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CLASSIFICATION OF STUNTED AND NORMAL CHILDREN USING NOVEL FACIAL IMAGE DATABASE AND CONVOLUTIONAL NEURAL NETWORK

Malnutrition is a crucial problem that affects children's development. Data released by UNICEF in 2022 shows that more than 7 million children under the age of 5 are still experiencing acute malnutrition in Ethiopia, Kenya, and Somalia. Meanwhile, in 2020, Indonesia ranked fifth and fourth highest in the world for wasting and stunting rates. The traditional approach to detect children's nutritional status is by measuring the ratio between body weight and height at a certain age. The approach can be improved by simultaneously using facial biometrics, which can be accomplished automatically by employing facial recognition/classification based on computer vision and artificial intelligence methods. ***The goal*** *of this research was to employ convolutional neural networks (CNN) as a method in the artificial intelligence field to classify children with malnutrition based on their face images.* ***The method:*** *a computer simulation of two CNN architectures applied to children's facial image database. The simulation results were then evaluated to obtain the performance of the CNNs. The* ***first task*** *accomplished was to build a database of facial images of Indonesian children aged 2–5 years. The database comprises 4000 frontal facial images built from capturing images from 100 children, 50 normal/healthy, and 50 stunted children. In the database, some images were augmented using zoom-in, rotation, and shifting procedures. Using the database, we performed the* ***second task*** *by training two CNN architectures, AlexNet and ResNet34, to classify the images into normal children and children with malnutrition problems. We trained both architectures with 80% of the images and then validated and tested them with 10% of the images. Both architectures were learned with epochs: 20, 40, 60, 80, and 100, with a learning rate of 10^{-3}. The models' performances were shown in training, validation, and testing loss graphs and measured in accuracy, recall, precision, and F1 score. In* ***conclusion****, both architectures have shown promising results in classifying the images. Both architectures learned with epoch 60 rate 10^{-3} yielded the best models, with an accuracy of 0.9975 for AlexNet and 1 for ResNet34.*

Keywords: *early detection; malnutrition children; facial image database; stunting; biometrics; CNN.*

1. Introduction

1.1. Motivation for research and the State of the Art

Malnutrition is one of the results of nutritional imbalance in the body, which can cause the death of children [1]. The criteria for malnutritional children are the ratio between height and weight at certain ages: children who are too short compared to their age are defined as stunted; children who are too thin compared to their height are called wasting; and children who are too heavy for their height are overweight. UNICEF data for 2022 showed that malnutrition cases in children under 5 were 148.1 million for stunting, 45.0 million for wasting, and 37.0 million for overweight [2]. Indonesia is among the countries with the highest number of malnourished sufferers in Southeast Asia, especially those with stunting [3]. According to empirical study in [4], there are some determinants of stunting, such as gender, birth spacing, maternal knowledge, maternal parenting, parental income, and utilization of health services. Among these, maternal knowledge and maternal parenting are associated with the highest risk of stunting, whereas birth spacing is associated with the lowest risk.

Undernutrition, i.e., stunting and wasting children, may have long-term irreversible effects, such as cognitive development [5, 6], and impaired physical growth [7]. Moreover, undernutrition may reduce reproductive function and sensory-motor abilities and increase children's vulnerability to infections and hereditary diseases, such as diabetes [7,8]. In 2017, WHO, as a policy maker, initiated the Double-Duty Actions (DDA) program in an integrated manner to prepare appropriate policies and programs from all sectors to reduce the risk of undernutrition worldwide [9]. Some countries' governments, such as Indonesia [10], Senegal [11], and Ethiopia [12], have initiated sustainable programs to lessen the risks of undernutrition in children.

Children's nutritional status is detected by measuring body weight and length/height, which is performed periodically at the Integrated Health Centre. With this approach, nutritional status cannot be obtained immediately or at any time. The effectiveness of monitoring children's nutritional conditions can be improved by using alternative methods that complement existing methods and can be used immediately at any time, for example, by automatic identification of nutrition status based on facial images.

Deep learning-based computer vision techniques have been applied to perform tasks based on images, such as land cover classification [13], pipe defect classification [14], and facial image characteristics, such as predicting gender and age [15, 16], and for detecting malnutrition [17] and children's malnutrition [9]. Generally, a child's face indicated by malnutrition can be seen from the cheeks that appear sunken, puffy and glazed eyes, dry, noisy, or wrinkled skin, and the face looks older than its age [18]. In addition, they may have decreased skin, respiratory, and gastrointestinal mucosal barrier reliability [19].

Research on deep learning used for the detection/classification of nutritional status based on body and facial images has been proposed by several researchers [9, 17, 20, 21]. In [20], researchers proposed a system to predict body dimensions based on height and waist circumference. They generated multi-view images from rendered digital 3D human body scans. Convolutional Neural Networks (CNNs) were then used to estimate height and waist circumference from the generated images. The researchers concluded that automatic malnutrition detection from single images appears feasible without further presenting prediction results on real images of children's bodies.

Works in [17] input facial images into a CNN that analyzes the input image and then groups it, whether it is an image of a malnourished or obese person. The researchers attempted to determine body weight and body mass index (BMI) from facial images. The body weight and BMI predicted values were then used to determine the nutritional status. The dataset of facial images was collected from the internet, including metadata containing information like gender, age, and BMI. The facial image is input to a deep learning machine with an architecture developed on the basis of Residual Network (ResNet).

In [21], a method to assess children's malnutrition status using facial images, several full-body images, and CNNs was proposed. The proposed system was applied to three image databases: 1. malnutrition database consisting of children's facial and body images collected from the internet, 2. adult facial and full body images with six different poses, and 3. school-age children's facial and full body images with six different poses. These images were used to train, test, and validate the ResNet, VGG, and DenseNet. The first database comprises images captured under uncontrolled settings. The images in the second and third databases were captured uniformly based on the six poses rule: frontal, back, lateral left, lateral right, hands wide, and facial selfies. It is worth noting that only the first database consists of children's images, presumably under the age of 5, although no such information was provided.

In [9], facial images, age, weight, and height were used as input to CNN (AlexNet) to classify children's nutritional status under the age of 5 into three categories: malnutrition, risk of malnutrition, and normal. This work showed that the AlexNet architecture can differentiate the children's images within those categories. However, it did not mention where or how the images were collected.

1.2. Objectives and approaches

Based on reports from recent literature, research interest in predicting people's nutritional status based on images and CNNs is growing [9, 17, 20, 21]. However, research using children's facial images as input to deep learning architecture is limited. These images are not available for other researchers to use for further research [9] or are captured under uncontrolled settings [21]. These factors can lead to difficulty in analyzing, comparing, and benchmarking the performances of several CNNs. To fill this gap, we present a novel and accessible facial image database of Indonesian children under the age of 5. The database contains original normal and malnourished (stunted) children's facial images. These images were captured with the consent of the children's parents/guardians and can be used for research. Each step in the image-capturing process is documented and presented in this article. We also present the performance of CNN architectures (AlexNet and ResNet34) using these images as input.

The proposed work classifies children's nutritional status based on facial images with the following contributions:

1) building a database of children's facial images from normal and stunted children. The database will be made available to the research community in computer vision, pattern recognition, deep learning, and so on. This article presents a procedure for image capturing. Therefore, it is possible to add more images to the current database if the capturing process complies with the presented mechanism;

2) provide preliminary performances of two CNNs, namely AlexNet and ResNet34 architectures in

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recognizing normal and stunted children using the image database. These performances can be used as benchmarks for further research. With the availability of the image database and the performances of those deep-learning networks, further research can be conducted, including embedding the resulting model into mobile-based applications, which can accomplish real-time malnutrition detection.

The rest of this paper is organized as follows: section two presents the materials and methods used in the research**,** including the procedures for training, validation, and testing AlexNet and Resnet34. Section three demonstrates the results and discussion. The conclusion is presented in the last section.

2. Materials and method of research

2.1. Material: Children's Face Database

The database comprises frontal facial images from 100 children, 50 normal/healthy children, and 50 stunted children, aged less than 5 years. From all children, the images were captured ten times, so the total number of images was 1000: 500 normal images and 500 stunted images. Images were collected from several Integrated Health Centre based on nutritional status data obtained from the Health Office. The pediatrician/care giver/health worker from the Community Health Center examined the children and stated the children's health condition before the images could be captured. In accordance with the code of ethics for publications protecting children's identity, parents or guardians must know the purpose and process of taking images of their child's face. We prepared a consent form to be signed by the parent/guardian of the children [22].

The procedure for taking the children's facial images is shown in Figure 1. Database collection was performed at the Integrated Health Centre using a CANON EOS M50 camera set to auto mode. The children were positioned 50 cm from the camera. Ring lights were positioned at the camera's left and right sides to obtain a brighter and clearer image. The image acquisitions were accomplished in the morning (9 AM - 12 PM) with temperature between 25 ℃ - 27 ℃, and humidity between 50% and 60 %. Figure 2 (a) shows some images of normal children and (b) those of stunted children. The original image size was 1620 x 1080 pixels.

In obtaining a good quality image, the main factor that is most carefully considered is the condition and situation of the child when being photographed. A comfortable atmosphere will make the child stand up or sit with a perfect attitude. To get the correct picture of the child, you need to communicate effectively so that the child does not cry when the picture is taken. Based on the child's age, there is a significant correlation between the atmosphere of communication, attention, and concession in children. The younger the child, his/her communication skills, attention, and concentration are lower. Therefore, it is more difficult to collect data using movements or demonstrations of movement, and the process of repeating photos must be increased. For children who cannot yet walk, taking photos is carried out in the child's position, assisted by their parents or guardians.

For training and testing purposes, we prepared the images according to the restrictions of ResNet34 and AlexNet. The original images with a size of 1620 x 1080 were cropped to 650x650 pixels. Then, these images were resized into 224x224 pixels for ResNet34 and 227x227 pixels for AlexNet. Then, the data augmentation is carried out. Augmentation is used to increase the amount of data to increase the accuracy of the CNN model. There were 3 augmentation techniques applied, namely zoom in, rotation with 3 rotations, namely 10°, 15°, and 20°, and translation by shifting the images to the right by 10% of the image width. From each augmentation technique, 1000 images were generated, resulting in 4000 images, including the original images. Examples of augmented images are shown in Figure 3.

2.2. Method: training, validation, and testing of AlexNet and Resnet34

AlexNet and ResNet are CNN architectures that won the ImageNet Large Scale Visual Recognition Challenge (ILSVRC), or simply ImageNet Competition, in 2012 and 2016, respectively. Both architectures can be considered a breakthrough in CNN development. Therefore, we want to provide a benchmark in recognizing normal and stunted children based on these architectures.

The structure of AlexNet is shown in Figure 4. AlexNet comprises 5 convolution layers, 3 max-pooling layers, 2 fully connected layers, and 1 SoftMax layer. Each convolution layer consists of a convolution filter and a non-linear activation function called "ReLU". The pooling layers perform the max-pooling function. AlexNet has over 60 million parameters [23].

The ResNet34 architecture is shown in Figure 5. ResNet conceptually differs from previous CNN designs, such as AlexNet and VGG-10. ResNet has more layers than AlexNet and VGG-19. However, what makes ResNet different from those two is the shortcut concept known as Identity Shortcut. The shortcut was proposed to solve the vanishing gradient that commonly occurs if the layers become too deep. The layers in ResNet34 are grouped into 5 stages; each stage has convolution and identity blocks. The identity blocks are replicated blocks because of the shortcut procedure applied in ResNet. Input is passed through these 5 stages, then pooled using

Fig. 1. The procedure of capturing the children's facial images

the average function, flattened, and passed through a fully connected layer and softmax function. ResNet34 has over 20 million parameters [24].

We built AlexNet and used Resnet34 to classify images of stunted and normal children. Figure 6 shows the flow diagram of the simulations. Input to these architectures is a grayscale version of the images, resized according to the requirements of the architecture. The input to AlexNet was 227 x 227 pixels, and input to the ResNet was 224 x 224 pixels. We trained both architectures with 80% of the images; 1600 images of stunted children and 1600 images of healthy children. We validated each of them with 10% of the images; 200 images of stunted children and 200 images of healthy children. The testing was done using the remaining 10% of the images. Both architectures learned with epochs: 20, 40, 60, 80 and 100, learning rate 10^{-3}, and batch size 32. We used Stochastic Gradient Descent (SGD) as optimizer, and cross entropy as a loss function.

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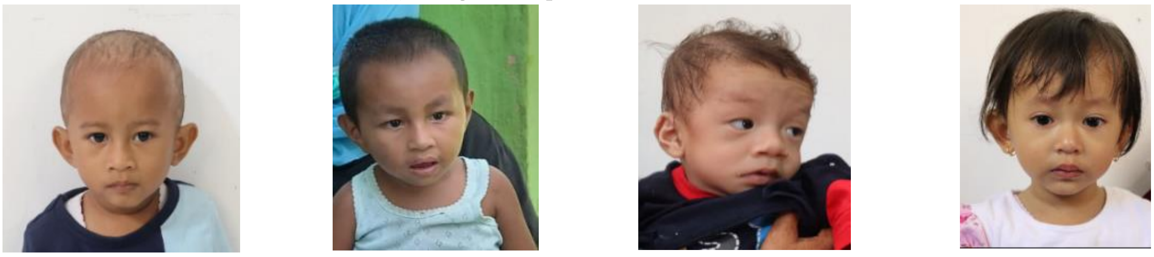
(a) Image examples of normal children



(b) Image examples of stunted children

Fig. 2. Image examples from normal and stunted children

(a) Original image (b) zoomed-in (c) rotated 20 degrees (d) translated

Fig. 3. Image examples from augmentation process

We present and discuss graphs from the training and validation stages. Evaluation of the models produced from the training and validation stages was measured using accuracy, recall, precision, and F1 score. Accuracy measures the number of correct predictions/classifications yielded by a model compared with the total number of predictions made. Recall is the percentage of images that a deep learning model correctly identifies as true positives out of the total images in the class. Precision measures the quality of a positive prediction made by the model, i.e., the comparison of true positives to all positive occurrences.

3. Results and Discussion

From the simulations, we present and discuss two points: (1) performance of AlexNet and ResNet34 as the epoch is increased and (2) performance comparison of both CNNs. Figures 7 (a) and (b) show the training and validation losses of AlexNet with epochs 20 and 100; and Figures 7 (c) and (d) show the curves of ResNet34.

Fig. 7 (a) and (b) show that the validation and training losses of AlexNet reduced as the epochs increased, and simultaneously, the validation loss is getting closer to the training loss, with some fluctuations. The validation curve with epoch 20 was mostly higher than that of the training curve. The curve has some fluctuations, and there was no indication that it will converge. On the other hand, with epoch 100, the validation curve converges to the training curve beginning around epoch 50.

The training and validation loss curves of ResNet34 with epochs 20 and 100 were steadier than those of AlexNet. In Figure 7 (c), at the beginning of the epoch, the validation loss curve lies below the training loss curve, and at epoch 10, the validation curve converges to the training curve. This suggests that the ResNet34 has already been learned so well that the error at the beginning of the validation stage is smaller than that in the training stage. ResNet34 training and validation curves with epoch 100 have a similar tendency to those of epoch 20. The training and validation curves converge starting from epoch 10 and continue to converge until epoch 100.

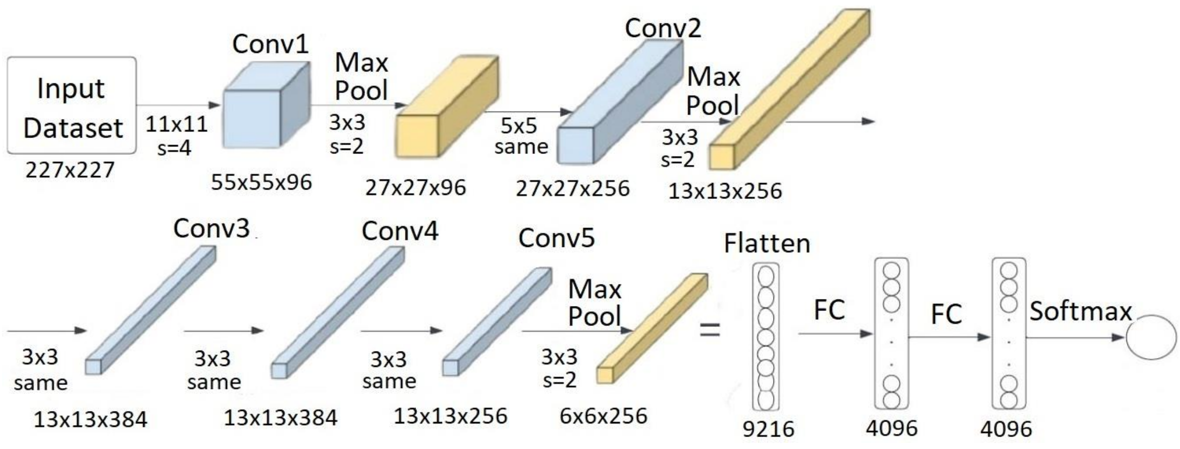


Figure 4. AlexNet Architecture

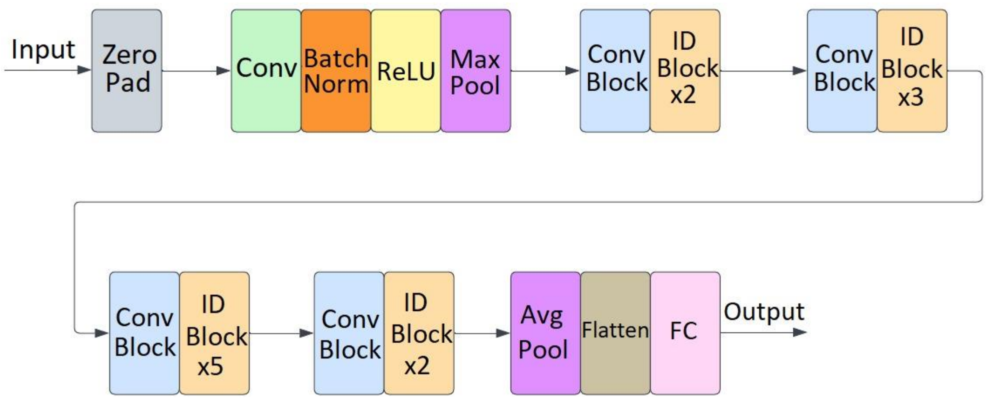


Fig. 5. ResNet34 Architecture

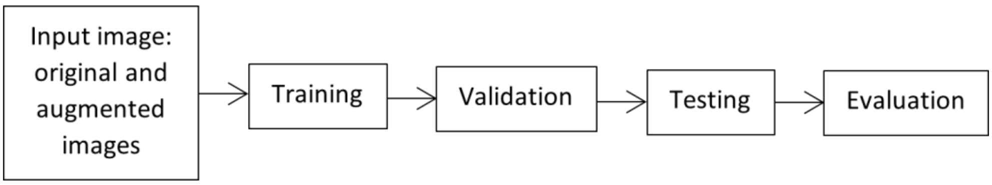


Fig. 6. Flow diagram of the simulations

Results of the testing phase are shown in Table 1 and Figure 8. Table 1 shows the testing results of AlexNet and ResNet34 from ten models, respectively. We provide the confusion matrixes of the testing phase from AlexNet and ResNet34 with epochs 20, 60 and 100 to further illustrate the performance of the models. All values are the average values of both classes (normal and stunted images). For example, the accuracy of AlexNet with epochs 60 was obtained by averaging the accuracy of each class, i.e.

$$((199/200) + (200/200)) /2 \text{ class} = 0.9975.$$

Overall, the testing results reveal a trend similar to the training and validation phases. For AlexNet, the accuracy of epoch 20 was the lowest, whereas for ResNet34, the accuracy of all epochs was steady at a value of 0.9975 unless the one with epoch 60 had an accuracy of 1.000. It turned out that AlexNet at epochs 40 and 60 resulted in the highest accuracy. Testing results suggested that the task of classifying images of normal and stunted children can be properly accomplished by a CNN that is less deep than ResNet but slightly deeper than AlexNet. In the future, we plan to broaden the

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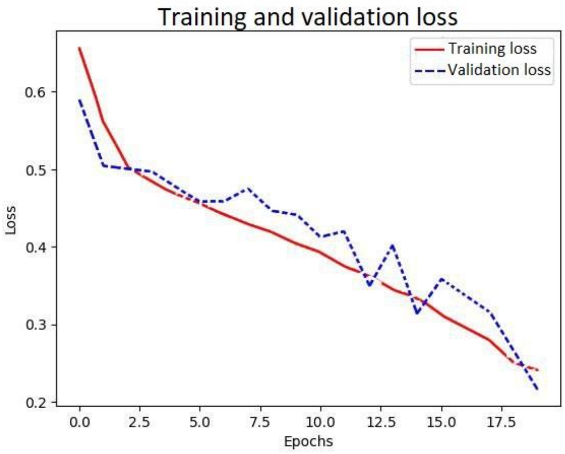
benchmarking data using other available CNN architectures, such as VGG-19, EfficientNet and MobileNet.

The work in [21] introduced a method with similar aims, yet with a broader approach, using facial and body images with five different body poses in parallel. Because of the parallel approach, the image database prepared for training and validation supposedly consists of face and body images. Unfortunately, the article did not mention that the database of malnourished children has five different body poses. These images were used to train and validate three CNNs, namely ResNet, VGG, and DenseNet. The highest accuracy was 71%, which was achieved by ResNet. Both [21] and the proposed method attempted to assess ResNet performance; however, they used different methods and images. Therefore, the accuracy of [21] was not directly comparable to that of the proposed method.

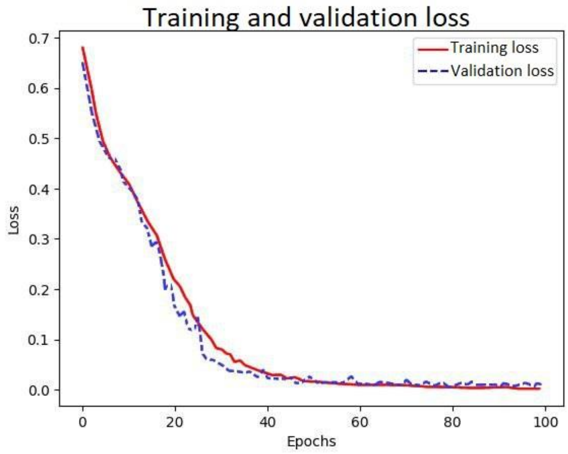
The results in this work are closest to those in [8], in which AlexNet and the children's facial images were used. The highest accuracy of [8] was 96%, achieved with a learning rate of 10^{-3}. With the same learning rate, this work achieved an accuracy of 99.75% with the epoch 60. The images used in both articles are not directly comparable. A total of 500 images were used in [8], and 1000 images were used in this work. The fact that there are twice as many images in this work as images in the [8] implies that the performance can be improved by increasing the number of training images. Our present work has good potential to be improved for a detection system based on images and deep learning algorithms for the early detection of stunting. By doing so, a proper image database should be built.

Conclusions

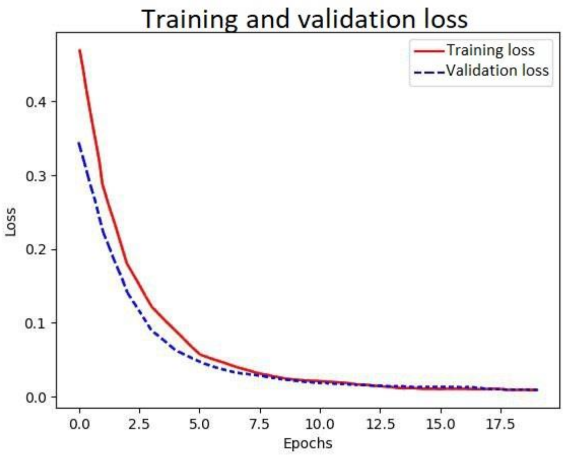
We present a classification method for stunted and normal children based on their facial images using two available CNN architectures. We built a novel image database to train and test CNNs. The main contribution of this work is the availability of an original image database for research purposes and a preliminary benchmarking on



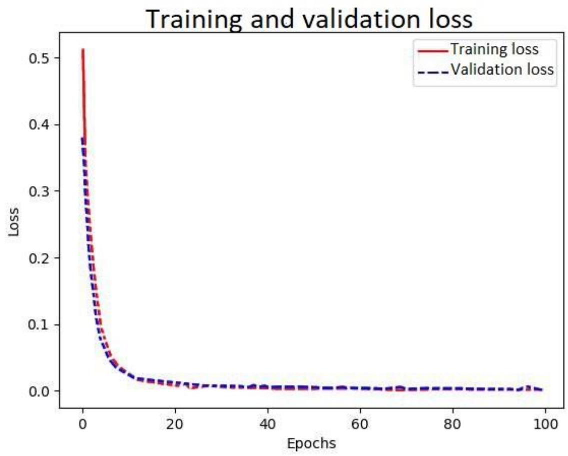
(a) Training and validation loss of AlexNet with epochs 20



(b) Training and validation loss of AlexNet with epochs 100



(c) Training and validation loss of ResNet-34 with epochs 20



(d) Training and validation loss of ResNet-34 with epochs 100

Fig. 7. Training and validation loss of AlexNet and ResNet with epochs 20 and 100

Table 1

Testing results of AlexNet and ResNet34

Architecture	Epoch	Accuracy	Precision	Recall	F1-Score
AlexNet	20	0.9050	0.9821	0.8250	0.8967
	40	0.9975	0.9950	1.000	0.9975
	60	**0.9975**	**1.000**	**0.9950**	**0.9975**
	80	0.9950	0.9950	0.9950	0.9950
	100	0.9950	1.000	0.9900	0.9950
ResNet-34	20	0.9975	0.9950	1.000	0.9975
	40	0.9975	1.000	0.9950	0.9975
	60	**1.000**	**1.000**	**1.000**	**1.000**
	80	0.9975	0.9950	1.000	0.9975
	100	0.9975	0.9950	1.000	0.9975

two CNNs, namely AlexNet and ResNet34 architectures, in recognizing normal and stunted children using the proposed image database. Furthermore, because the capturing procedure of the images was presented in detail, additional images can be added to the database by following the procedure.

The image database was built from 1000 original images captured from 100 frontal facial images of children, 50 normal/healthy children, and 50 stunted children. From these images, 4000 images were created, including some augmented images by zoom-in, rotating, and shifting operations. AlexNet and ResNet34, were trained using these images. Models from both architectures performed well, with the highest testing accuracy of 99.75 for AlexNet and 1 for ResNet34.

We plan to experiment with other CNNs, such as EfficientNet and MobileNet, and further fine-tune those CNN parameters to obtain a robust and best model**.** The best model can then be embedded into a smart mobile phone, and with a proper user interface, it can be used by pediatrician/care giver/health workers, even parents/guardians, to help monitor/early detect the children's nutritional status.

Contributions of authors: conceptualization, methodology – **Yunidar, Fitri Arnia, Nasaruddin, Yusni**; formulation of tasks, analysis **– Yunidar, Fitri Arnia, Nasaruddin, Yusni;** development of model, software, verification **– Yunidar, Roslidar, Maulisa Oktiana;** analysis of results **– Yunidar, Fitri Arnia, Nasaruddin, Yusni;** visualization, writing original draft preparation **– Yunidar, Roslidar, Maulisa Oktiana, Nasaruddin, Yusni, Fitri Arnia**; writing – review and editing **– Yunidar, Fitri Arnia.**

Conflict of interest

The authors declare that they have no conflict of interest in relation to this research, whether financial, personal, authorship, or otherwise, that could affect the research and its results presented in this paper.

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Data availability

Images for simulation will be made available upon request to the corresponding author.

Use of Artificial Intelligence

The authors confirm that they did not use artificial intelligence technologies when creating the current study.

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All the authors have read and agreed to the published version of this manuscript.

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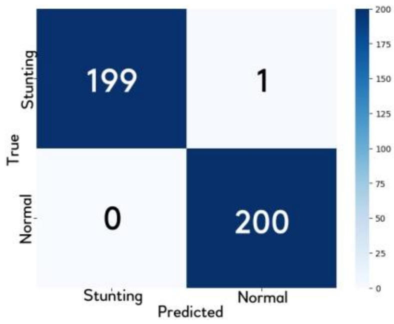
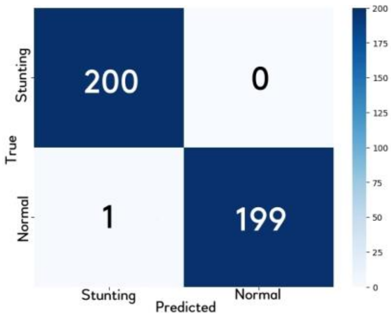
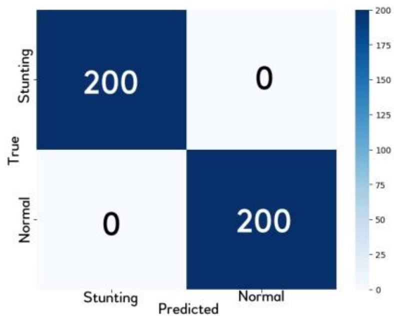
(a) Confusion matrix of AlexNet with epochs 20



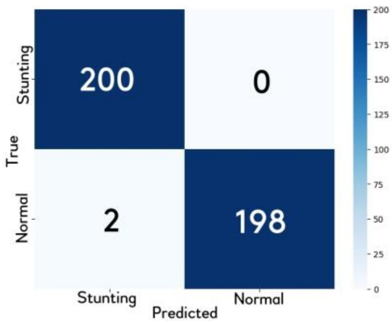
(b) Confusion matrix of ResNet34 with epochs 20



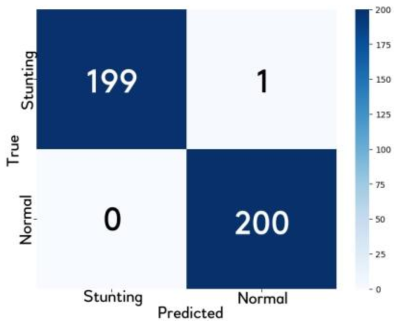
(c) Confusion matrix of AlexNet with epochs 60



(d) Confusion matrix of ResNet34 with epochs 60



(e) Confusion matrix of AlexNet with epochs 100



(f) Confusion matrix of ResNet34 with epochs 100

Fig. 8. Confusion matrixes of AlexNet and ResNet34 with epochs 20, 60 and 100

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КЛАСИФІКАЦІЯ ДІТЕЙ З ЗАТРИМКОЮ РОЗВИТКУ ТА НОРМАЛЬНИХ ДІТЕЙ З ВИКОРИСТАННЯМ НОВОЇ БАЗИ ДАНИХ ЗОБРАЖЕНЬ ОБЛИЧЧЯ ТА ЗГОРТКОВОЇ НЕЙРОННОЇ МЕРЕЖІ

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Недоїдання є важливою проблемою, яка впливає на розвиток дітей. Дані, опубліковані ЮНІСЕФ у 2022 році, показують, що понад 7 мільйонів дітей віком до 5 років все ще відчувають гостре недоїдання в Ефіопії, Кенії та Сомалі. Тим часом у 2020 році Індонезія посідала п’яте та четверте місце у світі за рівнем виснаження та відставання в рості. Традиційний підхід до визначення стану харчування дітей полягає у вимірюванні співвідношення між масою тіла та зростом у певному віці. Цей підхід можна покращити шляхом одночасного використання біометрії обличчя, що може бути виконано автоматично за допомогою розпізнавання/класифікації обличчя на основі методів комп’ютерного зору та штучного інтелекту. Метою дослідження було використання згорткових нейронних мереж (CNN) як одного з методів у сфері штучного інтелекту для класифікації дітей із недоїданням на основі зображень їхніх облич. Метод: комп’ютерне моделювання двох архітектур CNN, застосоване до бази даних зображень обличчя дітей. Результати моделювання потім були оцінені для отримання продуктивності CNN. Перше виконане завдання полягало в створенні бази даних зображень облич індонезійських дітей віком від 2 до 5 років. База даних містить 4000 зображень обличчя, створених на основі зображень 100 дітей, 50 нормальних/здорових і 50 дітей із затримкою росту. У базі даних деякі зображення були доповнені процедурами збільшення, обертання та зміщення. Використовуючи базу даних, ми виконали друге завдання, навчивши дві архітектури CNN, AlexNet і ResNet34, класифікувати зображення на нормальних дітей і дітей з проблемами недоїдання. Ми навчили обидві архітектури за допомогою 80% зображень, а потім перевірили та протестували їх за допомогою 10% зображень. Обидві архітектури були вивчені з епохами: 20, 40, 60, 80 і 100, зі швидкістю навчання 10^{-3}. Ефективність моделей була показана на графіках втрат у навчанні, перевірці та тестуванні та виміряна за точністю, запам’ятовуванням, точністю та оцінкою F1. Підсумовуючи, обидві архітектури показали багатообіцяючі результати в класифікації зображень. Обидві архітектури, вивчені з епохою 60 зі швидкістю 10^{-3}, дали найкращі моделі з точністю 0,9975 для AlexNet і 1 для ResNet34.

Ключові слова: раннє виявлення гіпотрофії дітей; база даних зображень обличчя; відставання в рості; біометрія; CNN.

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