Examination of AI Algorithms for Image and MRI-based Autism Detection

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Abstract: - Precise identification of autism spectrum disorder (ASD) is a challenging task due to the heterogeneity of ASD. Early diagnosis and interventions have positive effects on treatment and later skills development. Hence, it is necessary to provide families and communities with the resources, training, and tools required to diagnose and help patients. Recent work has shown that artificial intelligence-based methods are suitable for the identification of ASD. AI-based tools can be good resources for parents for early detection of ASD in their kids. Even AI-based advanced tools are helpful for health workers and physicians to detect ASD. Facial images and MRI are the best sources to understand ASD symptoms, hence are input required in AI-based model training. The trained models are used for the classification of ASD patients and normal kids. The deep learning models are found to be very accurate in ASD detection. In this paper, we present a comprehensive study of AI techniques like machine learning, image processing, and deep learning, and their accuracy when these techniques are used on facial and MRI images of ASD and normally developed kids.

Key-Words: - ASD, Autism Detection, Machine Learning, Image Processing, Deep Learning, Support Vector Machine, Haar Cascade, CNN, 3D-CNN.

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1 Introduction

Autism spectrum disorder (ASD) is a neurological and developmental disorder affecting the interaction of patients with others. ASD patients have difficulty in communication, learning, and behaviors. Autism symptoms generally appear at an early stage in kids, when they are two years old. At that age, kids are not in a position to talk about their difficulties with their parents. However, parents can play a role in detecting autism in kids if they are aware of it. Parents have to observe their kids and talk to doctors about the development of kids, [1]. A patient and his family are affected financially, and emotionally because of ASD. Continued care of a patient also creates physical burdens over the individual's lifespan and family caretaker. It also stretches the healthcare system of local and federal agencies as they have to support them medically and financially during the lifespan of a patient. Consequently, continuous research is required to find better ASD-specific interventions and better ways to enable families and communities with resources, training, and tools required to diagnose and help patients, [2]. Autism patients are 1% of the world's population, [3]. Hence serious attention is required for the detection and support required for patients of ASD. It has been observed that high stability has been found for clinical diagnoses between ages 2 and 3 years, [4]. Thus, early diagnosis and interventions during preschool or before, are required to have major positive effects on treatment and later skills development, [5]. Most of the time kids are with their parents hence it is better to train them and provide tools so that they can observe their kids and report ASD related symptoms to doctors for further investigation and diagnosis. Artificial intelligence (AI) has the potential to play a big role in developing interactive systems to assist in autism detection using machine and deep learning. The data points required to develop these systems are images of different types covering the brain and face. These systems are useful to parents, healthcare workers, and doctors. The data used to develop models for AI-based systems are facial features, facial landmarks, facial expressions, brain MRI, electroencephalogram (EEG) signals, eye tracking, and eye contact, [6]. Classification and clustering approaches are common to detect ASD. Additional data required can be captured using questionnaires.

This article presents a comprehensive study of various models developed using existing state-of-the-art artificial intelligence-based models for ASD detection. The data used in the models is from the open source and has facial images as well as MRI images. It then provides a comparison of different models and discusses research gaps and potential areas that should be explored in the future to make further progress in this field. It also suggests the potential applications of these approaches for parents of ASD kids and physicians.

2 Use of Face Recognition in Autism Detection

ASD is a neurodevelopmental problem because of a brain disorder affecting the physical appearance especially the face of children. The facial features of ASD children are distinctively different from normally developed children hence facial features are useful to identify the ASD disorder.

The complexity in face detection arises because of

1) The large visual difference between human faces in the cluttered background of images, that is, extreme illuminations and exaggerated expressions can lead to large differences in the visual appearance of the face
2) The large search space for probable face size and position.

2.1 Support Vector Machine

The support vector machines (SVM) are a supervised binary classification method to find the optimal linear decision surface based on the concept of structural risk minimization. Support Vector Machines (SVM) operate by delineating hyperplanes within a multi-dimensional space, effectively segregating different classification categories. The essence of SVM lies in determining optimal boundaries, represented by these hyperplanes, which segregate the training dataset into distinct classes. In instances where the decision boundaries are not optimally determined, there's a potential risk of misclassifying new data. SVM gives precedence to extreme data points, known as support vectors, to ascertain these boundaries. These support vectors are pivotal in defining the hyperplane, calculated as the sum of the minimal distances from both positive and negative data points. SVMs are versatile and can address both regression and classification challenges, effectively managing datasets with multiple continuous and categorical attributes. SVMs are effective in high-dimensional spaces, even when the number of dimensions is greater than the number of samples.

In image classification having two classes as inputs for training, the images are classified as: (1) the dissimilarities between images of the same individual, and (2) dissimilarities between images of different people. The SVM model is trained using an image dataset, taking into consideration the kernel and the values for the upper bound margin. Once the model is trained, it generates a decision boundary or surface. During the testing phase, any samples that are falsely identified as positive are cataloged and then utilized as negative examples in the following training iterations. By incorporating these negative examples, particularly those from misclassified categories, the model's accuracy in detecting ASD is enhanced. In the realm of face recognition, SVM evaluates the decision boundary to gauge the degree of similarity between pairs of facial images. This evaluation process paves the way for the development of sophisticated face-recognition systems. SVM works well with small datasets, and it is also able to handle complex patterns and noisy data, [7].

2.2 Haar Cascade

The Haar Cascade (HC) algorithm was proposed by Paul Viola and Michael Jones. Haar Cascade is grounded in machine learning principles, where the cascade function undergoes training using an abundance of positive data points. These positive points are derived from regions showcasing the faces of children with ASD, while the negative data points are sourced from regions depicting the faces of typically developing children, [8]. The essence of Haar Cascade lies in its utilization of Haar-like features extracted from digital images to facilitate object recognition. These features are characterized by specific rectangular sections of an image, which are then further segmented into multiple sections. Often, these features are illustrated as juxtaposed black-and-white rectangles. The value of each feature, crucial for training, is computed by subtracting the sum of pixel values underneath the white rectangle from those beneath the black rectangle. Owing to its intrinsic design, Haar Cascades excels in identifying facial features like eyes, nose, and mouth. Consequently, they possess the ability to discern between children with ASD and those without, [8]. Haar Cascade is a multi-stage classifier and rapid detection framework as it reduces the processing time substantially. It is also able to achieve good accuracy and able to reduce false positives compared to a single-stage classifier, [9]. OpenCV provides a training method or pre-trained repository for Haar Cascade, [10].

2.3 Convolutional Neural Networks (CNN)

A convolutional neural network (CNN) is a type of neural network used in deep learning with convolutional layers. CNN has two types of layers (hidden): convolutional layers and pooling layers. These layers are arranged alternately in the network. The CNN mimics neurons and their connections and has m × n neurons that are connected to neighboring layers. The connection weights are shared in the network of CNN thus less training time is required for CNN. CNNs can be implemented in 1, 2, and 3 dimensions. 1-Dimensional (1D) CNN can recognize patterns in 1D signals such as time-series analysis. 1D-CNNs can learn from feature values and the order of the features. In 2-dimensional CNN, the CNN kernel moves in a 2-direction (x, y) and calculates the output, which is a 2D Matrix. In 3-D regions dimensional CNN, joint spatial-spectral information is processed simultaneously, [11]. In digital images, pixel values are stored in a two-dimensional (2D) grid, i.e., a two-dimensional array. In the CNN method, a kernel is applied to every position of the image to extract features. CNN is highly effective in image processing as it can extract features that may occur anywhere in the image. In CNN, output from one layer is passed to the next layer, hence hierarchically extracted features can become more complex as the network passes through the training dataset multiple times. The training on the dataset is done to optimize the parameters of the kernel, and it minimizes the difference between outputs and ground truth labels through an optimization algorithm called backpropagation and gradient descent. The final optimized and trained CNN is used for predictions, [12].

CNN is very good at visual data, such as images and videos. CNN can automatically learn features to capture complex visual variations by leveraging a large amount of training data. The CNN structure consists of 12-net CNN, 24-net, and 48-net structures, [13]. CNN gives better detection accuracy than Haar Cascade. However, Hence for native mobile applications, Haar Cascade is more suitable while the hybrid application CNN can be better.

2.4 Comparison of Models for SVM, HC, and CNN

The authors in, [14], developed models using SVM, HC, and CNN to detect ASD using facial images.
Authors, [14], have given an SVM mathematical model in an optimization problem that has been given below.

$$\min_{w,b,\xi}\left\{\frac{1}{2}w^T w + C\sum_{i=1}^{l}\xi_i\right\}, \quad \text{constrains to}$$

$$y_i(w^T\phi(x_i) + b) \geq 1 - \xi_i, \xi_i \geq 0,$$

where $(x_i, y_i), i = 1, \dots, l$ is an instance-label pair, $x_i \in \mathbb{R}^n, y \in \{1, -1\}^l, \phi$ is a mapping function, $C > 0$ is a penalty parameter. The function $K(x_i, x_j) \equiv \phi(x_i)^T\phi(x_j)$ is called the kernel function.

The Kernel structure and function types are also given by the authors, [14], that has been given below.

Linear function: $K(x_i, x_j) = x_i^T x_j$,

Polynomial function: $K(x_i, x_j) = (\gamma x_i^T x_j + r)^d, \gamma > 0$,

Radial basis function: $K(x_i, x_j) = \exp(-\gamma\|x_i - x_j\|^2), \gamma > 0$,

Sigmoid function: $K(x_i, x_j) = \tanh(\gamma x_i^T x_j + r)$.

They used images from openly available databases. ASD image data was divided into test sets, train sets, and valid sets. The models were trained with 2536 images (1268 autistic and 1268 non-autistic) and validated with 100 images (50 autistic and 50 non-autistic). Finally, trained models were tested with 300 images (150 autistic and 150 non-autistic). The dataset is summarized in below Table 1.

Table 1. Number of samples for training and test data

Attributes	Train	Valid	Test
Autism	1268	100	300
Non-Autism	1268	100	300

The classifiers used for SVM, HC, and CNN are as below.

1) The SVM model was trained using the “Kernel Regularization Function”.
2) The Haar Cascade was implemented using “Cascade Trainer GUI”.
3) The CNN model has been implemented using “VGG16”.

Three models were developed using the below steps as shown in Figure 1.

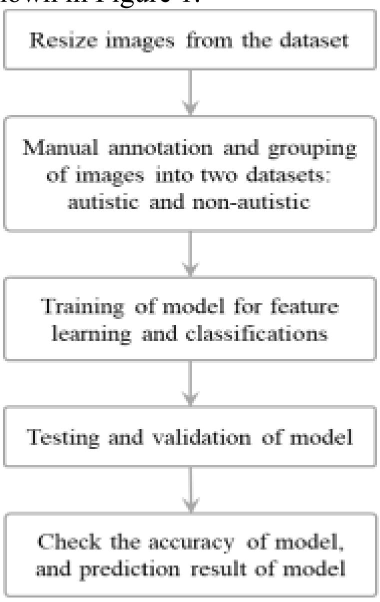

Fig. 1: Model Development Steps

The output of all trained models for the methods SVM, HC, and CNN are summarized for accuracy below in Table 2.

Table 2. Accuracy of models/algorithms, [14]

.Methods / Algorithms	Accuracy (%)
Support Vector Machines (SVM)	65
Haar Cascade (HC)	72
Convolutional Neural Networks CNN)	90

The model accuracy from the above table shows CNN has the highest accuracy 90% as compared to SVM and HC models. The CNN model has 90% accuracy hence it is reliable to use for ASD detection.

3 Use of Pre-Trained CNN Models

A pre-trained model refers to a neural network that has undergone training on an extensive collection of images. Such models can either be employed directly or be fine-tuned using transfer learning to tailor them for specific tasks. The essence of transfer learning in image classification lies in its presumption: if a model has been extensively trained on a diverse and vast dataset, it's equipped to handle unfamiliar visual content. Instead of initiating training from scratch on large datasets, the features learned by these models can be harnessed directly or fine-tuned further. Transfer learning offers the flexibility to repurpose these pre-established models for diverse image classifications and predictions, [15]. Over the years, a plethora of pre-trained models, built on the backbone of Convolutional Neural Networks (CNN), have emerged, including but not limited to VGG1, VGG16, VGG19, MobileNet, MobileNetV2, Densenet, Inception V3, Resnet50, and Xception. Each model boasts its unique architecture and set of parameters. Developed over the previous decade, these models have undergone various iterations and enhancements to remain relevant and effective for different imaging tasks, [16]. Researchers leveraging transfer learning often draw from the ImageNet dataset. For instance, when comparing various models, MobileNetV2 was found to be more parameter-efficient than its counterparts. In terms of accuracy, MobileNet achieved between 70 to 89.5%, MobileNetV2 scored in the 71 to 90% range, both VGG16 and VGG19 ranged from 71 to 90%, while ResNet50 showcased a commendable 74 to 92% accuracy. The result showed that MobileNetV2 performance was relatively better than other models, and it also used less disk space and parameters when compared with other pre-trained models, [16]. The accuracy of various models is summarized in below Table 3.

Table 3. Accuracy of CNN pre-trained models, [16]

Methods	Dataset	Accuracy (%)
MobileNet	ImageNet	70 to 89
MobileNetV2	ImageNet	71 to 90
VGG16	ImageNet	71 to 90
VGG19	ImageNet	71 to 90
ResNet50	ImageNet	74 to 92

The authors in, [17], used three types of deep learning algorithms to detect ASD using facial images. They used a dataset consisting of 2,940 face images. Half of the images were of autistic children while the other half were of non-autistic children. They collected datasets from various websites and Facebook pages. The dataset was open and there was no issue of privacy. The dataset is summarized in below Table 4.

Table 4. Number of samples for Training and Test data

Attributes	Train	Valid	Test
Autism	1270	100	300
Non-Autism	1270	100	300

The research was focused on the use of three pre-trained models for ASD using facial feature images: NASNetMobile, VGG19, and Xception. The empirical results of these models are as in Table 5. It can be seen that the Xception model attained the highest accuracy of 91%, [17].

Table 5. Accuracy of Models/Algorithms, [17]

Methods / Algorithms	Accuracy
NASNetMobile	75 to 82 %
VGG19	65 to 78 %
Xception	70 to 91 %

By using the YoloV8 model, [18], on a dataset of Kaggle, Subhash and the team achieved 89.6% accuracy in the classification of ASD with an F1-score of 0.89, [18]. The “Accuracy” is consistently high in the majority of models. The accuracy from Table 1 and Table 2 indicate that deep learning models are good for ASD detection compared to traditional machine learning models. Even Table 2 indicates that there is no need to develop new models from scratch, rather pre-trained models can be used. Similarly, pre-trained models can be used for ASD detection with some retraining.

4 Use of Radiomics

Radiomics Radiomics involves the precise measurement of characteristics in medical imaging modalities such as MRI (Magnetic Resonance Imaging), CT (Computed Tomography), and PET (Positron Emission Tomography). In this context, MRI plays a crucial role for medical professionals in the accurate diagnosis of Autism Spectrum Disorder (ASD). MRI techniques are divided into functional (fMRI) and structural (sMRI) imaging. However, the process of diagnosing ASD through these MRI techniques can be quite tedious and time-intensive as in [19]. To aid specialists, the application of AI (Artificial Intelligence)-based tools is beneficial. Techniques in machine learning (ML) and deep learning (DL) are increasingly being employed to analyze MRI data for ASD diagnosis. The radiomics workflow is depicted in Figure 2. Initially, the workflow involves identifying and marking the region of interest (ROI) in 2D or the volume of interest (VOI) in 3D. These ROIs/VOIs are areas identified for their significant radiomic features. Following this, the next phase is image segmentation, which can be performed manually, through semi-automatic methods like region-growing or thresholding algorithms, or automatically by employing deep learning algorithms, [20]. Next, images are processed so that they can be homogenized. It is done for radiomic feature extraction based on pixel spacing, grey-level intensities, bins of the grey-level histogram, etc., [20]. Not all radiomic features are useful in a model development hence non-reproducible, redundant, and non-relevant features are removed from the feature list. This step is known as dimension reduction and it may be a multi-step process, [20]. Feature extraction refers to the calculation of features where feature descriptors are used to quantify characteristics of the grey levels within the ROI/VOI, [21]. The step-by-step process is shown in Figure 2.

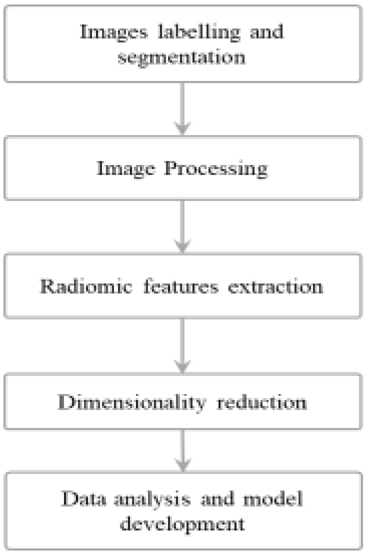

Fig. 2: The Radiomics Pipeline

4.1 Cortical Thickness and Support Vector Machine

ASD is linked to atypical development of certain brain regions during the initial years of life. MRI scans serve as valuable tools in detecting these developmental deviations in the brain. Identifying specific markers in brain images associated with autism is crucial for understanding the underlying causes of the condition, [22]. Notably, individuals with autism exhibit increased cortical thickness, [22]. In a study, a group of 76 children, comprising 40 diagnosed with ASD and 36 neurotypical children, were subjected to MRI scans. The T1-MPRAGE sequences were analyzed to extract features of regions of interest and average cortical thickness (CT) was measured for each ROI. The extracted features were used as input for an SVM classifier to detect kids with autism. The best accuracy 84%, was achieved with concatenating the gray matter thickness of the eight ROIs, [22]. Studies in the realm of neuroimaging have revealed a connection between human cognitive abilities and specific brain structures, particularly the thickness of the cerebral cortex. There's a positive correlation between general intelligence and cortical thickness in various areas of the association cortex spanning both hemispheres of the brain, [23].

4.2 rsfMRI Data and Graph CNN

The study, [24], analyzed a dataset comprising 539 ASD subjects and 573 neurotypical individuals. This dataset encompassed both sMRI and rsfMRI scans of each participant, accompanied by various attributes: scan location, participant's gender, age at the time of scanning, hand dominance, and scores from multiple tests, among other factors. Before leveraging this data to construct a model, it demanded preprocessing. Given the inherent variability in brain size and structure across individuals, it's essential during the feature extraction or segmentation process to ensure consistency across brain images. Graph CNN was used to train the model. The combination was temporal graph convolution and adjacency convolution layer. It resulted in 70% accuracy of output, [24]. This means that a specific point in one brain image should correspond to the same anatomical location in another. Discrepancies in image sizes can hinder the neural network's ability to discern patterns based on individual brain structures. To counteract this, it's pivotal to standardize all brain images to a uniform shape and size, utilizing a predefined template. This standardized approach enhances the neural network's learning efficiency and mitigates potential distortions, [25].

4.3 rsfMRI Data and 3D-CNN

The authors in, [26], utilized rsfMRI data from the ABIDE-I dataset, applying a 3D CNN model for ASD prediction. Their preprocessing steps for the ABIDE-I data encompassed slice timing adjustments, motion rectification, global mean intensity normalization, and alignment of functional data to the MNI space at a 3x3x3 mm resolution. Subsequently, they extracted a time series of Regions of Interest (ROI). For this extraction, they employed seven atlases, including Harvard-Oxford (HO), Craddock 200 (CC200), Eickho-Zilles (EZ), Talaraich and Tournoux (TT), Dosenbach 160 (DOS160), Automated Anatomical Labelling (AAL), and Craddock 400 (CC400). Implementing a CNN with 10-fold cross-validation, they reported an accuracy of approximately 73%. In a different study, [27], suggested integrating phenotypic data with rsfMRI information. This phenotypic data covered age, gender, hand dominance, overall IQ, and eye status during the fMRI scan (whether the eyes were open or closed per the imaging protocol). They introduced six techniques to amalgamate the phenotypic and fMRI data into one cohesive network. For their model, they fed rsfMRI time-series inputs into an LSTM-based architecture, which, when trained, achieved an accuracy of 70% on the ABIDE dataset.

Meanwhile, [28], refined the approach to preprocess the ABIDE-I dataset and train a CNN model, aiming to elevate the accuracy of autism detection based on fMRI. Their methodology involved a dual-phase process to generate 3D data.

1) The Time series data were generated utilizing three different atlases: AAL, DosenBatch, and CC200. Subsequently, connectivity matrices were derived using three distinct methods to determine connectivity likelihood: the correlation approach, the covariance approach, and the tangent space embedding technique. By combining the three atlases with the three connectivity likelihood methods, a total of nine foundational metrics were established.
2) For each subject, they formulated enhanced 3D matrices. This was done by distinguishing between high-weight and low-weight connections, leveraging both the maximum spanning tree and the minimum spanning tree, resulting in nine refined metrics.

These 3D metrics were then integrated into seven advanced deep learning architectures: ResNet152V2, Inception, ResNet50, InceptionResNet, Xception, VGG19, and VGG16, each pre-trained with ImageNet weights. By employing these seven CNN architectures in various combinations, they devised 126 unique classification strategies. Impressively, over two-thirds of these strategies achieved an accuracy surpassing 70%. By incorporating a dropout layer into the transfer learning architectures and using cross-validation, they enhanced the models' robustness, mitigating the risk of over-fitting. Among the results, the ResNet152V2 stood out, reaching a pinnacle accuracy of 91% when paired with tangent-enhanced matrices across all atlases. Notably, in every enhancement strategy scenario, ResNet152V2 consistently outperformed other models. A comprehensive breakdown of the techniques applied to the MRI data and their respective accuracies can be found in Table 6.

Table 6. Accuracy of Models/Algorithms for MRI data

Methods / Algorithms	Highest Accuracy (%)
MRI (Cortical Thickness) and Support Vector Machine, [22]	84
rsfMRI and Graph CNN, [24]	70
rsfMRI and 3D- CNN, [26]	73
rsfMRI along with phenotypic data and LSTM, [27]	70
rsfMRI Data and 3D- CNN ResNet152V2, [28]	96

5 Results and Discussion

In this work, we explored several methods of artificial intelligence covering machine learning and deep learning to classify ASD and neurotypical subjects. The data types used are face images of kids and MRI data. A total of sixteen algorithms are studied in this paper and accuracy is projected in Table 7. The accuracy ranges from 65% to 91%.

The accuracy for a support vector machine and Haar Cascade is less compared to deep learning models. However, for MRI data, deep learning models have not performed very well except the RestNet model. The predefined models have given good results for face image data and achieved the highest accuracy of 92%. For MRI data, the highest accuracy achieved is 96%, which is also the highest in this study. For face image data, the accuracy results are consistent for deep learning models whereas MRI data has given inconsistent results. Considering the accuracy of deep learning models, efforts are required to add more samples covering various geographies of the world. Better pre-trained models are required for easy implementation of systems with better accuracy. It is also necessary to develop models considering the need for mobile apps required for field workers to detect autism. These mobile-based applications will be helpful to parents for early detection of ASD. Similarly, decision support can be developed using face images and MRI data to support physicians in ASD detection.

Table 7. Summary of Accuracy of Models/Algorithms

Methods / Algorithms	Data Type	Highest Accuracy (%)
Support Vector Machines (SVM), [14]	Face Image	65
Haar Cascade (HC), [14]	Face Image	72
Convolutional Neural Networks (CNN), [14]	Face Image	90
MobileNet, [16]	Face Image	89
MobileNetV2, [16]	Face Image	90
VGG16, [16]	Face Image	90
VGG19, [16]	Face Image	90
ResNet50, [16]	Face Image	92
NASNetMobile, [17]	Face Image	82
VGG19, [17]	Face Image	78
Xception, [17]	Face Image	91
Support Vector Machine, [22]	MRI (Cortical Thickness)	84
Graph CNN, [24]	rsfMRI	70
3D- CNN, [26]	rsfMRI	73
LSTM, [27]	rsfMRI along with phenotypic	70
3D- CNN ResNet152V2, [28]	rsfMRI	96

6 Application of Proposed Study

In the 21st century, most organization was unaware of the power of IT, and at that time IT dept. was limited in software handling where the importance of digital data was unknown according to, [29]. According to the increment of applications, generated data is needed for further preprocessing. The data may be characterized by volume, complexity, variation, and specificity where these characteristics define the formulation of an application model, [30]. The proposed study can help us for a good understanding of supervised and deep learning applications in autism. Various models of deep learning and supervised learning have been discussed in autism detection. Each application is an important part of autism detection. The maximum data that has been utilized for the detection of autism is MRI scan data. Convolutional Neural Networks (CNN), MobileNet, VGG, ResNet, NASNetMobile, Xception, and 3D-CNN are supervised and deep learning models that accept MRI scan data for the detection of autism but these techniques are very cost-effective. Parents of an autistic baby from a rural area will not get a benefit from such kind of system due to the lack of availability for the MRI scanning process. The detection of autism in the early stage is fruitful for reducing autism symptoms. According to the above models, MRI scan data of the brain is a primary requirement whereas an MRI scan of the brain of a baby is not a good suggestion for radiation. According to the rapid growth of social media, massive digital data has been generated that is very useful due to a large number of participants of individuals. Many NLP-based applications have been developed using these generated data in various domains using NLP techniques and machine learning models, [31]. Many parents of autistic babies are using social sites to share their experiences with autism. These statements from the parents of autistic babies can be a good source for application development of autism detection and any parent can participate from any area on such kind of applications. The detection of autism from parents' experiences is our future research work.

7 Conclusion

The document provides a thorough examination of various artificial intelligence (AI) methodologies, particularly machine learning and deep learning techniques, in the context of Autism Spectrum Disorder (ASD) detection through face images and MRI data. The early identification of ASD is critical due to its diverse nature, and AI presents a promising avenue for enhancing early detection accuracy. Among the techniques evaluated using facial images, deep learning models, especially Convolutional Neural Networks (CNN), consistently outperformed traditional machine learning methods like Support Vector Machines (SVM) and Haar Cascade. Pre-trained models on face images, such as ResNet50, achieved high accuracies, indicating their potential utility for practical applications. The utilization of pre-trained models for image classification, such as VGG16, VGG19, and MobileNetV2, yielded substantial accuracy, emphasizing the potential of leveraging existing architectures and applying transfer learning for ASD detection. Given the high accuracy of certain models, there is an opportunity to develop mobile applications for field workers and parents for early ASD detection. Such applications can play a pivotal role in facilitating timely interventions. The document underscores the need for more extensive datasets that cover diverse global populations. This would ensure the generalizability of the models. Furthermore, there is a call to develop better pre-trained models and systems optimized for mobile devices, enabling broader accessibility and use. In essence, AI, especially deep learning, offers promising tools for enhancing the accuracy and timeliness of ASD detection. With further research and development, these tools can be refined and made widely accessible, ensuring early and effective interventions for individuals with ASD. The exponential increase in social media usage has led to the creation of a vast amount of digital data, enriched by the diverse contributions of its users. This data trove has become a cornerstone for the development of numerous applications in various fields, leveraging Natural Language Processing (NLP) techniques and advanced machine learning models. Significantly, parents of children with autism are increasingly using social media platforms to share their personal experiences and challenges. These firsthand accounts are invaluable, offering a rich resource for developing applications aimed at detecting autism. Such applications have the potential to be universally accessible, allowing parents from any location to participate and contribute. The exploration of autism detection through the analysis of parents' shared experiences on social media is a key area of our future research endeavors.

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