COGNITIVE SCIENCES AND HUMAN DEVELOPMENT

# A Novel Hybrid Unet-RBF and CNN-RBF Algorithm for Autism Spectrum Disorder Classification

**Lim Huey Chern & Abdulrazak Yahya Saleh***
Faculty of Cognitive Science and Human Development, Universiti Malaysia Sarawak, Kota Samarahan, Sarawak

## ABSTRACT

The 2021 CDC report indicates that Autism Spectrum Disorder affects 1 in 44 children, necessitating advanced classification methods. This article proposes a hybrid deep learning approach for ASD classification, merging U-net and Radial Basis Functions for medical image segmentation and integrating Convolutional Neural Network with RBF for ASD classification. Achieving 94.79% accuracy surpasses previous studies, highlighting deep learning's potential in neuroscience. Future research should explore diverse algorithms, validating them across varied datasets with different hyperparameters to enhance ASD classification efficiency.

**Keywords:** autism spectrum disorder, convolutional neural network, deep learning, radial basis function, U-Net

ARTICLE INFO
Email address: ysahabdulrazak@ unimas.my (Abdulrazak Yahya Salleh)
*Corresponding author
https://doi.org/10.33736/jcshd.6778.2024
e-ISSN: 2550-1623

Manuscript received: 7 March 2024; Accepted: 27 March 2024; Date of publication: 31 March 2024

## 1 INTRODUCTION

Autism Spectrum Disorder (ASD) signifies a complex disorder, and it is challenging to diagnose and detect (Eslami et al., 2019; Hammed & Albahri, 2023). People with ASD have difficulty speaking, social interaction problems, repetitive habits, and motor skill impairments because of the dysfunction of the neurological system that it causes (Kang et al., 2020). Current diagnostic methods can often diagnose this disease starting at age three (Khodatars et al., 2020). In general, boys are about 4 or 5 times more likely than girls to get ASD. According to the Centers for Disease Control and Prevention (CDC), the prevalence of ASD increased from 2004 until 2021. States may be able to estimate the number of adults with ASD (both diagnosed and undiagnosed) based on prevalence and case estimates (Dietz et al., 2020). In 2021, the prevalence rate of ASD increased to 1 in 44 children. The ASD prevalence rate is shown in Figure 1. Many children were still being diagnosed beyond the age of four, even though autism may be reliably identified as early as two (Maenner et al., 2021). For those with ASD, early identification in the first few years of life may have dramatically improved outcomes, yet there is frequently a delay in detecting and diagnosing ASD. In addition, ASD has wide-ranging effects on the brain, affecting many different regions. ASD is difficult to diagnose and detect due to lacking pathophysiological markers. Instead, only psychological criteria may be used (Yazdani, 2020).

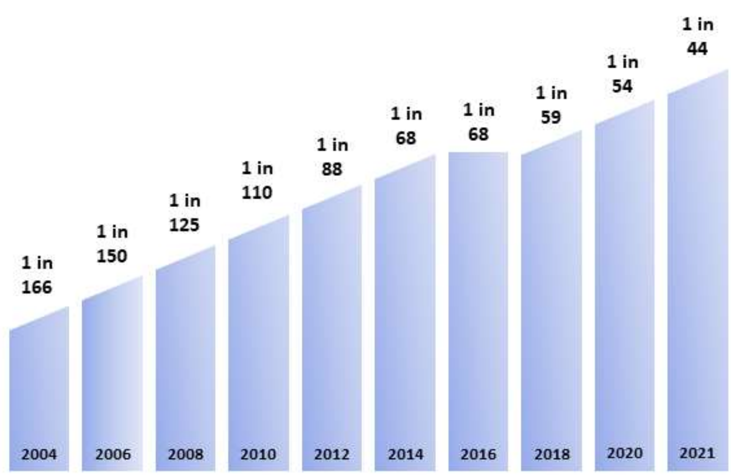



**Figure 1.** ASD prevalence rate from 2004 to 2021.

Furthermore, deep learning is a subfield of machine learning called artificial neural networks. Deep learning represents a type of machine learning that expands traditional machine learning by adding more complexity to the model (Kamilaris & Prenafeta, 2018). It is a large neural network that uses the model data with a complex structure that combines distinct non-linear transformations. Deep learning algorithms improved the latest artificial intelligence tasks such as object detection, speech recognition and machine translation (Al-Fraihat et al., 2024). In addition, deep learning has seen much coverage in the last ten years, with many promising findings. Moreover, deep learning can also be applied to image segmentation. For medical image analysis, deep learning extracts boundaries and measures tissue volumes (Chahal & Gulia, 2019). Magnetic resonance imaging (MRI) studies have provided many implications for neurodevelopmental features underlying ASD since the neuroimaging approach is one of the few methods allowing direct brain observation in vivo (Assimopoulos et al., 2023).

Recently, medical imaging has been used as a screening technique in hospitals. According to previous research, medical image analysis with segmentation, classification, and abnormality detection in images are currently the most common applications (Anwar et al., 2018). In 2015, Ronneberger proposed Unet for medical image segmentation. Unet is a special neural network architecture specially used for semantic segmentation, instance segmentation and object detection. From a traditional CNN, Unet expanded with some changes and improved from it (Ronneberger et al., 2015). In 2021, Nagashree's study demonstrated that by using Unet as an image segmentation approach, autism may be detected automatically (Nagashree et al., 2021).

On the other hand, Radial basis functions (RBF) are simply a class of functions. In principle, they could be employed in any sort of model (linear or nonlinear) and any sort of network (single-layer or multi-layer). In previous research, the radial basis function (RBF) was used to interpolate and approximate dispersed data (Smolik et al., 2018). RBF can be addressed through a generalisation of least squares regression. In support vector machines, the most powerful kernel is RBF (Azzeh et al., 2023).

In addition, Convolution Neural Network (CNN) is a common deep learning algorithm used for classification, detection, recognition, and so on. In several computer vision and machine learning problems, the Convolutional Neural Network (CNN) has demonstrated excellent results (Alzubaidi et Al., 2021). However, CNN has certain limitations when it comes to medical imaging. (Kshatri & Singh, 2023: Salehi et al., 2023). This is because CNN lacks localization from the desired output in biomedical image processing. According to the previous result, Ruuska proposed the CNN model to classify ASD and got 70.22% accuracy (Ruuska et al.,2018). ASD classification is not warranted based on this performance.

It is advisable to integrate deep learning with other algorithms for improved problem classification in medical imaging (Lundervold & Lundervold, 2019). In simple terms, this method first prepares and adjusts the images, then uses deep learning to identify complex patterns, and finally applies traditional algorithms for detailed classification. This fusion benefits from deep learning's ability to detect broad patterns and traditional methods' precision in classification, improving accuracy in medical diagnoses. Therefore, this research utilizes hybrid deep learning algorithms, which merge Unet and RBF for image segmentation, and CNN and RBF for ASD classification. The proposed algorithms may get better performance in ASD classification. The ABIDE dataset used for this research was collected from the NeuroImaging Tools and Resources Collaboratory (NITRC) website. The dataset comprises functional magnetic resonance imaging (fMRI), structural MRI data, and demographic, behavioural, and clinical information about the participants. The goal of ABIDE is to facilitate collaboration and advance research in the field of autism by providing researchers with extensive, standardized data on brain structure and function in individuals with

ASD compared to control subjects. The results from this research will fill the research gap that benefits the neuroscience and artificial intelligence fields.

## 2 METHOD

### Data Augmentation

Existing image augmentation methods can be categorized into two broad categories: traditional white-box or black-box methods based on deep neural networks. This section introduces several methods that have significantly impacted image synthesis and augmentation. Firstly, traditional transformations are discussed. The most widely adopted data augmentation practice currently involves combining affine image transformations with colour modification. Affine transformations such as rotation, reflection, scaling, and shearing are commonly utilized in this context.

Geometric distortions or deformations are commonly used to increase the number of samples for training deep neural models to balance the size of datasets. Their efficiency improvement is widely used as affine transformations for data augmentation. However, it is still the subject of research. The most popular methods are histogram equalization, enhancing contrast or brightness, white balancing, sharpening, and blurring. Those easy-to-understand methods have been proven fast, reproducible, and reliable.

This study uses Python, a programming language, for data augmentation—the image data generator imports from TensorFlow and Keras to set up the parameters. The total number of images increased to 22,980 after data augmentation. The parameters of data augmentation are shown in Table 1.

**Table 1.** Parameters of data augmentation.

| Rotation range | Width shift range | Height shift range | Shear range | Zoom range |
|---|---|---|---|---|
| 45 | 0.2 | 0.2 | 0.2 | 0.2 |

### Dataset Split

There are two types of data splitting: ‘training’ and ‘testing.’ Training is the part of the dataset used for ‘calibration.’ Testing is the part of the dataset that is used for ‘prediction’ (Morais et al., 2019). The training set is used to construct models and feature sets; it serves as the foundation for parameter estimation, model comparison, and all other operations necessary to arrive at a final model. Only after the completion of these actions is the test set utilized to estimate a final, impartial evaluation of the model's performance. This study's dataset is split into training, validation, and testing. The validation dataset is a subset of data used to objectively assess a model’s fit to the training data while tweaking model hyperparameters. Table 2 shows the different dataset splits.

**Table 2.** Dataset split.

| Dataset split | Training | Validation | Test | Total |
|---|---|---|---|---|
| 0.2 | 14707 images | 4596 images | 3677 images | 22980 images |
| 0.3 | 11260 images | 6894 images | 4826 images | 22980 images |
| 0.4 | 8272 images | 9192 images | 5516 images | 22980 images |

Based on Table 2, the dataset split of 0.2 means 20% of the dataset as a test set, while the remaining dataset is split into 80% as a training set and 20% as the validation set. For dataset 0.3, 30% of the dataset is used as a test set, and the remaining dataset is split into 70% as the training set and 30% as the validation set. While for dataset 0.4, 40% of the dataset is a test set, the remaining dataset is split into 60% as a training set and 40% as the validation set.

**Learning Rate**

The learning rate is a hyperparameter that determines how much the model should be altered each time the model weights are updated in response to the projected error. Choosing the learning rate is problematic since a value too small may result in a lengthy training process that may get stuck. However, a value too great may result in learning an inefficient set of weights too quickly or in an unstable training process. This shows that the learning rate controls how quickly the model is adapted to the problem. Training deep learning neural networks makes setting the learning rate correctly difficult. It might be an essential hyperparameter for the model.

When constructing a neural network, the learning rate may be the most critical hyperparameter (Ottoni et al., 2023). As a result, understanding how to assess the effect of the learning rate on model performance and developing a knowledge of the learning rate's dynamics on model behaviour is crucial. A common default setting for the learning rate is 0.1 or 0.01, which may be a reasonable starting point for the task (Bengio, 2012). In this research, the configuration of learning rate value for training is 0.1, 0.01, 0.001, 0.0001, 0.00001, 0.000001.

**Proposed Analytical Model**

In this research, RBF merges with Unet in the fully connected layer to become a new model for segmentation. The Unet-RBF model is better than other methods due to its enhanced feature extraction and generalisation capabilities. Specifically, it integrates the RBF kernel function into the Unet architecture, which helps capture more complex patterns and relationships in the data. This integration improves segmentation accuracy, particularly in medical imaging, where the precise delineation of anatomical structures or pathological regions is crucial. The RBF kernel's ability to handle non-linear data makes the Unet-RBF method more robust and effective in dealing with the variability and complexity of medical images compared to standard Unet or other convolutional neural network-based methods. Figure 2 shows the Unet-RBF model architecture.

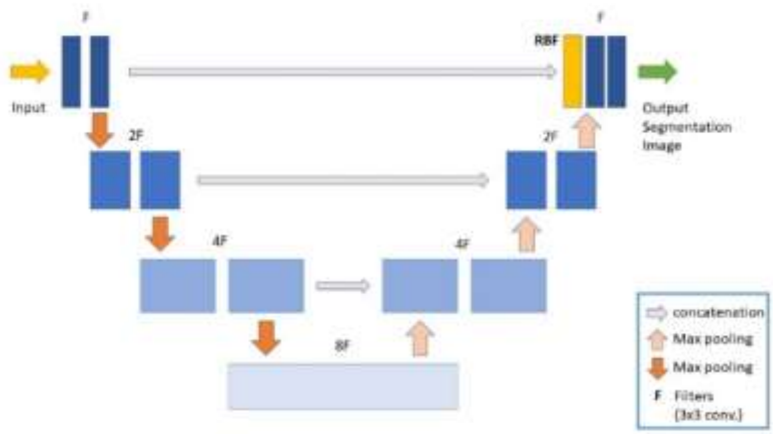



**Figure 2.** Unet-RBF model architecture.

The Unet-RBF is used to segment the cerebellum from brain imaging data. Although the cerebellum is well known for its role in motor control, it also plays a role in cognition, including the ability to communicate verbally. The segmented data is then used to train and classify ASD and non-ASD. Figure 3 shows the segmented data after applying the Unet-RBF model.

(a) (b)

**Figure 3.** Segmented Data for (a) ASD and (b) non-ASD

After image pre-processing and segmentation using Unet-RBF, the CNN-RBF model was proposed in jupyter notebook. The CNN-RBF model combines convolutional neural networks (CNNs) with radial basis function networks (RBFs) for autism classification from medical imaging data. This hybrid approach aims to leverage the feature extraction capabilities of CNN and the function approximation abilities of RBFs to improve classification accuracy. In the CNN-RBF model, RBF is integrated before the dense (fully connected) layers. This integration involves merging the outputs of CNN convolutional layers with radial basis functions before classification. By doing so, the model benefits from the RBF capability to capture complex patterns in the feature space learned by CNN.

Integrating RBF offers advantages such as improved function approximation and flexibility. By combining RBF with CNN, the model can effectively discern autism and non-autism cases with higher accuracy. The hybrid architecture addresses the limitations of individual models and capitalises on their complementary strengths. This combination enhances the model's ability to capture intricate relationships in the data and improves its overall performance.

Mathematically, the CNN-RBF model incorporates convolutional neural networks (CNN) and radial basis function networks (RBF) for medical image classification. Firstly, the CNN extracts hierarchical features from input images through convolutional layers, represented as

$$f(\mathbf{X}) = \sigma(\mathbf{W}_i * \mathbf{X} + \mathbf{b}_i) \tag{1}$$

where $\sigma$ denotes the activation function, $\mathbf{W}_i$ and $\mathbf{b}_i$ are learned filters and biases, and $\mathbf{X}$ represent the input image. Secondly, the RBF layer computes activations $a_k$ using Gaussian radial basis functions, incorporating outputs from the CNN, expressed as

$$a_k = \sum_{i=1}^{N} w_{ki} \exp\left(-\frac{|F - C_i|^2}{2\sigma_k^2}\right) \tag{2}$$

where $\boldsymbol{F}$ is the CNN's output feature map, $\boldsymbol{C_i}$ represents learned prototypes, $w_{ki}$ denotes weights, $\sigma_k^2$ and $N$ is the total number of prototypes. Finally, concatenated RBF layer outputs are processed by fully connected layers for classification, where

$$z = W_d \cdot a + b_d \tag{3}$$

and

$$y = \text{softmax}(z) \tag{4}$$

yield predicted probabilities for autism and non-autism classes. This integration enables the model to classify medical images effectively, leveraging learned features and prototype distances from both CNN and RBF. The CNN-RBF model is shown in Figure 4.

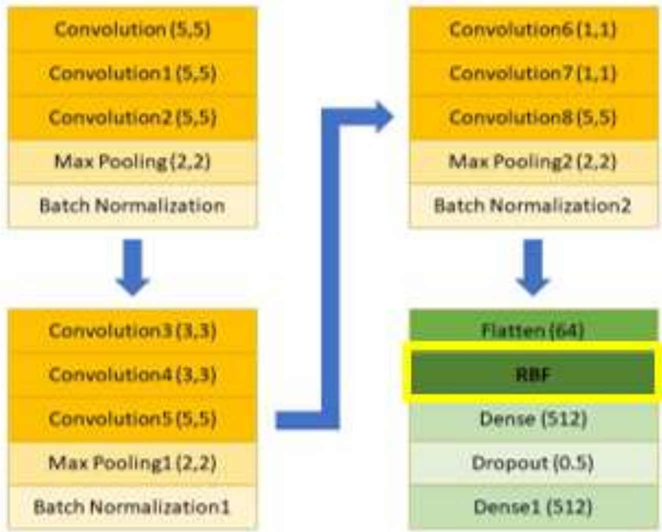



**Figure 4.** CNN-RBF model.

Based on Figure 4, the CNN-RBF model architecture is designed with meticulous attention to detail, structured into four distinct stages that progressively process and transform input data. The initial three stages follow a pattern comprising convolutional layers, max pooling layers, and batch normalization layers. Convolutional layers are fundamental in feature detection, applying filters of sizes 5x5 and 3x3 to identify edges, textures, or patterns. Max-pooling layers reduce spatial dimensions by selecting maximum values from neuron clusters, aiding computational efficiency. Batch normalization normalizes activations within each batch to address the internal covariate shift problem, enhancing training stability.

The fourth stage commences with a flattened layer, converting 2D feature maps into a 1D feature vector. This vector undergoes transformation in the radial basis function (RBF) layer, which measures similarity to a prototype vector, facilitating classification in subsequent dense layers. The dense layers, each comprising 512 units, further process data through complex transformations, enabling the model to learn non-linear combinations of extracted features. A dropout layer, strategically placed between the dense layers, randomly omits 50% of neuron connections during training to prevent overfitting, ensuring the model's generalization to new data.

The CNN-RBF architecture harmonizes spatial feature extraction, dimensionality reduction, normalization for training stability, non-linear transformation, and classification, leveraging the strengths of each component to create a robust and effective deep learning model.

## 3 RESULTS AND DISCUSSION

Before implementing the CNN-RBF model, the dataset is split into 80% for the training set and 20% for the testing set. Some of the hyperparameters like an epoch and learning rate, have been set up for better performance. In this experiment, early stopping is used to determine the epoch.

Regularization refers to a collection of solutions for overcoming the curse of overfitting, and early stopping is one of them. In addition, the learning rate is 0.00001 and the batch size is 12. The 'Adam' has been chosen for optimizers. The reason for choosing Adam is that it is computationally efficient and has few memory requirements. Adam is the best among the adaptive optimizers in most cases.

**Comparison of learning rate and dataset**

Tables 3, 4 and 5 display the classification accuracy performance of the CNN-RBF, custom CNN, and Radial basis network (RBN) model for various dataset splits and learning rates. A custom CNN is a convolutional neural network architecture tailored for specific tasks or datasets, unlike using pre-existing architectures like AlexNet or ResNet, design custom CNNs by determining the number of layers, their arrangements, and activation functions based on their data. In addition, RBNs are neural networks using radial basis functions as activation functions. These functions depend on the distance from a centre point in the input space. RBNs typically consist of input, hidden, and output layers. The hidden layer computes distances between inputs and centres using radial basis functions, while the output layer combines these activations for the final output.

**Table 3.** Results of the CNN-RBF model.

| Accuracy of CNN-RBF model (%) | | | |
|---|---|---|---|
| Learning Rate | 20% of the dataset as a test set, and the remaining dataset was split into 80% as a training set and 20% as a validation set. **(0.2)** | 30% of the dataset as a test set, and the remaining dataset was split into 70% as a training set and 30% as a validation set **(0.3)** | 40% of the dataset as a test set and the remaining dataset was split into 60% as a training set and 40% as a validation set **(0.4)** |
| 0.1 | 49.92 | 50.06 | 49.27 |
| 0.01 | 49.93 | 50.07 | 50.72 |
| 0.001 | 50.12 | 49.62 | 50.73 |
| 0.0001 | 88.42 | 77.39 | 86.87 |
| 0.00001 | **94.79** | 92.36 | 92.07 |
| 0.000001 | 89.26 | 90.32 | 90.81 |

According to Table 3, the best classification accuracy for the 0.2 dataset split was 94.79% at a learning rate of 0.00001. The best classification accuracy obtained for the 0.3 and 0.4 dataset split was 92.36% and 92.07%, respectively, at the learning rate of 0.00001. The learning rate of 0.00001 gives the highest classification accuracy for the CNN-RBF model.

**Table 4.** Results of the CNN model.

| Accuracy of CNN model (%) | | | |
|---|---|---|---|
| Learning Rate | Dataset split **(0.2)** | Dataset split **(0.3)** | Dataset split **(0.4)** |
| 0.1 | 48.79 | 49.71 | 49.35 |
| 0.01 | 49.52 | 49.84 | 49.47 |
| 0.001 | 49.97 | 50.15 | 49.53 |
| 0.0001 | 84.83 | 86.74 | 79.43 |
| 0.00001 | **89.25** | 87.72 | 87.51 |
| 0.000001 | 84.98 | 86.03 | 82.66 |

Based on Table 4, the highest accuracy of the CNN model for the 0.2 dataset split was 89.25%, the same as at the learning rate of 0.00001. For the 0.3 and 0.4 dataset split, 87.72% and 87.51% at the learning rate of 0.00001 represent the best accuracy. In the CNN model, the learning rate of 0.00001 also gives the highest classification accuracy.

**Table 5.** Results of the RBN model.

| Accuracy of RBN model (%) | | | |
|---|---|---|---|
| Learning Rate | Dataset split **(0.2)** | Dataset split **(0.3)** | Dataset split **(0.4)** |
| 0.1 | 49.97 | 49.84 | 50.46 |
| 0.01 | 56.61 | 50.15 | 49.53 |
| 0.001 | 55.91 | 53.29 | 57.65 |
| 0.0001 | 57.15 | **65.10** | 60.63 |
| 0.00001 | 57.31 | 57.90 | 56.77 |
| 0.000001 | 56.76 | 57.86 | 56.24 |

In Table 5, the highest accuracy was 65.10%, which is in the 0.3 dataset split at a learning rate of 0.0001. However, for the 0.2 and 0.4 dataset split, the accuracy was 57.31% and 60.63%, respectively, at the learning rate of 0.00001 and 0.0001%. The learning rate of 0.0001 gives the highest classification accuracy for the RBN model.

**Comparison of accuracy and loss performance**

The accuracy of a classification model is a way of evaluating its overall performance. It is most often represented as a percentage of the total. A prediction's accuracy may be expressed as the number of times a prediction's value equals the actual value. It is binary (either true or false) for a specific sample. During the training phase, accuracy is often graphed and monitored. However, the value is frequently related to the total or final model accuracy. Loss is more challenging to understand than accuracy.

When calculating the loss function (the cost function), consider how much a forecast deviates from the actual value. The model's performance can now be seen in greater detail. While accuracy measures the number of false positives, loss measures the total number of false negatives in training and validation sets. Figure 5 shows a statistical graph for the CNN-RBF model to demonstrate train accuracy and loss.

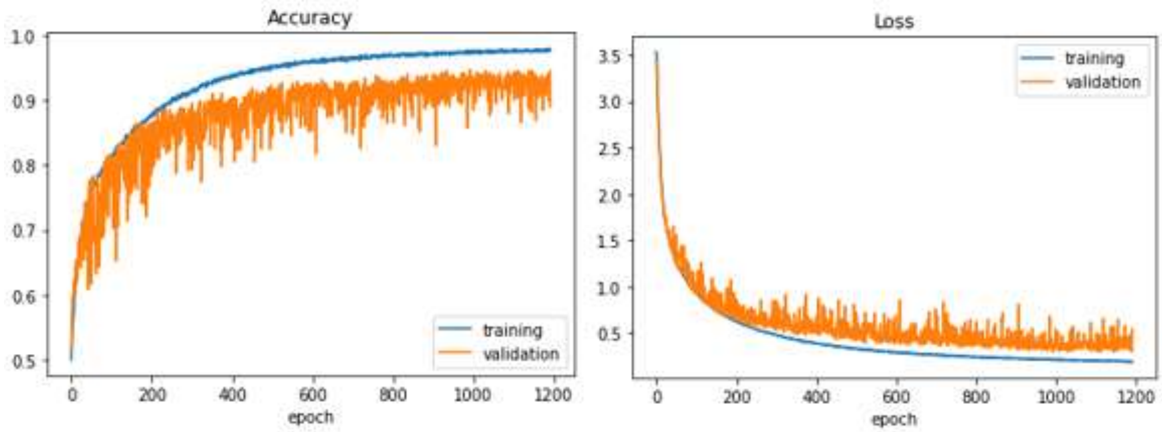



**Figure 5.** Statistical graph of accuracy and loss performance for CNN-RBF.

According to Figure 5, graph trend of the grows absolutely for the training and validation accuracy, yet the training and validation loss decreases continuously. The custom CNN model remains the same as the original CNN principle. Figure 6 shows a statistical graph to demonstrate the accuracy and loss of the CNN model.

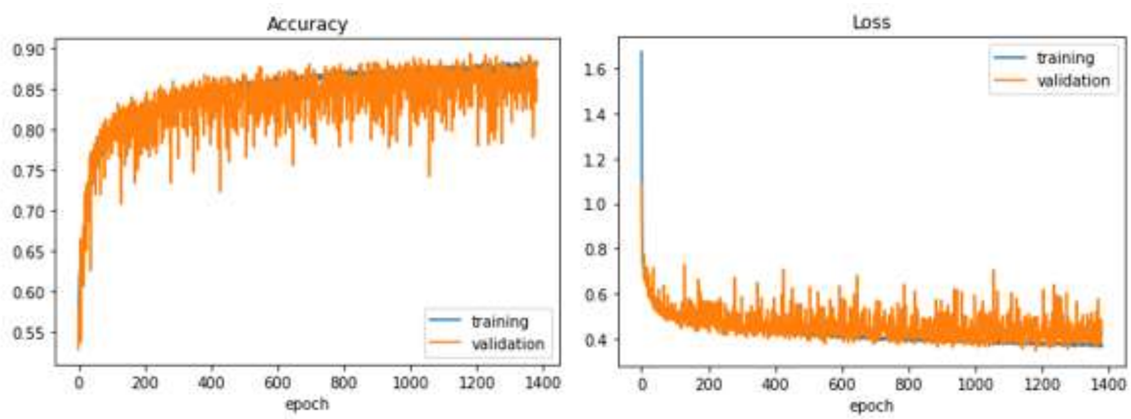



**Figure 6.** Statistical graph of accuracy and loss performance for CNN.

From Figure 6, the training and validation accuracy increases sharply until epoch 500 and increases slowly. Besides, the loss shows decreasing.

Radial basis networks (RBNs) are an uncommon subtype of neural networks that uses radial basis functions as the activation function. They can be used for function approximation. Figure 7 displays the statistical graph of accuracy and loss performance for the RBN model.

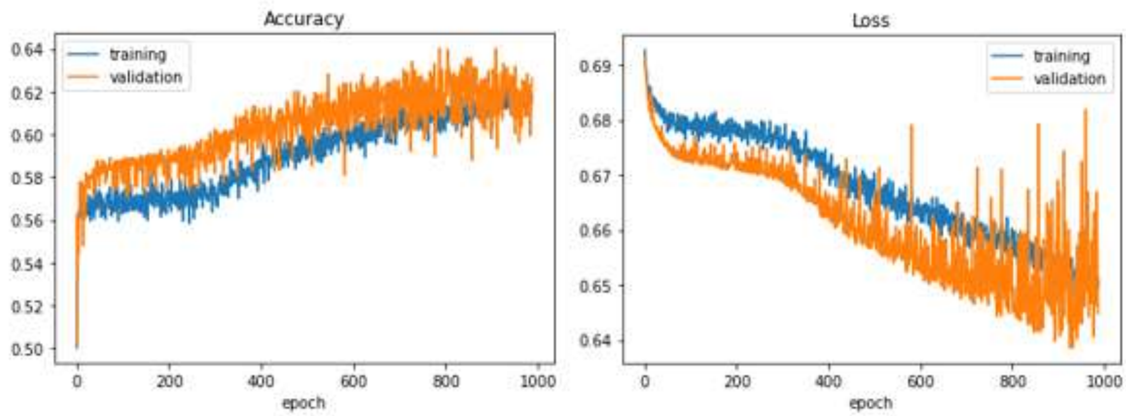



**Figure 7.** Statistical graph of accuracy and loss performance for RBN.

Based on Figure 7, epoch 0 until epoch 50 shows the training accuracy increases dramatically and, after that, increases slowly while the loss decreases constantly from 0.6693 to 0.6232.

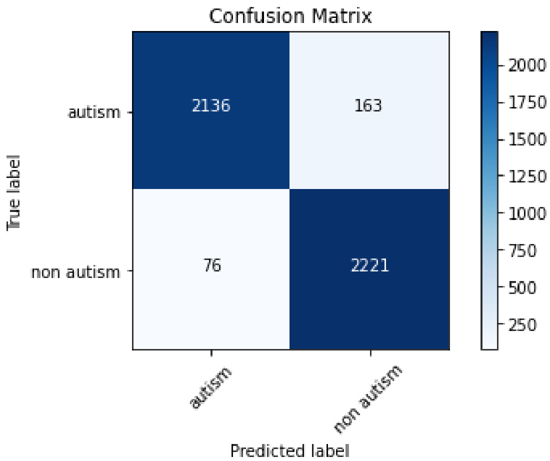
**Confusion Matrix**

In this study, the evaluation method chosen is a binary classification confusion matrix. Figure 8 shows the confusion matrix of a custom CNN model, CNN-RBF model and RBN model.

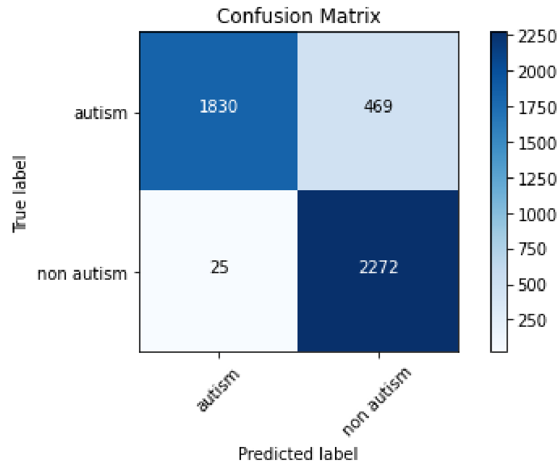
A confusion matrix is often utilized to explain the performance of a classification model on known-true test data. The confusion matrix is not difficult to grasp, but some terms are impenetrable to certain people. In Figure 8, for the CNN-RBF model, the true positive is 2136, and the true negative is 2221; however, the false positive is 76, and the false negative is 163. Besides, for the custom CNN model, the true positive is 1830, and the true negative is 2272 however, the false positive is 25, and the false negative is 469. Furthermore, for RBN model, the true positive is 362, and true negative is 3312, while the false positive is 124 and the false negative is 3096. Table 6 shows the results from the confusion matrix.

**Table 6.** Results from confusion matrix.

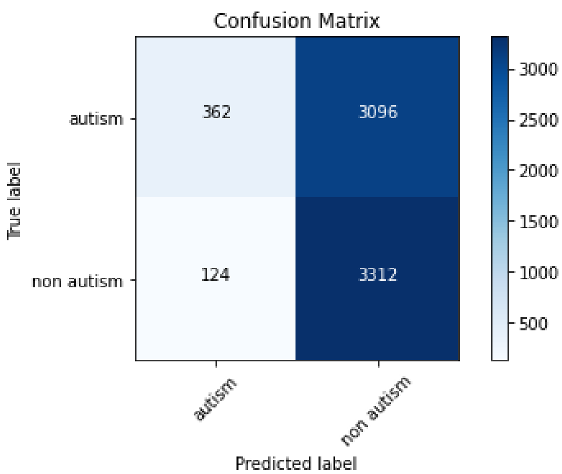
| | CNN-RBF model | Custom CNN-model | RBN |
|---|---|---|---|
| Accuracy (%) | **94.79** | 86.18 | 53.29 |
| Sensitivity (%) | **92.90** | 77.59 | 10.46 |
| Specificity (%) | **96.69** | 94.77 | 96.39 |
| Precision (%) | **96.56** | 93.69 | 74.48 |




(a)




(b)




(c)

**Figure 8.** Confusion Matrix for (a) CNN-RBF model, (b) CNN model, (c) RBN model.

Based on Table 6, for the CNN-RBF model, the test accuracy from the confusion matrix is 94.79%. In addition, other results like sensitivity with 92.90%, specificity with 96.69%, and precision with 96.56% have been calculated based on the confusion matrix. Besides, for the custom CNN model, the test accuracy from the confusion matrix is 86.18%. In comparison, other results like sensitivity with 77.59%, specificity with 94.77%, and precision with 93.69% have been calculated based on the confusion matrix. Moreover, for RBN, the test accuracy from the confusion matrix is 53.29%, sensitivity is 10.46%, specificity is 96.39%, and precision is 74.48% based on the confusion matrix.

## 4 CONCLUSION

The main goal of this research is to use a hybrid deep learning algorithm to classify autism spectrum disorder (ASD) and non-ASD. In this study, the accuracy performance of ASD classification is 94.79% after using Unet-RBF model for segmentation and CNN-RBF model for classification. This research also successfully achieved the research objectives, which are pre-process the fMRI data of ASD using the segmentation method, to propose new hybrid algorithms, which are Unet-RBF and CNN-RBF for ASD classification and to evaluate the effectiveness of the algorithm based on binary classification confusion matrix. In the future, several types of hybrid deep learning algorithms must be proposed to classify ASD for comparison. Additionally, other algorithms can be merged to create new hybrid models for enhanced performance. Furthermore, additional image data should be included in the study to improve accuracy, potentially increasing accuracy to 99%. Moreover, the CNN-RBF model can be applied to other medical fields beyond ASD classification.

## ACKNOWLEDGEMENTS

The authors are grateful to the Faculty of Cognitive Sciences and Human Development, Universiti Malaysia Sarawak for supporting the publication.

## REFERENCES

Al-Fraihat, D., Sharrab, Y., Alzyoud, F., Qahmash, A., Tarawneh, M., & Maaita, A. (2024). Speech Recognition Utilizing Deep Learning: A Systematic Review of the Latest Developments. *Human-centric Computing and Information Sciences*, *14*, 15. https://doi.org/10.22967/HCIS.2024.14.015

Alzubaidi, L., Zhang, J., Humaidi, A. J., Al-Dujaili, A., Duan, Y., Al-Shamma, O., ... & Farhan, L. (2021). Review of deep learning: Concepts, CNN architectures, challenges, applications, future directions. *Journal of Big Data*, *8*, 1-74. https://doi.org/10.1186/s40537-021-00444-8

Anwar, S. M., Majid, M., Qayyum, A., Awais, M., Alnowami, M., & Khan, M. K. (2018). Medical image analysis using convolutional neural networks: A review. *Journal of Medical Systems*, *42*, 1-13. https://doi.org/10.1007/s10916-018-1088-1

Assimopoulos, S., Beauchamp, A., & Lerch, J. P. (2023). Preclinical Models of Autism Spectrum Disorder. In *Neurodevelopmental Pediatrics: Genetic and Environmental Influences* (pp. 309-325). Cham: Springer International Publishing. https://doi.org/10.1007/978-3-031-20792-1_19

Azzeh, M., Elsheikh, Y., Nassif, A. B., & Angelis, L. (2023). Examining the performance of kernel methods for software defect prediction based on support vector machine. *Science of Computer Programming*, *226*, 102916. https://doi.org/10.1016/j.scico.2022.102916

Bengio, Y. (2012). Practical recommendations for gradient-based training of deep architectures. In *Neural Networks: Tricks of the Trade: Second Edition* (pp. 437-478). Berlin, Heidelberg: Springer Berlin Heidelberg. https://doi.org/10.1007/978-3-642-35289-8_26

Chahal, A., & Gulia, P. (2019). Machine learning and deep learning. *International Journal of Innovative Technology and Exploring*, *8*(12), 4910-4914. https://doi.org/10.35940/ijitee.L3550.1081219

Dietz, P. M., Rose, C. E., McArthur, D., & Maenner, M. (2020). National and state estimates of adults with autism spectrum disorder. *Journal of Autism and Developmental Disorders*, *50*(12), 4258-4266. https://doi.org/10.1007/s10803-020-04494-4

Eslami, T., Mirjalili, V., Fong, A., Laird, A. R., & Saeed, F. (2019). ASD-DiagNet: a hybrid learning approach for detection of autism spectrum disorder using fMRI data. *Frontiers in Neuroinformatics*, *13*, 70. https://doi.org/10.3389/fninf.2019.00070

Hammed, S. H., & Albahri, A. S. (2023). Unlocking the potential of autism detection: Integrating traditional feature selection and machine learning techniques. *Applied Data Science and Analysis*, *2023*, 42-58. https://doi.org/10.58496/ADSA/2023/003

Kamilaris, A., & Prenafeta-Boldú, F. X. (2018). Deep learning in agriculture: A survey. *Computers and Electronics in Agriculture*, *147*, 70-90. https://doi.org/10.1016/j.compag.2018.02.016

Kang, J., Han, X., Song, J., Niu, Z., & Li, X. (2020). The identification of children with autism spectrum disorder by SVM approach on EEG and eye-tracking data. *Computers in Biology and Medicine*, *120*, 103722. https://doi.org/10.1016/j.compbiomed.2020.103722

Khodatars, M., Shoeibi, A., Sadeghi, D., Ghaasemi, N., Jafari, M., Moridian, P., ... & Berk, M. (2021). Deep learning for neuroimaging-based diagnosis and rehabilitation of autism spectrum disorder: A review. *Computers in Biology and Medicine*, *139*, 104949. https://doi.org/10.1016/j.compbiomed.2021.104949

Kshatri, S. S., & Singh, D. (2023). Convolutional neural network in medical image analysis: a review. *Archives of Computational Methods in Engineering*, *30*(4), 2793-2810. https://doi.org/10.1007/s11831-023-09898-w

Lundervold, A. S., & Lundervold, A. (2019). An overview of deep learning in medical imaging focusing on MRI. *Zeitschrift für Medizinische Physik*, *29*(2), 102-127. https://doi.org/10.1016/j.zemedi.2018.11.002

Maenner, M. J., Shaw, K. A., Bakian, A. V., Bilder, D. A., Durkin, M. S., Esler, A., & Cogswell, M. E. (2021). Prevalence and characteristics of autism spectrum disorder among children aged 8 years—autism and developmental disabilities monitoring network, 11 sites, United States, 2018. *MMWR Surveillance Summaries*, *70*(11), 1-16. https://doi.org/10.15585/mmwr.ss7011a1

Morais, C. L., Santos, M. C., Lima, K. M., & Martin, F. L. (2019). Improving data splitting for classification applications in spectrochemical analyses employing a random-mutation Kennard-Stone algorithm approach. *Bioinformatics*, *35*(24), 5257-5263. https://doi.org/10.1093/bioinformatics/btz421

Nagashree, N., Patil, P., Patil, S., & Kokatanur, M. (2021, June). Alpha beta pruned UNet-a modified unet framework to segment MRI brain image to analyse the effects of CNTNAP2 gene towards autism detection. In *2021 3rd International Conference on Computer Communication and the Internet (ICCCI)* (pp. 23-26). IEEE. https://doi.org/10.1109/ICCCI51764.2021.9486783

Ottoni, A. L. C., Novo, M. S., & Costa, D. B. (2023). Hyperparameter tuning of convolutional neural networks for building construction image classification. *The Visual Computer*, *39*(3), 847-861. https://doi.org/10.1007/s00371-021-02350-9

Ronneberger, O., Fischer, P., & Brox, T. (2015). U-net: Convolutional networks for biomedical image segmentation. In *Medical Image Computing and Computer-Assisted Intervention–MICCAI 2015: 18th International Conference, Munich, Germany, October 5-9, 2015, Proceedings, Part III 18* (pp. 234-241). Springer International Publishing. https://doi.org/10.1007/978-3-319-24574-4_28

Ruuska, S., Hämäläinen, W., Kajava, S., Mughal, M., Matilainen, P., & Mononen, J. (2018). Evaluation of the confusion matrix method in the validation of an automated system for measuring feeding behaviour of cattle. *Behavioural Processes*, *148*, 56-62. https://doi.org/10.1016/j.beproc.2018.01.004

Salehi, A. W., Khan, S., Gupta, G., Alabduallah, B. I., Almjally, A., Alsolai, H., & Mellit, A. (2023). A Study of CNN and Transfer Learning in Medical Imaging: Advantages, Challenges, Future Scope. *Sustainability*, *15*(7), 5930. https://doi.org/10.3390/su15075930

Smolik, M., Skala, V., & Majdisova, Z. (2018). Vector field radial basis function approximation. *Advances in Engineering Software*, *123*, 117-129. https://doi.org/10.1016/j.advengsoft.2018.06.013

Yazdani, S., Capuano, A., Ghaziuddin, M., & Colombi, C. (2020). Exclusion criteria used in early behavioral intervention studies for young children with autism spectrum disorder. *Brain Sciences*, *10*(2), 99. https://doi.org/10.3390/brainsci10020099