DEVELOPMENT OF AN IMAGE-BASED CALORIE DETECTION MODEL IN INDONESIAN FOOD FOR STUNTING PREVENTION

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ABSTRACT

Stunting is a global health problem, especially in developing countries including Indonesia. One of the main causes of stunting is malnutrition, especially in children aged 0-23 months. Therefore, this study aims to develop an AI-based model to detect calories in Indonesian food images for stunting prevention, using the Transfer Learning method with AlexNet. In this article, we propose a new deep learning-based food image calorie detection model called, Alexnet Interactive Transfer Learning (AITL). AITL is built based on Alexnet's Convolution Neural Network architecture, and further modified at the last Convolution layer and classification layer. AITL was evaluated using a dataset from the Indonesian food database. Experiments were conducted on the dataset to detect food types and their calorific content. There are ten classes of authentic Indonesian food types, which include: Rendang, Bika Ambon, Pempek, Sate Ayam, Gado-gado, Ayam Pop, Kerak Telor, Rawon, Lemang, and Ayam Betutu. The accuracy of the developed AITL model reached 95.33%. The results of the tests conducted show that Alexnet-based AITL outperforms other CNNs in terms of accuracy and efficiency.

KEYWORDS AI, CNN, Food Calorie Detection, Calories, Stunting

INTRODUCTION

Stunting is one of the global health problems, especially in developing countries including Indonesia. The Ministry of Health of the Republic of Indonesia in 2022 indicated that toddlers affected by stunting in Indonesia were around 21.6% of the total 30.73 million toddlers (Pokhrel, 2024), (Fitriani et al., 2022). Stunting can occur in children who experience chronic malnutrition, especially at the age of 0-23 months (Selviyanti et al., 2022). Stunting is influenced by various things, namely poor maternal nutrition, infant nutrition, family economic factors and the environment (Husaini et al., 2023). The impact of stunting can affect adulthood, such as lowering IQ, reducing work productivity, and increasing the risk of chronic diseases(Setiawan et al., 2018). The first problems that contribute to the high stunting rate include: Lack of Nutritional Intake, Inappropriate Parenting, Poor Environmental Sanitation and Hygiene, Limited Access to Health Services making early detection of stunting difficult, and the lack of Utilisation of AI-based Technology to help monitor child growth and provide data-based recommendations. The second problem faced today is the absence of a model that can comprehensively integrate the various determinants of stunting in an AI-based system. Existing AI models tend to focus on one particular aspect, such as predicting child growth based on anthropometric data, without considering other factors that contribute to the incidence of stunting. Therefore, this study aims to develop an AI-based integrative approach model in stunting prevention that can provide more accurate analyses, better predictions, and more effective intervention recommendations for mothers and health workers.

In recent years, research on artificial intelligence-based food detection has been conducted. Previous research by (Eluis Bali Mawartika & Guntur, 2021) Mawartika (2021), Expert System Application for Food Selection Based on Nutritional Needs Using the Forward Chaining Method. This research reviews an expert system application that offers information about nutritional needs and suggests a food menu that matches individual nutritional needs. The research produced an expert system software as a tool that provides information about food menus that match individual nutritional needs by applying the Forward Chaining method. The resulting information aims to help people understand their nutritional needs and find suitable food menus, as well as help patients control the types of food they consume to ensure nutritional needs are met. In the same year (Muhammad Rizqi Zamzami, Dahnial & Fitriyah, 2021), Food Type Identification System and Calorie Calculation based on HSV Colour and Loadcell Sensor using K-Nearest Neighbor (KNN) Method based on Raspaberry Pi. In his research, a system is presented that aims to evaluate the number of calories in food by identifying the type of food and determining its weight. Food identification is done using the KNN method as well as a loadcell sensor to measure food weight. The system will take pictures and measure the weight of the food using a camera module and a loadcell sensor. The image is then processed on the Raspberry Pi 3 B to extract colour values from the mean HSV. The extracted value is used as a feature to recognise the type of food, which is then used to calculate the number of calories based on the identification and measurement of the loadcell sensor. The output of the system is displayed through a 16×2 LCD screen. System trials were conducted using 5 samples of each food type. From the test results, it was found that at k=3, the system accuracy reached 96%, at k=5 it was 92%, and at k=7 it was 92%.

There is also previous research by Hakima & Pitria (2023), Mobile-Based Balanced Nutrition Guide Application with Lean UX Method, in this study using the Lean UX Method to analyse needs and design application features. From this process, four main features were successfully produced and tested on potential users. These features include a main page that displays food menus according to meal times, a calculator to view food content and total daily calories, a report to see a recap of food consumption, and an account feature to manage user data and view calorie count history. Thus, the app provides an effective solution for users in managing their diet. In the same year (Aklani et al., 2023), Analysis and Development of Artificial Intelligence Diet Mobile Application with Challenge Based Approach, this study aims to evaluate the acceptance and effectiveness of a food planner application that uses machine learning technology by students in Batam. This application is designed to assist in diet and daily calorie monitoring. The results show that the ease of use of the app affects the perceived benefits, and both affect the user's attitude towards the app. Thus, the app is useful for users in daily calorie and nutrition monitoring and supporting a healthy lifestyle. This research is expected to help the development of similar apps in the future and improve nutritional literacy.

From the description above, it can be seen that research that pays attention to detecting calorific value in Indonesian food for stunting prevention is rarely done. the research conducted aims to develop an artificial intelligence model to estimate the number of calories consumed from food images for stunting prevention. The model uses an artificial intelligence model to detect food through a camera on a mobile device. The model used is Alexnet Interactive Transfer Learning (AITL) which is the novelty of the proposed model. Interactive Transfer Learning with Alexnet can offer several advantages that can help overcome common limitations in the field of medical image analysis. Alexnet itself is known for its ability to extract meaningful features and representative features from images. By utilising interactive transfer learning, the pre-trained Alexnet model can capture relevant features from large-scale datasets. This has the potential to improve the accuracy and robustness of the segmentation process (Humayun et al., 2022).

In addition, alexnet has demonstrated its effectiveness in various computer vision tasks, including object recognition and object segmentation. By fine-tuning these models on image data, such as food images, the network can learn to generalise well to specific characteristics and variations present in food images, which contributes to improved segmentation performance. In addition, alexnets are designed to achieve a good balance between model size and performance. They have shown superior efficiency in terms of computational resources and memory requirements compared to other deep learning architectures (Al-Yasriy et al., 2020). This article mainly contributes to the following:

1. Developing a new transfer learning model named Alexnet Interactive Transfer Learning (AITL) that uses alexnet CNN architecture for food classification.
2. Evaluating the impact of data augmentation on the performance of the proposed model. Tests were conducted on datasets, both with and without the implementation of data augmentation, to address data skewness.
3. Evaluate the optimal optimisation methods to demonstrate the performance of the proposed model, especially in terms of accuracy and execution time.

The content of this paper is organised as follows: Section 2 reviews existing techniques for predicting calories in foods. Section 3 describes the proposed method, which utilises alexnet and transfer learning from CNN models. Experiments and comparisons with other methods as well as a discussion study are presented. Conclusions are presented in section 4. Discussion on potential future research is discussed in section 5.

RESEARCH METHOD

1. Dataset

The data can be in the form of images or videos of food accompanied by calorie information. The data is taken directly and in the process of taking the picture, distance and lighting are tested, this is done to get the best variation of distance and lighting for data collection. Based on the test results with a distance of 50cm, 60cm and 70 cm respectively and lighting 200lux, 300lux and 500lux, it is found that with a distance of 50cm and lighting 500lux objects can be detected maximally. The sample data used in the study can be seen in Figure 1.

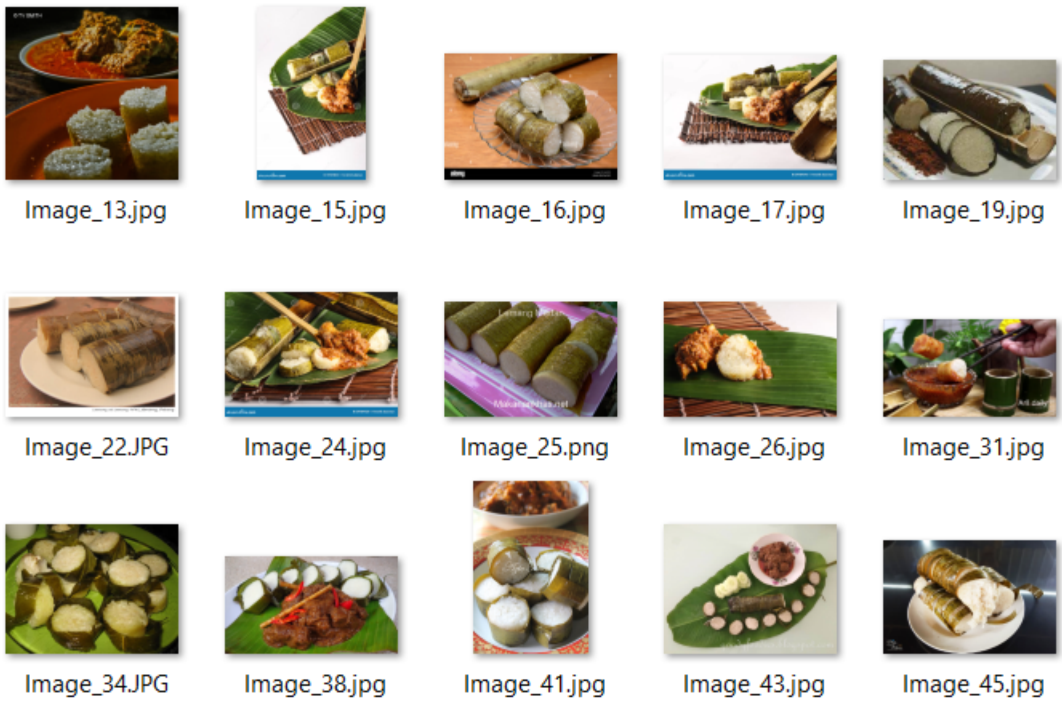

Figure 1. Food Image Dataset

2. Proposed Method

The stages of the proposed method are shown in Figure 2.

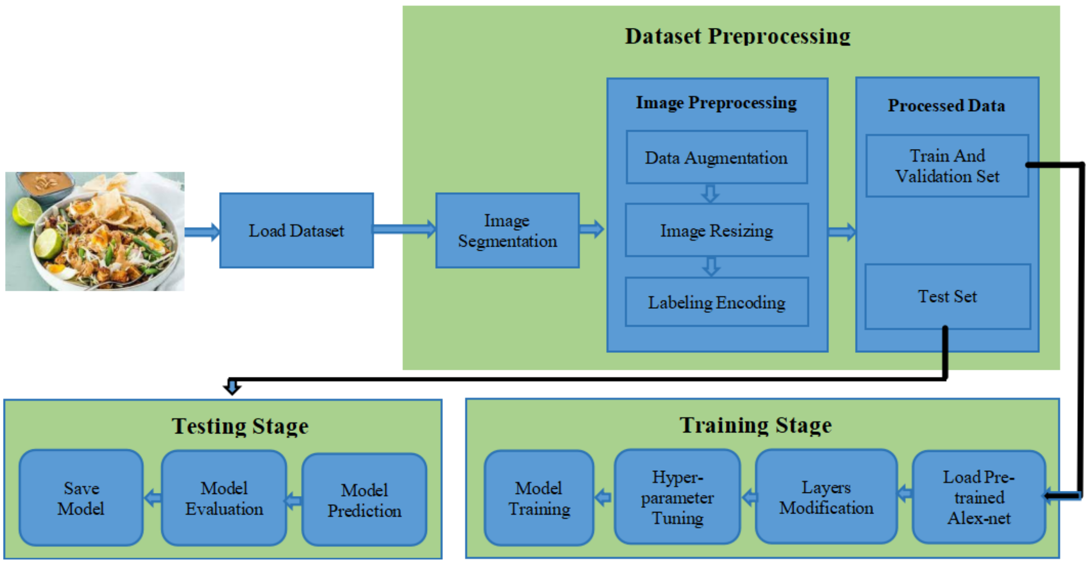

Figure 2 Proposed Method

a. Food Segmentation

Food segmentation is using morphological operation method.

b. Pre-Processing

At this stage, food image data will be processed in order to obtain more optimal results. Data processing is done by segmenting automatically to get a clear food image. Furthermore, the data is changed in size 227 × 227 × 3 according to the input size in the

Alexnet architecture. The next pre-processing stage is data augmentation. Data augmentation aims to get a larger amount of data with diverse results. The augmentation technique performed in this research is rotation. Rotation is done by rotating the image data by 00, 450, 900, and 1800. The data that has gone through the pre-processing stage will later be used as input data in the classification process.

c. Proposed architecture

This section discusses in detail the transfer learning paradigm with Alexnet architecture. Transfer learning with alexnet architecture is shown in Figure 3.

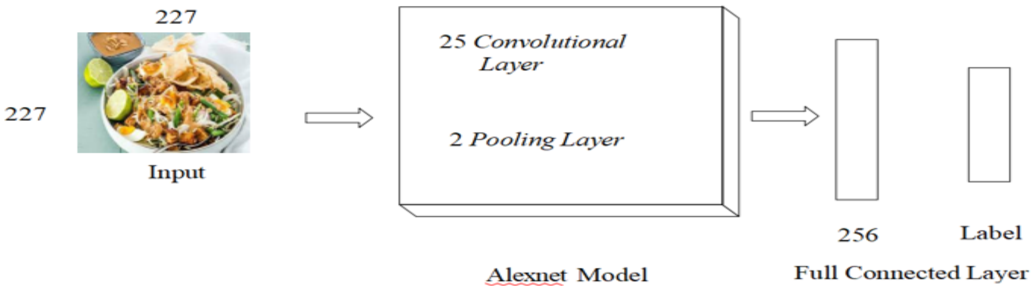

Figure 3: Transfer Learning Model

The steps in interactive transfer learning can be explained as follows:

1) To retrain SqueezeNet to classify a new image, replace the last 2-D convolution layer and the final classification layer of the network. In SqueezeNet, these layers have the names “conv5” and “ClassificationLayer” respectively.
2) In the Designer panel, drag the new convolution2dLayer onto the canvas. To match the original convolution layer, set FilterSize to 1.1. Edit NumFilters to the number of classes in the new data, in this example, 2. Figure 4. shows the process of setting up the convolution layer.

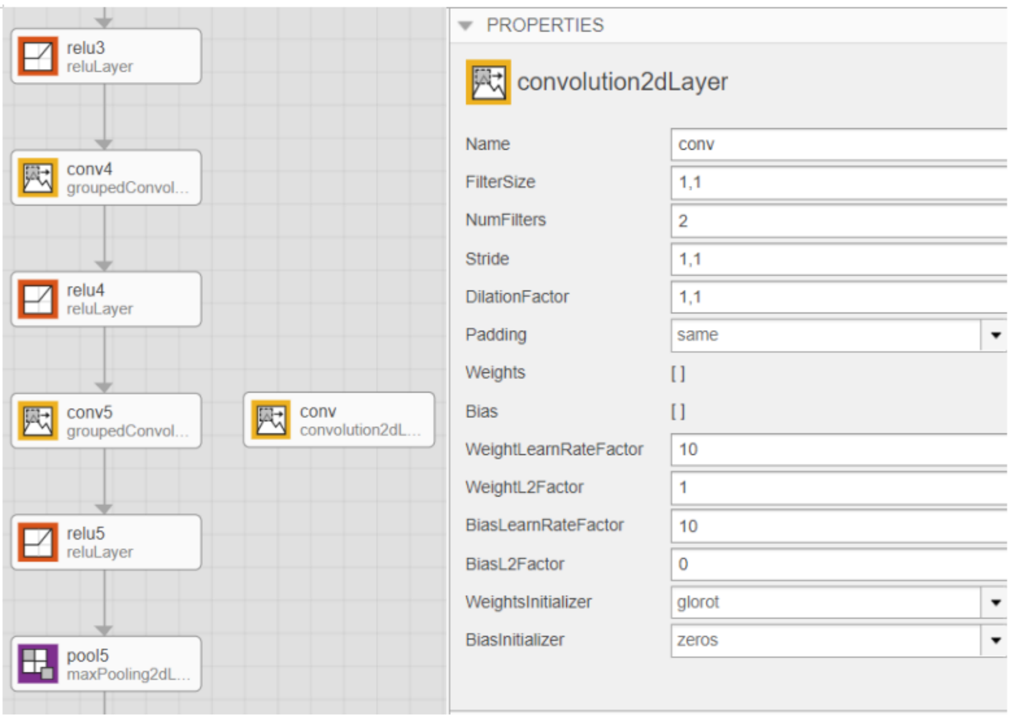

Figure 4: Settings on the Convolution Layer

3) Delete the last 2-D convolution layer and connect a new layer.
4) To change the output layer, scroll to the end of the library layer and drag the new classification layer to the canvas. Delete the original output layer and connect the new layer in its place. The settings of the classification layer are shown in Figure 5.

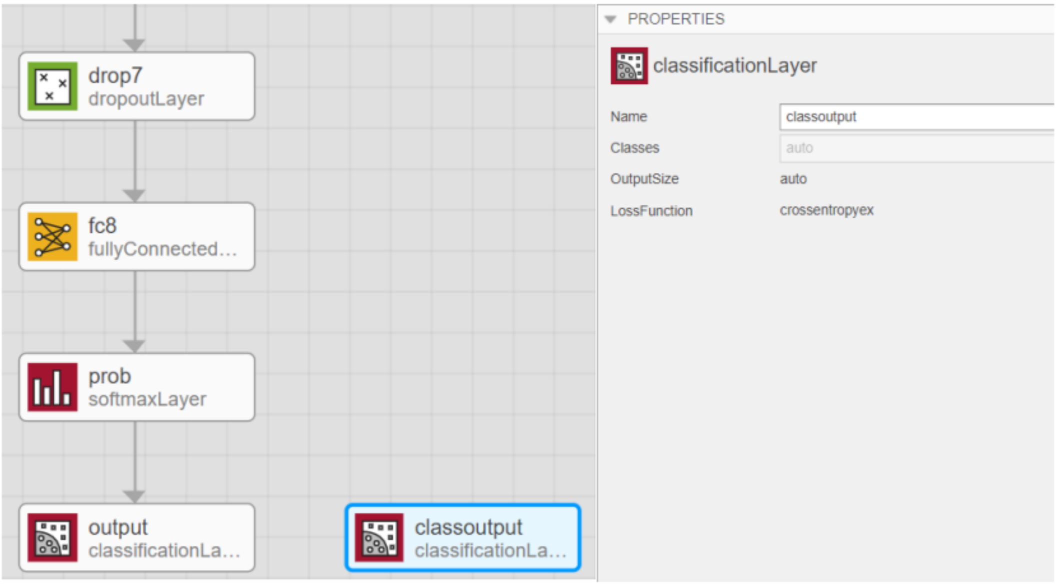

Figure 5: Settings on the Classification Layer

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RESULT AND DISCUSSION

This section provides a comprehensive discussion of the evaluation measures used to assess the performance of the proposed method. In addition, it covers the system and software requirements needed for the training and evaluation of the model. Furthermore, a thorough analysis of the results obtained through the proposed method is presented in this section.

1. Evaluation Measures

Evaluation measures are quantitative metrics used to evaluate the performance of deep learning models. They are used to compare the performance of different models or algorithms on a particular task, assess the effectiveness of the model or algorithm in solving a particular problem, and identify areas for improvement. The evaluation measures used in this study are ROC curves, and confusion matrices. Receiver Operating Characteristic (ROC): A graph that represents the performance at each threshold of a classification model. ROC represents two parameters, namely, True Positive rate (TPR) and False Positive Rate (FPR) given by Eqs. (1) and (2).

$$TPR = \frac{\mathrm{TP}}{\mathrm{TP} + \mathrm{FN}} \quad (1)$$

$$FPR = \frac{\mathrm{FP}}{\mathrm{FP} + \mathrm{TN}} \quad (2)$$

2. Hyper-parameter Settings

To achieve optimal performance in model training and obtain desired results for food classification, various hyperparameters were refined through empirical experiments. These hyper-parameters include batch size, optimisers, learning rate, epochs, and loss function.

3. Analysis of results

In this study, a Deep Learning approach is proposed for food classification using Alexnet Interactive Transfer Learning (AITL) pre-trained on food images. The datasets used are Indonesian cash food images totalling 750 each. The dataset used is already segmented food images. The food dataset and the content in the food per 100 Grams are shown in Table 1.

Table 1. Food Dataset Per 100 Grams

No	Food Name	Calories (kcal)	Fat (g)	Carbohydrates (g)	Protein (g)	Cholesterol (mg)	Fibre (g)	Vitamins A (IU)	Vitamins E (mg)	Vitamins K (mcg)	Vitamins C (mg)	Sodium (mg)
1	Rendang	319	20	3	28	110	1	0	0.7	1.8	4.8	670
2	Bika_Ambon	325	12	55	3	90	0.1	76	0.1	0.3	0.1	40
3	Pempek	222	9	25	11	80	1	46	0.6	0.2	3.5	600
4	Sate_Ayam	220	12	4	24	83	0	7	0.1	0.1	1.5	460
5	Gado_gado	135	8	11	5	0	3	287	2.4	24	14	240
6	Ayam_Pop	275	18	0	28	110	0	100	0.5	1	0	70
7	Kerak_telor	260	11	18	17	230	1	0	0.4	0.7	0.2	60
8	Rawon	117	4	3	16	55	1	3,03	1.8	1.1	18.6	35
9	Lemang	178	4	34	2	0	1	0	0.4	0.3	0	3
10	Ayam_betutu	211	9	1	30	95	0	260	0.7	0.4	1	53

From Table 1, it can be seen that the types of food used in this study are traditional Indonesian foods which include: Rendang, Bika Ambon, Pempek, Sate Ayam, Gado-gado, Chicken Pop, Kerak Telor, Rawon, Lemang, and Ayam Betutu.

The first test is testing the Alexnet Interactive Transfer Learning (AITL) method with alexnet. comparing testing using methods based on the amount of training data with the Stochastic Gradient Descent with Momentum (SGDM) optimisation method. The number of datasets used is 1500 data. The number of classes is 10. The division of data is 60:40, 70:30, 80:20 and 90:10. Number of epochs is 6, learning rate initialisation is 0.0001, bath size: 10, the number of layers used is 25 layers. The optimisation method used is Stochastic Gradient Descent with Momentum (SGDM). The results of testing the Alexnet Interactive Transfer Learning (AITL) and alexnet models are shown in Table 2.

Table 2. AITL and Alexnet Testing Results

Testing	Division of Training and Testing Data	Alexnet Interactive Transfer Learning		Alexnet	
		Time (Minutes)	Accuracy (%)	Time (Minutes)	Accuracy (%)
Testing-1	900:600 (60%)	97.03	92.17	120.3	92.5
Testing-2	1050:450 (70%)	81.54	91.78	87.26	91.33
Testing-3	1200:300 (80%)	72.37	94.67	79.3	82.67
Testing-4	1350:150 (90%)	**75.37**	**95.33**	**68.04**	**94.00**

Based on Table 2, the optimal amount of training data for food detection with Alexnet Interactive Transfer Learning (AITL) using SGDM optimisation is 90:10 (1350:150) with an accuracy percentage of 95.33%. The model accuracy curve and los function with 90:10 training data with SGDM optimisation can be seen in Figure 6.

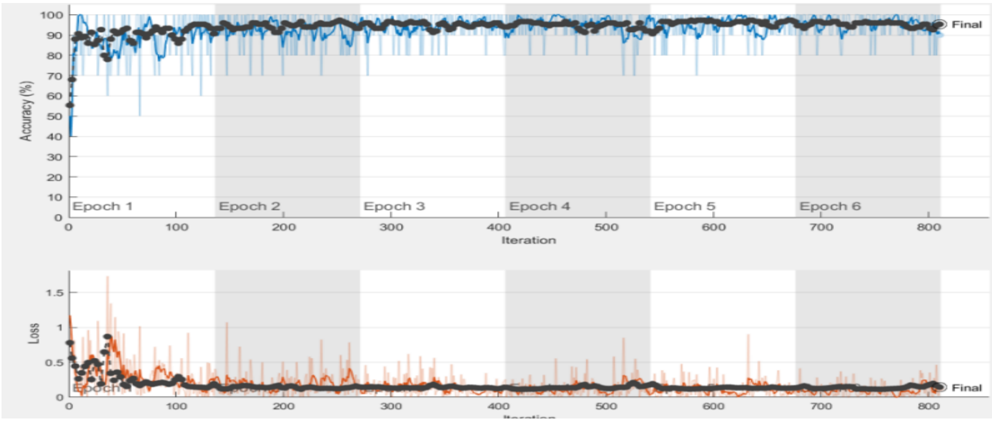

Figure 6. Model training, validation accuracy and los curve with 90:10 Optimas SGDM Training Data

The second test is testing using the Alexnet Interactive Transfer Learning (AITL) method based on the amount of training data with the adaptive moment estimation (ADAM) optimisation method. The number of datasets used is 1500 data. The number of classes is 2 (cancer and artery (non-cancer). Data division is 60:40, 70:30, 80:20 and 90:10. The number of epochs is 6, the learning rate initialisation is 0.0001, the number of layers used is 25 layers. The results of testing the Alexnet Interactive Transfer Learning (AITL) model are shown in Table 3.

Table 3. AITL Testing Results Based on ADAM Optimisation

Testing	Division of Training and Testing Data	Alexnet Interactive Transfer Learning		Alexnet	
		Time (Minutes)	Accuracy (%)	Time (Minutes)	Accuracy (%)
Testing-1	900:600 (60:40)	102.52	93.50	90.28	89.33
Testing-2	1050:450 (70:30)	82.13	91.78	105.	81.33
Testing-3	1200:300 (80:20)	97.27	91.67	69.44	81.33
Testing-4	1350:150 (90:10)	72.12	95.33	79.29	85.33

Based on Table 3, the optimal amount of training data to detect lung cancer with Alexnet Interactive Transfer Learning (AITL) using ADAM optimisation is 60:40 (900:600) with an accuracy percentage of 93.50%. The model accuracy curve and los function with 60:40 training data with ADAM optimisation can be seen in Figure 7.

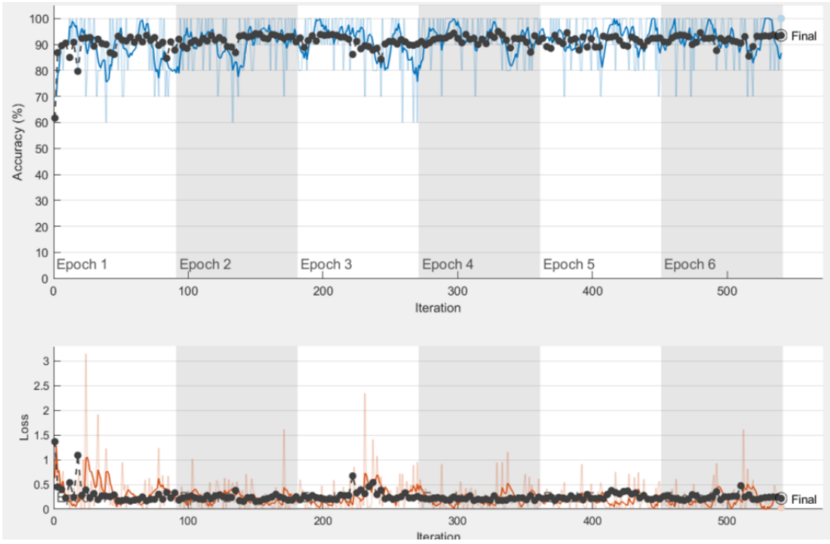

Figure 7. Model training, validation accuracy and los curve with 90:10 Optimas ADAM Training Data

The third test is testing using the Alexnet Interactive Transfer Learning (AITL) method based on the amount of training data with the Root Mean Square Propagation (RMSProp) optimisation method. The number of datasets used is 1500 data. The number of classes is 10 classes. Data division is 60:40, 70:30, 80:20 and 90:10. The number of epochs is 6, the learning rate initialisation is 0.0001, the number of layers used is 25 layers. The results of testing the Alexnet Interactive Transfer Learning (AITL) model are shown in Table 4.

Table 4. AITL Testing Results Based on RMSPROP Optimisation

Testing	Division of Training and Testing Data	Alexnet Interaktif Transfer Learning		Alexnet	
		Time (Minutes)	Accuracy (%)	Time (Minutes)	Accuracy (%)
Testing-1	900:600 (60:40)	**90.37**	**89.33**	**104.35**	**91.33**
Testing-2	1050:450 (70:30)	101.51	92.67	102.56	81.56
Testing-3	1200:300 (80:20)	98.51	92.67	76.32	77
Testing-4	1350:150 (90:10)	54.12	92	49.47	77.33

Based on Table 4, the optimal amount of training data for food detection with Alexnet Interactive Transfer Learning (AITL) using Root Mean Square Propagation (RMSProp) optimisation is 80:20 (1200:300) with an accuracy percentage of 95%.

The model accuracy curve and los function with 80:20 training data with RMSProp optimisation can be seen in Figure 8.

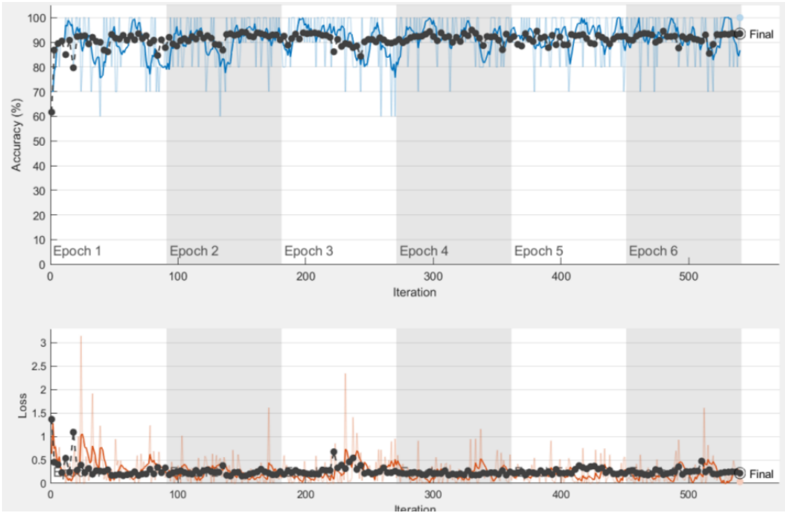

Figure 8. Model training, validation accuracy and los curve with 80:20 optimised training data RMSProp

4. Discussion

To assess the general capability of the proposed AITL to detect food calories, we conducted an ablation study covering several key parameters. This study aims to investigate the impact of various factors on the performance of the model and gain insight into its behaviour under various conditions. In this section, we present the findings of our ablation study, which includes the analysis of computational complexity, the effect of data augmentation techniques, the effect of different data splits, the comparison of the model with and without transfer learning, and the training of the proposed model for the classification of different types of food.

a. Computational Complexity

A comprehensive analysis of the computational complexity of the proposed Alexnet Interactive Transfer Learning model has been determined. The evaluation considers various factors, including the number of network parameters, network size, training training time, inference time, and testing accuracy. Table 6 provides a computational summary of the fine-tuned AITL and its variants along with other deep learning architectures trained and evaluated on the same dataset under the same hyper-parameter settings. Starting with Alexnet it is seen that this model has a relatively simpler structure. AITL without augmentation and AITL. In this section, the model is evaluated by comparing transfer learning using augmentation and that without augmentation. The respective results are presented in Table 5.

Tabel 5. The influence of AITL with and without data augmentation.

Testing	**Division of Training and Testing Data**	**With Data Augmentation**		**Without Data Augmentation**	
		Time (Minutes)	**Accuracy (%)**	**Time (Minutes)**	**Accuracy (%)**
Testing-1	900:600 (60%)	97.03	92.17	120.3	92.5
Testing-2	1050:450 (70%)	81.54	91.78	87.26	91.33
Testing-3	1200:300 (80%)	72.37	94.67	79.3	82.67
Testing-4	1350:150 (90%)	**75.37**	**95.33**	49.56	94

It can be seen that the results of a well-organised AITL are relatively better with augmentation. By introducing deep variations in the train set, the model becomes more resilient to changes in orientation, position, and scale of the images, making it better equipped to handle a wide range of food image instances that may exhibit variations in shape, size, or orientation. Data augmentation also helps to alleviate the problem of limited training data by artificially expanding the dataset, effectively increasing the number of samples available for training. This helps to reduce overfitting, where the model becomes too specialized on the training data and fails to generalize well to unseen data.

b. The Effect of Different Data Splits

Several experiments have been conducted to explore the impact of different data splits. We evaluated the performance of the model by varying the proportion of training and testing sets. We have analyzed and compared the results obtained from different data splits, namely 60:40, 70:30, 80:20 and 90:10. The complete results are shown in Table 5. From Table 5, it shows that the performance of the model is affected by the data split. The size of the training set plays an important role in the effectiveness of the transfer learning method. Based on our experiments, we found that the performance of the model is better at 90:10 data division. This observation suggests that using a smaller training set, as facilitated by transfer learning, can indeed produce good results in terms of classification accuracy and overall performance.

c. Comparison of Models with and Without Transfer Learning

The proposed methodology is based on the interactive transfer learning approach using medical image datasets. A number of experiments have been conducted to analyse the impact of using interactive transfer learning methods on certain types of datasets. So, for this purpose, the experiments conducted were to test the model with alexnet interactive transfer learning and alexnet method. The results achieved through this ablation study are summarized in Table 4. Without transfer learning (alexnet), the following observations were made:

1) The model tends to overfit during training and testing.
2) The model is biased towards the food class as it contains more images in the testing set.
3) As the model gets deeper, the generalization of alexnet gets better.

This research paper presents an interactive transfer learning approach using alexnet to detect calories from food images. The proposed method exhibits several strengths that contribute to its effectiveness and potential practical application. One of the main strengths is the utilisation of pre-trained deep neural networks and interactive transfer learning. By utilising the knowledge learnt from large-scale natural image datasets, AITL is well organised to effectively extract relevant features from food images. This approach significantly reduces the computational resources and time required for training while maintaining a high level of accuracy. The experimental results demonstrate the strength of the proposed method. AITL consistently outperforms other CNN architectures in terms of accuracy and efficiency. The achieved accuracy is 95.33%. The test results demonstrate the potential of AITL as a powerful tool for automatic detection of calories in food.

However, it is important to recognize certain limitations of the current method. The performance of the proposed model can be further improved by utilising a larger dataset. Incorporating additional diverse data samples will improve the model's ability to generalise and handle variations in the case of calorie detection in foods. Moreover, the implications of our findings extend to future research in the area of food classification, specifically focusing on the potential of transfer learning with Alexnet Interactive Transfer Learning (AITL). This approach opens up exciting avenues for exploration and improvement in food image analysis. One potential future direction is the investigation of alternative deep learning architectures combined with transfer learning. Although Alexnet Interactive Transfer Learning (AITL) has shown outstanding performance in our research, exploring other advanced architectures may result in further improvements in accuracy and efficiency. Models such as ResNet, DenseNet, or InceptionNet can be evaluated to assess their effectiveness in the context of food image classification. Furthermore, the incorporation of additional clinical data holds promises for future research. Expanding the dataset to include more cases could provide valuable insights into the interactions between various factors and improve the robustness of classification models. Finally, future research could explore the application of transfer learning with Alexnet on larger datasets. Increasing the dataset size will further validate the effectiveness of the proposed approach in real-world scenarios and improve its generalizability.

CONCLUSION

Transfer learning with AITL has been shown to improve the generalisation performance of the model. By utilising representation learning from natural images, the model can capture robust features and transferable features that can be applied to food image imaging. This can result in better performance and improved accuracy in food classification, especially when working with limited imaging data, e.g., results from cameras. Training artificial neural networks from scratch on large food datasets can be computationally expensive and time-consuming. Using transfer learning with AITL, can significantly reduce the training time and computational resources required, this is done by building on pre-trained models. This allows researchers and practitioners to iterate and experiment with different architectures and hyperparameters more efficiently. Overall, AITL offers a powerful approach to utilising pre-trained models and exploiting the power of models in food classification. This makes it possible to utilise the knowledge gained from natural image datasets and apply it effectively to food images. The experimental results demonstrate the robustness of the proposed method. AITL consistently outperforms other CNN architectures in terms of accuracy and efficiency.

REFERENCES

Aklani, S. A., Studi, P., Informasi, S., Ilmu, F., Batam, U. I., Ladi, B., Indah, T., & Batam, K. (2023). *2365-Article Text-6353-1-10-20230225*. *6*(1), 48–58.

Al-Yasriy, H. F., Al-Husieny, M. S., Mohsen, F. Y., Khalil, E. A., & Hassan, Z. S. (2020). Diagnosis of Lung Cancer Based on CT Scans Using CNN. *IOP Conference Series: Materials Science and Engineering*, *928*(2). https://doi.org/10.1088/1757-899X/928/2/022035

Eluis Bali Mawartika, Y., & Guntur, M. (2021). Application Expert System for Food Selection Based onNutritional Needs using Forward Chaining. *Cogito Smart Journal* |, *7*(1), 96–110.

Fitriani, Barangkau, Masrah Hasan, Ruslang, Eka Hardianti, Khaeria, Resti Oktavia, & Selpiana. (2022). Cegah Stunting Itu Penting! *Jurnal Pengabdian Kepada Masyarakat (JurDikMas) Sosiosaintifik*, *4*(2), 63–67. https://doi.org/10.54339/jurdikmas.v4i2.417

Humayun, M., Sujatha, R., Almuayqil, S. N., & Jhanjhi, N. Z. (2022). A Transfer Learning Approach with a Convolutional Neural Network for the Classification of Lung Carcinoma. *Healthcare (Switzerland)*, *10*(6), 1–15. https://doi.org/10.3390/healthcare10061058

Husaini, A., Hoeronis, I., Lumana, H. H., & Puspareni, L. D. (2023). Early Detection of Stunting in Toddlers Based on Ensemble Machine Learning in Purbaratu Tasikmalaya. *Jurnal Sistem Dan Teknologi Informasi (JustIN)*, *11*(3), 487. https://doi.org/10.26418/justin.v11i3.66465

Muhammad Rizqi Zamzami, Dahnial, S., & Fitriyah, H. (2021). Sistem Identifikasi Jenis Makanan dan Perhitungan Kalori berdasarkan Warna HSV dan Sensor Loadcell menggunakan Metode K-NN berbasis. *Jurnal Pengembangan Teknologi Informasi Dan Ilmu Komputer*, *5*(3), 936–942.

Pokhrel, S. (2024). No TitleΕΛΕΝΗ. *Αγαη*, *15*(1), 37–48.

Selviyanti, E., Roziqin, M. C., Putra, D. S. H., & Noor, M. S. (2022). Intelligent Application of Stunting Monitoring and Mapping Systems (Smart Ting) in Toddlers Based on Android in Jember. *Proceedings of the 2nd International Conference on Social Science, Humanity and Public Health (ICOSHIP 2021)*, *645*(Icoship 2021), 147–157. https://doi.org/10.2991/assehr.k.220207.024

Setiawan, E., Machmud, R., & Masrul, M. (2018). Faktor-Faktor yang Berhubungan dengan Kejadian Stunting pada Anak Usia 24-59 Bulan di Wilayah Kerja Puskesmas Andalas Kecamatan Padang Timur Kota Padang Tahun 2018. *Jurnal Kesehatan Andalas*, *7*(2), 275. https://doi.org/10.25077/jka.v7i2.813