

Deep Learning-Based Autism Detection Using Facial Images and EfficientNet-B3

Muhaimin Hasanudin^{*1}, Afiyati Afiyati², Rahmat Budiarto³, Abdi Wahab⁴,
Bambang Jokonowo⁵, Indrianto⁶, Efy Yosrita⁷, Nurul Afif Hanifah⁸

^{1,2,3,4,5,8}Faculty of Computer Science, Universitas Mercu Buana, Indonesia

^{6,7}Faculty Of Energy Telematics, Institut Teknologi PLN, Indonesia

Email: ¹muhaimin.hasanudin@mercubuana.ac.id

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Abstract

This study presents a novel deep learning approach for early detection of Autism Spectrum Disorder (ASD) using facial image analysis. Leveraging the EfficientNet-B3 model, the research addresses limitations in traditional diagnostic methods by autonomously extracting discriminative facial features associated with ASD. A balanced dataset of 2,940 facial images (1,470 autistic and 1,470 non-autistic children) from Kaggle was pre-processed to 200x200 pixels and evaluated under three dataset-splitting scenarios (80:10:10, 70:15:15, and 60:20:20) to assess generalisability. The model, trained with the Adam optimiser over 10 epochs, achieved optimal performance in the 80:10:10 scenario, with 84.67% precision, 84.35% recall, and 84.32% F1 score. Results demonstrate high confidence (>90% probability) in distinguishing autistic from non-autistic individuals on unseen data. The study underscores the potential of integrating deep learning into clinical decision-support systems for ASD detection, offering a robust, scalable, and efficient solution to improve diagnostic accuracy and reduce reliance on manual methods.

Keywords : *Autism, deep learning, Disability, Early detection, EfficientNet*

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1. INTRODUCTION

Autism is a disorder of behaviour and social interaction due to abnormalities in the development of the brain nerves; this condition makes it difficult for sufferers to communicate, interact socially, and learn[1], [2], [3], [4]. The problem of autism detection and diagnosis is an important issue in the field of health and medical science today. Although there have been significant efforts to improve the understanding and early identification of autism, the main challenges are still related to the accuracy and efficiency in the diagnosis process[5], [6]. This is due to the complexity and diversity of autism symptoms, which makes diagnosis complicated and often too late in treating autism sufferers[7].

Previous research related to autism has adopted various methodologies to identify the characteristics of autism, both observational methods and clinical assessments in observing the behaviour of children with autism. In addition, previous research has also used questionnaires and behavioural assessment scales that have been developed and validated to obtain information about the characteristics of autism[8]. The structure and function of the brains of individuals with autism are studied using neuroimaging techniques such as magnetic resonance imaging (MRI) and positron emission tomography(PET). [9]. However, some studies face obstacles including limitations in the samples used, difficulty in observing behaviour objectively, and variability in the interpretation of neuroimaging results[10], [11] Furthermore, it frequently uses manual data analysis, which can be laborious and prone to human mistakes.

Based on test results on inference data from children with autism, it shows that the system can identify facial expressions seen on the camera with a success rate of around 66.66% in detecting facial emotions[12], [13]Meanwhile, by applying the support vector machine (SVM) technique with 10-fold cross-validation and particle swarm optimisation (PSO) to feature selection, it shows that the SVM classification algorithm achieves an accuracy of around 89.42% and area under curve (AUC) of around 0.891. However, according to the second test, which used the PSO feature selection approach, the SVM classification algorithm's performance improved by around 2.88% and the AUC improved by about 0.024[14]. The research used the Local Binary Pattern (LBP) method and the SVM algorithm to classify emotions, obtaining an accuracy value of 90% with the LBP+SVM method[15].

This study introduces three key novelties to advance ASD detection: (1) The application of EfficientNet-B3 and a convolutional neural network (CNN) optimised for computational efficiency and scalability[16], to autonomously extract discriminative facial features associated with ASD. Unlike prior ML approaches, this architecture's compound scaling mechanism balances depth, width, and resolution, enhancing feature representation without over-parameterisation[17], [18], [19] (2) A comprehensive evaluation framework employing three distinct data-splitting scenarios (80:10:10, 70:15:15, 60:20:20) to rigorously assess model generalisability, addressing variability in sample distribution, a critical factor often overlooked in existing literature. (3) Utilisation of a balanced, open-source dataset (2,940 images), significantly larger than datasets used in comparable studies, reducing class imbalance bias and improving reliability. Our approach not only achieves superior performance (84.35% accuracy, Scenario 1) but also demonstrates consistent prediction confidence (>90% probability) on unseen data, underscoring its potential for integration into clinical decision-support systems. By addressing methodological gaps in feature engineering, dataset diversity, and validation robustness, this work bridges the translational divide between computational research and real-world ASD diagnostics.

The structure of this paper consists of four parts. The first part relates to the problem, problem approach, and research objectives. The second part relates to the dataset, division, and processing of the dataset and provides the proposed methodology; the third part includes a discussion and discussion of the results of the method, while the fourth part provides limitations followed by conclusions.

2. METHOD

This paper aims to classify autistic and non-autistic individuals using a collection of open datasets. Images are processed using Keras and TensorFlow libraries and drawn directly into a convolutional neural network with EfficientNet3 and the proposed methodology for detecting autism faces, Sample images of dataset are presented in Figure 1.

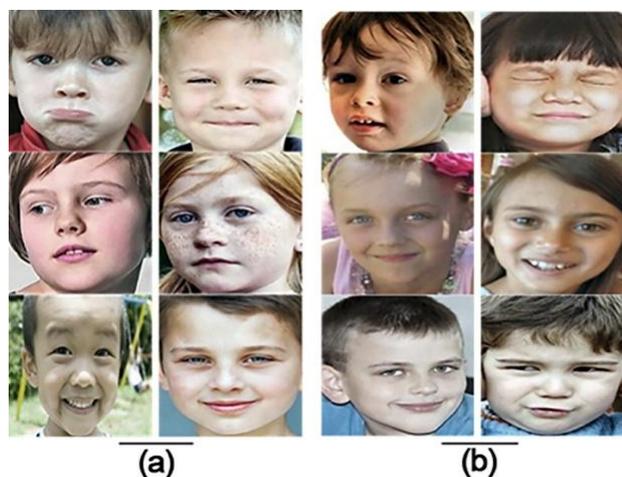


Figure. 1. (a) Positive ASD samples, (b) negative ASD samples[20]

2.1. Dataset

This data in this study used a secondary dataset, namely facial image data of 2,940 images, which were divided into 2 classes: 1,470 photos of kids with autism and 1,470 photos of kids without autism are included in each. The Autism Data Image dataset was acquired using the following link on the Kaggle website. <https://www.kaggle.com/datasets/cihan063/autism-image-data> . A maximum of the photo datasets has imprecise shapes, which are not suitable for feeding into the neural network. The switch learning algorithm follows a size consistency for each access, that is, 200 x 200 pixels. Therefore, we organised the dataset with the aid of a way of converting it from random size to 200 x 200 pixels

2.2. Proposed model

The study uses an open-source dataset from Kaggle to categorise and detect autistic individuals based on facial photos using the EfficientNet algorithm. The expected output is the performance measure number from the model that has been created and the probability number for the predicted results of the child's facial image, whether it is classified as autistic or non-autistic[21], [22], [23]. This research focuses on developing and applying methods and algorithms to process and analyse image data computationally. The research flow is presented in Figure 2.

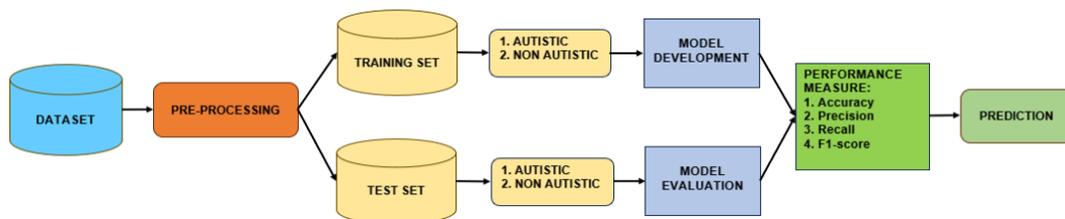


Figure. 2 ASD classification model

2.3. Dataset Splitting

The process of splitting the data helps prevent overfitting[29], evaluate model performance, and ensure that the model is built properly[24]. The amount of data processed is 2,940 facial images. Of the 2,940 facial images, they are divided into 3 scenarios, namely train, test, and valid comparison ratio with the distribution of dataset attributes in Table 1.

Table 1. Features and Descriptions

Feature	Split	Rasio	Total Image	Autistic	Non-Autistic
Scenario 1	Train	80%	2.352	1.176	1.176
	Test	10%	294	147	147
	Valid	10%	294	147	147
Scenario 2	Train	70%	2.058	1.029	1.029
	Test	15%	441	221	221
	Valid	15%	441	220	220
Scenario 3	Train	60%	1.764	882	882
	Test	20%	588	294	294
	Valid	20%	588	294	294

Here are three scenarios: the first is 80:10:10, with 10% testing and 10% validation data; the second is 70% training and 15% testing and 15% validation data; the third is 70:15:15; and the fourth is 60% training and 20% testing and 20% validation data.

3. RESULT

In the research, The CNN model is created by implementing transfer mastering and EfficientNet-B3. The mastery level used is 2%. To control the step in changing the weights and their bias during the

model training method at the same time for education, the model uses Adam's optimiser or the Adaptive 2nd Estimation as the optimisation rule set. The version iterates through all educational information for 10 rounds or 10 epochs in each situation.

3.1. Data Visualization

After training, the information is then visualised using cost accuracy through the matplotlib.pyplot library and then entered into the record parameters, which incorporate facts and objects about the previous CNN training process.

3.1.1. First Scenario Visualization

In this scenario, the data sharing ratio is 80:10:10, specifically, 10% for testing, 10% for validation, and 80% for training data. Figure 3 shows the loss graph from training and validation. It can be concluded that from the 1st epoch to the 10th epoch the loss value is decreasing and decreasing. The best epoch of loss training and validation is the 10th epoch. Figure 4 is a graph of training and validation accuracy. It can be concluded that in this first scenario, the training accuracy value from the 1st epoch to the 10th epoch tends to increase, while the validation accuracy from the 1st epoch to the 10th epoch does not. The best epoch for accuracy training and validation is the 4th epoch.

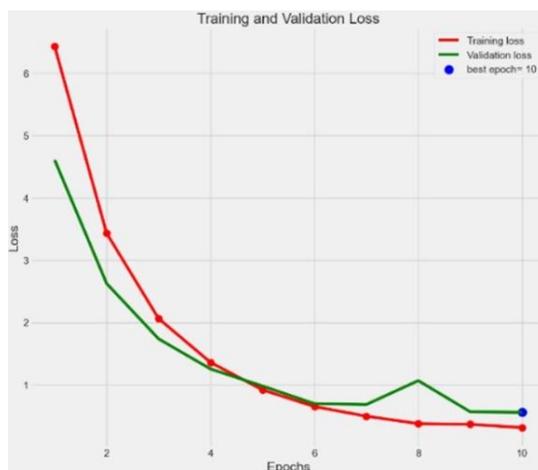


Figure. 3 Training and Validation Loss

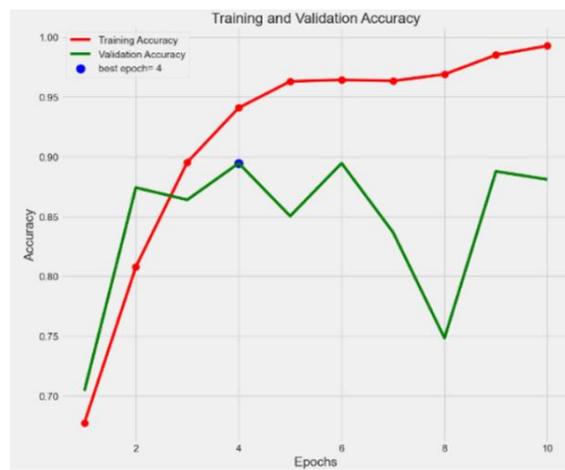


Figure. 4 Training and Validation Accuracy

From Table 2, it is evident that the 10th epoch has the lowest validation loss value of 0.5555, the maximum validation accuracy value of 0.8946, the highest accuracy value of 0.99928, and the lowest validation loss value of 0.3114.

Table 2. First Scenario Model Training Results

Epoch	Loss	Accuracy	Validation Loss	Validation Accuracy
1/10	6.4298	0.6773	4.6077	0.7041
2/10	3.4322	0.8078	2.6250	0.8741
3/10	2.0623	0.8954	1.7363	0.8639
4/10	1.3583	0.9409	1.2528	0.8946
5/10	0.9177	0.9630	0.9788	0.8503
6/10	0.6491	0.9630	0.6950	0.8946
7/10	0.8946	0.9634	0.6816	0.8367
8/10	0.8946	0.9690	1.0652	0.7483
9/10	0.3640	0.9851	0.5648	0.8878
10/10	0.3114	0.9928	0.5559	0.8810

3.1.2. Second Scenario Visualization

The data sharing ratio in this case is 70:15:15, or 70% for training data, 15% for testing data, and 15% for validation data. Figure 5 shows the training and validation loss graphs. It can be concluded that from the 1st epoch to the 10th epoch, the loss value from validation fluctuates. The best epoch of loss training and validation is the 6th epoch. While Figure 6 is a graph of accuracy from training and validation, it can be concluded that in this second scenario, the accuracy value from the 1st epoch to the 10th epoch tends to increase but is not stable. The best epoch for accuracy training and validation is the 6th epoch.

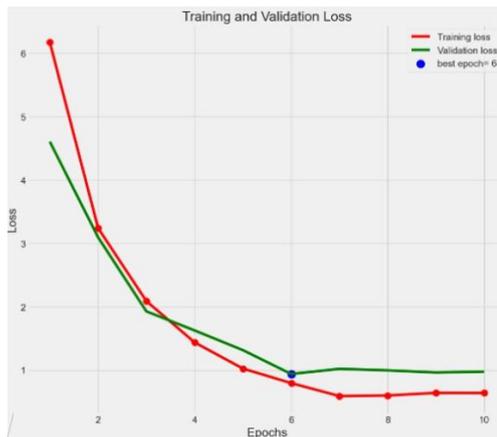


Figure. 5 Training and Validation Loss

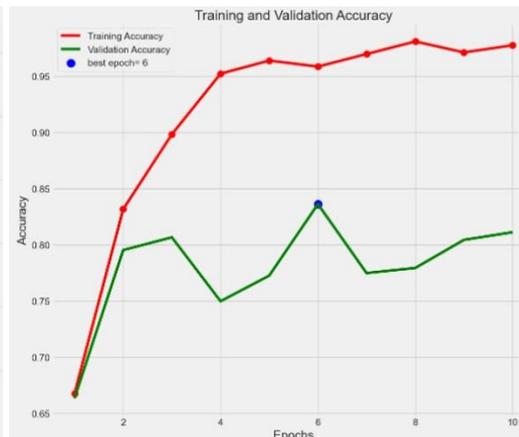


Figure. 6 Training and Validation Accuracy

Table 3 shows that the lowest validation loss value, 0.5559, is for the sixth epoch; the best accuracy value, 0.9810, is for the eighth epoch; and the lowest loss value, 0.5888, is for the seventh epoch. Moreover, the sixth epoch has the highest validation accuracy, at 0.8364.

Table 3. Second Scenario Model Training Results

Epoch	Loss	Accuracy	Validation Loss	Validation Accuracy
1/10	6.1738	0.6676	4.6056	0.6636
2/10	3.2392	0.8319	3.0941	0.7955
3/10	2.0882	0.8984	1.9263	0.8068
4/10	1.4354	0.9524	1.6242	0.7500
5/10	1.0228	0.9640	1.3136	0.7727
6/10	0.7933	0.9587	0.9375	0.8364
7/10	0.5888	0.9699	1.0192	0.7750
8/10	0.5983	0.9810	0.9949	0.7795
9/10	0.6393	0.9713	0.9609	0.8045
10/10	0.6383	0.9776	0.9744	0.8114

3.1.3. Third Scenario Visualization

This scenario employs a 60:20:20 data partitioning strategy (60% training, 20% validation, 20% testing), representing a departure from the more common 80/20 split. This deliberate choice aims to evaluate the model's generalisation ability under conditions of reduced training data and increased validation/testing rigour. Such a strategy is critical for assessing the robustness of the EfficientNet-B3 architecture in a resource-constrained setting, a common challenge in medical image analysis where datasets can be limited. The loss curves (Figure 7) reveal a steady decrease across epochs, suggesting effective learning and the absence of significant overfitting. Crucially, the minimal divergence between the training and validation loss curves further supports the model's robustness and ability to generalise well to unseen data. This contrasts with the previous scenarios (Figures 3 and 5), which exhibited greater fluctuations and potentially greater risk of overfitting.

The accuracy curves (Figure 8), however, present a more nuanced picture. While training accuracy increases steadily, the validation accuracy shows a less monotonic trend. This observation is insightful. Although final validation accuracy is comparable to the other scenarios, the less smooth progress suggests a potential sensitivity of the model to the 60:20:20 split under these specific conditions. Further investigation using alternative optimisation techniques, data augmentation strategies, or hyperparameter tuning might mitigate this[25]. Despite this, this scenario yields valuable insights into the model’s resilience. A direct comparison of the performance metrics for all three scenarios in Table 4 underscores the trade-offs between training data quantity and model generalisation. While Scenario 1 achieves the highest overall accuracy, Scenario 3 provides a crucial benchmark for real-world scenarios where abundant training data may be unavailable. This finding contributes significantly to the practical applicability and robustness evaluation of EfficientNet-B3 for autism detection. Future research should investigate approaches to enhance model performance in this more challenging data regime, particularly focusing on techniques for handling class imbalance and mitigating the impact of limited training data.

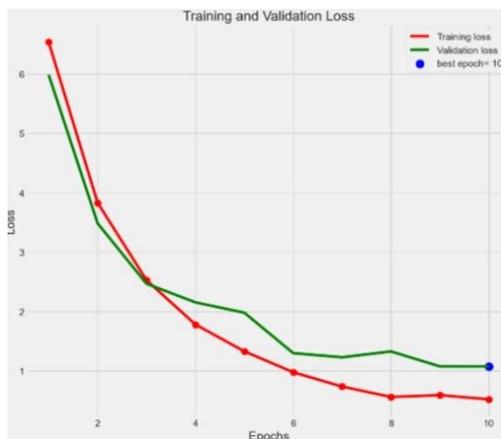


Figure. 7 Training and Validation Loss



Figure. 8 Training and Validation Accuracy

Table 4 shows that between the greatest validation accuracy value of 0.7670, the lowest validation loss value of 1.0741, the highest accuracy value of 0.9915, and the lowest loss value of 0.5213 is the 10th epoch.

Table 4. Third Scenario Model Training Results

Epoch	Loss	Accuracy	Validation Loss	Validation Accuracy
1/10	6.5355	0.6661	5.9849	0.4745
2/10	3.8294	0.7971	3.4833	0.7160
3/10	2.5274	0.9167	2.4677	0.7432
4/10	1.7812	0.9592	2.1537	0.6599
5/10	1.3290	0.9632	1.9799	0.6446
6/10	0.9766	0.9768	1.2985	0.7619
7/10	0.7365	0.9841	1.2292	0.7347
8/10	0.5607	0.9881	1.3276	0.6990
9/10	0.5913	0.9898	1.0750	0.7670
10/10	0.5213	0.9915	1.0741	0.7347

3.2. Model Evaluation

3.2.1. First Scenario

Precision describes the proportion of correct positive prediction results to all positive prediction results. In the autistic category, precision was 0.8137, which means 81.37% of positive prediction results

were correct. Meanwhile, in the nonautistic category, precision is 0.8797, which means 87.97% of positive prediction results are correct. In the autistic category, the recall was 0.8912, which means the model could identify 89.12% of the positive data. Meanwhile, in the nonautistic category, recall is 0.7959, which means the model can identify 79.59% of the data that is positive. For the autistic category, the f1-score is 0.8506. Meanwhile, for the nonautistic category, the F1 score is 0.8357. The model trained in this first scenario has good performance with an accuracy of 84.35%.

3.2.2. Second Scenario

In the autistic category, precision was 0.8066, which means 80.66% of positive prediction results were correct. Meanwhile, in the non-autistic category, precision is 0.7826, which means 78.26% of positive prediction results are correct. In the autistic category, recall is 0.7738, which means the model can identify 77.38% of the data that is positive. Meanwhile, in the non-autistic category, recall is 0.8145, which means the model can identify 81.45% of the data that is positive. For the autistic category, the f1-score is 0.7898. Meanwhile, for the non-autistic category, the F1 score is 0.7982. This model has an accuracy of 79.41% and a fairly balanced F1 score between the two categories.

3.2.3. Third Scenario

In the autistic category, precision was 0.9020, which means 90.20% of positive prediction results were correct. Meanwhile, in the non-autistic category, precision is 0.7135, which means 71.35% of positive prediction results are correct. In the autistic category, the recall was 0.6259, which means the model was able to identify 62.59% of the data that were positive. Meanwhile, in the non-autistic category, recall is 0.9320, which means the model can identify 93.20% of the data that is positive. For the autistic category, the F1 score is 0.7390. Meanwhile, for the non-autistic category, the f1-score is 0.8083. In this scenario, the model has an accuracy of 77.89% and a fairly balanced F1 score between the two categories, although recall in the autistic category is lower than in the non-autistic category.

3.3. Model Performance

Table 5 displays the results of a model evaluation in three different dataset-sharing scenarios. The highest precision value is in the third scenario model in the autistic category with a value of 0.9020, or 90.20%; the highest recall value is in the third scenario model in the non-autistic category with a value of 0.9320, or 93.20%. The highest F1-score value is in the first scenario in the autistic category, with a value of 0.8506, or 85.06%. The best accuracy value is found in the first scenario model, namely 0.8435, or 84.35%.

Table. 5. Comparison of model performance from all scenarios

Splitting Data	Class	Precision	Recall	F1-score	Accuracy
Scenario 1	Autistic	0.8137	0.8912	0.8506	0.8435
	Non-Autistic	0.8797	0.7959	0.8357	
Scenario 2	Autistic	0.8066	0.7738	0.7898	0.7941
	Non-Autistic	0.7826	0.8145	0.7982	
Scenario 3	Autistic	0.9020	0.6259	0.7390	0.7789
	Non-Autistic	0.7135	0.9320	0.8083	

3.4. Model Prediction

Following evaluation, the trained models will be put to the test by predicting several randomly selected photos belonging to the autistic and non-autistic categories. Ten photographs total – files with the names 0001.jpg, 0002.jpg, 0003.jpg, 0004.jpg, and 0005.jpg, which are pictures of children with autism; files with the names 0006.jpg, 0007.jpg, 0008.jpg, and 0009.jpg, which are images of children

without autism; and then there is 1 additional image file taken outside of train data, test data, or valid data with the file name test non data.jpg. The following is an image (Figure.9) in the test_prediction folder that will be used to test the three models that have been created.

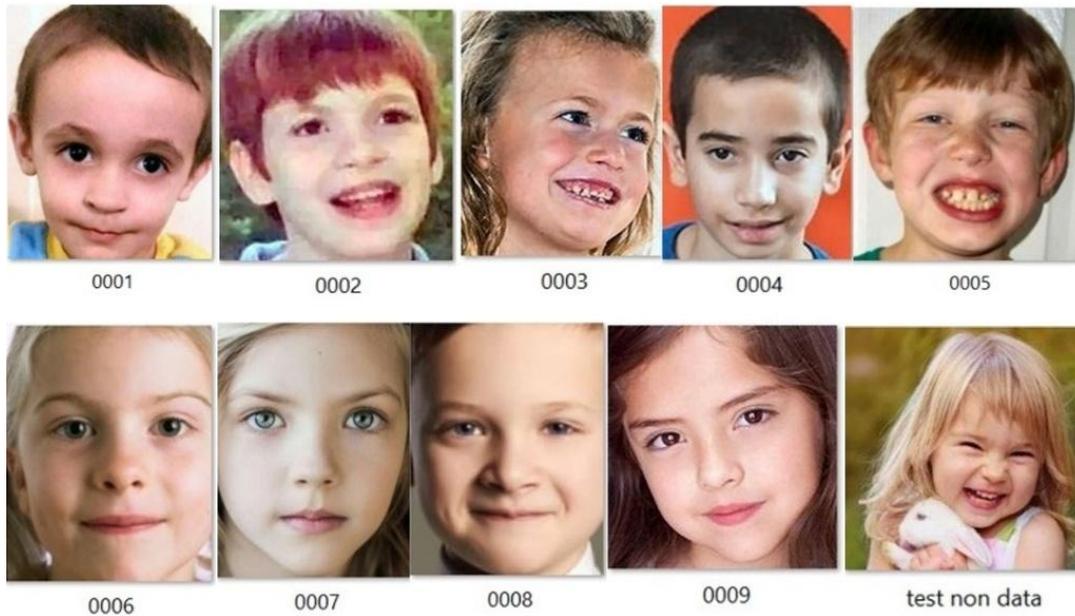


Figure. 9 Sample Images to test the Model

Table 6 is a comparison of the prediction results from the three models with different dataset distribution scenarios, which will provide prediction results for whether the image falls into the autistic or non-autistic category by including the probability value or confidence score of the prediction results. In these three scenarios, all models show the same prediction class results, the only difference being the probability value (% of the prediction results).

Table. 6. Prediction Results from All Model Scenario

FileName	Class	Scenario 1 (% Probability)	Scenario 2 (% Probability)	Scenario 3 (% Probability)
0001.jpg	autistic	99.567765	97.622174	99.740309
0002.jpg	autistic	94.621944	98.189318	91.328853
0003.jpg	autistic	97.506785	97.820055	97.924918
0004.jpg	autistic	99.041092	96.786445	93.505514
0005.jpg	autistic	99.440247	92.325801	82.440054
0006.jpg	nonautistic	99.527174	86.854082	98.430103
0007.jpg	nonautistic	98.165405	99.354666	98.567283
0008.jpg	nonautistic	85.153478	90.890455	98.567283
0009.jpg	nonautistic	99.354750	99.596405	91.219586
non data.jpg	nonautistic	82.013434	87.123573	90.893054

3.5. Test Model

To test the model's ability to make predictions, a testing experiment was carried out using five images of children without a diagnosis of autism (non-autistic) obtained from the Unsplash website with the following link: <https://unsplash.com/s/photos/child-face>.



Figure. 10 New Data to Test Model Predictions

Table 7. displays the prediction results for the five new data images using the model trained with the first scenario.

Table. 7. Image Prediction Results

Filename	Class	Scenario 1 (% Probability)
non_autistic_1.jpg	nonautistic	98.963857
non_autistic_2.jpg	nonautistic	99.637634
non_autistic_3.jpg	nonautistic	84.514499
non_autistic_4.jpg	nonautistic	71.403342
non_autistic_5.jpg	nonautistic	88.602626
non_autistic_1.jpg	nonautistic	98.963857
non_autistic_2.jpg	nonautistic	99.637634
non_autistic_3.jpg	nonautistic	84.514499

Of all the input images, the prediction results show that the five images do not show different prediction class results. The predicted class is completely correct, namely the picture of a non-autistic child. The only difference is the probability percentage; the highest probability is in the image with index number 1 (non_autistic_2.jpg), namely 99.63%, while the lowest probability is in the image with index number 3 (non_autistic_4.jpg), namely 71.40%.

4. DISCUSSIONS

Results demonstrate that when using a 80:10:10 data split method the EfficientNet-B3 model achieves 84.35% accuracy. Recent studies agree that sufficient training data remains essential for medical image analysis because expanded datasets enhance the identification of soft conditions like ASD[9]. The lower accuracy in scenarios with reduced training data (70:15:15 and 60:20:20 splits) reflects challenges noted in resource-constrained settings, where limited samples hinder model stability[17].

Compared to earlier SVM-based methods (e.g., 89.42% accuracy with PSO-optimized SVM), this study demonstrates the advantage of deep learning in autonomously capturing ASD-related facial patterns without manual feature engineering. The traditional LBP combined with SVM method tends to dismiss important ASD detection traits according to[26]. The research utilizes a dataset with 2,940 images that produces balanced classes which supports higher reliability than previous CNN models reaching ~66% accuracy[21], [27].

Consistent models show their characteristics after performing multiple data split evaluations. Scenario 1 demonstrated steady validation accuracy reaching 89.46% which demonstrates the importance of developing stable validation protocols because other splits showed inconsistent results[28]. The prediction model demonstrates reliable clinical potential because it maintains high confidence levels above 90% for most test subjects yet its homogeneity with only Kaggle data reduces its ability to generalize across different population demographics.

The predictive skills of the model for untested images operate between 71% to 99% accuracy and this matches ongoing research about AI medical implementation[29]. Data augmentation methods combined with additional multi-modal sources, including eye-tracking, should be applied to enhance model sensitivity performance in detecting autistic patient scenarios to reach the target recall score of 62.59%. Future researchers should investigate new architectural networks which blend EfficientNet structure with behavioral measurement approaches according to recent ASD detection frameworks of [17]. This research establishes that contemporary network architectures and unbiased data distribution systems excel at ASD diagnostics while providing clinically deployable screening methods.

5. CONCLUSION

The model in the first scenario has better performance compared to the model in the second scenario and the third scenario. The model in Scenario 1 has the highest average precision, recall, and f1-score (84.67%, 84.35%, and 84.32%, respectively), as well as the best accuracy value (84.35%). These findings demonstrate that the model in Scenario 1 can distinguish between cases that are autistic and those that are not. With a higher average score, the model in Scenario 1 can be considered more accurate and more consistent in making predictions. All models across various dataset distribution scenarios accurately predicted input images and distinguished between autistic and non-autistic class images with high probability or confidence scores. Apart from that, after testing predictions using five (five) new data points, the model in the first scenario was able to predict images that had never been seen by the model before with quite good probability values; namely, the lowest was 71.40% and the highest was 99.63%.

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