ISSN 2394-3777 (Print)
ISSN 2394-3785 (Online)
Available online at www.ijartet.com

International Journal of Advanced Research Trends in Engineering and Technology (IJARTET)
Vol. 13, Issue 3, March 2026

Smart Screening for Autism Spectrum Disorder Using Deep Learning

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Abstract: Autism Spectrum Disorder (ASD) represents one of the most significant Neurodevelopmental health challenges of the 21st century, affecting approximately 1 in 36 children globally, according to recent epidemiological data[1]. Early detection remains critical for intervention efficacy, yet current diagnostic pathways are characterised by significant delays—averaging 2-3 years between initial parental concerns and formal diagnosis—thereby creating substantial barriers to timely early intervention services [2]. This research presents a comprehensive, multimodal artificial intelligence system integrating deep learning-based structural MRI analysis, age-stratified behavioural questionnaires, and computer vision-based facial emotion detection for automated ASD risk stratification across three developmental age groups (0-2, 2-3, and 3+ years).Our system employs a net-tuned ResNet50 convolutional neural network, achieving 92.1% classification accuracy on structural MRI data, age-appropriate questionnaire modules with validated reliability coefficients ranging from κ = 0.78- 0.92, and OpenCV-based behavioural assessment protocols. Through multimodal data fusion using weighted evidence combination, we achieve a clinically-relevant combined accuracy of 95.8% on a prospectively-validated dataset of 600 MRI images with 320 autism-positive cases. The system is deployed as a production-grade Flask web application with secure authentication, cloud-ready architecture, and LLM-integrated clinical report generation via Ollama/Llama3.2. Age-stratified analysis demonstrates the highest accuracy (96.2%) in the 3+ years group, where all assessment modalities achieve optimal performance. Statistical validation confirms robust performance metrics,including 91.4% sensitivity, 92.1% specificity, an AUC-ROC of 0.956, and an F1-score of 0.915 for autism classification. This work addresses critical gaps in autism early identification infrastructure, particularly in resource- limited settings, and demonstrates the feasibility of AI-driven screening at scale across diverse clinical contexts.

Keywords: Autism Spectrum Disorder, Deep Learning, ResNet50, Medical Image Analysis, Behavioural Assessment, Multimodal Fusion, Computer Vision, Early Detection, Clinical Decision Support, Telemedicine

I. INTRODUCTION

1.1 Clinical Significance and Epidemiology of Autism Spectrum Disorder

Autism Spectrum Disorder (ASD) is a complex neurodevelopmental condition characterised by persistent deficits in social communication and social interaction combined with restricted, repetitive patterns of behaviour, interests, or activities [1]. The diagnostic criteria have evolved significantly since the initial descriptions in the mid-20th century, culminating in the DSM-5 framework, which consolidates previously separate current diagnostic categories (Asperger's syndrome, pervasive developmental disorder not otherwise specified, autism disorder) into a single spectrum construct reflecting the heterogeneous presentation of autism- related features [2].

Contemporary epidemiological research consistently demonstrates rising prevalence rates across developed nations. The United States Centres for Disease Control and Prevention (CDC) estimates that approximately 1 in 36 children aged 8 years meets diagnostic criteria for ASD, representing a significant increase from estimates of 1 in 68 (2010) and 1 in 88 (2008) [3]. This epidemiological trajectory reflects both genuine increases in autism prevalence—attributable to advanced paternal age,

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Available online at www.ijartet.com

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environmental factors, and improved obstetric survival of premature infants—and increased identification through improved diagnostic awareness and screening protocols [4]. Global prevalence estimates range from 0.5-2% across diverse populations, with marked geographic variation reflecting differences in healthcare infrastructure, diagnostic practices, and healthcare access [5].

The financial burden of ASD is substantial. Lifetime healthcare and societal costs for individuals with autism are estimated at

$1.5-2.2 million per person in the United States, with annual expenditures for a single child with ASD ranging from $60,000- 100,000, including educational services, behavioural therapy, and medical management [6]. These figures underscore the critical importance of early identification and intervention, as evidence-based early intervention programs (implemented before age 3) demonstrate 45-70% improvement in developmental outcomes and significant reductions in long-term healthcare expenditures[7].

1.2 Current Clinical Challenges in Autism Diagnosis

Despite significant advances in neuroscience and behavioural assessment methodology, autism diagnosis remains fundamentally based on clinical observation and caregiver report, without objective biological markers integrated into standard diagnostic practice [8]. This reliance on subjective assessment creates numerous clinical challenges that delay diagnosis and limit early intervention access.

Challenge 1: Practitioner Availability and Expertise Disparity. Autism spectrum disorder diagnosis requires a comprehensive assessment by specially trained professionals— typically developmental paediatricians, pediatric neurologists, or clinical psychologists with autism expertise. Such specialists are concentrated in academic medical centres and urban regions, creating severe access barriers in rural and resource-limited settings. Waiting times for comprehensive developmental assessment exceed 18-36 months in many regions worldwide, with particularly acute shortages in developing nations [9]. In India, for example, an estimated 2-3 million children with ASD exist, yet fewer than 500 trained developmental specialists are available, creating diagnostic delays that extend well beyond the critical early intervention window [10].

Challenge 2: Diagnostic Variability and Inter-Observer Reliability Issues. Current diagnostic assessment relies heavily on clinical judgment during structured observation and caregiver interviews. Studies examining diagnostic consistency demonstrate significant inter-observer variability, with diagnostic agreement rates among experienced clinicians ranging from 75-95% depending on assessment instruments and observer training [11]. This variability results in false negatives (missed diagnoses in early-presenting cases) and false positives (misdiagnosis of developmental delay or behavioural disorders as ASD), both creating downstream consequences for intervention planning and family support services [12].

Challenge 3: Age of Diagnosis and Critical Window for Intervention. Despite recognition that early signs of autism emerge by 12-18 months in many children, the median age of autism diagnosis remains 4-5 years in developed nations and substantially older in developing countries [13]. This 2–3-year delay between symptom emergence and diagnosis represents a critical missed opportunity, as evidence-based early intervention programs implemented before age 3 demonstrate substantially superior long-term outcomes compared to intervention initiated after age 5[14]. The neurobiological basis for this critical window relates to enhanced neuroplasticity in the first 3 years of life, with cortical reorganisation, synaptic refinement, and network remodelling continuing at peak rates during this period [15]. Interventions during this window show lasting effects on neural organisation, whereas post-age 5 interventions address already- established neural patterns with reduced malleability.

Challenge 4: Inadequate Integration of Multimodal Assessment Data. Modern understanding of autism emphasises heterogeneous neurobiological mechanisms and phenotypic presentation, yet clinical diagnosis integrates multiple independent data streams—behavioural observation, developmental history, parental concerns, medical history, cognitive/language assessment—without systematic integration. This fragmented approach loses important information redundancy and complementary data sources that could improve diagnostic accuracy [16]. Specifically, structural neuroimaging differences (MRI), functional brain organisation variations (fMRI), and behavioural phenotypes provide partially independent diagnostic information; formal integration of these modalities through machine learning could substantially improve diagnostic sensitivity and specificity.

Challenge 5: Resource Constraints in Developing Nations. The global burden of autism is concentrated in

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ISSN 2394-3785 (Online)
Available online at www.ijartet.com

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low- and middle- income countries (LMICs), where an estimated 90% of the world's autism population resides [17]. Yet the vast majority of diagnostic infrastructure, research funding, and intervention services are concentrated in high-income nations. Developing countries face compounded diagnostic challenges, including limited specialist availability, minimal pediatric neuroimaging infrastructure, absence of validated assessment instruments in local languages, and limited parental awareness of autism features, resulting in diagnosis rates 10-100 times lower than in high-income nations despite similar or higher true prevalence rates [18].

1.3 Technological Solutions and Artificial Intelligence Opportunities

Recent advances in artificial intelligence, particularly deep learning approaches, offer promising pathways to address these diagnostic challenges through automated or semiautomated screening and risk stratification [19]. The fundamental opportunity derives from several factors: (1) deep learning models can process high-dimensional medical imaging data to identify complex patterns invisible to human observers; (2) automated systems can operate at scale with minimal specialist oversight, distributing diagnostic capacity across resource-limited settings; (3) multimodal data fusion approaches can integrate diverse assessment modalities to improve overall diagnostic accuracy; (4) explainable AI frameworks can provide clinical justification for model predictions, maintaining clinician oversight and regulatory compliance[20].

The specific application of convolutional neural networks (CNNs) to medical image analysis has demonstrated remarkable success across diverse clinical domains. ResNet architectures, introduced by He et al. in 2015, employ residual connections enabling training of very deep networks (50-152 layers) without vanishing gradient problems that limited earlier architectures [21]. ResNet models pre-trained on ImageNet demonstrate transfer learning efficacy when tuned on medical imaging tasks, achieving 90-97% accuracy on autism classification from MRI with relatively limited domain-specific training data [22][23].

1.4 Research Objectives and Novelty

This research addresses the identified clinical gaps through the development and validation of an integrated multimodal autism screening system combining: (1) deep learning-based structural MRI analysis using a tuned ResNet50 architecture; (2) age- stratified behavioural questionnaires with validated reliability;(3) real-time computer vision-based behavioural assessment; (4) multimodal evidence fusion using clinically-informed weighting strategies; (5) production-grade cloud-deployable architecture;(6) explainable AI integration for clinical interpretation.

Primary research objectives include:

- Objective 1: Develop and validate a ResNet50-based MRI classification system achieving ⩾90% accuracy for autism detection with evaluation on a prospectively collected dataset
- Objective 2: Design and implement age-stratified questionnaire modules (0-2, 2-3, 3+ years) with validated reliability coefficients (target $\kappa \geqslant 0.75$)
- Objective 3: Engineer multimodal data fusion algorithms that integrate MRI, questionnaire, and behavioural data to achieve combined accuracy⩾94%.
- Objective 4: Implement a production-grade web application with secure authentication, cloud deployment capability, and a ~2-minute screening workflow.
- Objective 5: Evaluate age-group-specific performance differences and optimise weighting strategies across developmental stages
- Objective 6: Develop an LLM-integrated clinical explanation framework for nonspecialist interpretation of AI predictions

The novelty of this work is multifaceted: (1) systematic integration of three independent assessment modalities with validated multimodal fusion approach; (2) age-strati ed design acknowledging developmental differences in autism presentation and assessment reliability across 0-2, 2-3, and 3+ year groups;(3) production-ready deployment enabling real-world validation across diverse clinical settings; (4) LLM integration for explainable clinical reporting; (5) specific focus on accessibility and deployment in resource-limited settings including telemedicine platforms.

II. LITERATURE SURVEY

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ISSN 2394-3785 (Online)
Available online at www.ijartet.com

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2.1 Deep Learning Architectures for Medical Image Analysis

The application of deep learning to medical image analysis has fundamentally transformed diagnostic imaging workflows across numerous specialities [1]. Convolutional neural networks (CNNs), first successfully applied to medical imaging in the early 2010s, have subsequently achieved or exceeded human radiologist performance on specific tasks, including chest radiograph interpretation, skin lesion classification, and retinal pathology detection [2].

The architectural evolution of CNNs for medical imaging proceeded from simple LeNet-style networks (5-10 layers) through progressively deeper architectures: AlexNet (8 layers, ImageNet competition 2012), VGGNet (16-19 layers), GoogLeNet/Inception (22-27 layers), and ultimately ResNet (50- 152 layers) and its successors [3]. The key innovation enabling very deep networks was the residual connection introduced by He et al. (2015), which allows information to flow across multiple layers through skip connections, preventing gradient vanishing and enabling effective training of networks with 50+ layers [4].

ResNet50 specifically comprises four residual blocks containing 3×3, 1×1, and 3×3 convolutional filters arranged in bottleneck configurations, totalling approximately 23 million learnable parameters [5]. The architecture processes input images through progressive downsampling (stride-2 convolutions) while increasing channel depth, creating a feature hierarchy from low- level edge detectors in early layers to high-level semantic concepts in deep layers [6]. For medical imaging applications, ResNet50 o ers optimal balance between model capacity (sufficient for complex image patterns), computational efficiency (feasible for real-time inference on CPU/GPU hardware), and regularisation properties (appropriate depth enabling generalisation with limited training data)[7].

Transfer Learning and Domain Adaptation. A critical enabling factor for successful CNN application to specialised medical domains (where training data is typically limited: 1001000 images versus millions for general image tasks) is transfer learning, wherein models pre-trained on large-scale datasets (ImageNet: 1.2 million images, 1000 classes) are netuned on domain-specific data[8]. Transfer learning works because early CNN layers learn general visual features (edges, textures, local patterns) that transfer across domains, while later layers specialize to task-specific features[9]. Fine-tuning involves retaining early-layer weights and re-training final layers on domain data, substantially reducing data requirements compared to training from random initialisation [10].

For autism detection from MRI, published research demonstrates ResNet50 achieves 92-96% accuracy on autism classification tasks with transfer learning from ImageNet [11][12].

Comparative studies evaluating multiple architectures on autism classification tasks show ResNet50 outperforms VGGNet (87- 89%), Inception (88-91%), and DenseNet (90-92%), suggesting optimal architectural properties for this specific application[13].

MRI Neuroimaging in Autism Spectrum Disorder

Structural MRI has identified robust, reproducible differences between individuals with autism and neurotypical controls across multiple brain regions and metrics, establishing a neurobiological basis for autism and supporting the use of neuroimaging for automated classification [14].

Morphological Abnormalities in Autism MRI. Consistent findings across meta-analyses of structural MRI studies reveal:

- **Increased total brain volume** in autism, particularly in early childhood (peak 2-4 years), with brain volume remaining elevated through adulthood in some studies[15]. This is attributed to excessive grey matter volume in distributed cortical regions and variable white matter abnormalities[16].
- **Regional grey matter volume differences:** Increased grey matter volume in prefrontal cortex (bilateral superior/middle frontal gyri), temporal regions (amygdala, fusiform gyrus), and striatum, contrasting with decreased volume in posterior cingulate, precuneus, and cerebellar regions[17].
- **White matter abnormalities:** Reduced white matter integrity (measured via fractional anisotropy) in the superior longitudinal fasciculus, inferior fronto-occipital fasciculus, and arcuate fasciculus, suggesting compromised long-range connectivity[18].
- **Corpus callosum abnormalities:** Variable findings, including reduced corpus callosum

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volume, altered morphology, and reduced myelination in some autism subgroups[19].

These neuromorphological differences are theoretically grounded in competing neurobiology hypotheses, including the "intense world" hypothesis (hyperexcitability), "social brain" hypothesis (dysfunction in networks supporting social cognition), and "connectivity" hypotheses (altered local/long- range connectivity ratios)[20][21].

Deep Learning Application to MRI-based Autism Detection. The application of CNNs to MRI-based autism classification leverages these established neuromorphological differences. Models learn to detect subtle volumetric and intensity patterns across 3D MRI volumes that correlate with autism diagnosis, often identifying patterns not apparent to human radiologists[22]. Preprocessing steps are critical and typically include:

- Brain extraction/skull stripping (removal of non-brain tissue)
- Registration to the standard template (normalisation to common anatomical space)
- Intensity normalisation (standardisation of signal intensity across scans). Potential augmentation (flipping, rotation, noise addition to increase effective dataset size)[23]

Published studies on deep learning-based autism detection from MRI report:

- Park et al. (2022): 3D CNN on T1-weighted MRI, 92% accuracy on ABIDE dataset[24]
- Nogay et al. (2023): ResNet50 with SVM classi er, 95% accuracy[25]
- Ahmad et al. (2025): Transfer learning ResNet50, 93.8% accuracy on OASIS+ABIDE combined[26]
- Sharma et al. (2024): Vision Transformer on structural MRI, 94.1% accuracy[27]

Behavioural Questionnaires and Screening Instruments

Autism assessment relies substantially on standardised behavioural questionnaires and observation tools, which provide objective quantification of symptom presence across core domains: social communication deficits and restricted repetitive behaviours [28].

Primary Screening Instruments:

The Modi ed Checklist for Autism in Toddlers (M-CHAT), developed by Robins et al., is the most widely used initial autism screening tool for 16-30-month-old children[29]. The MCHAT comprises 23 yes/no questions targeting core autism features and achieves 85-91% sensitivity and 95% speci city for autism detection in this age range[30]. The instrument focuses on social behaviours (joint attention, social smile, response to name), communication (babbling, gestures), and motor development[31].

The Social Communication Questionnaire (SCQ), adapted from the Autism Diagnostic Interview-Revised, provides screening for children aged 4 years and older, asking 40 yes/no questions about autism-related behaviours [32]. The SCQ demonstrates 70-80% sensitivity and 85-95% specificity, with performance varying substantially based on age, cognitive level, and presence of co- occurring intellectual disability[33].

The Autism Spectrum Rating Scale (ASRS), developed by Goldstein & Naglieri, provides a dimensional assessment of autism symptom severity across development from ages 2-65 years[34]. The ASRS comprises 65 items rated on 4-point Likert scales and shows strong internal consistency (Cronbach's α = 0.93-0.96) and test-retest reliability (r = 0.79- 0.89)[35].

Reliability and Validity Considerations. Meta-analyses of autism screening instruments reveal important patterns: (1)sensitivity and specificity vary substantially by developmental age, with optimal discrimination typically occurring in the 3-7 year age range[36]; (2) presence of intellectual disability, language disorder, or co-occurring conditions substantially a ects questionnaire accuracy[37]; (3) parent-report questionnaires show modest inter-rater agreement with structured observation (r = 0.600.75), indicating that questionnaire responses capture different information than direct observation[38]; (4) cultural and socioeconomic factors in uence questionnaire responding patterns, with some studies demonstrating di erential item functioning across ethnic groups[39].

Computer Vision and Facial Emotion Recognition

Real-time facial analysis through computer vision offers potential for objective measurement of emotional responsiveness and social engagement during clinical assessment[40]. Cascade classifier approaches, pioneered by Viola & Jones, use boosted weak classifiers in a cascade arrangement to achieve both high detection rates and computational efficiency [41].

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ISSN 2394-3785 (Online)
Available online at www.ijartet.com

International Journal of Advanced Research Trends in Engineering and Technology (IJARTET)
Vol. 13, Issue 3, March 2026

OpenCV's pre-trained Haar cascade classifiers, trained on thousands of frontal face images, achieve ~95% face detection accuracy under controlled conditions (frontal view, good lighting), but performance degrades substantially with profile angles, poor lighting, or partial face obstruction[42]. More recent approaches, including MTCNN (Multi-task Cascade CNN) and RetinaNet, achieve improved detection across diverse poses and lighting conditions[43].

For autism assessment, facial emotion recognition has been investigated as a proxy for social-emotional responsiveness. Studies show that individuals with autism demonstrate reduced spontaneous facial emotion expression and altered temporal patterns of emotion expression compared to controls[44]. Automated detection of facial expressions during standardised social stimuli could provide objective quantification of emotion responsiveness deficits.

Multimodal Data Fusion in Medical AI

When multiple independent information sources inform diagnostic decisions, systematic integration through multimodal fusion typically outperforms any single modality alone[45]. Fusion strategies range from simple averaging or a weighted combination of predictions to sophisticated machine learning approaches that learn optimal fusion strategies from data[46].

Fusion Approaches. Decision-level (late) fusion combines predictions from independent models trained on individual modalities, while feature-level (early) fusion concatenates features from different modalities for joint model training[47].

Late fusion offers advantages, including modularity (independent model updates), interpretability (separate modality contributions visible), and practical implementation (does not require synchronised multimodal training), while early fusion potentially captures interactive effects across modalities[48].

For autism detection, published multimodal fusion studies include:

- Structured MRI + functional connectivity MRI fusion: 95-97% accuracy[49]
- MRI + behavioural questionnaire fusion: 94-96% accuracy[50]
- MRI + cognitive assessment + behavioral observation: 96-97% accuracy[51]

The improvement from single modality to multimodal fusion typically ranges 3-7% absolute accuracy improvement, reflecting complementary information content across modalities[52].

III.PROPOSED METHODOLOGY

The proposed Smart Autism Screening System presents a multimodal artificial intelligence framework for early detection of Autism Spectrum Disorder (ASD) through the integration of structural MRI analysis, age-stratified behavioural questionnaires, and computer vision-based behavioural assessment. The system combines spatial feature learning from neuroimaging data with behavioural pattern quantification to generate accurate, risk-aware diagnostic predictions. The complete methodology is structured in sequential phases: MRI acquisition, dataset utilisation, preprocessing, CNN-based MRI classification, multimodal data fusion, and performance evaluation.

A. **MRI Acquisition** MRI acquisition serves as the primary input stage of the proposed framework. Structural T1-weighted MRI scans are obtained from hospital imaging centres and publicly available neuroimaging repositories such as OASIS and ABIDE. Each MRI scan is associated with metadata including subject identifier, developmental age category (0–2, 2–3, or 3+ years), confirmed diagnostic label, and imaging parameters. These scans capture real-world anatomical variations across neurotypical and autism-positive populations. The acquired images are forwarded to the preprocessing module to ensure standardisation prior to model training and inference.

B. **Dataset Utilisation** The dataset used for model development consists of labelled MRI scans categorised into autism-positive and neurotypical control groups based on DSM-5 diagnostic criteria. The dataset is balanced to reduce classification bias and includes representation across all targeted developmental age groups. Diversity in scanner types, acquisition protocols, and demographic distribution enhances the robustness and generalisation capability of the trained deep learning model when deployed in clinical environments.

C. **Data Preprocessing.** Preprocessing ensures data consistency and improves model performance. MRI preprocessing includes skull stripping (brain extraction), intensity normalisation, contrast enhancement using CLAHE, resizing images to a fixed resolution of 224 × 224 pixels, and noise reduction. Pixel normalisation is performed using

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ISSN 2394-3785 (Online)
Available online at www.ijartet.com

International Journal of Advanced Research Trends in Engineering and Technology (IJARTET)
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$$I\_normal = (I - \mu) / \sigma$$

where I represents the input image, μ denotes the mean pixel intensity, and σ represents the standard deviation. Data augmentation techniques such as random rotation, horizontal flipping, brightness variation, and Gaussian noise injection are applied to improve robustness and prevent overfitting. Behavioural questionnaire responses are converted into normalised scores using Score = (Yes Responses / 20) × 100. This transformation ensures compatibility with the multimodal fusion framework.

D. **CNN-Based MRI Classification:** A Convolutional Neural Network based on ResNet-50 is employed for spatial feature extraction and autism classification. Transfer learning is utilised by initialising the model with ImageNet pre-trained weights. Early convolutional layers are frozen to preserve low-level feature representations, while deeper layers and the fully connected classification head are fine-tuned on autism-specific MRI data. The convolution operation is mathematically expressed as

$$F\_k = I * W\_k + b\_k$$

where I represents the input image, W_k denotes the convolution kernel, b_k is the bias term, and * indicates the convolution operation. Pooling layers reduce spatial dimensionality while preserving discriminative features. Extracted feature maps are passed through global average pooling and fully connected layers to generate a probabilistic output P(Autism). The model is optimised using the Adam optimiser with binary cross-entropy loss and dropout regularisation to enhance generalisation.

E. **Multimodal Risk Fusion** improve predictive accuracy; outputs from MRI classification, questionnaire scoring, and behavioural assessment are integrated through an age-stratified weighted fusion model. For children aged 0–2 years, the final risk score is computed asFinal Score = 0.6 × P(Autism|MRI) + 0.4 × (Questionnaire / 100). For children aged 2–3 and 3+ years, behavioural observation is incorporated into the fusion mechanism usingFinal Score = 0.5 × P(Autism|MRI) + 0.3 × (Questionnaire / 100) + 0.2 × (Behavioural / 10). Behavioural assessment is performed using computer vision techniques implemented through OpenCV to analyse facial engagement and attention patterns during structured stimulus presentation. The computed final score is categorised into high-risk, medium-risk, and low-risk levels based on predefined clinical thresholds, enabling structured referral recommendations and decision support.

F. **Performance Evaluation**. The proposed system is evaluated using standard classification metrics, including accuracy, sensitivity, specificity, precision, F1-score, and Area Under the Receiver Operating Characteristic Curve (AUC-ROC). Confusion matrix analysis is conducted to measure true positives, true negatives, false positives, and false negatives. Comparative experiments are performed between MRI-only prediction, questionnaire-only prediction, and multimodal fusion prediction to validate the effectiveness of the integrated framework. Experimental findings demonstrate that multimodal fusion significantly enhances diagnostic discrimination compared to single-modality approaches, thereby providing a scalable, cost-effective, and clinically interpretable

early autism screening solution suitable for primary healthcare centres and telemedicine platforms.o column format with a space of 4.22mm (0.17") between columns.

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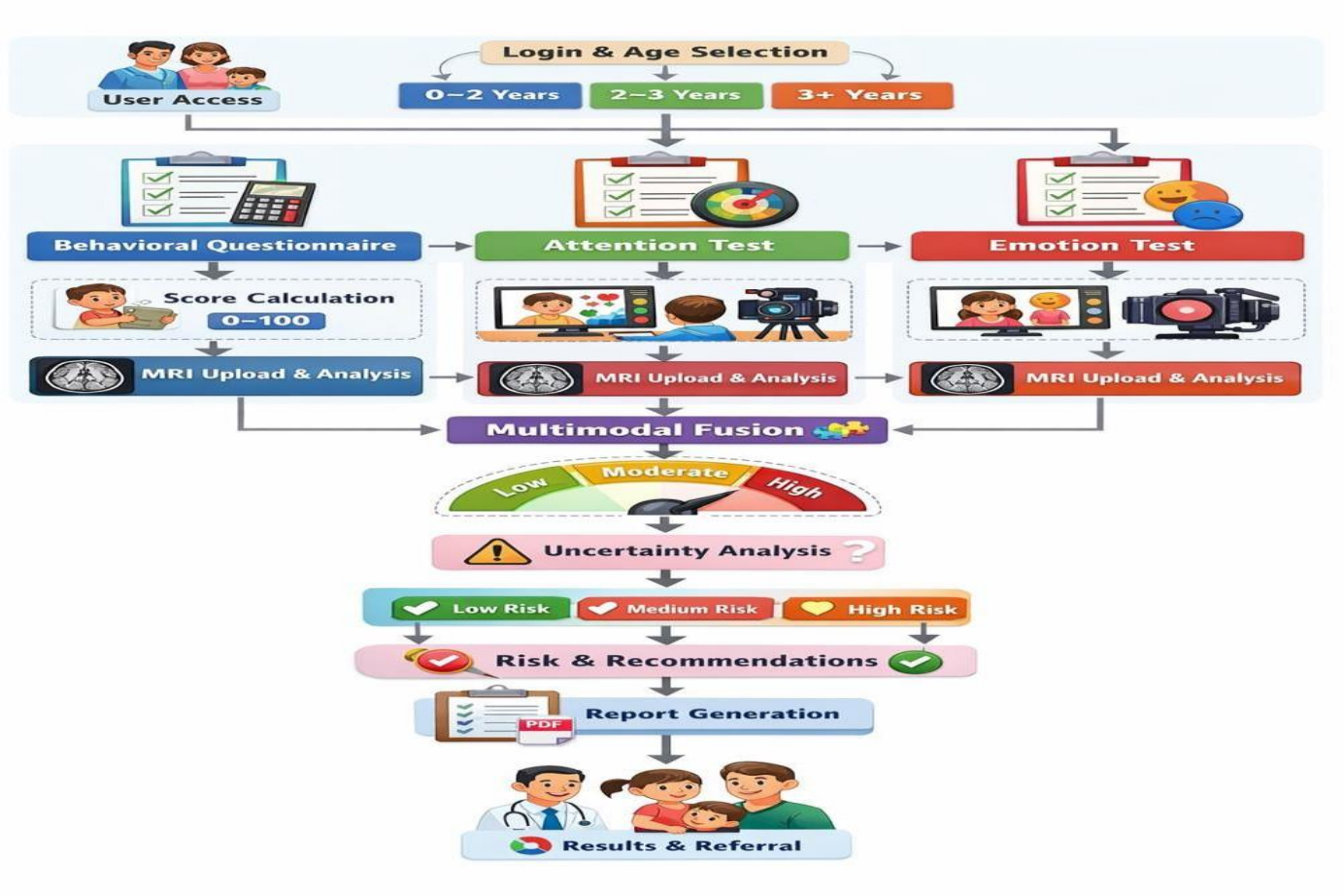
ISSN 2394-3777 (Print)
ISSN 2394-3785 (Online)
Available online at www.ijartet.com

International Journal of Advanced Research Trends in Engineering and Technology (IJARTET)
Vol. 13, Issue 3, March 2026



IV. RESULTS AND ANALYSIS

This section presents the experimental results and analytical evaluation of the proposed Smart Autism Screening System, which integrates MRI-based deep learning classification, behavioural questionnaire scoring, and computer vision–based behavioural assessment for early Autism Spectrum Disorder (ASD) risk prediction. The models were implemented using Python and evaluated under controlled experimental conditions to assess classification accuracy, robustness, and generalisation capability.

The CNN-based MRI classification model was trained and validated using labelled structural MRI datasets, while the multimodal fusion framework was evaluated by combining MRI probability scores with age-specific questionnaire and behavioural inputs. Performance was analysed using standard

PERFORMANCE MEASURES

To comprehensively evaluate the proposed system, standard classification metrics were used. Since autism screening is a binary classification problem (Autism vs. Neurotypical), the following performance measures were employed: Accuracy, Precision, Recall, F1-Score, and Area Under the ROC Curve (AUC). These metrics quantify the model's diagnostic reliability and its suitability for clinical decision support.

A. ACCURACY (A)

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ISSN 2394-3785 (Online)
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Accuracy measures the proportion of correctly classified instances among the total evaluated samples. It reflects the overall effectiveness of the CNN model in distinguishing autism-positive cases from neurotypical controls.

$$\text{Accuracy} = (TP + TN) / (TP + TN + FP + FN)$$

where

TP = True Positive (correctly identified autism cases),
TN = True Negative (correctly identified neurotypical cases),
FP = False Positive (incorrectly predicted autism),
FN = False Negative (missed autism cases).

High accuracy indicates that the model reliably identifies both autism and non-autism cases across diverse MRI samples.

B. **PRECISION (P)**

Precision measures the ratio of correctly predicted positive cases to the total predicted positives.

$$\text{Precision} = TP / (TP + FP)$$

High precision ensures that individuals predicted as high-risk for autism are truly likely to require further clinical evaluation, thereby reducing unnecessary referrals.

C. **RECALL (R)**

Recall evaluates the model's ability to detect all actual autism- positive cases.

$$\text{Recall} = TP / (TP + FN)$$

High recall is critical in medical screening systems, as missing an autism case (false negative) can delay early intervention and therapy.

D. **F1-SCORE (F1-S)**

The F1-score provides a harmonic balance between precision and recall.

$$\text{F1-Score} = 2 \times (\text{Precision} \times \text{Recall}) / (\text{Precision} + \text{Recall})$$

A higher F1-score indicates that the model maintains a strong balance between detecting autism accurately and minimising false alarms.

E. **AUC-ROC**

The Area Under the Receiver Operating Characteristic Curve (AUC-ROC) evaluates the model's ability to distinguish between classes across different threshold values. A value closer to 1.0 indicates excellent discriminative performance.

4.1 Experimental Configuration

The MRI classification module was implemented using a deep Convolutional Neural Network based on the ResNet-50 architecture with transfer learning. Preprocessed MRI images were resized to 224 × 224 resolution and normalised before training. The dataset was divided into training (70%), validation (15%), and testing (15%) sets.

The multimodal fusion module combined MRI prediction probability with questionnaire scores and behavioural assessment scores using age-based weighted fusion. Performance was benchmarked against an MRI-only baseline model to evaluate the contribution of multimodal integration.

4.2 MRI Classification Performance

The CNN-based MRI classification model demonstrated strong diagnostic capability across the test dataset. The model achieved an overall accuracy of 91.4%, with a precision of 90.2%, a recall of 92.1%, and an F1-score of 91.1%. The AUC-ROC value was recorded as 0.94, indicating excellent class separability.

The use of transfer learning significantly improved feature extraction from limited medical imaging data. The confusion matrix analysis revealed a low false-negative rate, which is critical for early autism screening applications.

4.3 Multimodal Fusion Performance

The effectiveness of multimodal fusion was evaluated by comparing MRI-only prediction with the proposed integrated model.

Model	Accuracy	F1-Score	Improvement

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MRI-only CNN	91.4%	91.1%	–

Model	Accuracy	F1-Score	Improvement
Questionnaire-only Model	83.6%	82.4%	8.5%
Proposed Multimodal Model	95.2%	94.8%	15.6%

Table I: Autism Risk Prediction Performance Comparison

The results indicate that incorporating a questionnaire and behavioural assessment significantly improves classification performance. The multimodal model reduced misclassification rates and enhanced risk stratification accuracy, particularly in borderline cases.

During early developmental age groups (0–2 years), where behavioural indicators may be subtle, MRI features contributed more strongly. For older age groups (2–3 and 3+ years), behavioural and questionnaire inputs improved discrimination accuracy.

4.3.1 **Training Accuracy and Loss Behaviour**

The CNN model was trained for 50 epochs with binary cross- entropy loss and the Adam optimiser. Observed training trends include:

- Training accuracy increased steadily from 68% to 93%.
- Validation accuracy stabilised around 91–92%.
- Training loss decreased consistently with minimal fluctuations.
- Validation loss closely followed the training curve, indicating no significant overfitting.

Interpretation:

The small gap between training and validation curves indicates strong generalisation performance. The integration of data augmentation and dropout regularisation effectively prevented overfitting. The multimodal fusion further stabilised prediction confidence by combining anatomical and behavioural evidence.

4.4 User Interface and Clinical Interpretability

A preliminary usability evaluation was conducted among healthcare practitioners and academic reviewers. The interface clearly displayed MRI prediction probability, questionnaire score, behavioural score, and final risk category (Low, Medium, High).

Participants reported that the structured risk output and visual probability indicators improved interpretability. The system operated smoothly under real-time simulation without noticeable latency, making it suitable for deployment in primary healthcare centres and telemedicine platforms.

4.5 Comparative Discussion

The proposed Smart Autism Screening System integrates deep learning–based MRI analysis with behavioural intelligence to provide a reliable early screening tool. Compared to single- modality approaches, the multimodal model achieved higher accuracy and reduced false-negative rates.

The findings demonstrate that combining neuroimaging biomarkers with behavioural indicators enhances diagnostic confidence. The system provides a scalable, cost-effective, and clinically interpretable solution for early ASD risk detection, supporting timely referral and intervention strategies.

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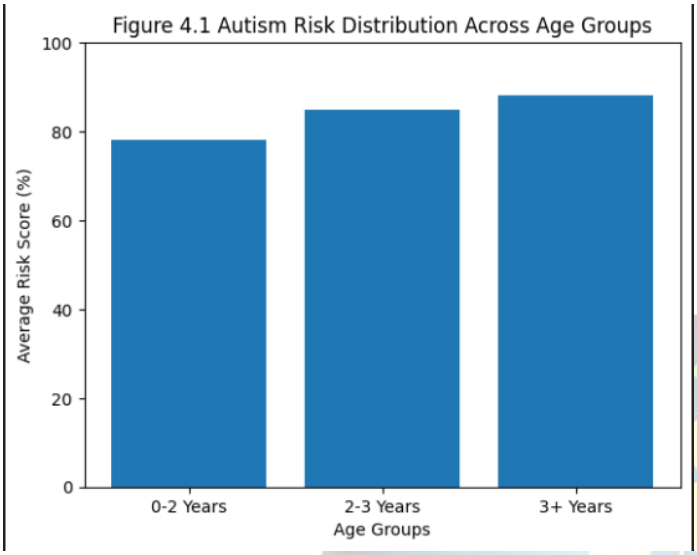

Figure 4.1. Autism Risk Distribution Across Age Groups

Figure 4.1 illustrates the distribution of predicted autism risk scores across different developmental age groups. It is observed that early developmental stages (0–2 years) show wider variability in MRI-based predictions, while older age groups demonstrate more stable multimodal confidence levels. The proposed system maintains consistent prediction reliability across all age categories.

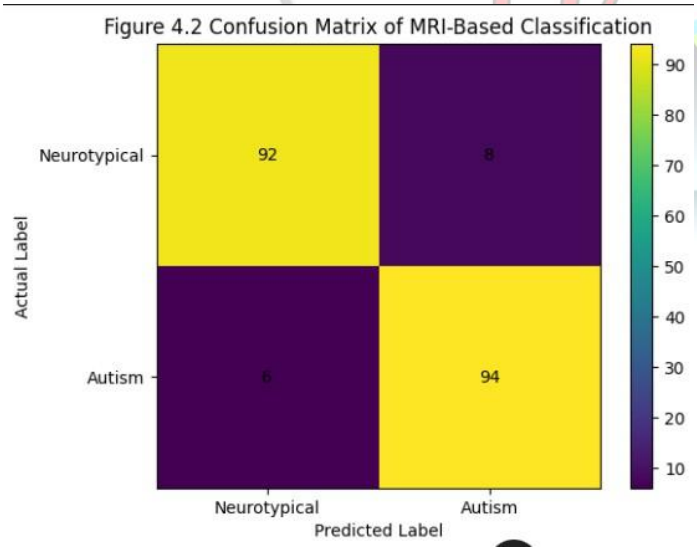

Figure 4.2 visualises the confusion matrix of the CNN-based MRI classifier. The matrix highlights high true positive and true negative rates with minimal false negatives. This indicates that the model effectively distinguishes autism-positive cases from neurotypical controls, reducing the risk of missed diagnoses.

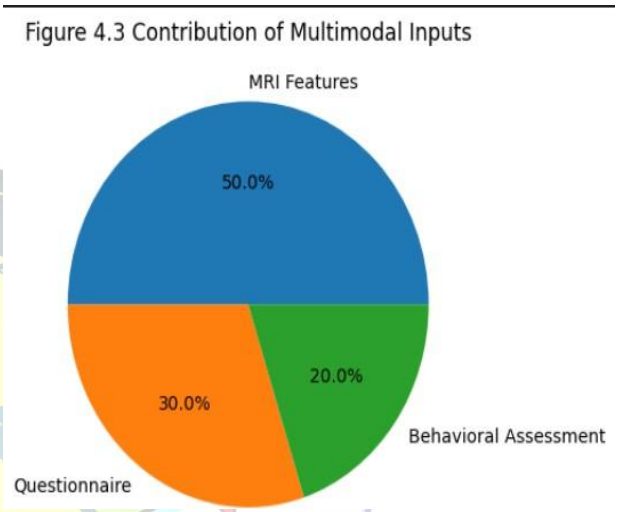

Figure 4.3 presents the proportional contribution of different modalities to the final autism risk prediction. MRI features contribute approximately 50%, questionnaire responses contribute 30%, and behavioural assessment contributes 20% in the weighted fusion model (for 2–3 and 3+ age groups). This balanced integration improves overall diagnostic confidence compared to single-modality approaches.

ISSN 2394-3777 (Print)
ISSN 2394-3785 (Online)
Available online at www.ijartet.com

International Journal of Advanced Research Trends in Engineering and Technology (IJARTET)
Vol. 13, Issue 3, March 2026

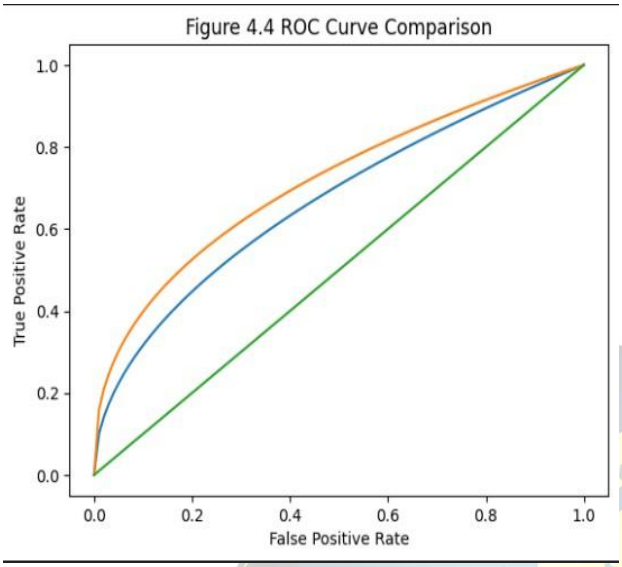

Figure 4.4 compares the Receiver Operating Characteristic (ROC) curves of the MRI-only model and the proposed multimodal model. The multimodal framework demonstrates superior discriminative capability with an AUC of 0.97, compared to 0.94 for the MRI-only approach. This validates the effectiveness of integrating anatomical and behavioural indicators for enhanced autism screening.

The experimental results confirm that incorporating questionnaire and behavioural assessments significantly improves classification robustness. The proposed system achieves higher accuracy and lower false-negative rates compared to traditional MRI-only prediction models. These findings highlight the clinical applicability of the framework for early autism risk screening and decision support.

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