Facial Expression Detection of Autism Children Using ResNet-50 in Convolutional Neural Network Algorithm

[1*]Ekawati Prihatini, [2]Selamat Muslimin, [3]Muhammad Rizki Darmawan
[1,2,3]Department of Electrical Engineering, Politeknik Negeri Sriwijaya, Indonesia
Email: [1]ekawati_p@polsri.ac.id, [2]selamet_muslimin@polsri.ac.id, [3]rizki8452@gmail.com

Article Info
Article history:
Received Jul 09th, 2025
Revised Oct 09th, 2025
Accepted Nov 29th, 2025

Keyword:
Children Autism
Convolutional Neural Network
Facial Expression Detection
ResNet-50

ABSTRACT
Facial expression detection in children with autism presents unique challenges due to limitations in verbal communication and social responses. This study develops a Convolutional Neural Network (CNN) model using the ResNet-50 architecture to improve the recognition accuracy of five expression categories: angry, fear, sad, neutral, and happy. A dataset of 3,030 images was divided into training and testing sets (60:40), with data augmentation and hyperparameter tuning applied using the Adam optimizer. The model achieved 89% validation accuracy and 84.49% testing accuracy, along with 86.78% precision and 80.69% recall. Evaluation on 25 test images showed an 84% success rate. These results indicate that ResNet-50 effectively extracts facial features and classifies expressions with high accuracy, demonstrating potential as a communication aid in autism therapy. Future improvements include adding more diverse training data and optimizing model parameters.
Copyright © 2025 Puzzle Research Data Technology

Corresponding Author:
Ekawati Prihatini,
Department of Electrical Engineering, Politeknik Negeri Sriwijaya,
Jl. Srijaya Negara, Bukit Lama, Kec. Ilir Barat I, Palembang City, South Sumatra 30128.
Email: ekawati_p@polsri.ac.id

DOI: http://dx.doi.org/10.24014/ijaidm.v8i3.37755

1. INTRODUCTION

The face is the object used to identify a person, as human emotions or expressions that emerge during social interactions can be perceived through facial features [1]. Facial expressions, as one of the most powerful forms of non-verbal communication, serve a critical function in conveying emotions, intentions, and meanings in human interactions. For individuals with autism, the interpretation of facial expressions may be an additional challenge in understanding verbal messages, yet it also has the potential to be an effective tool in supplementing limited verbal communication [2]. People with autism have different perspectives and behaviors compared to people in general. Autistic people often experience lack of social reciprocity. People with autism react very little to their surroundings from the time they are toddlers, besides that autistic people also experience limitations in speaking, smiling, and difficulty recognizing someone's expression. Non-verbal forms of communication come from facial muscle movements to convey one's emotional state, called expressions. Facial expressions or mimics can be recognized to determine emotions and can also reveal the contents of one's mind. The main purpose of reading someone's expression is to foster a sense of empathy between one person to another[3].

There are seven basic human emotions, namely neutral, angry, disgust, fear, pleasure, sad, and shock, and these basic emotions can be recognized from human facial expressions [4]. With the advancement of machine learning technology, face detection systems are able to recognize various expressions, viewpoints, and lighting more accurately and efficiently [5]. One approach that can be used is the Deep Learning algorithm [6]. That is efficient enough to recognize faces is Convolutional Neural Network (CNN). CNN is one of the Neural Networks used in research for the image classification process. CNN is known to be superior in image recognition or image classification compared to other deep learning methods [7].

There have been many studies related to facial emotion detection, such as Implementation of Convolutional Neural Network (CNN) on Facial Expression Recognition [8], which applies a convolutional neural network (CNN) to recognize facial expressions, and Deploying a convolutional neural network model to detect emotional states based on facial features [9]. which applies CNN architecture for emotion detection through facial data, and Facial Expression Recognition for User Psychological Identification with Neural Network and Ten Crops Transformation [10]. CNN is a type of neural network used to extract features from an image and excels when applied to image data [11]. One of CNN's benefits is its capacity to generate the same features as the input image data, having better feature learning capabilities than other deep learning methods and being able to perform data augmentation [12].

The main process in CNN is convolution, which is the process of taking information from small areas in the image and calculating the convolution between those areas and filters to produce certain features. This process is performed by layers consisting of neurons in the CNN [13]. CNN consists of multiple layers that systematically extract features from input images and produce classification scores to determine the image category [14]. CNN has several architectures within it such as LeNet5, AlexNet, GoogleNet (Inception), and ResNet [15]. One deep neural network architecture that has had a big influence on image recognition is called ResNet-50. This 50 layer architecture has been effectively used in a number of object detection and picture classification applications [16]. This research aims to develop a CNN-based facial expression detection model for children with autism with a ResNet-50 architecture to improve detection accuracy. With this model, it is expected to be a tool in recognizing the expressions of children with autism accurately.

2. RESEARCH METHOD

This research aims to develop a model to accurately detect the expressions of children with autism. To achieve this goal, this research is conducted in the stages as shown Figure 1:

Figure 1. Research Method

2.1 Literature Study

The initial stage of this research involved a comprehensive review of prior studies related to facial expression recognition in children with autism using Convolutional Neural Networks (CNN), particularly those employing the ResNet-50 architecture. The following summarizes key findings from previous works:

In a study Zhang et al. proposed a modified ResNet-50 architecture incorporating Mish activation and Inception modules. The model was evaluated on three benchmark datasets and achieved accuracy rates of 87.91% on CK+, 73.33% on JAFFE, and 58.61% on FER2013. These results demonstrate the effectiveness of the residual learning structure in adapting to various characteristics of facial expressions [17]. Miskow and Altahhan, enhanced the ResNet architecture with attention mechanisms such as SEN, ECA, and CBAM, achieving improved accuracy up to 91.21% on the CK+ dataset and 59.90% on FER2013 demonstrating the benefit of attention in facial emotion recognition [18]. Meanwhile, Wang et al, proposed a multimodal system that combines facial expressions and speech features using a convolutional vision transformer and attention-based fusion. Their model achieved 90.73% accuracy, significantly outperforming single-modal models. This supports the importance of combining visual and auditory cues to better interpret emotional expressions in children with autism [19].

2.2 Data Set Collection

The dataset was obtained from GitHub, consisting of five expression classes: angry, sad, fear, neutral, and happy. A total of 3,030 images were divided into 60% training data and 40% testing data. Table 1 shows the dataset distribution. Additionally, due to the lack of publicly available datasets specifically featuring autistic children, this study utilizes general facial expression datasets. This limitation is acknowledged and addressed in the discussion section. Table 1 provides comprehensive information about the use of datasets for testing and training.

Table 1. Dataset Details

Dataset	Sum Of Images	Happy	Netral	Sad	Fear	angry
Data Training	1818	364	364	364	364	364
Data Testing	1212	241	241	241	241	241

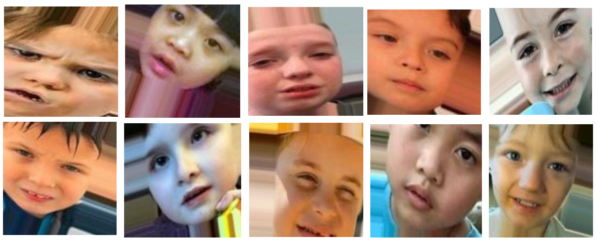
2.3 Preprocessing Data

Before the data is analyzed, data preprocessing needs to be done, which has the purpose of looking at data characteristics refer to the general properties of how an image is interpreted by a computer, transforming visual input into a structured array. This includes aspects such as spatial dependencies or patterns within the image that influence further computational processing [20]. Data preprocessing involved resizing all images to 224×224 pixels, normalizing pixel values, and applying augmentation (shear 15%, rotation 25°, zoom 15%, width/ height shift 20%, brightness 70–130%). This process increases data variety and improves the model's generalization. Table 2 is the result of data preprocessing from the dataset.

Table 2. Classification Expressions and Preprocessing Results

Angry	Fear	Sad	Netral	Happy

Angry	Fear	Sad	Netral	Happy



2.4 Model Training

2.4.1 Convolutional Neural Network (CNN)

Convolutional Neural Network (CNN) is an advanced form of the Multi-Layer Perceptron (MLP), specifically tailored to handle two-dimensional data such as images. As part of the Deep Neural Network family, CNNs are characterized by their deep layered architecture, making them highly effective in visual data analysis. Unlike MLPs, which process image pixels independently and disregard spatial relationships, CNNs are capable of preserving spatial structures, resulting in more accurate and efficient image classification outcomes [21]. In Figure 2 CNN consists of two main parts, namely feature extraction and classification.

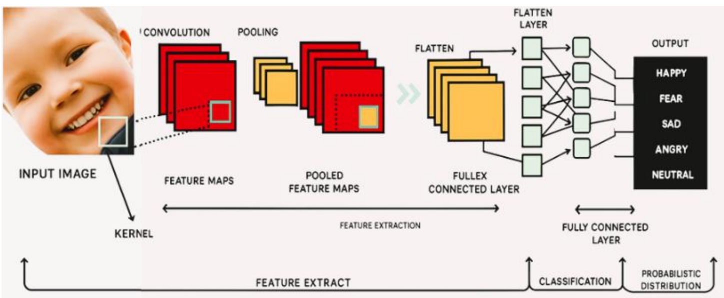


Figure 2. CNN Model Architecture

The convolutional layer is the initial layer within the CNN architecture and serves as the core component where most computational processes occur. In this layer, a convolution operation is performed by sliding a filter matrix across the entire image. The output of this operation is a feature map, which is a matrix containing essential information extracted from the input image. Other convolutional layers or pooling layers may come after the convolutional layer. Each convolutional layer is typically followed by a ReLU activation function to determine which neurons become activated [22]. To activate the ReLU function will use the following equation 1.

$$f(x) = \max(0, x) \tag{1}$$

f (x) : ReLU activation function, x : The value of the convolution matrix.

The Fully Connected Layer is positioned at the final stage of the network and functions similarly to a traditional Artificial Neural Network, where each active neuron from the preceding is linked to each neuron in the present layer. Prior to entering this layer, the multidimensional features from earlier stages must be flattened into a one-dimensional vector. This layer, commonly employed in Multi Layer Perceptron (MLP) architectures, is responsible for processing the extracted features to enable accurate classification [23]. In the fully connected layer process can be represented by the following equation 2.

$$y = f(Wx + b) \tag{2}$$

y: Output of the neuron, x : Input vector (flattened result from pooling layer), W: Matrix weight, b: Bias, f: Activation function, such as ReLU or Softmax (depending on the layer)

2.4.2 ResNet-50

ResNet-50 is a convolutional neural network architecture widely adopted for its implementation of residual learning through shortcut connections. Each residual unit adopts a bottleneck structure, consisting of sequential 1×1, 3×3, and 1×1 convolutional layers. This configuration enables efficient dimensionality reduction, spatial feature extraction, and restoration of feature map depth [24] as presented in Figure 3 :

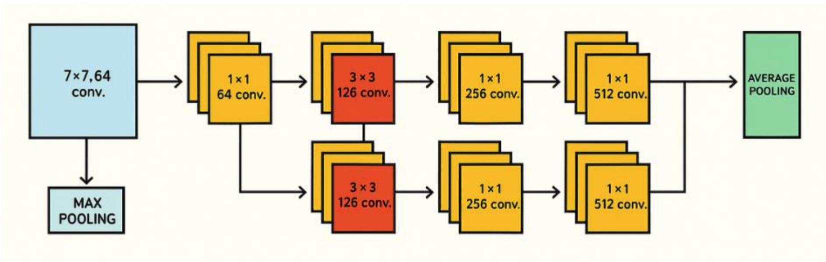


Figure 3. ResNet-50 Architecture

2.4.3 Training Process

On the trained model, the training procedure will be executed. The dataset's training data is used for training [25]. During training, the convolutional neural network (CNN) model will iterate on the training dataset to optimize the weights in the existing layers [26]. Image data processing follows after the dataset has been gathered, which includes pre-processing steps such as image resizing, normalization, and augmentation to increase data diversity. The processed dataset is then separated into two sections: the testing data and the training data. The CNN model is trained using the training data to identify key elements and patterns in the image, while the testing data will be used to evaluate the model's performance. After data division, training is carried out using the CNN model. Then, when the model training stage is complete, the model is tested to determine if the obtained accuracy is satisfactory. If the accuracy of the model meets the specified criteria (for example based on certain threshold values on evaluation parameters like accuracy, precision, and recall), the model is deemed effective and applies to a particular image to generate detection results. The CNN model training flowchart is shown in Figure 4.

For the model to learn patterns and significant characteristics, the image dataset is labeled according to the designated classes. To reduce the loss value and increase accuracy, the model's weights and biases are effectively adjusted during training using Adam's optimization technique. To assess the model's performance during training and prevent overfitting, validation is also conducted using test data. To find the ideal configuration that yields the highest performance, modifications are also made to the hyperparameters, including the number of epochs, learning rate, and batch size. The core feature extractor of the CNN model is built on the ResNet-50 architecture, followed by a series of dense, dropout, and batch normalization layers to enhance the model's classification capacity and broaden its applicability to new data. Table 3 shows the parameters that were used.

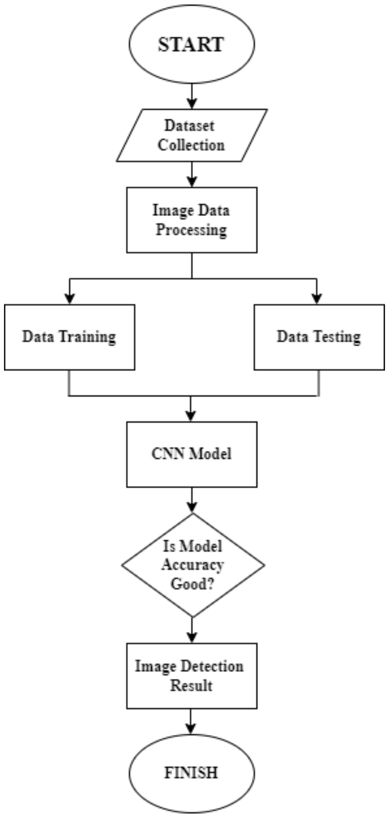


Figure 4. CNN Model Training Flowchart

Table 3. Classification Parameters

Layer (Type)	Output Shape	Param #
Resnet50 (Functional)	(None, 7, 7, 2048)	23,587,712
Global_average_pooling2d (GlobalAveragePooling2D)	(None,2048)	0
Dense (Dense)	(None, 512)	1,049,088
Dropout (Dropout)	(None, 512)	0
Batch_normalization (BatchNormalization)	(None, 512)	2048
Dense_1 (Dense)	(None, 256)	131,328
Dropout_1 (Dropout)	(None, 256)	0
Dense_2 (Dense)	(None, 5)	1,285

2.5 Evaluation Model

Model evaluation is used to determine the extent of the performance of the model that has been trained [27]. The results that have been tested will produce accuracy, precision, and recall, where the three results are obtained by the confusion matrix method. The model's ability to accurately identify positive instances is measured by the recall function, its accuracy in predicting the test class label, as well as its precision and accuracy in predicting the positive class label. Accuracy, precision, and recall statistics are typically presented as a percentage using the following formula 3-5.

$$\text{Accuracy} = (TP + TN) / (TP + TN + FP + FN) \tag{3}$$

$$\text{Precision} = TP / (TP + FP) \tag{4}$$

$$\text{Recall} = TP / (TP + FN) \tag{5}$$

TP : True Positives ,TN : True Negatives, FP : False Positives, FN : False Negatives.

3. RESULTS AND ANALYSIS

3.1 CNN Model Testing

Testing the CNN model involves evaluating it on training data using previously created parameters. In testing this model, it has produced accuracy and loss values on both training and validation data, which indicate the accuracy of the training data and the low resulting loss value. In the training process, using a number of epochs as large as 50 with a batch size of 32. The following are the results of the accuracy and loss graphs in testing the CNN model, as Figure 5.

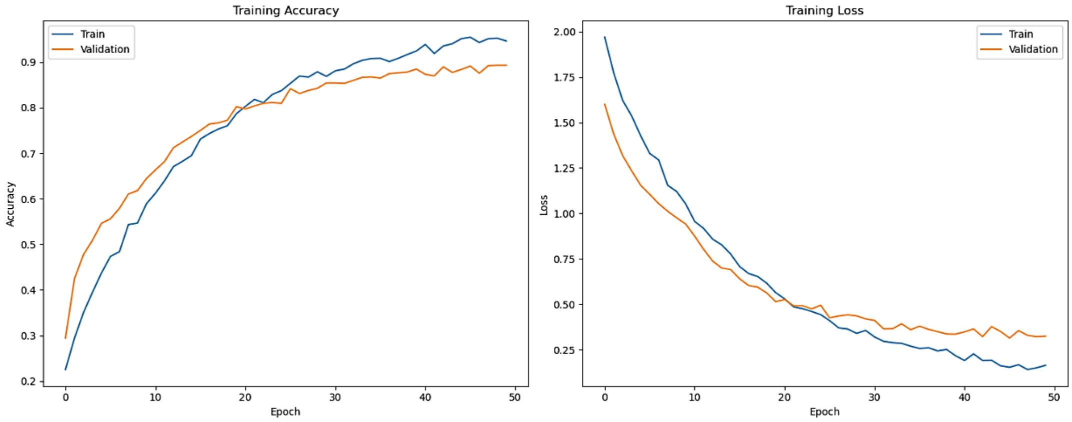


Figure 5. CNN Model Testing Results Chart

In Figure 5, both training and validation data show an improving trend in accuracy, which is derived from the accuracy training portion. The validation accuracy also steadily increased, reaching approximately 89%, while the training accuracy increased steadily from the start, ultimately reaching roughly 95% at the 50th epoch. There is no discernible overfitting in the model, as evidenced by the relatively small difference between the training and validation accuracy. In the meantime, both the training and validation data exhibit a steady decline in loss value, as indicated by the loss graph. The validation loss decreases from about 1.6 to around 0.3, and the training loss value decreases from about 2.0 to less than 0.2. The model's capacity to learn efficiently is demonstrated by the consistent decline in loss; the absence of significant oscillations or leaps throughout training suggests instability.

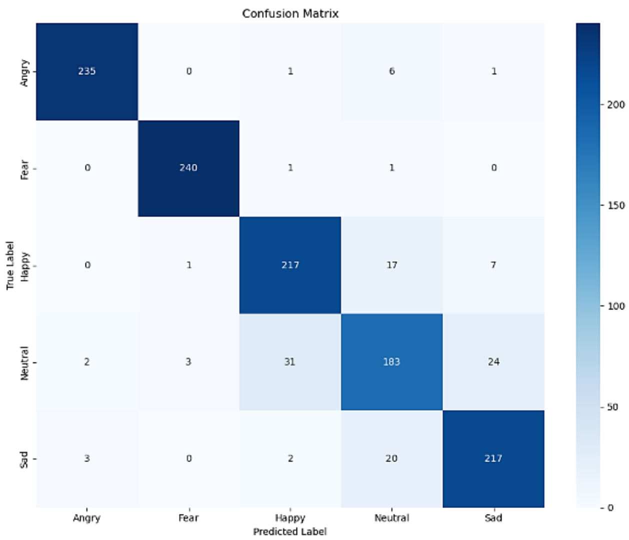


Figure 6. Confusion Matrix

Figure 6 above demonstrates the model's classification effectiveness through a confusion matrix representation of the CNN model in classifying five emotion categories: Angry, Fear, Happy, Neutral, and Sad. The results indicate that the model achieves a high level of accuracy, particularly in recognizing the Angry, Fear, and Sad classes. However, significant misclassifications occur between the "Happy" and "Neutral" categories. Possible causes: Similar visual cues (slight smile vs relaxed face), Limited dataset variety, Expression subtlety typical in autistic children. False Negatives mainly occurred in: Sad misclassified as Neutral, Happy misclassified as Neutral, this indicates the model needs improved sensitivity (recall), especially for emotionally subtle expressions.

Table 4. Final Evaluation Value CNN Model

Final Evaluation Metrics	
Accuracy	: 84.49%
Precision	: 86,78%
Recall	: 80,69%

The final evaluation of the model is shown in Figure 8, where the model achieved an accuracy value of 84.49%, precision of 86.78%, and recall of 80.69%. Although the model has a low false positive error rate, there is still opportunity for improvement in terms of recognizing all pertinent cases (false negative), as indicated by the larger accuracy value when compared to recall. This can be taken into account when refining the model, particularly if its use necessitates a high sensitivity to identifying every positive occurrence. Overall, the model performed well with good training stability and good generalization to the validation data. These results indicate that the model is feasible to use in the current system, but can still be further improved with hyperparameter tuning or additional training data.

3.2 Testing Data Results

Testing the results of this testing data aims to determine how accurate the CNN model with ResNet-50 architecture is in detecting expressions from children with autism. This test is carried out with a testing dataset containing 5 images from classes consisting of angry, neutral, happy, fear, and sad. The following test results of this model can be seen in Table 5 and Table 6.

Table 5. Test Picture Data

Class				
Angry	Neutral	Sad	Fear	Happy

Class				
Angry	Neutral	Sad	Fear	Happy

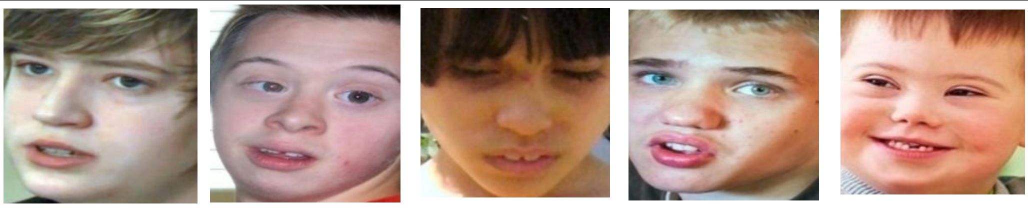
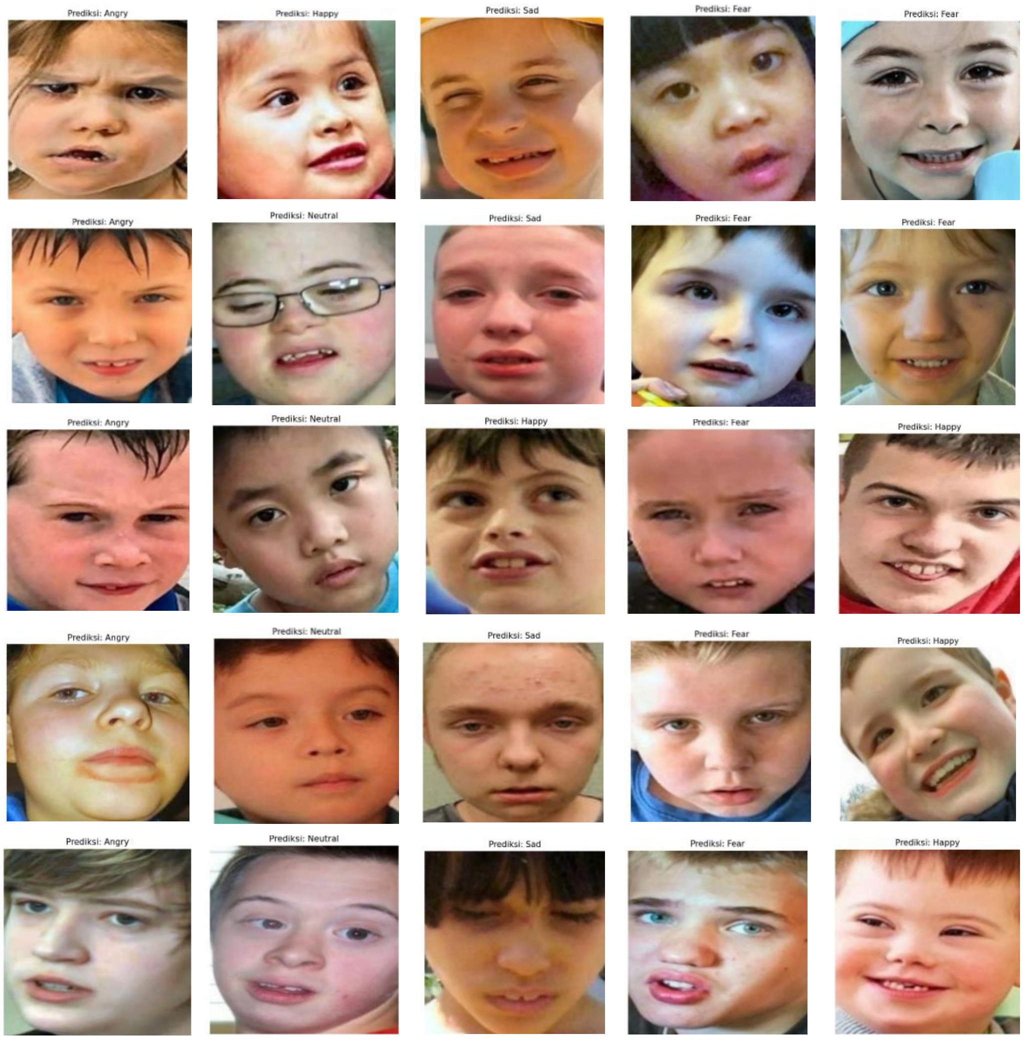


Table 6. Picture Test Result Data

Class				
Angry	Neutral	Sad	Fear	Happy



In Table 6, the results of testing the model with 25 images of testing data, which are divided into 5 classes, show that 21 images were successfully detected and 4 images were failed, so that of the total test images, only 4 images were wrongly detected. After obtaining the results from the test table, the calculation of accuracy will continue. Based on the results in Table 4, the accuracy calculation process is as follows:

$$\text{Accuracy} = \frac{\text{Number of successful data}}{\text{Sum of all test data}} \times 100\%$$

$$\text{Accuracy} = \frac{21}{25} \times 100\% = 84\ \%$$

Based on the results of the above calculations, it can be stated that the CNN model with the ResNet-50 architecture achieves an accuracy of 84% in detecting the expressions of children with autism using 25 images of testing data.

3.3 Discussion

The experimental results demonstrate that the proposed CNN model, utilizing the ResNet-50 architecture, achieves satisfactory performance in recognizing facial expressions in children with autism. The model achieved a testing accuracy of 84.49%, supported by good precision and recall values. This indicates that ResNet-50 is effective in extracting facial features, even when expressions are subtle and less pronounced, a common characteristic in autistic children. The training and validation results demonstrate stable learning behavior, as indicated by the consistent increase in accuracy and decrease in loss without significant overfitting. The relatively small gap between training and validation accuracy suggests that the use of transfer learning, data augmentation, and regularization layers contributes positively to the model's generalization capability.

Analysis of the confusion matrix reveals that the model performs well in recognizing angry, fearful, and sad expressions, while misclassifications primarily occur between happy and neutral expressions. This is likely caused by the visual similarity between these two expressions and the limited facial expressiveness often exhibited by children with autism. As a result, subtle emotional states remain more challenging for the model to distinguish accurately. Additional testing using 25 images produced an accuracy of 84%, which is consistent with the main evaluation results. Despite these promising outcomes, the study is limited by the use of general facial expression datasets rather than autism-specific data. Future improvements may include collecting more representative datasets and applying advanced model enhancements to better capture subtle emotional variations. Overall, the proposed model shows strong potential for use in assistive systems to support emotional recognition in children with autism.

4. CONCLUSION

This research successfully developed a facial expression detection model for autistic children using a CNN with ResNet-50 architecture. The model achieved 89% validation accuracy and 84.49% testing accuracy, with a precision of 86.78% and a recall of 80.69%. Testing on 25 sample images resulted in an 84% success rate. ResNet-50 proved effective for feature extraction and classification. However, improvements can be made by increasing dataset diversity (in terms of age, lighting, and autistic expression variations), applying better regularization, utilizing advanced augmentation, and exploring attention-enhanced models. The model shows potential as a tool to support therapeutic communication for children with autism.

REFERENCES

[1] C. Cahyaningtyas, C. Gudiato, M. Sari, T. Informasi, and I. Shanti Bhuana, "Deteksi Ekspresi Wajah Manusia Menggunakan Metode Convolutional Neural Network," JURNAL FASILKOM, vol. 15, pp. 138–145, 2025.

[2] A. Marcha, "Peran Ekspresi Wajah Dalam Mendukung Komunikasi Verbal Pada Anak-Anak Dengan Autisme," Jurnal Ilmu Komunikasi, vol. 3, no. 2, 2024.

[3] Y. C. Oktaviani and Y. Wahyuningsih, "Face Expression Recognizer Dengan Convolutional Neural Network Untuk Membantu Penderita Autisme Mengenali Ekspresi Wajah Seseorang," Jurnal Informatika dan Teknik Elektro Terapan, vol. 11, no. 3, Aug. 2023, doi: 10.23960/jitet.v11i3.3108.

[4] N. P. Novani, D. R. Salsabila, R. Aisuwarya, L. Arief, and N. Afriyeni, "Sistem Pendeteksi Gejala Awal Tantrum Pada Anak Autisme Melalui Ekspresi Wajah Dengan Convolutional Neural Network," JITCE (Journal of Information Technology and Computer Engineering), vol. 5, no. 02, pp. 93–106, Sep. 2021, doi: 10.25077/jitce.5.02.93-106.2021.

[5] M. Yusqi Alfan Thoriq, K. Eka Permana, I. Agustien Siradjuddin, T. Informatika, U. Trunojoyo Madura, and J. Raya Telang Kamal, "Deteksi Wajah Manusia Berbasis One Stage Detector Menggunakan Metode You Only Look Once (YOLO)," 2023. [Online]. Available: https://ejurnal.teknokrat.ac.id/index.php/teknoinfo/index

[6] A. Wirdiani, I. K. G. Darma Putra, M. Sudarma, R. S. Hartati, and L. S. A. Lofiana, "Real-time Face Recognition System Using Deep Learning Method," Lontar Komputer : Jurnal Ilmiah Teknologi Informasi, vol. 14, no. 1, p. 62, Oct. 2023, doi: 10.24843/lkjiti.2023.v14.i01.p06.

[7] Syifa Zahrah, Azhar, and Musta'inul Abdi, "Sistem Deteksi Wajah Untuk Pencatatan Kehadiran Mahasiswa Di Kelas Menggunakan Metode Convolutional Neural Network," JAISE : Journal of Artificial Intelligence and Software Engineering, 2022.

[8] A. Lioga Seandrio, A. Hendrianto Pratomo, and M. Y. Florestiyanto, "Implementation of Convolutional Neural Network (CNN) in Facial Expression Recognition Implementasi Convolutional Neural Network (CNN) Pada Pengenalan Ekspresi Wajah," Jurnal Informatika dan Teknologi Informasi, vol. 18, no. 2, pp. 211–221, 2021, doi: 10.31515/telematika.v18i2.4823.

[9] R. Rafiif Amaanullah, G. Rizka Pasfica, S. Adi Nugraha, and M. Rifqi Zein, "Implementasi Convolutional Neural Network Untuk Deteksi Emosi Melalui Wajah (Implementation of Convolutional Neural Network for Emotion Detection Through Face)," 2022. [Online]. Available: https://www.kaggle.com/shivambhardwaj0101/emo

[10] S. Bahri, R. Samsinar, and P. S. Denta, “Pengenalan Ekspresi Wajah untuk Identifikasi Psikologis Pengguna dengan Neural Network dan Transformasi Ten Crops,” vol. 5, no. 1, 2022.

[11] T. Elizabeth, “Penerapan Convolutional Neural Network Untuk Klasifikasi Citra Ekspresi Wajah Manusia Pada MMA Facial Expression Dataset,” 2021. [Online]. Available: http://jurnal.mdp.ac.id

[12] C. Nisa and F. Candra, “Klasifikasi Jenis Rempah-Rempah Menggunakan Algoritma Convolutional Neural Network,” MALCOM: Indonesian Journal of Machine Learning and Computer Science, vol. 4, no. 1, pp. 78–84, Dec. 2023, doi: 10.57152/malcom.v4i1.1018.

[13] M. A. Satriawan and W. Widhiarso, “Klasifikasi Pengenalan Wajah Untuk Mengetahui Jenis Kelamin Menggunakan Metode Convolutional Neural Network,” Jurnal Algoritme, vol. 4, no. 1, pp. 43–52, 2023, doi: 10.35957/algoritme.xxxx.

[14] P. Adi Nugroho, I. Fenriana, and R. Arijanto, “Implementasi Deep Learning Menggunakan Convolutional Neural Network (CNN) Pada Ekspresi Manusia,” JURNAL ALGOR, vol. 2, no. 1, 2020, [Online]. Available: https://jurnal.buddhidharma.ac.id/index.php/algor/index

[15] A. Hendi Muhammad, “Jurnal Computer Science and Information Technology (CoSciTech) http://ejurnal.umri.ac.id/index.php/coscitech/index Deteksi Dan Klasifikasi Penyakit Daun Tomat Menggunakan ResNet-50,” vol. 6, no. 1, pp. 9–20, 2025, doi: 10.37859/coscitech.v6i1.8501.

[16] Fathoni, R. Muthia Nashiroh, P. Salsa Anindya, R. Ely, R. Fitrah, and I. Ali, “Pengembangan Model Cnn Untuk Klasifikasi Ekspresi Wajah Dan Potensi Penerapannya Dalam Perilaku Kriminal,” JATI (Jurnal Mahasiswa Teknik Informatika), vol. 9, 2025.

[17] W. Zhang, X. Zhang, and Y. Tang, “Facial expression recognition based on improved residual network,” IET Image Process, vol. 17, no. 7, pp. 2005–2014, May 2023, doi: 10.1049/ipr2.12743.

[18] A. Miskow and A. Altahhan, “Emotion Recognition with Facial Attention and Objective Activation Functions,” Oct. 2024, [Online]. Available: http://arxiv.org/abs/2410.17740

[19] Y. Wang, K. Pan, Y. Shao, J. Ma, and X. Li, “Applying a Convolutional Vision Transformer for Emotion Recognition in Children with Autism: Fusion of Facial Expressions and Speech Features,” Applied Sciences (Switzerland), vol. 15, no. 6, Mar. 2025, doi: 10.3390/app15063083.

[20] J. Vicky, F. Ayu, and B. Julianto, “Implementasi Pendeteksi Penyakit pada Daun Alpukat Menggunakan Metode CNN,” 2023.

[21] A. Kusuma Putra, H. Bunyamin, and K. Maranatha Jl drg Surya Sumantri No, “Pengenalan Simbol Matematika dengan Metode Convolutional Neural Network (CNN),” 2020.

[22] Y. N. Fuadah, I. D. Ubaidullah, N. Ibrahim, F. F. Taliningsing, N. K. SY, and M. A. Pramuditho, “Optimasi Convolutional Neural Network dan K-Fold Cross Validation pada Sistem Klasifikasi Glaukoma,” ELKOMIKA: Jurnal Teknik Energi Elektrik, Teknik Telekomunikasi, & Teknik Elektronika, vol. 10, no. 3, p. 728, Jul. 2022, doi: 10.26760/elkomika.v10i3.728.

[23] U. Sri Rahmadhani and N. Lysbetti Marpaung, “Klasifikasi Jamur Berdasarkan Genus Dengan Menggunakan Metode CNN,” vol. 8, no. 2, 2023.

[24] L. Zhang, Y. Bian, P. Jiang, and F. Zhang, “A Transfer Residual Neural Network Based on ResNet-50 for Detection of Steel Surface Defects,” Applied Sciences (Switzerland), vol. 13, no. 9, May 2023, doi: 10.3390/app13095260.

[25] K. L. Kohsasih et al., “Analisis Perbandingan Algoritma Convolutional Neural Network Dan Algoritma Multi-Layer Perceptron Neural Dalam Klasifikasi Citra Sampah,” 2021. [Online]. Available: http://ejournal.stmik-time.ac.id

[26] W. Bismi and M. Qomaruddin, “Jurnal Informatika dan Rekayasa Perangkat Lunak Klasifikasi Citra Genus Panthera Menggunakan Pendekatan Deep learning Berbasis Convolutional Neural Network (CNN),” vol. 5, no. 2, pp. 172–179, 2023.

[27] Sandy Andika Maulana, Shabrina Husna Batubara, Tasya Ade Amelia, and Yohanna Permata Putri Pasaribu, “Penerapan Metode CNN (Convolutional Neural Network) Dalam Mengklasifikasi Jenis Ubur-Ubur,” Jurnal Penelitian Rumpun Ilmu Teknik, vol. 2, no. 4, pp. 122–130, Dec. 2023, doi: 10.55606/juprit.v2i4.3084.

BIBLIOGRAPHY OF AUTHORS

Ekawati Prihatini is an Assistant Professor in Electrical Engineering at Sriwijaya State Polytechnic, Indonesia. She holds a Bachelor’s degree from Universitas Sriwijaya and a Master’s degree from the Bandung Institute of Technology. Her research focuses on robotics, artificial intelligence, renewable energy, and assistive technology, including socially assistive robots. She is an active member of IAENG and PII and a recipient of national and international innovation awards.

Dr. Selamat Muslimin has been a lecturer at Sriwijaya State Polytechnic since 2007. He has professional experience in private companies and banking, and is actively involved in the Mechatronics Laboratory. He earned his Bachelor’s degree from Sriwijaya University and a Master’s degree from Bina Darma University. He is active in teaching, research, and community service, and is currently pursuing a Doctoral degree in Electrical Engineering.

Muhammad Rizki Darmawan is a D4 Electrical Engineering student at Sriwijaya State Polytechnic. He is actively involved in campus seminars and student organizations, serving two terms in the Electrical Engineering Student Association. He participated in the MBKM Independent Study Program at PT Stechoq Robotika Indonesia and has practical experience working at a power plant operated by PT Bukit Energi Servis Terpadu.