonal values in the matrix. Almost all categories such as "Chicken Potato Porridge," "Quail Egg Steamed Noodles," "Vegetable Egg Fish Team Rice," and "Vegetable Spinach Scrambled Egg" have perfect correct prediction rates. The misclassifications that do arise are only minor, generally occurring in classes with very similar visual characteristics (e.g. between "Catfish Team Porridge" and "Minced Catfish Chicken Team Rice"), which is reasonable given the visual homogeneity of the complementary food dataset. Quantitatively, the ResNet50 model achieved accuracy of 98.28%, precision of 99.14%, recall of

98.28%, and F1-score of 98.28%, making it the best-performing model compared to other architectures

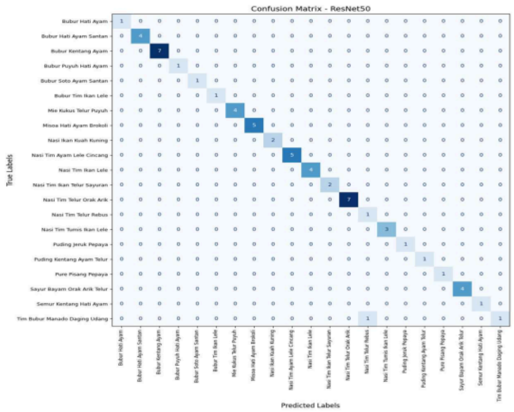

Fig. 9. ResNet50-Confusion Matrix.

3.5. Discussion

Experimental results show that the three Convolutional Neural Network (CNN) architectures EfficientNetB0, MobileNetV2, and ResNet50 are able to perform classification of complementary food images with high accuracy, but with different performance characteristics and computational efficiency. A comparison of the test results is shown in Table 1. and Fig. 10.

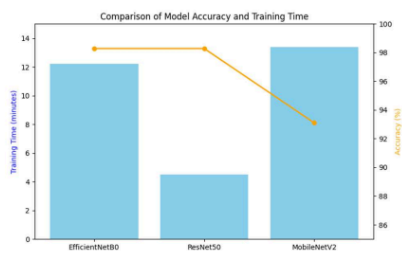

Fig. 10. Comparison of Model Accuracy and Training Time

Among the three CNN architectures, ResNet50 showed the best balance between accuracy and computation time, achieving 98.28% accuracy in about 4.5 minutes. EfficientNetB0 achieves comparable accuracy (98.28%) but requires longer computation time (~12 minutes) due to its complex network structure and initial model loading overhead. Meanwhile, MobileNetV2, which is designed for lightweight computing, performed the slowest training (13 minutes) but only achieved 93.10% accuracy, indicating that simplicity in model design does not necessarily guarantee faster convergence.

Table 1. Comparasion Of Performance and Computation Time of Three CNN Architectures on ComFoodID21 Dataset

Model	Epoch	Average Per Epoch (seconds)	Total Training Time (minutes)	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
EfficientNetB0	30	7.0 (+527 initial)	12.2	98.28	97.62	97.62	96.83
MobileNetV2	30	8.5 (+558 initial)	13.4	93.10	89.68	90.87	88.21
ResNet50	**30**	**8.9**	**4.5**	**98.28**	**99.14**	**98.28**	**98.28**

When compared with previous studies, this result is consistent with the findings of [47], who reported that ResNet50 provides the highest accuracy (97.8%) compared to EfficientNet and MobileNet in the classification of Mediterranean foods. The study showed that a deeper architecture with residual learning is more effective in distinguishing foods with high visual similarity, a phenomenon also seen in complementary food images. However, the results of this study are more challenging as the ComFoodID21 dataset has a high degree of homogeneity in colour and texture in contrast to common datasets such as Food-101 or UEC-FOOD256 which contain richer visual variations. Thus, achieving high accuracy in the complementary food domain signifies the success of the model in extracting discriminative features from images with low intra-class variation.

Furthermore, [66] reported that MobileNetV2, although computationally efficient, suffers from limitations in generalisation to objects with similar shapes and colours, similar to the low results observed in this study. In addition, previous research [67] showed that transfer learning-based models such as ResNet50 are superior in recognising complex food ingredients than lightweight models such as MobileNet, confirming the importance of architectural depth in capturing complex food semantic features.

4. Conclusion

This study proposes and evaluates a computer vision-based complementary food recognition system using a CNN architecture, utilising the ComFoodID21 dataset, which has a high level of visual homogeneity. The results of the experiment show that the CNN model is capable of learning relevant visual representations even though many food classes have similar colours, textures, and shapes. Among the three architectures tested, ResNet50 delivered the best performance with an accuracy of 98.28% and the fastest training time, followed by EfficientNetB0 with similar accuracy but longer training time, while MobileNetV2 showed the lowest accuracy and longest training time, indicating that lightweight architectures do not always excel in highly homogeneous image domains.

The visual homogeneity of complementary foods such as porridge, puree, and soft soups poses a major challenge because the model must extract highly discriminative deep features. The ComFoodID21 dataset plays an important role as an initial benchmark for deep learning-based baby food recognition research and opens up opportunities for developing adaptive models that are more suitable for homogeneous domains. Future research directions include exploring hybrid CNN-Transformer approaches, domain-adaptive fine-tuning techniques, and integrating automatic nutrient content estimation into AI-based smart nutrition monitoring systems to support more effective child nutrition and health analysis.

Author Contribution: **Nani Purwati** contributed to conceptualisation, methodology, data acquisition, software development, validation, formal analysis, investigation, resources, initial draft writing, review and editing, visualisation, and funding procurement. **R Rizal Isnanto** contributed to validation, review and editing, and supervision, while **Martha Irene Kartasurya** contributed to validation, review and editing, and supervision. **Andino Maseleno** contributed to validation, review and editing, and supervision.

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