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# DEEP LEARNING PERFORMANCE ANALYSIS FOR FACIAL EXPRESSION BASED AUTISM SPECTRUM DISORDER IDENTIFICATION

*The **subject matter** of this paper revolves around the utilization of Deep Learning techniques for the identification of Autism Spectrum Disorder (ASD) through facial expression analysis. The **goal** is to assess the performance of various Deep Learning architectures in this context, aiming to support the evaluation of AI-based ASD identification technologies within medical imaging standards. The **tasks** undertaken include conducting a comprehensive performance analysis of different Deep Learning models, emphasizing the significance of data augmentation techniques, and evaluating the convergence ability of these models. **Methods** employed involve a simulation setup for evaluating Deep Learning architectures using facial expression images of children with ASD. The research utilizes secondary data from open-source sharing platforms comprising 2,840 optical images. The evaluation is conducted with consideration of data ratio settings and data augmentation procedures. **Results** indicate that data augmentation significantly improves the recall performance, with ResNet-101 architecture demonstrating superior accuracy, precision, and convergence ability compared to ResNet-50 and VGG-16. Finally, the **conclusion** drawn from this analysis highlights the efficacy of ResNet-101 with augmented data. It stands out as the most suitable model for ASD identification based on facial expressions, emphasizing its potential for early intervention and increased awareness. the scientific novelty of the results obtained lies in its contribution to advancing the state of the art in AI-driven ASD identification, adhering to medical standards, enhancing model performance through data augmentation, and facilitating early intervention strategies for improved patient outcomes.*

***Keywords:*** *Autism Spectrum Disorder (ASD); identification; performance evaluation; facial expression.*

## 1. Introduction

### 1.1. Motivation for research

Autism Spectrum Disorder (ASD) refers to several developmental disabilities that can cause significant social, communication, and behavioral challenges in children [1]. Its prevalence is consistently increasing worldwide. In Indonesia, new autism cases are predicted to occur in approximately 500 cases annually [2]. The severity of ASD varies because of the wide range of this spectrum. Children with ASD can attempt to have a good quality of life similar to others. Moreover, some children with ASD have very high levels of IQ. However, behavioral disorders inhibit their potential. The early intervention to correct the disorder through several treatments and therapy highly affected their positive development. Early detection of ASD is normally done by evaluating the growth and development path of the children and observing some mental behavior expressions by pediatricians [3, 4]. Some parents with good knowledge of children's growth and development are better aware of identifying something abnormal in their children. Visiting experts to confirm diagnosis and treatment recommendations should follow this awareness. Unfortunately, most parents still lack information and knowledge about ASD. Hence, the ability to recognize the symptoms of ASD as early as possible is limited.

### 1.2. State of Art

Artificial Intelligence has been extensively used to help medical experts support their diagnoses. This AI is not only used in the medical field, but is also useful in various fields such as business, entertainment, education, and others. A study utilized AI implemented in an online webcam to monitor employees. This research proves the effectiveness of implementing an AI system using Python with the MediaPipe library [5]. Perepelitsyn et al. provide an important contribution by providing insight

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into the application of FPGAs in accelerating the implementation of AI in service [6]. In the case of ASD, AI has been developed to confirm the diagnosis by analyzing the brain signal [7, 8] and identifying facial expressions through thermal imaging of children with ASD [9, 10]. In addition, some researchers have also focused on identifying typical facial expressions of children with ASD based on optical camera sensors [11, 12]. Technological advancements have the potential to greatly enhance the existing process of detecting ASD [13]. It can be attached to the growth and development screening software to support early ASD symptoms. Previous research has explored facial image analysis for ASD diagnosis, employing classical Machine Learning methods alongside Deep Learning techniques such as Automated Machine Learning (AutoML). Melinda et al. analyzed EEG signals in people with ASD using a Support Vector Machine (SVM) as a classifier and Discrete Wavelet Transform (DWT) as feature extraction which achieved an accuracy of 95% [14]. Notably, AutoML exhibited superior performance, achieving approximately 96% accuracy, thus emphasizing its efficacy in facilitating accurate ASD diagnosis without requiring extensive human intervention for feature engineering [15]. Hazra et al. researched emotion recognition in human speech using Deep Learning. This study proposes a CNN-LSTM model that produces an accuracy of 84.35% in emotion recognition [16]. Subsequent research was conducted using ResNet-101 for the diagnosis of ASD and Mental Disorder Diagnosis (MDD), with the number of datasets used being 573 training data images and 120 test data images for ASD. For the MDD data, 480 training data images and 120 test data were used. The accuracy obtained in ASD data is 85.8%, and in MDD data is 83.3% [8].

Among the presented research, the performance analysis is mostly captured from the accuracy point of view. AI algorithm development evaluation with comprehensive performance metric evaluation should be presented as one of the AI approach evaluation aspects in medical imaging [17]. In addition, every parameter in the performance metric for the classification model represents different aspects that should be supported by each other [18]. Recall is one of the most important performance parameters in the medical field. It relates to evaluating false negative diagnoses that are highly avoided in medical practice. Performance evaluation fallacy on medical diagnosis analysis could be produced by only evaluating accuracy without considering recall value evaluation.

The state of the art of the proposed research is on proper performance evaluation that copes with medical requirements. It is intended to support the appropriate evaluation of any proposed AI-based ASD identification technology with image modality subject to value assessment of AI in medical imaging standards. It focuses on the AI Algorithm Development assessment performance metric aspect. We analyze Recall besides accuracy and precision, which other papers do not. Analyzing Recall for medical cases is important because the false negative is strongly avoided. Then, we also evaluate the convergence of the Deep Learning performance to ensure it reaches the global optimum. Although some studies have attempted to solve this problem using the same dataset [15, 19].

Various approaches using Deep Learning and Machine Learning have been used to diagnose ASD in children based on facial images. Elshosky et al. investigated various Machine Learning methods to build predictive models, and achieved accuracy results of approximately 96% [15]. Mouatasim et al. proposed using a Control Subgradient Algorithm (CSA) using Deep CNN. CSA improves the convergence and classification speed compared with the baseline method. The model obtains an accuracy of 96% [19]. This research also integrates transfer learning to improve the performance of Deep Learning models. Deep Learning systems that integrate multiple facial marker features are recommended for identifying children with ASD. Using this system can reduce costs and increase the effectiveness of the detection process [20].

With a focus on developing AI algorithms for ASD identification based on facial images, this research seeks to provide a deeper understanding of the most effective and efficient approaches. The performance analysis evaluated focuses on two aspects: performance metrics (accuracy, recall, and precision) and convergence ability to determine which models, such as VGG-16, ResNet-50, and ResNet-101, are the most suitable for improving diagnostic results. In addition, this study produces a performance comparison of the use of augmentation.

This research chose to test these three Deep Learning methods because VGG-16, ResNet-50, and ResNet-101 have proven effective in identifying facial expression patterns, including in complex image classification tasks. This paper performs a comprehensive performance analysis of various Deep Learning models, emphasizes the importance of data augmentation techniques, and evaluates the convergence ability of these models. The proven method makes it possible to compare the performance of new models with that of existing models, thereby facilitating a more objective assessment of technological advances in facial expression-based ASD identification. Nonetheless, the exploration of new architectures or specialized models designed specifically for ASD identification may provide valuable additional insights and stimulate progress in this field.

### 1.3. Objective and Approach

This research presents a performance evaluation of some Deep Learning architecture approaches to identify

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children with ASD based on their facial expression vision. This study is intended to support the appropriate evaluation of any proposed AI-based ASD identification technology with image modality subject to value assessment of AI in medical imaging standards. It focuses on the AI Algorithm Development assessment performance metric aspect. Several Deep Learning approaches are employed for evaluation. Comprehensive performance metrics and convergence ability subject to several simulation settings are analyzed.

The major contributions of this study can be summarized as follows:

1. Conduct a comprehensive performance analysis of several Deep Learning architectures for identifying ASD in children based on facial expression images.

2. Emphasizes the importance of evaluating AI-based ASD identification technologies within the context of medical imaging standards.

3. Demonstrates the effectiveness of data augmentation techniques in improving the performance metrics and convergence ability of the Deep Learning models.

4. Through performance analysis, this study identified ResNet-101 with augmented data as the most suitable model for ASD identification based on facial expressions. This model exhibits the best recall, accuracy, precision, and convergence ability compared with ResNet-50, ResNet-101, and VGG-16.

## 2. Case study

In this chapter, a systematic research review mapping is presented. This study is intended to confirm the validity, research challenge, and opportunities in exploring AI in the early detection of autism spectrum disorders in children. In addition, the simulation setting and identification method scenario for the evaluation of Deep Learning architectures on facial expressions of children with ASD identification are also presented.

### 2.1. Research on AI innovation related to ASD

The exploration of AI in medical fields has been increasing tremendously. It can be seen from the publication documents index in Scopus which shows a consistent increment of publications in terms of AI for medical purposes. Since 2018, there has been a significant increase in the number of publications on AI in medicine. It can be concluded that AI has a powerful impact in medical fields. At the same time, medical experts have been open to engineering (AI) innovation to support their work.

AI encompasses the capacity of machines to undertake activities traditionally associated with human intelligence, such as recognizing patterns within data and applying that knowledge to new data without explicit programming. The integration of AI holds promise for enhancing and expediting diverse facets of regenerative medicine research and development, especially in scenarios involving intricate patterns, although they are not limited to them [21].

Recently, numerous studies have conducted analysis and development on ASD using AI technology. Nahas et al. employed comprehensive bioinformatics, advanced Machine Learning techniques, and explainable AI methodologies to decipher the intricate genetic terrain of ASD [22]. Sundas et al. evaluated ASD techniques using IoT devices and AI algorithms and demonstrated that IoT devices with SS networks can improve the quality of life of patients with ASD [23]. The study by Paolucci et al. developed an AI pre-screening tool to detect early signs of ASD in pre-verbal interactions, with the main finding emphasizing the early detection of sensorimotor features related to ASD identification [24]. AI can be effectively utilized to enhance the accuracy and interpretability of facial image-based ASD diagnosis [25].

### 2.2. AI in autism

An analysis of the literature reviews that discuss AI on Autism Spectrum Disorder is also presented in this chapter. The 200 most relevant publication articles on AI in ASD were generated and analyzed. The main issues discussed in the research work are exploring AI for developing automatic identification of ASD with certain inputs [26], exploring AI technology for children with ASD treatment [27, 28], and meta-analysis on AI innovation in ASD [29, 30].

Early identification is required to support early treatment and intervention to improve the quality of life for children with ASD. Specifically on the AI exploration for automatic ASD identification, various Machine Learning algorithms have been adopted to construct an ASD Automatic Detection. Some intelligence systems to identify ASD were developed using various Deep Learning architectures.

The impressive work had been done by [26]. It was constructing automatic ASD identification based on gaze tracking. Data Augmentation was also employed to mitigate tiny data and Kernel Extreme Learning Machine was adopted as the classification model. The accuracy achieved is impressive, 98.8%. However, there is no information on other performance metrics. Another approach to constructing intelligence ASD detection was done by [31]. It proposed the combination of EEG records, facial expressions, and eye contact as the recognition features. Weighted Naive Bayes was employed to develop the identification capability. It achieved 87.5% accuracy [31].

Among all presented research, both traditional Machine Learning and Deep Learning-based approaches

have been explored to develop the identification capability. Deep Learning and traditional Machine Learning do not outperform each other. The input ranges from facial expressions, gazing tracking, eye contact, and EEG recordings. The taken features are based on the most common symptoms of ASD. Among the presented works, a detailed analysis of the performance aspect has not yet been presented. On another hand, comprehensive analysis of accuracy, precision, and recall is urgent in evaluating AI-based algorithms for medical applications.

## 3. Materials and methods of the research

A simulation was set up to evaluate the Deep Learning architecture potential for identifying ASD based on facial expressions on optical images. We used a laptop processor Intel Core i3, with 4 GB RAM.

The tools used in this research allow for limiting the computational efficiency and scalability of the Deep Learning models tested, especially high-performance architectures such as ResNet-101. The use of more powerful computing resources, such as high-performance computing clusters, can improve model performance and scalability. Higher-performance devices allow models to process more data and more complex algorithms in shorter periods, resulting in more accurate results.

### 3.1. Datasets

This study evaluates some Deep Learning algorithms for identifying facial expressions of children with ASD. The evaluation is subject to training, testing, and validation data setting ratio and data augmentation procedures. To evaluate the proposed design, secondary data are employed. Secondary facial expression images of typical children and children with ASD have been gathered from open-source sharing data [32]. It consists of 2,840 optical images of facial expressions, with 1,420 images classified as facial expressions of children with ASD.

Trustworthy secondary datasets were used in this research. This study is intended to promote transparency and reproducibility in research, as the datasets used in our research are accessible to other researchers for validation and further investigation. This encourages collaboration and contributes to the advancement of knowledge in the field of ASD identification. In addition, this research is part of preliminary research in our research roadmap on developing AI-based automatic ASD screening. This research support on exploring Deep learning potential on identifying ASD through facial expression with optical images. We are currently working on developing primary data for the corresponding case with an Indonesian background.

In consequence of using this open dataset, this study might has limitations in the generalizability of these findings. The characteristics of the dataset do not fully represent the diversity of facial expressions, ethnic backgrounds, and image quality that exist in the broader population. However, the use of secondary data used by this study allowed access to a large and diverse data set consisting of 2,840 optical images, with 1,420 images specifically classified as facial expressions of children with ASD.

### 3.2. Identification scenario

This research focuses on evaluating the performance of some Deep Learning architectures on facial expression identification in children with ASD. It is performed subject to the data ratio setting and data augmentation procedure. The research methodology was set up as shown in Fig. 1 below.

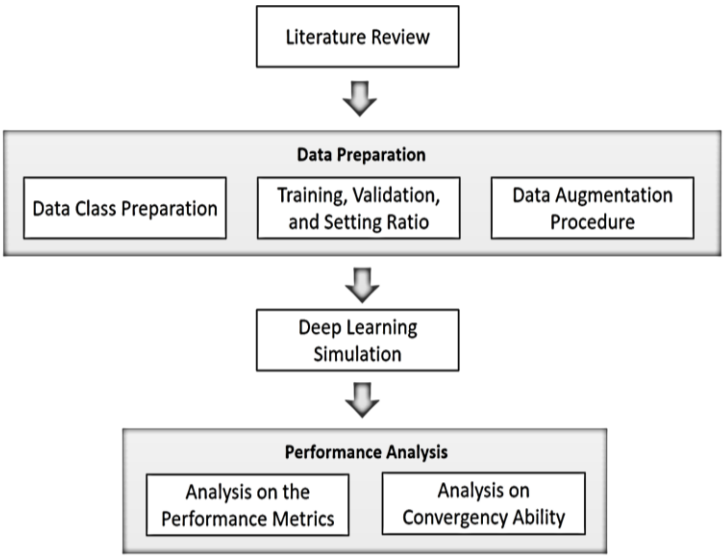


Fig. 1. Identification method development scenario

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The literature review was conducted to provide a solid research background. It synthesized the AI innovations in the Medical Area, specifically what has been done on Autism Screening. This validates the urgency and feasibility of AI innovation in assisting medical practitioners and Parents in providing initial diagnosis for early awareness of children with ASD. Some steps in data preparation continue the methodology. It consists of Data Class preparation for easy access to the simulation code, Training, validation, testing ratio setting, and Data Augmentation procedure.

### 3.3. Data augmentation

The data augmentation procedure is proposed to improve learning ability regarding performance metrics and convergence. Flipping, 300 rotation, and bright manipulation were applied as the data augmentation procedure. It sizes up the data five times compared with the initial one. This data augmentation procedure is proposed to provide a wide learning experience to learning architecture, improving the performance metric and convergence rate.

Although the augmentation technique in this study is relatively basic, this study shows that the use of this technique successfully improves the model learning experience and improves performance metrics and convergence rate. Nevertheless, it is necessary to explore more sophisticated augmentation techniques or generative models, which may result in further improvements in model performance. By conducting further research in this regard, it is possible to make a greater contribution to progress in the field of facial expression-based ASD identification. Utilizing these techniques allows for the development of a broader and more varied dataset to train DL models, thus enabling the generation of additional images with nuanced differences from the originals [33].

Recent research has evaluated the use of Generative Adversarial Network (GAN) in diagnostic classification from brain MRI. However, there are limitations such as mode collapse experienced during training. To address this issue, Huynh et al. proposed the use of Progressive-GAN and its combination with Variational Autoencoder (VAE). The results show that GANs have the potential to improve classification performance [34].

### 3.4. VGG-16 and ResNet Deep Learning architecture

Once the data preparation had been completed, the Deep Learning architecture was set up, and the learning simulation was started. Three Deep Learning architectures, VGG-16 [35], ResNet 50 [36], and ResNet 101 [12] were employed. VGG-16 and ResNet are Deep Learning architectures initially developed on the Convolutional Neural Network framework for image modality. These architectures were trained on a bunch of images on ImageNet datasets.

VGG-16 is one of the Visual Geometric Group Deep Learning architecture variants with 16 layers and a total of 138 million trained parameters. It is considered a simple but robust Deep Learning architecture that is frequently used in image-based identification [37]. In the 2014 ImageNet Challenge, VGG models demonstrated superior performance, securing top positions in both the localization and classification categories. Notably, they achieved an error rate of 6.8% in the classification track and 25.3% in the localization track on the test set [33]. VGG is widely employed as a CNN model because of its remarkable accuracy in recognizing large-scale images [38].

ResNet 50 and ResNet 101 are variants of the Residual Neural Network, ResNetXX architecture. It is a CNN-based Deep Learning architecture that solves the "vanishing gradient" problem by proposing two kinds of shortcut connections: Identity shortcut and projection shortcut [33]. Despite being much deeper than VGG networks, it simplifies complexity, improves optimization, and achieves an impressive error rate [33]. The XX index represents the number of layers. ResNet 50 and ResNet 101 train 25 million and 44 million parameters, respectively. It can be observed, in terms of computational complexity, that ResNet architecture has a smaller complexity compared to VGG architecture. VGG-16 and ResNet architectures are chosen subject to their ability on image-based modality recognition.

### 3.5. Performance analysis

The main contribution of this paper is the evaluation of the AI approach model on the automatic ASD identification of children based on the facial expression dataset. It is intended to support the appropriate evaluation of any proposed AI-based ASD identification technology with image modality subject to value assessment of AI in medical imaging standards. The analysis focuses on two aspects: performance metrics analysis and convergence ability analysis. The performance metrics analysis involves Accuracy, Recall, and Precision parameters [27, 31].

In this study, our main focus was on recall, accuracy, precision, and convergence ability in identifying facial expression-based ASD. With the evaluation of the metrics used, the comparison of the performance of the models tested in this study provides a strong basis for more reliable and effective clinical application in identifying ASD. Nevertheless, incorporating more nuanced evaluation metrics such as the F1-score, Receiver Operating Characteristic Area Under the Curve (AUC-ROC), or Matthews Correlation Coefficient (MCC) can provide

a more comprehensive performance analysis, especially in medical diagnostic applications where balancing sensitivity and specificity is critical.

The analysis is subject to the data ratio setting (Table 1) and the attached data augmentation procedures. The analysis of convergence ability is performed by analyzing the loss function and running time. This is done subject to the attached data augmentation procedure.

## 4. Results and Discussion

This section discusses the evaluation of some Deep Learning architectures applied to facial expression detection in children with ASD. The data were simulated based on the methodology shown in Fig. 1. There are two mains of analysis: the first is on the performance metric, and the second is on the convergence ability analysis.

### 4.1. The analysis of the performance metric

Table 2 presents the performance evaluation of some Deep Learning architectures for identifying the face typology of children with ASD. The three employed architectures have various training, validation, and testing ratio settings. The three architectures are VGG-16, ResNet-50, and ResNet-101. Performance evaluation works on the data setting and data augmentation treatment.

Besides the data ratio setting, the augmentation process consistently improves the performance metric out of the initial data. The improvement is quite significant. The accuracy, recall, and precision can be increased to 5.38%, 10.46%, and 2.52%, respectively. Deep diving into the recall, the improvement made by the augmentation procedure, 10.46%, is significant. Improvement in recall means decreasing the number of false negatives. False negatives in medical practice, especially in the diagnosis aspect, are highly avoided. Hence, improvement in recall is having a significant impact on medical areas. Improved recall of automatic ASD detection will result in higher awareness and early intervention. It will significantly support the growth and the life quality of children with ASD in future years. Subject to the training, validation, and testing data set, the performance metric is slightly different between the initial data and the data with augmentation. It increases the training data ratio on initial data, consistently improving performance metrics (accuracy, recall, and precision). It improves the average accuracy by 4.86%, recall by 4.91%, and precision by 4.86%. However, this consistent improvement only occurs on data with augmentation. The performance metric is intended to decrease the higher training data ratio, and it is only slightly improved. On average, the accuracy decreases to 0.74%, and precision decreases to 2.32%.

The number of initial data is 2,840. In contrast, the augmented data amount is five times the initial data. Increasing the training data ratio on huge data tends to decrease the generalization capability of the algorithm. Hence, the performance metric tends to decrease.

Table 1

Data simulation scenario set up

| Deep Learning Architecture Regular | Data Ratio Set up1 | Data Augmentation Procedures |
|---|---|---|
| VGG-16 | 60:10:30 | Flipping, 300 |
| ResNet 50 | 70:10:20 | Rotation, bright |
| ResNet 101 | 80:10:10 | Manipulation |

1 the ratio for the data simulation = training data: validation data: testing data.

Table 2

Performance evaluation on Deep Learning architecture

| **Initial Dataset, n = 2,840** | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| **Ratio of Training, Validation, Testing** | **60:10:30** | | | **70:10:20** | | | **80:10:10** | | |
| **Algorithm** | **Accuracy** | **Recall** | **Precision** | **Accuracy** | **Recall** | **Precision** | **Accuracy** | **Recall** | **Precision** |
| VGG-16 | 79.02% | 79.57% | 79.02% | 84.50% | 75.35% | 92.24% | 85.56% | 97.18% | 78.85% |
| ResNet-50 | 76.76% | 66.90% | 83.33% | 82.74% | 76.40% | 87.50% | 89.08% | 85.91% | 91.72% |
| ResNet-101 | 78.05% | 81.12% | 76.37% | 81.16% | 76.76% | 84.16% | 88.02% | 88.73% | 87.50% |
| **With Augmentation Data, n = 11,360** | | | | | | | | | |
| **Ratio of Training, Validation, Testing** | **60:10:30** | | | **70:10:20** | | | **80:10:10** | | |
| **Algorithm** | **Accuracy** | **Recall** | **Precision** | **Accuracy** | **Recall** | **Precision** | **Accuracy** | **Recall** | **Precision** |
| VGG-16 | 83.34% | 84.05% | 83.87% | 87.54% | 88.38% | 86.92% | 88.02% | 89.96% | 86.61% |
| ResNet-50 | 90.75% | 87.71% | 93.50% | 89.39% | 91.44% | 87.84% | 88.11% | 86.75% | 89.13% |
| ResNet-101 | 92.91% | 91.71% | 94.04% | 91.23% | 93.45% | 89.47% | 85.91% | 92.95% | 81.48% |

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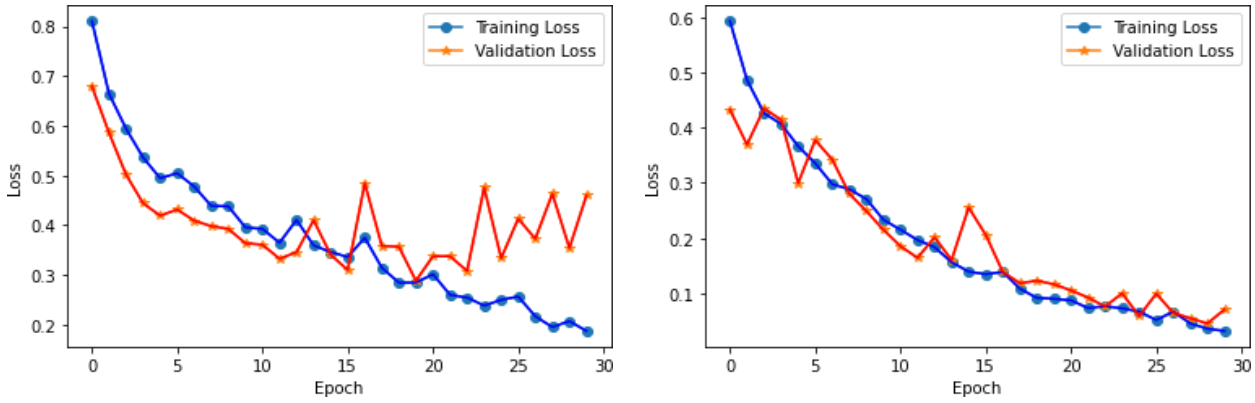
### 4.2. Analysis of convergence

In terms of convergence ability, we analyze the effect of augmentation on the improvement. Figures 2–4 present the convergence movement of the corresponding Deep Learning architecture subject to initial data and data with augmentation.

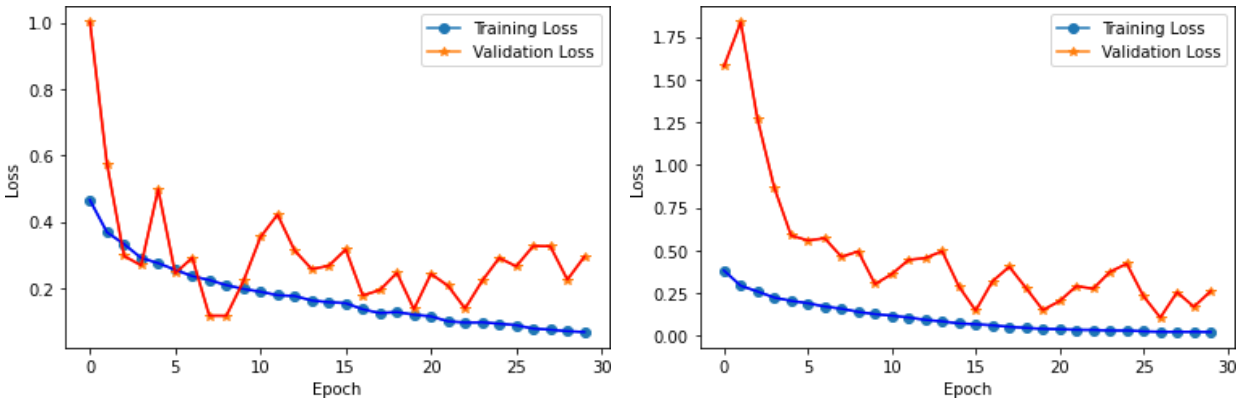
Based on Figs. 2–4, it can be observed that the augmentation data procedure improves the convergence ability of the Deep Learning architecture. In Fig. 2(a), the VGG-16 architecture does not show convergence. Convergence is reached when the augmentation data are applied, as shown in Fig. 2(b). ResNet-101 shows the superiority of other Deep Learning architectures and has good convergence ability. The data augmentation procedure also significantly improves the convergence speed of ResNet-101.

Overall, the model derived from ResNet-101 with Augmentation data is the fittest to be deployed. It consistently performs the best recall and supports accuracy and precision with good convergence ability. The best



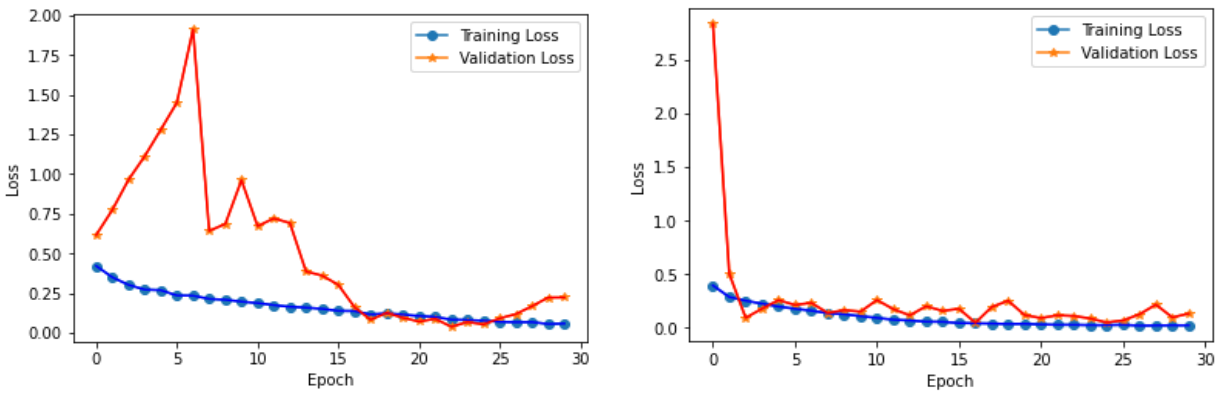

(a) (b)

Fig. 2. Convergence of VGG-16 learning; (a) On the initial dataset; (b) On the data with augmentation




(a) (b)

Fig. 3. Convergence of ResNet-50 learning; (a) On the initial dataset, (b) On the data with augmentation




(a) (b)

Fig. 4. Convergence of VGG-16 learning; (a) On the initial dataset, (b) On the data with augmentation

data set for this algorithm is 60:10:30. This setting is beneficial because it requires less training data. In terms of running time, compared with ResNet-50 and VGG-16, it is significantly better.

## Conclusions

This paper presents an appropriate and comprehensive performance analysis of several Deep Learning Architectures as an AI approach to identify autism in children based on facial expression images. The performance analysis examines the performance metric and the curve of the loss function in detail to observe the recognition and convergence abilities of the employed Deep Learning architectures. The metric performance analysis was performed subject to the data ratio setting and data augmentation procedure. It is concluded that increasing the training ratio effectively improves the performance metric on the initial data. However, it does not happen in the augmented data setting. In this simulation, the number of initial data is 2,840, and the amount of augmented data is five times that of the initial data. This means that increasing the training data ratio on huge data tends to decrease the generalization capability of the algorithm. Hence, the performance metric tends to decrease. The most consistent way to improve the performance metric is by attaching data augmentation procedures to the model learning methodology. It improves the performance metric and consistently improves the convergence ability. Analysis of recall values was also done since it's a significant performance metric in medical diagnosis. It relates to observing the false negatives that should be avoided in medical practice. Regarding recall, improvement was made by the augmentation procedure. It improved significantly up to 10.46% on average. Improved recall of automatic ASD detection will result in higher awareness and early intervention. Overall, the model derived from ResNet-101 with Augmentation data is the fittest to be deployed. It performs the best recall and consistently supports accuracy and precision with the best convergence ability. The best dataset for this algorithm is 60:10:30. This setting is beneficial because it requires less training data. In terms of running time, compared to ResNet-50 and VGG-16, it is significantly better. This setting is beneficial because it requires less training data. In terms of running time, compared with ResNet-50 and VGG-16, it is significantly better. This study provides a comprehensive analysis of several Deep Learning architectures for ASD identification based on facial expression images in children. However, there are several limitations, including the use of secondary data that may limit generalizability and relatively basic data augmentation techniques. Additional evaluation metrics such as F1-score, AUC-ROC, or MCC are also needed for a more comprehensive performance analysis. Furthermore, the simulation setup using a laptop with low specifications may limit the computational efficiency and scalability of the tested Deep Learning models.

**In future research,** it is important to consider incorporating additional metrics such as the F1-score, AUC-ROC, or MCC to provide a more comprehensive assessment of model performance. Additionally, exploring newer or more specialized Deep Learning architectures and hybrid models could uncover more effective solutions for ASD identification based on facial expressions. It would be highly beneficial to extend this research by testing more sophisticated data augmentation techniques, such as GANs for synthetic data generation, to address the limitations of data availability and enhance model robustness against overfitting.

**Contributions of authors:** conceptualization, methodology – **Melinda Melinda, Nur Afni Catur Andriyani, I Ketut Agung Enriko;** formulation of tasks, analysis **– Melinda Melinda, Yudha Nurdin, Veni Khariyunnisa, Nur Afni Catur Andriyani;** development of model, software, verification **– Yudha Nurdin, Yulita Yulita;** analysis of results, visualization **– Melinda Melinda, I Ketut Agung Enriko, Nur Afni Catur Andriyani;** writing – original draft preparation, writing – review and editing **– Yudha Nurdin, Veni Khariyunnisa.**

### Conflict of Interest

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

### Financing

This study was conducted without any financial support.

### Data Availability

The study has associated data in the data repository.

### Use of Artificial Intelligence

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

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# АНАЛІЗ ЕФЕКТИВНОСТІ ГЛИБОКОГО НАВЧАННЯ ДЛЯ ВИЗНАЧЕННЯ РОЗЛАДУ СПЕКТРУ АУТИЗМУ НА ОСНОВІ ВИРАЗУ ОБЛИЧЧЯ

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Предметом цієї статті є використання методів глибокого навчання для ідентифікації розладу аутистичного спектру (РАС) за допомогою аналізу виразу обличчя. Мета полягає в тому, щоб оцінити продуктивність різних архітектур глибокого навчання в цьому контексті, щоб підтримати оцінку технологій ідентифікації РАС на основі ШІ в рамках стандартів медичної візуалізації. Виконувані завдання включають проведення всебічного аналізу ефективності різних моделей глибокого навчання, підкреслюючи важливість методів розширення даних і оцінюючи здатність цих моделей до конвергенції. Використані методи передбачають установку моделювання для оцінки архітектур глибокого навчання з використанням зображень виразу обличчя дітей з РАС. У дослідженні використовуються вторинні дані з відкритих платформ обміну, що містять 2840 оптичних зображень. Оцінка проводиться з урахуванням налаштувань співвідношення даних і процедур доповнення даних. Результати свідчать про те, що розширення даних значно покращує продуктивність відкликання, а архітектура ResNet-101 демонструє вищу точність, точність і здатність конвергенції порівняно з ResNet-50 і VGG-16. Нарешті, висновок, зроблений на основі цього аналізу, підкреслює ефективність ResNet-101 із доповненими даними. Вона виділяється як найбільш підходяща модель для ідентифікації РАС на основі виразу обличчя, підкреслюючи її потенціал для раннього втручання та підвищення обізнаності. Наукова новизна отриманих результатів полягає в їхньому внеску в розвиток сучасного стану ідентифікації РАС за допомогою штучного інтелекту, дотримання медичних стандартів, підвищення ефективності моделі за рахунок доповнення даних і сприяння стратегіям раннього втручання для покращення результатів для пацієнтів.

**Ключові слова:** розлад аутистичного спектру (ASD); ідентифікація; оцінка ефективності; вираз обличчя.

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