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Early detection of autism spectrum disorder through hybrid deep learning and classical machine learning approaches

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ABSTRACT

Early detection of autism spectrum disorder (ASD) is essential for timely intervention. This study presents a hybrid artificial intelligence framework for non-invasive ASD pre-screening using children's coloring, drawing, and handwriting activities. The proposed framework combines deep convolutional neural networks (VGG16, ResNet50, and EfficientNetB0) as feature extractors with a support vector machine (SVM) classifier to distinguish four diagnostic categories: non-ASD, mild ASD, moderate ASD, and severe ASD. Experimental results demonstrate task-specific performance across architectures. ResNet50–SVM achieved perfect classification for coloring tasks, with 100% accuracy, precision, recall, and F1-score. VGG16–SVM performed best for drawing, achieving 88% accuracy and recall, 89% precision, and an F1-score of 87%. EfficientNetB0–SVM produced the highest handwriting performance, achieving 96% across all evaluation metrics. These findings demonstrate the potential of computer vision-based analysis of children's expressive activities as an effective, non-invasive ASD pre-screening tool. Future work will focus on expanding dataset diversity and integrating multimodal behavioral cues to improve model generalization and clinical applicability.

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1. INTRODUCTION

Autism spectrum disorder (ASD) is a complex, heterogeneous neurodevelopmental condition manifesting within the first three years of life, characterized by atypical brain development that impacts social communication and behavior [1], [2]. In Malaysia, the prevalence of ASD has risen excessively over the past decade. Ministry of Health data indicates that autism prevalence among school-aged children jumped from 6.34 per 1,000 in 2018 to 9.29 per 1,000 in 2022 [3]. Concurrently, children diagnosed and registered with the Department of Social Welfare (JKM) skyrocketed from 6,991 in 2013 to 53,323 in 2023, emphasizing an urgent need for widespread screening strategies [4]. While the exact etiology of ASD remains unknown, current medical research points to a combination of genetic and environmental factors.

Notably, maternal bacterial infections during pregnancy elevate autism risks by an estimated 18% [5]. Timely identification remains crucial, enabling targeted early interventions that foster crucial developmental progress, empower families with adaptive coping mechanisms, and significantly enhance long-term quality of life [5], [6].

To optimize screening, machine learning (ML) and deep learning (DL) have emerged as powerful tools for identifying diagnostic patterns [7]. Prior studies utilizing structured data, behavioral questionnaires, or facial features achieved notable classification success; logistic regression (LR) with feature selection attained 97.54% accuracy [8], while convolutional neural networks (CNN) exceeded 98% accuracy [9]. Other frameworks explored hybrid CNN-SVM pipelines or leveraged SHAP explainability [10]. Despite these advancements [8]–[13], a critical research gap persists. Most models focus strictly on structured datasets or binary classification (ASD vs. non-ASD). They rarely investigate children's creative visual outputs—such as coloring, drawing, and handwriting—which express unique cognitive and motor patterns. Furthermore, limited research evaluates pre-trained CNNs combined with traditional classifiers like SVMs for multi-class severity classification.

This paper addresses these gaps by leveraging AI to analyze creative visual media, establishing a user-friendly tool for practical, early multi-class screening. The structure of this paper is organized as follows; section 2 will further discuss the related work from various methods and technique. Section 3 discusses the research proposed methodology and the application techniques. Section 4 presents the result and discussion of the experiments carried out. Section 5 is the concluding section of the research, which also offers recommendations based on the research findings.

2. RELATED WORK

A variety of ML and DL techniques have been investigated for the detection and classification of ASD. For example, three feature selection methods which are selection operator (LASSO), least absolute shrinkage, and Chi-square has been proposed for evaluating ML approaches that are suitable for both regression and classification tasks. The techniques assessed included k-nearest neighbors (K-NN), random forest (RF), and LR. Among these, the LR model achieved the highest accuracy of 97.541% where the model used 13 selected features by Chi-square technique [8]. Moreover, study by Joudar *et al.* [9] has explored the specific approaches to analyze and classify ASD cases. They utilized several ML models including LR, Naïve Bayes, K-NN, SVM, CNN, and neural networks. Their study employed three ASD datasets: children, adults, and adolescents that comprise of 292, 740, and 104 samples respectively where each of the dataset containing 21 attributes. The experimental results revealed that the CNN model achieved the highest accuracy rates where it achieves 98.30% accuracy for children, 99.53% for adults, and 96.88% for adolescents. This result demonstrates its effectiveness in detecting ASD across different age groups.

Masum *et al.* [10] proposed a range of techniques and methods for detecting and identifying ASD. They employed various ML approaches, including traditional classifiers and neural network-based models. The efficiency of the suggested approach was evaluated thoroughly using three different datasets: children, adolescents, and adults. The experimental results indicated that certain ML classifiers outperformed others in terms of accuracy, precision, F-beta score, and recall. Additionally, SHAP was applied to all three datasets to identify and analyze the most influential features contributing to ASD prediction.

Furthermore, another study by Bala *et al.* [11] has proposed a technique to determine the most effective method for assessing ASD by evaluating several classifiers, including SVM and Gaussian radial basis function (RBF) kernel. Authors also highlight the challenges that affect model accuracy like imbalanced or irrelevant dataset, inappropriate sampling method, and features redundant must be solved to achieve high model performance [12]. Beyond structured datasets, another study by [13] applied CNN models to identify facial features that were significantly associated with ASD. A second CNN model was then used to detect relevant facial expressions, achieving a highest prediction accuracy of 94.44%.

3. METHOD

3.1. Overview of proposed approach

This study proposes hybrid image classification pipelines that leverages deep feature extraction using pre-trained CNN models combined with a classical SVM for the classification of ASD into four severity classes: ASD_Mild, ASD_Moderate, ASD_Severe, and Non_ASD. This classical SVM classifier was selected due to its effectiveness with high-dimensional feature spaces generated by CNNs.

A study by Alhamad *et al.* [14] also proven the effectiveness of hybrid CNN and SVM classifier particularly for handwritten digit recognition where they achieve accuracy of 99.28% by utilized the MNIST handwritten dataset. In this study, the methodology consists of five major stages which are dataset acquisition, image preprocessing and enhancement, feature extraction, model training, performance evaluation, and development. The proposed methodology is illustrated in the flowchart presented in Figure 1.

The process begins with a raw ASD image dataset that will undergo a standardized image preprocessing pipeline. Following preprocessing, the dataset is used to train and evaluate three distinct classification models. In each configuration, the CNN is employed as a fixed feature extractor, while the SVM serves as the classifier. The next stage involves comprehensive model evaluation to assess the effectiveness of each model in distinguishing between various ASD severity levels and the non-ASD class. Finally, the final step is to deploy the web-based system by integrating the best performing classification model. This pipeline ensures a consistent and reproducible approach to model development and comparison across different DL architectures.

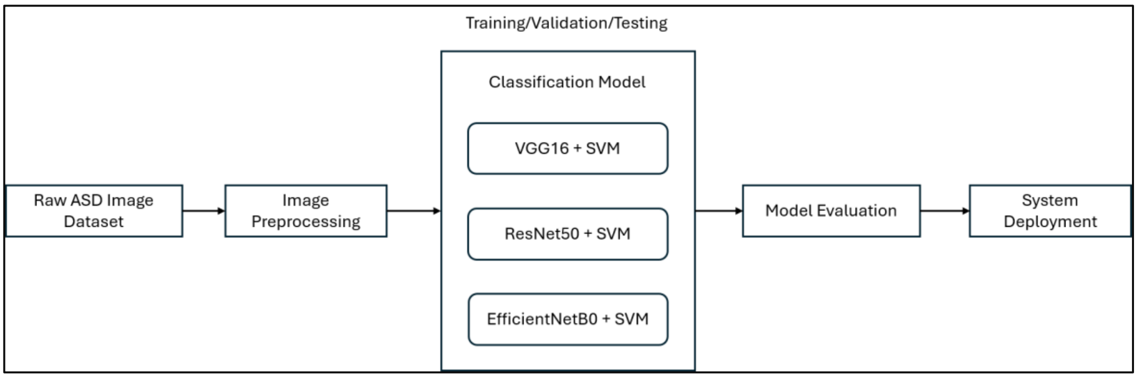

Figure 1. Flowchart of proposed methodology

3.2. Dataset description and preprocessing

The dataset used in this study was obtained from the publicly available Kaggle repository and consists of labeled image samples categorized into four classes: non-ASD, mild ASD, moderate ASD, and severe ASD. The images were collected from children aged 3 to 12 years, both with and without ASD. While the dataset source did not specify the exact number of unique participants and the demographic details, its contents and labeling were verified by an occupational therapist from the Centre for Rehabilitation and Special Needs Studies (iCaRehab). This verification ensured that the class definitions of the dataset and its sample characteristics were consistent with established clinical understanding. The dataset comprises three types of freehand visual tasks: coloring predefined shapes, drawing random elements, and handwriting different characters. These activities are intended to capture behavioral, cognitive, and motor control differences commonly observed across varying ASD severity levels. For the coloring task, a total of 254 images were used, while the drawing task comprised 266 images and the handwriting task contained 251 images. The dataset was split into training, validation, and testing sets with proportions of 70%, 20%, and 10%, respectively. The dataset was organized into a hierarchical directory structure stored in Google Drive, with three main folders which are train, test, and validation where each containing four subfolders corresponding to the class labels. This structure facilitated seamless loading and preprocessing in Google Colaboratory since it enable straightforward integration with DL frameworks.

Figure 2 show an example of each category from the dataset used in this study. Figure 2 shows representative examples from each category: Figure 2(a) a coloring task by a child with mild ASD, involving geometric shapes such as circles, triangles, and rectangles; Figure 2(b) a drawing task from a subject with moderate ASD, depicting a freehand smiling face as unstructured creative expression; and Figure 2(c) a handwriting task from a non-ASD subject, consisting of numerals (0–11), uppercase letters (A–F), and characters resembling Jawi script arranged within boxed grids. These examples illustrate the diversity of visual-motor patterns across ASD severity levels and form the foundation for this study’s feature extraction and classification pipeline.

A custom image processing function was implemented to standardize and enhance all images before input into CNN architectures. All images are first read using OpenCV library in Python and converted from BGR to grayscale to reduce computational complexity and focus on shape and stroke patterns rather than color. Each image was first read from its directory using cv2.imread() and converted to grayscale (cv2.cvtColor) to reduce computational complexity. The grayscale conversion removes color information to reduce noise and focus on structural features such as line thickness, curvature, and spatial arrangement. Histogram equalization (cv2.equalizeHist) was applied to enhance contrast and highlight relevant details by redistributing pixel intensities which makes fine handwriting and drawing details more prominent. This step helps normalize variations caused by lighting or scanning conditions. Subsequently, the images were then resized to a fixed resolution of 224×224 pixels (cv2.resize) for model compatibility.

Finally, the images were converted back to RGB format to meet the input requirements of DL models which expects a 3-channel input. This pipeline ensured standardized, contrast-enhanced images suitable for robust CNN feature extraction. Data augmentation techniques such as random rotation, flipping, and zooming were initially tested to increase dataset variability. However, experimental results showed a drop in classification performance when augmentation was applied. This is likely due to the nature of the task—handwriting, drawing, and coloring contain fine-grained spatial details that are crucial for class separation. Augmentation transformations tended to distort these details, introducing noise rather than beneficial variability. Therefore, augmentation was excluded from the final preprocessing pipeline to preserve essential feature integrity.

(a) (b) (c)

Figure 2. Handfree activity from subjects; (a) coloring data from mild ASD, (b) drawing data from moderate ASD, and (c) handwriting data from non-ASD

3.3. Model development

In this study, model development was conducted using a transfer learning approach with three widely recognized CNN architectures: VGG16, EfficientNetB0, and ResNet50. These networks were selected due to their proven effectiveness in various computer vision tasks and their availability with pre-trained weights on the ImageNet dataset. The pre-trained CNNs were utilized as feature extractors by removing the top classification layers while retaining the convolutional base. This allowed the models to leverage their pre-learned feature representations while adapting to the specific characteristics of the handwriting, drawing, and coloring image datasets.

All input images were preprocessed before being converted back into three-channel RGB format to match the input requirements of the pre-trained CNN architectures. Each image was then resized to 224×224 pixels to consistently match with the standard input size for these models. The extracted feature maps from the CNN backbones were subsequently flattened and used as input to a separate classifier. Rather than employing the traditional fully connected layers with SoftMax output, this study integrates a SVM classifier to perform the final classification task across four classes: non-ASD, mild ASD, moderate ASD, and severe ASD. This hybrid approach combines the powerful feature extraction capability of CNNs with the robust decision boundaries of SVMs which aim to improve the generalization and classification performance.

4. RESULTS AND DISCUSSION

This section presents a comprehensive performance evaluation of the three proposed hybrid models; VGG16+SVM [15]–[17], ResNet50+SVM [18]–[20], and EfficientNetB0+SVM [21]–[25], in detecting ASD based on children’s visual activity data. The study focuses on three distinct input task modalities: coloring, drawing, and handwriting, where each of the task represents different levels of visual structure, complexity, and motor coordination. These tasks were used to simulate common activities in early childhood education which make the proposed methodology practical and accessible for real-world implementation. Apart from that, to ensure robust model development and fair evaluation, the dataset was split into three subsets: 70% for training, 20% for validation, and 10% for testing. Dataset splitting allowed the models to learn from a sufficient amount of data while ensuring that unseen samples were available to test generalization performance. The evaluation results are organized by task modality and summarized in Table 1 (coloring task), Table 2 (drawing task), and Table 3 (handwriting task).

Table 1. Models performance for coloring task

Model	Accuracy	Recall	Precision	F1-score
VGG16+SVM	0.96	0.96	0.96	0.96
ResNet50+SVM	1.00	1.00	1.00	1.00
EfficientNetB0+SVM	0.96	0.96	0.96	0.96

Table 2. Models performance for drawing task

Model	Accuracy	Recall	Precision	F1-score
VGG16+SVM	0.88	0.88	0.89	0.87
ResNet50+SVM	0.79	0.79	0.81	0.78
EfficientNetB0+SVM	0.71	0.71	0.79	0.71

Table 3. Models performance for handwriting task

Model	Accuracy	Recall	Precision	F1-score
VGG16+SVM	0.91	0.92	0.94	0.91
ResNet50+SVM	0.91	0.92	0.94	0.91
EfficientNetB0+SVM	0.96	0.96	0.96	0.96

As shown in Table 1, all models achieved high and consistent performance in the coloring task. The ResNet50+SVM model outperformed the others by achieving perfect scores which is 100% across all metrics, indicating flawless classification of ASD severity levels from coloring activities. Both VGG16+SVM and EfficientNetB0+SVM also demonstrated strong performance, with identical accuracy, recall, precision, and F1-score values of 96%. The superior result of ResNet50 suggests that its deeper residual architecture is particularly well-suited to capturing the rich texture and pattern information typically present in colored regions of children's artworks.

In contrast to the coloring task, the drawing task yielded more varied results across the models, as shown in Table 2. The VGG16+SVM model delivered the best performance, achieving an accuracy of 88% and an F1-score of 87%. The ResNet50+SVM model followed with an accuracy of 79% and F1-score of 78%, while EfficientNetB0+SVM showed the weakest performance at 71% for both accuracy and F1-score. These results suggest that drawing-based features may be more abstract or varied, making them harder to capture, especially for smaller or lightweight models like EfficientNetB0. The better performance of VGG16 in this task may be attributed to its consistent and simpler architecture, which appears to generalize better on line-based or unstructured input.

As reported in Table 3, the handwriting task demonstrated robust classification results across all models, with EfficientNetB0+SVM showing the highest performance. It achieved an accuracy, recall, precision, and F1-score of 96%, indicating excellent ability to extract discriminative features from handwritten input. Both VGG16+SVM and ResNet50+SVM performed identically in this task, each scoring 91% in accuracy and F1-score. These findings suggest that handwriting, being more structured and repetitive in nature, provides consistent patterns that are easier to model regardless of architecture. The outstanding performance of EfficientNetB0 in this case may reflect its ability to extract fine-grained features efficiently despite its smaller parameter size. In conclusion, the experimental outcomes emphasize that task suitability, model architecture, and data characteristics must be carefully aligned to ensure accurate ASD classification. The results strongly support the use of deep feature extraction with classical classification pipelines in behavioral computing, particularly in assistive and early detection tools for developmental disorders.

5. CONCLUSION

This study presented a novel hybrid DL framework for early screening of ASD in children through the analysis of visual activities such as freehand coloring, drawing, and handwriting. By leveraging pre-trained CNNs (VGG16, ResNet50, and EfficientNetB0) as fixed feature extractors in combination with a SVM classifier, the system was able to efficiently classify ASD severity into four distinct categories: non-ASD, mild ASD, moderate ASD, and severe ASD. Future work will focus on improving the model's generalization capabilities by incorporating more diverse datasets and exploring multimodal behavioral inputs, such as speech or motion data, to enhance diagnostic accuracy. In addition, clinical collaboration will be sought to validate the system's usability and reliability in real-world settings. Ultimately, this research represents a promising step toward artificial intelligence-assisted, accessible, and early-stage autism detection that supports proactive intervention and lifelong developmental support for affected individuals.

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C : **C**onceptualization
M : **M**ethodology
So : **So**ftware
Va : **Va**lidation
Fo : **Fo**rmal analysis
I : **I**nvestigation
R : **R**esources
D : **D**ata Curation
O : Writing - **O**riginal Draft
E : Writing - Review & **E**diting
Vi : **Vi**sualization
Su : **Su**pervision
P : **P**roject administration
Fu : **Fu**nding acquisition

CONFLICT OF INTEREST STATEMENT
Authors state no conflict of interest.

DATA AVAILABILITY
The data that support the findings of this study are available at https://www.kaggle.com/datasets/imranliaqat32/autism-spectrum-disorder-in-childrenhandgestures.

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