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A Non-Invasive Allergy Detection using Convolutional Neural Network Model

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Abstract - Skin allergy detection is critical to detect allergies that trigger serious reactions such as anaphylaxis, so people can avoid allergens and reduce the risk of complications such as anaphylactic shock. Therefore, early allergy detection screening is essential to determine the risk of allergies. This research aims to develop a system to detect skin allergies caused by food, through sensors applied to human skin using the Convolutional Neural Network (CNN) model. The research steps include literature studies, data acquisition, preprocessing, learning processes, and testing. The developed system uses a camera to capture allergic reactions on the skin. Data acquisition consists of two types of data, namely primary data and secondary data. Primary data acquisition is done by taking images of normal and allergic patient skin. Meanwhile, secondary data acquisition is obtained from Kaggle. The captured images are processed by image processing and analyzed using the CNN model. The image dataset consists of four classes, namely atopic, angioedema, normal skin, and urticaria. The CNN model consists of several layers, including convolutional layers, pooling, and fully connected layers. The results of the research showed that the prototype product can detect changes in the skin surface due to allergic reactions, such as redness or swelling, quickly and accurately. Testing the learning process with the CNN model resulted in an accuracy rate of 92%. Meanwhile, the accuracy results of testing prototype products on patients with skin allergies were 93%. It shows that the system can detect types of allergies on the skin accurately and efficiently. This system provides a practical and fast solution for the public to detect allergies, while contributing to the advancement of medical technology.

Keywords - Allergy detection, Artificial intelligence, Convolutional Neural Network Model, Non-invasive

1. INTRODUCTION

World Allergy Organization (WAO) data shows that 22% of the world's population suffers from allergies and continues to increase every year. In 2021, it was estimated that food allergy cases occurred in 11% of adults and 14% of children. Food allergies are part of a hypersensitivity reaction, namely immunological hyperresponsiveness to specific antigens, which can come from food or pathogenic microorganisms or their products [1]. Food allergies can be caused by various foods, both from animals and plants. The prevalence in children is 5%, while in adults it is 2%. Anaphylactic reactions have been reported to occur due to foods from nuts. The most common foods that cause this are milk, eggs, peanuts, fish, shellfish, and other nuts. Fruits and vegetables can also cause allergies [2].

Food allergy is a reaction of the immune system to food after a certain exposure. Food is defined as a substance consumed by humans, whether processed, semi-processed, or raw. Food allergens are defined as certain food components or food ingredients (usually proteins) that are recognized by immune cells and then cause an immunological reaction [1]. Symptoms of food allergies can manifest in the skin and respiratory tract. Symptoms on the skin can be urticaria, angioedema, itching, flushing, and atopic dermatitis. Symptoms of the respiratory tract can be rhinitis, nasal congestion, asthma, cough, and laryngeal edema [2].

Urticaria is a skin reaction due to various causes. Synonyms for this disease are hives, urticaria, hives, and nettle rash. Characterized by local edema (swelling) that appears suddenly and disappears slowly, is reddish and pale, raised on the surface of the skin, and can be surrounded by circles [3]. Atopic dermatitis is a chronic inflammation of the skin. The basic concept of the occurrence of atopic dermatitis is through an immunological reaction mediated by immune cells from the bone marrow [4]. Angioedema is an edema that involves the deeper layers of the skin, namely the dermis, subcutaneous tissue, mucosa, and submucosa. This occurs due to increased capillary permeability due by inflammatory mediators. In angioedema, the edema that occurs is non-pitting, well-defined, pale, and not itchy, but angioedema can also occur together with urticaria so that it can be accompanied by itching and redness. Angioedema can occur in the face area, especially in the lips and eyes, ears, respiratory tract, digestive tract, cardiovascular system, hands, feet, and genitals [5].

Design engineering plays an important role in the development of sensor-based allergen test kits. Allergen test kits are devices used to detect the presence of allergens on the skin caused by food [6]. The development of sensor-based allergen test kits involves several stages, and design engineering plays a role in each stage. So this allergen test is very important to detect the type and cause of allergies that attack the human body, caused by food, by detecting it through the skin.

Current allergen detection methods tend to be time-consuming, expensive, and require specialized laboratories. Manual testing often cannot provide real-time results. The need for allergy detection is increasing with the increase in cases of food and environmental allergies. Advances in sensor technology, especially chemical or biological sensors, provide opportunities for the development of more effective allergen sensors. Increased support for biomedical research and medical technology provides additional resources for the development of these sensors. An increasingly health-conscious society is looking for solutions to manage allergies without disrupting daily life.

One of the effective deep learning models for allergy detection based on skin image analysis is CNN. CNN can be used for object recognition, image processing, computer vision, and facial recognition. One of the inputs for CNN is the image input [7]. Several studies that have been conducted show that CNN can be used to detect skin reactions during allergies. The CNN model can also be used to classify skin diseases [8]. CNN is very reliable and has high accuracy in recognizing complex patterns and features in images. Therefore, CNN is used to classify skin conditions related to allergies. This research utilizes image processing and skin image classification to identify skin reactions when allergic to food. There are 3 types of skin allergies caused by food, namely atopic dermatitis, angioedema, and urticaria. Another advantage of the CNN model is that the pre-processing stage does not need to extract features from the image, so that the classification process becomes more efficient.

2. RESEARCH METHOD

The research method used in this research is Research and Development, which is a research method that aims to develop products so that prototype products are produced and their effectiveness is tested [9]. The use of this research method can produce more efficient, effective, and productive products. One focus of this research method is the testing and evaluation step, so that the product can be accounted for [10].

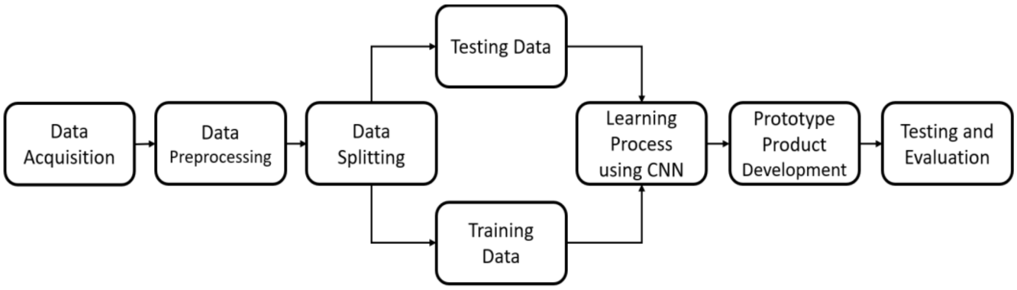


Figure 1. Research steps

This research consists of several main steps consisting of literature study, data acquisition, data preprocessing, learning process, prototype making, testing, and evaluation. The sequence of these steps can be seen in Figure 1.

2.1. Literature Study

Information about food allergies, types of allergies, types of foods that cause allergies, and non-invasive allergy detection technologies is collected from various sources, including textbooks, book chapters, international journal articles, international seminar articles, and interviews with competent medical personnel.

The information obtained from this stage includes an understanding of food allergies, their types, and causes, as well as state-of-the-art research developments and technology used to detect allergies. Symptom information for each type of allergy is used as a basis for determining the features of each class. Urticaria shows red, itchy patches of skin that can appear on various parts of the body. Angioedema shows symptoms of deep swelling of the skin and underlying tissue, often occurring on the face, lips, or eyelids. Atopic dermatitis shows symptoms of scaly, dry, itchy skin, and often appears in the folds of the elbows, knees, or neck.

2.2. Data Acquisition

The data used in this research consists of secondary data and primary data. Secondary data is image data taken from Kaggle with a size of 740 x 720 pixels. Meanwhile, primary data is skin image data taken directly by photographing the allergic skin. The total number of image data is 1200 with RGB (Red-Green-Blue) format, which is divided into 4 classes, namely atopic, urticaria, angioedema, and normal. Some examples of skin image data are presented in Figure 2.

Figure 2. Examples of image data used in research

2.3. Data Preprocessing and Splitting

Data pre-processing is used to remove noise, highlight features, detect patterns, and normalize data. The data preprocessing consists of cropping the image in the region of interest (ROI) area and resizing the entire image to 150 x 150 pixels. Resizing the image from 740 x 720 pixels to 150 x 150 pixels aims to reduce the computational process to be more efficient. Data preprocessing also performs filling of empty data, eliminating data duplication, and checking for data inconsistencies. Empty data can be caused by tool errors when collecting data [11].

The amount of data after data preprocessing is 1140 images of data. The next step is to split the image data into two parts, namely training data and testing data. To improve the performance of the learning process, the data is balanced proportionally for each class by reducing the amount of data in the majority class. The proportion of training data and testing data used in this research is 80%:20%. Therefore, the composition of the image data used in this research is presented in Table 1.

Table 1. Composition of the number of image data for each class

No.		Image Data		
	Class	Training	Testing	Amount of Data
1	Urtikaria	220	55	275
2	Angioedema	220	55	275
3	Atopic	220	55	275
4	Normal	220	55	275
Total		880	220	1100

2.4. Learning Process using Convolutional Neural Network Model

The model used in the learning process is a CNN. CNN is one of the main types of neural networks used for image recognition and classification. CNN has several uses, including object recognition, image processing, computer vision, and facial recognition. The input for a convolutional neural network is an image. CNN uses a convolution, which aims to extract features from image data. Image data is recognized as a pixel matrix, where each pixel can be represented by RGB (Red, Green, Blue) or grayscale values. Next, the image data is converted from the pixel matrix format into a form acceptable to CNN.

There are several layers used in CNN architecture, including Convolutional Layer, Pooling Layer, and Fully Connected Layer. The convolutional Layer is the first layer in the CNN model. Large input images will be divided into small image parts. In this layer, the input image will be filtered by multiplying the input image with the filter. The output of this layer is a feature map that will be used in the activation layer. A pooling layer or sub-sampling layer is a layer that will reduce the dimensions of the feature map produced by the convolutional layer. This layer will take part of the feature map and produce one output depending on the type of pooling used. The fully Connected Layer is the last layer in the CNN model. In this layer, all neurons from the previous layer will be taken. Then these neurons will be operated on by neurons in the current layer to produce an output. The purpose of the pooling layer is to reduce the parameters that are computed [12], [13].

2.5. Prototype Product Development

n this step, research activities are focused on creating product prototypes by designing an allergy detection system that includes a camera and minicomputer, as well as product design, and realizing product prototypes.

The tools and materials used in making the prototype product are a camera, a Raspberry Pi 4 minicomputer, an LCD, a cooling fan, and image processing software. The camera is used to capture images of allergic reactions on the skin. The Raspberry Pi 4 minicomputer is used to process data from sensors and cameras. Image processing software integrated with an artificial intelligence model aims to analyze and process data.

2.6. Testing and Evaluation

Testing aims to ensure that the prototype product functions to detect skin allergies correctly. Meanwhile, evaluation aims to evaluate whether the prototype product can detect skin allergic reactions with validity and high accuracy [14]. Therefore, the prototype product is tested on patients suffering from skin allergies. The results of the product prototype detection test were compared with the doctor's diagnosis. If the level of accuracy is convincing, the prototype product can be proposed for the production process so that it can contribute to the community to improve its health [15].

3. RESULTS AND DISCUSSION

CNN is able to train on data with a fairly large amount, and combines the feature extraction process and the classification process. AlexNet is one of the CNN model architectures used to process data with a grid structure, one of which is a two-dimensional image, and is also able to process high-dimensional data such as video. If the CNN model has achieved an accuracy performance above 90% from the training process, testing will be carried out using the testing data. If, during testing, the accuracy is below 90%, an evaluation of the training process will be carried out by improving the CNN architecture.

The architecture of the CNN model used in this research is presented in Figure 3, which consists of an input layer with a depth of 32 units. In this layer, the process of combining all matrices obtained in the pooling process is carried out. All pixels are converted into vectors with a length of a number of pixels from the matrix. The values obtained in this process are used for calculations at the hidden layer stage. There are 3 hidden layers with the first depth of 64 units, then 128 units, and 256 units. In this layer, the calculation process is carried out by multiplying the value of the input layer by the initialized weight and adding the bias value. Each hidden layer has a max pooling layer and a dropout layer. With the size of the max pooling layer being 2x2 and the size of the dropout being 18-40%. The max-pooling layer works to reduce the value of the feature map by sorting the maximum value in a certain area. The fully connected layer functions to change the 3-dimensional matrix into 1 dimension for the classification process. This layer consists of a dense layer and a dropout layer. The size of the dense layer is 256 units, and the output layer has 4 units because it uses 4 classification classes.

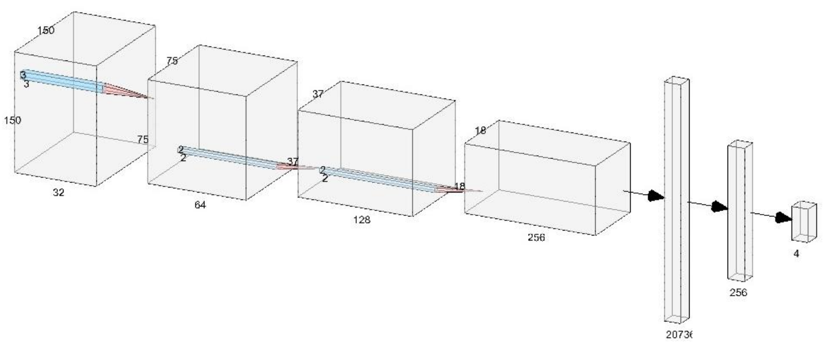


Figure 3. Architecture of CNN model for processing allergy sample image data: urticaria, atopic, angioedema, and normal

In the input layer, the image data is set with a size of 150 x 150 pixels. Furthermore, max pooling is performed to take the middle value of each image pixel passed through the filter. This process produces an image size, half the size of the image in the input layer to 75 x 75 pixels. This process is performed 3 times because it has 3 hidden convolution layers, so that the last pixel obtained is 9x9 pixels. To obtain a deep function representation, two parts of the CNN framework training parameters, namely the filter W and the bias b, which are collectively denoted by θ must be determined. In the training phase, the CNN framework f with L layers receives with training samples X_i, $i \in \{1, …., N\}$, and is formulated as (1).

$$f(X;\theta) = W_L h_{L-1} + b_l \quad (1)$$

Where $h_l, l \in \{1, \dots, L-1\}$ denotes the hidden vectors in the l^{th} layer in particular, h_0 represents the original input data.

Specifically, when training a CNN, the input image is first convolved with a convolutional layer with a set of convolutional kernels. The kernels of the convolution layer are referred to as W_l and are combined with the biterm b_l to convolve the input image. Next, a pointwise nonlinear activation function g(.) (usually the tanh function) is applied before the final output of this layer. Spatial pooling is performed to generate dominant features in non-overlapping windows for each feature map. The feed-forward process can be formulated as (2).

$$h_l = pool(g(h_{l-1} * W_l + b_l)) \quad (2)$$

After the parameters θ are trained, the unlabeled data set Y_j, $j \in \{1, 2, …., N\}$ can be encoded by (3).

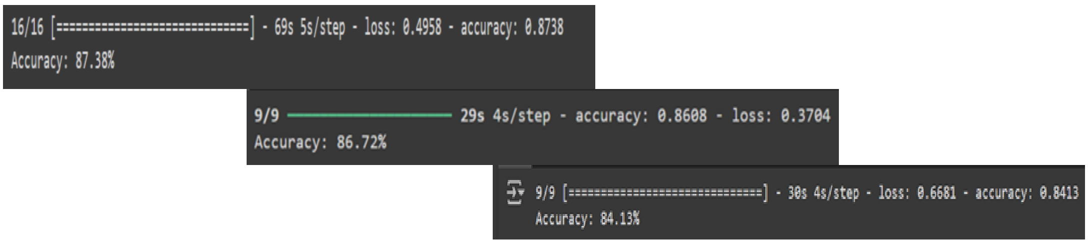
$$F_j = f(Y_j, \theta) \quad (3)$$

Depth features extracted from the CNN framework are generally effective in describing complex image patterns, especially in skin images of allergic reactions. Deep features with high abstraction levels are naturally unable to detect complex object edges at the pixel level. Object-based classification methods interpret high-resolution images with segmented objects that can preserve object edges and reduce the effects of spectral changes.

Based on Figure 4 on the training accuracy obtained at the beginning of training (epoch 0-10), the training (blue curve) and validation (orange curve) accuracies increase rapidly. In the middle of training (epoch 10-30), the training accuracy continues to increase, while the validation accuracy begins to fluctuate, showing signs of overfitting. At the end of training (epoch 30-50), the training accuracy reaches more than 95%, while the validation accuracy remains stable at around 85-90%. This shows a significant difference between the two and indicates overfitting. Overall, the model shows high training accuracy (>95%) and lower validation accuracy (85-90%), with clear indications of overfitting from the difference in accuracy.

Figure 4. The Curve of the first data training accuracy and data validation

After the training process, the model was evaluated with 220 test data images from a database of 32 images. The results obtained are presented in Figure 5(a). The model requires evaluation. Evaluations that can be done are improving the quality of input data, improving the architecture, and setting hyperparameters such as the number of epochs, batch size, and learning rate. In the calculation of accuracy with different testing data with the same epoch, which is 50, the accuracy is 86.72%, as shown in Figure 5(b). While in epochs of 100, the accuracy is 84.13%, as shown in Figure 5(c). In the first training data, 50 epochs were performed, while in the second training data, 100 epochs were performed.



(a) (b) (c)

Figure 5. The accuracy of data testing: (a) The first testing data with 50 epochs, (b) The Second testing data with 50 epochs, (c) testing data with 100 epochs

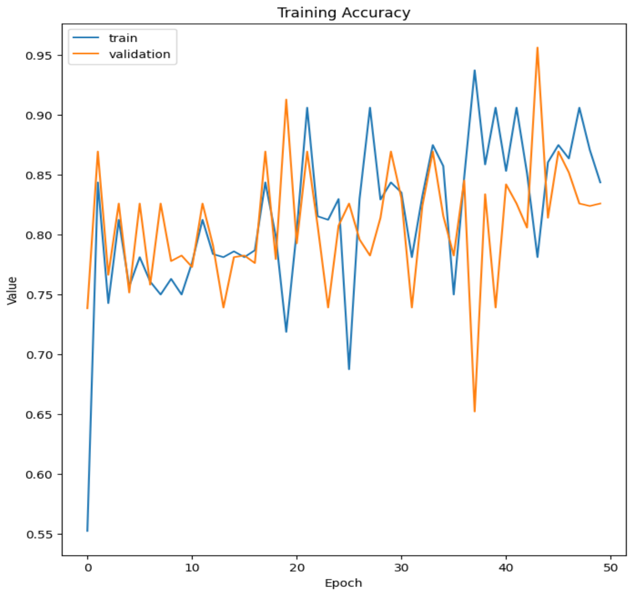


Figure 6. The Curve of the second data training accuracy and data validation

The graph in Figure 6 shows instability and high fluctuations without a clear trend, which can indicate problems in the training process that require re-evaluation of the data or the training process because the training model is unstable. Therefore, the number of epochs in data training causes a decrease in the level of accuracy in different data training.

For the research results to be implemented in patients, a prototype product needs to be developed. The initial step in developing a prototype product is the design of the prototype product, as presented in Figure 7. Prototype product production requires several tools and materials such as a camera, a Raspberry Pi 4 minicomputer, an LCD, a cooler fan, and image processing software. The camera functions to capture images of skin allergies. The Raspberry Pi 4 minicomputer functions to process data from the camera.

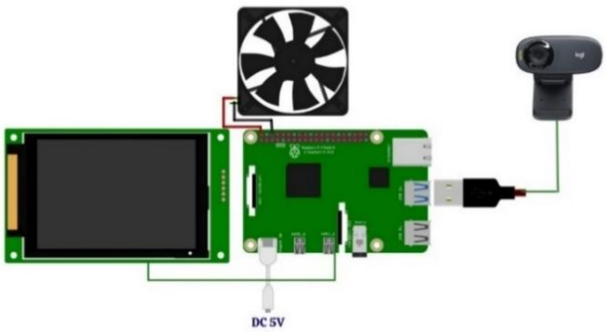


Figure 7. Prototype product design

The prototype product was tested on 30 people suffering from skin allergies. This trial aims to test the prototype product and evaluate the detection results. The test results showed that the prototype product worked well and was easy to operate. Meanwhile, the evaluation results showed that out of 30 people detected, 27 people produced correct detection, and 3 people produced inappropriate detection. Validation of the detection results of the prototype product was compared with the diagnosis results carried out by a dermatologist. Therefore, the detection accuracy of the prototype product was 93%. This shows that the prototype product produced from the research is quite valid when used to detect patient skin allergies.

4. CONCLUSION

The proposed system in this research successfully detected skin reactions caused by food allergies. Analysis using image processing model and Convolutional Neural Network (CNN) models has successfully detected four types of skin reactions, namely urticaria, atopic dermatitis, angioedema, and normal skin, with a high level of accuracy of 92%. This shows that the proposed system has been able to distinguish each type of skin allergy based on its specific features. Meanwhile, the accuracy results of testing prototype products on patients with skin allergies were 93%. The results of testing the system also show that this system can detect skin changes such as redness or swelling quickly and accurately. The system offers a practical and fast solution to detect allergies, thus increasing efficiency and accuracy in managing food allergies and contributing to the advancement of medical technology.

Further research to be developed is focused on several aspects to improve detection accuracy and efficiency, namely collecting sample data by increasing the size and diversity of the dataset, applying an appropriate feature extraction model, and data augmentation to make the model more robust to variations in image data.

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