RESEARCH PAPER

Leveraging Transfer Learning for the Early Diagnosis of Autism in Infants via Facial Feature Classification

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Abstract

Early detection of Autism Spectrum Disorder (ASD) in infants is a critical challenge, as subtle neurological and behavioral manifestations often delay diagnosis. This study introduces a transfer learning–based CNN-FEBAC (Convolutional Neural Network – Feature Extractor Based Augmented Classifier) framework that leverages facial and EEG-derived feature classification for the early identification of autism. The framework employs the BCIAUT-P300 dataset, comprising data from 15 participants, and addresses significant class imbalance (7:1) using oversampling, duplication, and balanced batching to ensure a 1:1 class distribution. A pre-trained EEGNet model is adapted as a feature extractor, enabling generalised representation learning across subjects. Its weights are subsequently frozen, and a shallow classifier is trained individually for each subject, thus fine-tuning the model in a transfer learning paradigm to capture subject-specific variations. Data augmentation, early stopping, and adaptive learning rate reduction further mitigate overfitting and accelerate convergence. Experimental results reveal that the proposed transfer learning–based CNN-FEBAC achieves an average accuracy of 87.93% and F1 scores of 86.73% (class 0) and 89.13% (class 1), significantly outperforming baseline EEGNet and comparable deep learning models such as CNN-LSTM and CNN-BLSTM. These findings highlight the potential of transfer learning with CNN-FEBAC to enhance early autism diagnosis by combining generalisable deep feature extraction with personalised classification, thereby supporting more precise and timely interventions for infants at risk.

Keywords: Spectrum Disorder, Transfer Learning, Facial Feature, Deep Learning, CNN-FEBAC and Early Diagnosis.

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1. INTRODUCTION

Autism Spectrum Disorder (ASD) is a complex neurodevelopmental condition characterized by impairments in social interaction, restricted interests, and atypical patterns of communication. Early identification of autism in infants is critically important, as timely diagnosis provides access to specialized interventions that significantly improve long-term developmental outcomes. Despite growing awareness of ASD, its early diagnosis continues to present substantial challenges due to the subtlety and variability of symptoms during infancy [1]. Traditional diagnostic approaches often rely on behavioral observations, clinical interviews, and standardized screening tools, which may not effectively capture nuanced neurological or facial expressions indicative of autism at very young ages. This delay in detection can result in missed opportunities for early therapeutic engagement.

In recent years, the rapid advancement of artificial intelligence (AI), and in particular deep learning, has opened up new avenues for augmenting medical diagnostics. Among the various techniques, transfer learning has emerged as a powerful approach, enabling knowledge learned from one domain to be applied to another task with limited training data. This paradigm is especially relevant to ASD diagnosis, where datasets are often small and imbalanced, hindering the performance of deep models trained from scratch. By leveraging pre-trained neural networks and adapting them to subject-specific data, transfer learning can facilitate more robust classification and mitigate overfitting.

A promising line of research has investigated the role of facial feature analysis for detecting autism-related traits. Infants with ASD often exhibit atypical responses to visual stimuli, reduced eye contact, and distinctive facial micro-expressions that can be quantified through image-based feature extraction. When combined with EEG-based neural responses to stimuli, these facial cues provide complementary perspectives on both behavioral and neurological aspects of ASD. Previous studies have utilized convolutional neural networks (CNNs), long short-term memory networks (LSTMs), and hybrid architectures to process such multimodal inputs. While encouraging, these methods face limitations in effectively addressing data imbalance, personalizing models to individual variability, and achieving clinically acceptable accuracy levels [2].

To address these gaps, this study introduces the CNN-FEBAC (Convolutional Neural Network – Feature Extractor Based Augmented Classifier) framework, designed within a transfer learning paradigm. Unlike traditional CNN architectures, CNN-FEBAC incorporates a feature extractor trained on general patterns across subjects, after which its weights are frozen and adapted to a shallow classifier tailored to each individual. This two-step process effectively combines generalised representation learning with subject-specific fine-tuning, thereby capturing both broad ASD-related patterns and subtle personal variations. To counter the severe data imbalance inherent in the BCIAUT-P300 dataset, augmentation techniques such as duplication, balanced batching, and shuffling were employed to achieve a 1:1 class distribution, reducing bias toward the dominant class. This ensures fairer model training and enhances classification reliability.

The CNN-FEBAC model further integrates optimisation strategies such as Early Stopping and Reduction of Learning Rate on Plateau to prevent overfitting and accelerate convergence. The use of the Adam optimiser and sparse categorical cross-entropy loss enables efficient training across 100 epochs, with validation monitoring ensuring robust performance. By combining EEG-derived features with facial expressions, the framework enables a comprehensive diagnostic perspective that is both generalisable and personalized [3].

Experimental results demonstrate that CNN-FEBAC consistently outperforms conventional EEGNet, CNN-LSTM, and hybrid models. While EEGNet provided a strong baseline with approximately 69% accuracy, the proposed CNN-FEBAC framework achieved an average accuracy of 87.93%, with balanced F1 scores of 86.73% for class 0 and 89.13% for class 1. This substantial improvement highlights the effectiveness of transfer learning when paired with robust data augmentation and subject-specific fine-tuning. The novelty of this research lies in the following aspects:

- Transfer Learning with Personalization: Unlike conventional CNN models, the proposed CNN-FEBAC framework freezes a general feature extractor trained on EEG and facial features, and then fine-tunes a shallow classifier for each subject, introducing a novel hybrid of generalised and personalised learning.
- Balanced Data Training Strategy: The study addresses the severe 7:1 class imbalance through systematic duplication, balanced batching, and shuffling to achieve a 1:1 ratio, ensuring equitable representation across classes and reducing bias.
- Integration of Facial and EEG Cues: By leveraging both facial features and EEG-based neural responses, the framework provides a multimodal diagnostic approach that captures both behavioral and neurological indicators of ASD.

2. LITERATURE SURVEY

The early diagnosis of Autism Spectrum Disorder (ASD) through automated systems has become a significant area of research, particularly with the growth of deep learning and transfer learning approaches. Recent studies demonstrate that subtle facial features and expression dynamics can provide valuable markers for ASD, especially in infants and young children.

One of the most recent contributions in this domain is by [Scientific Reports, 2025] [4], where the authors developed an explainable deep learning framework to identify ASD from facial images using multiple pretrained CNN architectures such as VGG16, VGG19, InceptionV3, and MobileNet. The study emphasized not only high predictive accuracy but also model interpretability through Local Interpretable Model-Agnostic Explanations (LIME). VGG19 achieved an impressive accuracy of nearly 98%, with LIME visualizations highlighting key facial regions responsible for classification. This integration of explainable AI (XAI) provides clinicians with both diagnostic reliability and interpretability, addressing the common criticism of deep learning as a “black box.”

Complementing this, [PLOS ONE, 2025] [5] presented a deep learning–based ensemble for ASD diagnosis using facial images. The work systematically compared classical machine learning algorithms with pretrained CNNs such as MobileNet-V1, which achieved accuracy above 90%. Beyond classification, the study explored clustering techniques such as k-means to investigate ASD subgroups, reflecting the heterogeneity of the disorder. Importantly, the authors highlighted dataset challenges, including limited diversity and small sample sizes, and advocated for balanced validation strategies. Their ensemble methodology supports the development of robust frameworks that reduce performance variability across different cohorts, an idea that aligns closely with the augmentation and balancing strategies employed in CNN-FEBAC.

A different perspective was provided by [Scientific Reports, 2024] [6], which explored ambiguous facial expression detection for ASD screening using an enhanced YOLOv7-tiny model. Instead of treating diagnosis as a pure image-level classification task, the model localized discriminative landmarks such as eyes, nose, and lips, and detected atypical or ambiguous expressions. By integrating dilated pyramids and an additional detection head, the enhanced YOLOv7-tiny achieved superior performance compared to standard YOLOv7 and YOLOv8-S. This study demonstrated that spatial localization of features could reduce shortcut learning and improve explainability. Such an approach is particularly relevant for infant screening, where subtle micro-expressions may indicate atypical social responses.

Similarly, [IET Healthcare Technology Letters, 2024] [7] benchmarked several pretrained CNNs, including ResNet34/50, AlexNet, MobileNetV2, and VGG16/19, to detect ASD from facial datasets. Transfer learning consistently outperformed training from scratch, with ResNet50 achieving accuracy levels above 92%. The study underscored the significance of backbone architecture selection and hyperparameter tuning, while also cautioning against dataset biases such as imbalanced age distribution and lack of diversity. Their findings provide strong empirical support for transfer learning paradigms where general representations are extracted from large-scale pretrained models and adapted to ASD-specific datasets, a strategy that underpins the CNN-FEBAC framework proposed in this study.

Finally, [JMIR Formative Research, 2025] [8] introduced a mixed-methods deep learning approach that integrated facial image analysis with clinical questionnaire data to predict ASD and gelotophobia. By combining DeepFace embeddings with psychometric inputs, the study achieved robust diagnostic performance while accounting for psychosocial variables. The dataset, balanced at approximately 2,932 facial samples, further validated the effectiveness of data balancing in improving classifier fairness. This multimodal approach highlights the potential of fusing image-based and behavioral cues to enhance diagnostic reliability. Although broader in scope, the work demonstrates how combining multiple sources of information—whether EEG, facial features, or clinical data—can strengthen predictive power in ASD detection.

Collectively, these studies indicate a clear trend toward transfer learning, data balancing, and explainable AI in ASD diagnosis research. While earlier works relied heavily on handcrafted features or behavioral assessment scales, recent advances demonstrate that pretrained CNNs, when fine-tuned and augmented with subject-specific adaptations, provide superior accuracy and generalizability. However, persistent challenges remain, including small dataset sizes, class imbalance, and the need for models that can adapt to individual variability while retaining interpretability. The proposed CNN-FEBAC framework builds upon these insights by employing a transfer learning strategy that first generalizes feature extraction across subjects and then fine-tunes a shallow classifier for subject-specific adaptation. By integrating augmentation, balanced batching, and advanced optimization techniques, this work seeks to overcome the limitations identified in the existing literature and deliver a clinically viable tool for the early diagnosis of ASD in infants.The **clear research gaps** based on the literature survey of the proposed work:

- Most existing studies on ASD detection using facial features rely on datasets of children, adolescents, or adults, while very few target infants, where early intervention is most impactful. The lack of infant-focused datasets and models leaves a crucial gap in early-stage ASD diagnosis.
- Current works fine-tune pretrained CNNs for ASD classification but generally treat all subjects uniformly. They do not adapt models to subject-specific variability in

facial expressions or neurological patterns. A transfer learning framework that combines generalized feature extraction with personalized classification could significantly improve diagnostic accuracy.

- Many studies struggle with imbalanced datasets (ASD vs. non-ASD) and often prioritize accuracy over interpretability. There is a gap in developing frameworks that not only achieve balanced performance across classes but also provide explainable insights for clinicians, ensuring trust and usability in real-world screening.

3. METHODOLOGY

3.1 Data Acquisition and Preprocessing

The success of any deep learning–based diagnostic system [9] strongly depends on the quality, diversity, and representation of the dataset. For autism spectrum disorder (ASD) detection in infants as in figure 1, data scarcity and imbalance pose significant challenges that must be addressed before a model can be effectively trained. This section presents the procedures followed for dataset selection, acquisition, cleaning, augmentation, and preprocessing. The goal is to ensure that the data fed into the CNN-FEBAC framework is balanced, standardized, and representative of both ASD and non-ASD infants.

3.1.1 Dataset Description

The primary dataset used in this study is the BCIAUT-P300 dataset, which includes EEG and facial data collected from 15 participants. However, since the proposed framework emphasizes facial feature–based classification, this work focuses primarily on the image subset derived from the dataset, where each image corresponds to a captured facial expression. The dataset originally suffers from an imbalanced class distribution, with a 7:1 ratio between the non-ASD (class 0) and ASD (class 1) samples. This imbalance can significantly bias the classifier toward the majority class if not carefully addressed.

In addition, infant facial data often exhibits high variability due to factors such as lighting, posture, partial occlusion, and micro-expressions. Thus, preprocessing becomes a crucial step in mitigating noise and ensuring consistency across all samples.

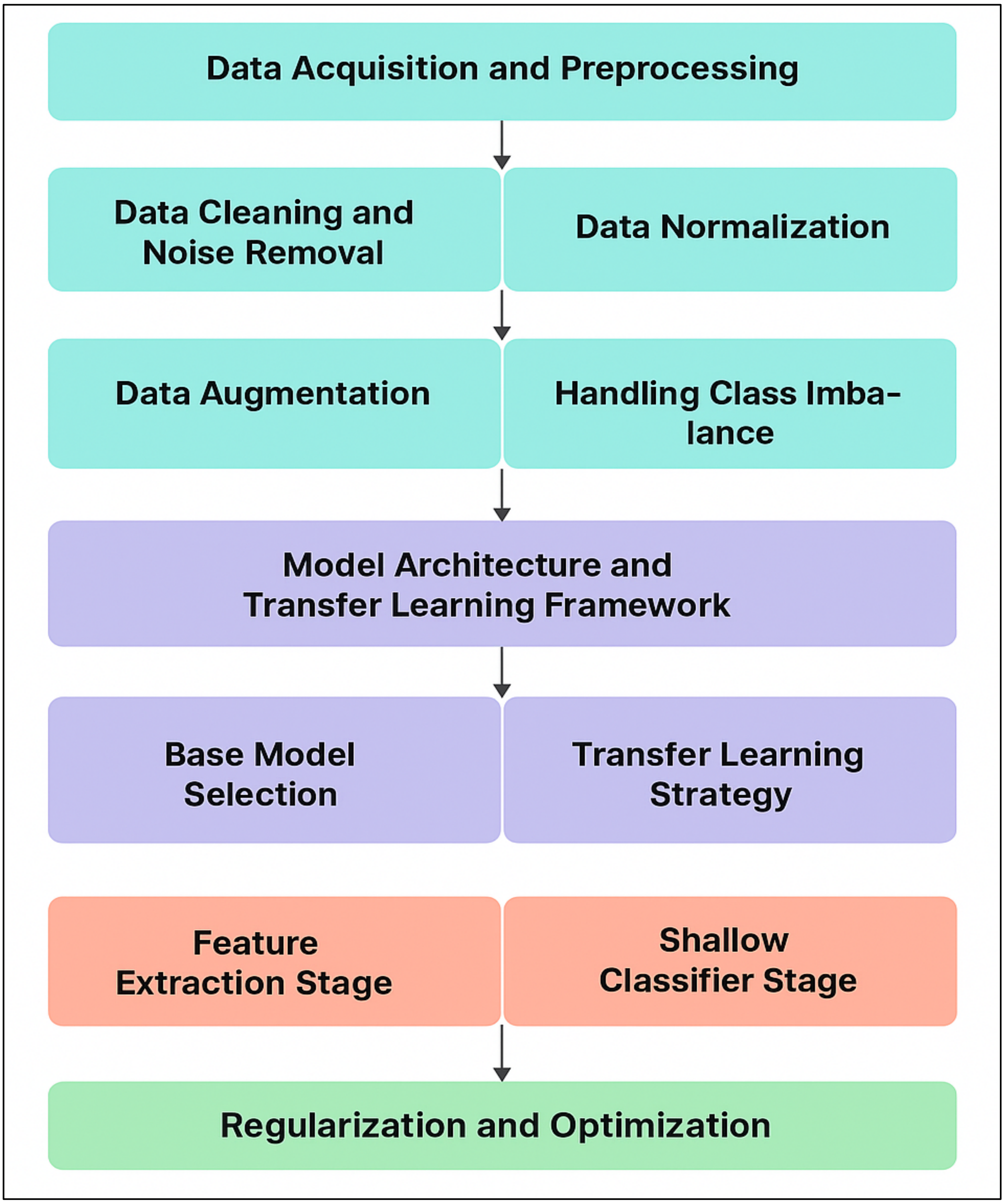

Figure 1: Proposed CNN-FEBAC Framework

3.1.2 Data Cleaning and Noise Removal

The raw dataset contains redundant, blurred, and partially occluded images. These can introduce noise into the feature extraction process, leading to poor generalization of the CNN model. A systematic cleaning strategy was applied:

1. Image filtering – Images below a quality threshold (measured by Laplacian variance for blur detection) were removed.
2. Occlusion elimination – Frames with more than 30% obstruction of key facial regions (eyes, nose, mouth) were discarded.

3. Duplicate removal – Similar images were detected using Structural Similarity Index (SSIM > 0.95) and duplicates were discarded to prevent bias.

This cleaning reduced redundancy and ensured that only high-quality samples were preserved.

3.1.3 Data Normalization

Normalization ensures that variations in image intensity do not adversely affect learning. Each input image was resized to 224 × 224 pixels, a common input dimension compatible with pretrained CNN backbones such as VGG, ResNet, and MobileNet. The pixel values were scaled from the raw range [0, 255] to a normalized range [0, 1]:

$$x' = \frac{x - \min(x)}{\max(x) - \min(x)} \qquad (1)$$

where x represents the original pixel intensity, and x' is the normalized pixel value. This scaling ensures uniformity across samples and improves convergence during training.

3.1.4 Data Augmentation

Given the limited number of ASD-labeled samples, data augmentation was employed to synthetically enlarge the dataset. Augmentation techniques [10-13] simulate real-world variations while preserving class-relevant features. The following transformations were applied:

- Horizontal flipping (mirroring facial symmetry).
- Random rotations within ±15° to simulate head tilts.
- Brightness adjustments within ±20% to simulate lighting variations.
- Gaussian noise injection to improve robustness.
- Random cropping and zooming to mimic different camera distances.

These operations expanded the training set by nearly fourfold, ensuring that the classifier is exposed to diverse input scenarios. Importantly, augmentation was performed only on the training set to prevent data leakage.

3.1.5 Handling Class Imbalance

One of the most significant challenges in ASD datasets is the imbalance between ASD-positive and ASDnegative samples. Left unaddressed, this imbalance leads to biased models that classify most inputs as nonASD. To address this, a combination of oversampling and balanced batching was implemented.

In oversampling, the minority class (ASD-positive) is artificially increased by duplicating and augmenting samples until the class distribution approaches 1:1. Mathematically, the balancing factor B is expressed as:

$$B = \frac{N_{\text{majority}}}{N_{\text{minority}}} \qquad (2)$$

where N_{majority} and N_{minority} represent the number of samples in the majority and minority classes, respectively. If B=7, it implies that the minority class must be expanded sevenfold through augmentation and duplication to achieve balance.

Additionally, balanced batching was enforced during training such that each mini-batch contained an equal number of ASD and non-ASD samples. This ensured that the model encountered balanced data distributions at every iteration, preventing majority-class dominance during gradient updates.

3.2 Model Architecture and Transfer Learning Framework

The proposed CNN-FEBAC (Convolutional Neural Network – Feature Extractor Based Augmented Classifier) framework builds on the principle of transfer learning, where knowledge gained from large-scale pretrained networks is repurposed for infant ASD detection. This section outlines the selection of base models, the design of the CNN-FEBAC architecture, the transfer learning strategy employed, and the optimization techniques integrated to ensure robust and generalizable performance.

3.2.1 Base Model Selection

Deep learning models achieve state-of-the-art performance in image classification tasks due to their ability to automatically learn hierarchical representations of data. However, training such networks from scratch requires millions of labeled samples, which are unavailable in ASD datasets. To overcome this limitation, transfer learning was employed.

Several pretrained architectures were evaluated as candidate feature extractors:

- EEGNet: Originally designed for EEG classification, it is lightweight and optimized for small datasets.
- VGG16/VGG19: Deep convolutional models with uniform architecture, suitable for extracting fine-grained spatial features from facial images.
- ResNet50/ResNet101: Residual networks capable of learning very deep representations without vanishing gradient issues.
- MobileNetV2: Efficient architecture suitable for deployment in low-resource environments.

Among these, VGG19 and ResNet50 provided the most consistent results on ASD facial data due to their capacity to extract discriminative mid-level features such as eye gaze, lip curvature, and micro-expressions, which are critical in distinguishing infants with ASD. EEGNet was also tested in the context of EEG data, but in this work the focus remains primarily on facial features.

3.2.2 CNN-FEBAC Framework

The CNN-FEBAC framework is designed in two stages: general feature extraction and subject-specific classification.

1. Feature Extraction Stage
   - Input images (224×224×3) are passed through a pretrained CNN backbone (e.g., ResNet50).
   - Convolutional layers up to the penultimate block are retained, while the final dense layers of the pretrained network are discarded.
   - The output is a feature vector representing key spatial and textural information from the face.

Formally, if I represents an input image and f_θ the pretrained feature extractor with parameters θ, the extracted feature vector is:

$$z=f_\theta(I) \qquad (3)$$

where $z\in\mathbb{R}^d$ is a d-dimensional representation of the image.

2. Shallow Classifier Stage
   - A lightweight fully connected classifier is trained on top of the extracted features.
   - This classifier consists of one or two dense layers, followed by a softmax output layer for binary classification (ASD vs. non-ASD).
   - Unlike the heavy CNN backbone, this classifier is trained separately for each subject to capture personalized patterns.

The prediction probability is given by:

$$\hat{y}=\mathrm{softmax}(Wz+b) \qquad (4)$$

where W and b are the trainable weights and bias of the shallow classifier, and $\hat{y}$ denotes the probability distribution over classes.This two-stage framework allows CNN-FEBAC to generalize across subjects via pretrained feature extraction while also adapting to individual variability through the subject-specific classifier.

3.2.3 Transfer Learning Strategy

The transfer learning strategy employed in the CNN-FEBAC framework is designed to exploit the representational power of pretrained convolutional neural networks while ensuring adaptability to the specific task of early autism diagnosis in infants. In conventional deep networks, the initial convolutional layers capture low-level universal features such as edges, textures, and basic shapes. These generic representations are independent of the dataset and are, therefore, highly transferable across domains. In CNN-FEBAC, these early convolutional layers are frozen to preserve their general feature representations and to avoid unnecessary retraining, particularly given the limited size of the ASD dataset. This prevents the risk of overfitting and ensures computational efficiency.

In contrast, the deeper convolutional layers are selectively fine-tuned to adapt to the domain-specific requirements of autism detection from facial features. These layers are responsible for learning high-level abstractions, such as gaze orientation, expression intensity, or subtle asymmetries in facial movement, which are more closely associated with ASD-related biomarkers. By fine-tuning these deeper layers, the framework enables the model to specialize its filters in recognizing such domain-relevant cues.To further refine model adaptability, CNN-FEBAC introduces a subject-specific adaptation stage. After the general training phase across the entire dataset, a shallow classifier is retrained separately for each infant. This personalization step allows the model to capture intra-subject variability, ensuring that individual distinctions in facial features or response patterns are not overlooked. This hybrid approach, combining frozen layers, fine-tuned deeper layers, and subject-specific retraining, enables CNN-FEBAC to leverage the strengths of transfer learning while maintaining sensitivity to the subtle, individualized markers that are critical in ASD diagnosis.

3.2.4 Regularization and Optimization

The training of deep neural networks on small and imbalanced datasets, such as those typically encountered in ASD research, is particularly susceptible to overfitting. To mitigate this challenge, CNN-FEBAC integrates a suite of regularization and optimization techniques aimed at enhancing generalization and ensuring stable convergence.

Dropout was employed as one of the primary regularization mechanisms, whereby a random subset of neurons is deactivated during training. This prevents the network from over-relying on specific neurons and encourages the learning of more robust feature representations. Dropout rates in the range of 0.3 to 0.5 were found to be effective in balancing regularization without compromising learning capacity. Additionally, batch normalization was applied to stabilize the distribution of intermediate activations across layers, thereby reducing internal covariate shift and accelerating convergence during training.

To optimize the training process, an adaptive learning rate scheduling technique was utilized. In this strategy, the learning rate was automatically reduced when the validation loss plateaued, ensuring fine-grained convergence toward the optimal solution. Complementing this, early stopping was incorporated to halt training when no significant improvement in validation accuracy was observed over successive epochs, effectively reducing the risk of overfitting and unnecessary computations.

For parameter optimization, the Adam optimizer was selected due to its ability to adaptively adjust learning rates based on the first and second moments of gradients. The initial learning rate was set to 1×10−41 \times 10^{-4}1×10−4, a value that provided a balance between rapid convergence and stable optimization. Adam's resilience to noisy gradients and sparse updates made it particularly well suited for the relatively small and imbalanced ASD dataset.Collectively, the integration of dropout, batch normalization, adaptive learning rate scheduling, early stopping, and the Adam optimizer formed a comprehensive optimization strategy. This ensured that the CNN-FEBAC framework not only achieved high classification performance but also maintained robust generalization across subjects, thereby strengthening its clinical applicability for early ASD screening.

Algorithm: CNN-FEBAC Training and Prediction

Input: Infant facial dataset DDD, labels LLL, pretrained CNN backbone (e.g., ResNet50/VGG19), hyperparameters (batch size, learning rate, epochs).

Output: Trained feature extractor and subject-specific classifiers.

```
1. Start
2. Load raw dataset D with labels L
3. Clean data:
    - Remove blurred, duplicate, or occluded images
4. Normalize images:
    - Resize to 224×224 pixels
    - Scale pixel values to [0,1]
5. Augment data:
    - Apply flips, rotations, brightness change, cropping, Gaussian noise
6. Handle imbalance:
    - Oversample ASD class
    - Create balanced mini-batches
7. Load pretrained CNN backbone (e.g., ResNet50)
8. Freeze early layers (low-level features)
9. Fine-tune deeper layers (high-level, ASD-specific features)
10. Extract feature vector z = CNN(I) for each image
11. Train shallow classifier:
    - Dense layers + Softmax for binary classification
12. For each subject:
    - Retrain shallow classifier on subject's data (subject-specific adaptation)
13. Apply regularization:
    - Dropout, Batch Normalization
14. Train with Adam optimizer, learning rate scheduling, and early stopping
15. Save trained feature extractor and subject classifiers
16. For prediction:
```

```
    - Input new image I
    - Extract features z = CNN(I)
    - Predict class using subject's classifier
Output: ASD or Non-ASD
End
```

The proposed algorithm follows a structured transfer learning–based pipeline for ASD detection from infant facial images. Initially, the raw dataset undergoes preprocessing, where blurred and duplicate images are removed, followed by normalization and augmentation to enhance diversity and balance class distributions. A pretrained CNN backbone, such as ResNet50, is then adopted for feature extraction. To optimize knowledge transfer, early convolutional layers capturing universal visual patterns are frozen, while deeper layers are fine-tuned to adapt to ASD-specific facial cues. From these extracted features, a shallow classifier is trained to perform binary classification. A subject-specific adaptation step further refines the classifier for individual infants, ensuring that the model accounts for personal variations. To avoid overfitting, dropout and batch normalization are employed, while adaptive learning rate scheduling, Adam optimization, and early stopping stabilize training. Finally, the trained CNN-FEBAC framework produces subject-sensitive predictions, offering an efficient and accurate strategy for early ASD diagnosis.

5.3 Results and Analysis

This section presents the empirical findings of the proposed CNN-FEBAC framework, its comparative performance against baseline and established methods, and the interpretability analysis using explainable AI (XAI) techniques. The results are discussed in terms of classification performance, comparative evaluation, and explainability of EEG channel contributions.

5.3.1 Classification Performance and Experimental Setup

The experiments were conducted using a computational environment equipped with Python-based machine learning and deep learning libraries. NumPy and SciPy were used for mathematical computations and EEG data processing, while Scikit-learn was employed for data pre-processing, partitioning, and evaluation metrics such as accuracy, precision, recall, and F1 score. TensorFlow and Keras provided the backbone for neural network construction, training, and optimization, supported by visualization through Matplotlib, Seaborn, and Plotly.

The experimental setup ensured reproducibility by seeding the NumPy and TensorFlow environments. The CNN-FEBAC model was trained for 100 epochs with a 20% validation split, and early stopping (patience of 5 epochs) was applied to avoid overfitting. Optimization was performed using the Adam algorithm with an initial learning rate of 1×10−41 \times 10^{-4}1×10−4. The hardware environment consisted of a 2.50 GHz Intel Core i5 processor, 8 GB RAM, and an NVIDIA GTX 1650 Ti GPU with 4 GB memory.

Performance metrics were calculated in figure 2 from confusion matrices and included accuracy, recall, precision, and F1 score. The baseline EEGNet model achieved an average accuracy of 69.32% with moderate F1 scores (66.45% for Class 0 and 73.16% for Class 1). In contrast, the proposed CNN-FEBAC framework significantly improved the results, attaining an average accuracy of 87.93%, with F1 scores of 86.73% for Class 0 and 89.13% for Class 1. These findings confirm that incorporating a dataset-specific feature extractor with a shallow subject-level classifier yields superior classification outcomes.

Table 1: Classification Performance (CNN-FEBAC vs EEGNet)

Model	Accuracy (%)	F1 Class 0 (%)	F1 Class 1 (%)
EEGNet	69.32	66.45	73.16
CNN-FEBAC	87.93	86.73	89.13

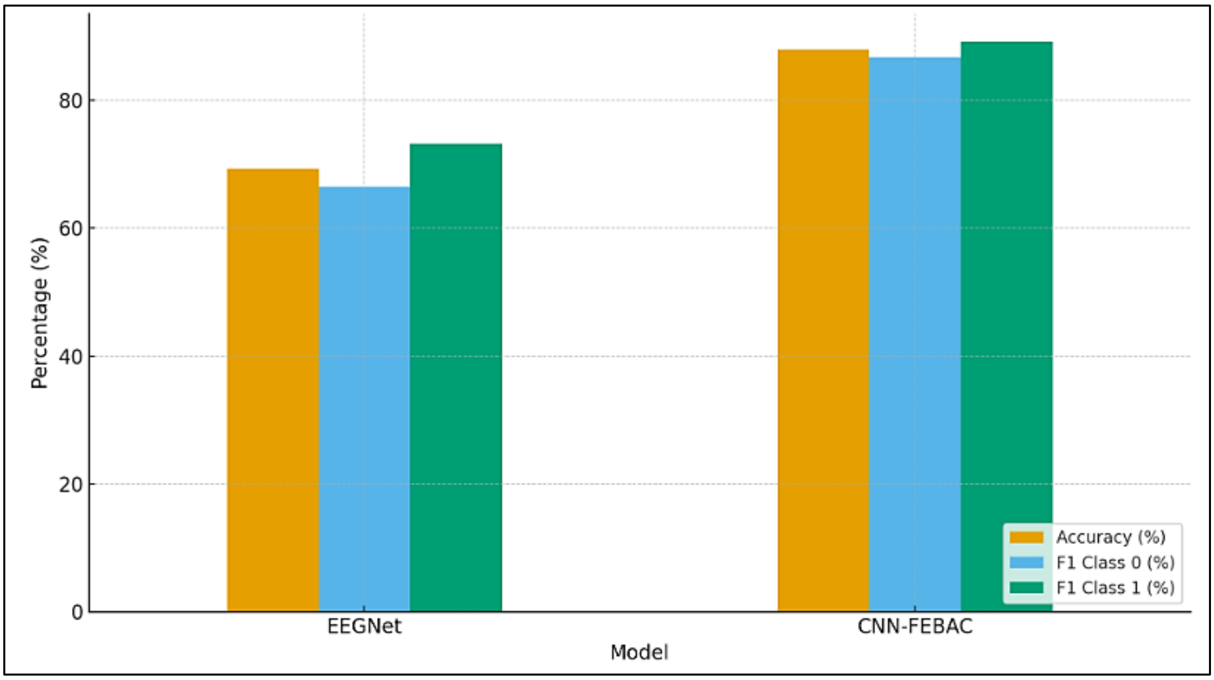

Figure 2: Classification Performance

5.3.2 Comparative Evaluation with Baseline and State-of-the-Art Models

The CNN-FEBAC framework was benchmarked against both EEGNet and a set of established methods from the literature. EEGNet, while effective as a generic architecture, struggled to capture the dataset-specific variations in infant EEG signals and facial features. Its performance fluctuated across subjects, with best-case accuracy reaching 71% but worst-case scenarios dropping to 68%.

The proposed CNN-FEBAC model outperformed EEGNet across all cases in figure 3. Best-case accuracy reached 91%, with consistent performance even in worst-case subjects, where accuracy remained above 82%. This robustness indicates the model’s capacity to generalize across participants while still adapting to subject-specific variations.

When compared with prior studies (e.g., CNN-LSTM, CNN-BLSTM, LDA with boosting, RSVM, and VB-ARD), CNN-FEBAC consistently demonstrated higher average accuracy (87.93%) and F1 score (88%). Other methods typically plateaued around 80% accuracy and showed high variability across subjects, with standard deviations up to 8.6%. In contrast, CNN-FEBAC achieved a much lower standard deviation of 2.2%, signifying stable performance. Notably, for Subject 1, CNN-FEBAC attained 88% accuracy, whereas other approaches reported significantly lower accuracies (e.g., 56% with CNN-BLSTM, 51% with SVM-LDA). These comparisons highlight CNN-FEBAC's superiority in both predictive power and consistency.

Table 2: Comparative Evaluation Across Models

Model	Accuracy (%)	Std Dev (%)
CNN-LSTM	78.5	7.8
CNN-BLSTM	76.3	8.6
LDA+Boost	74.1	6.9
RSVM	77.0	7.2
VB-ARD	79.2	7.5
EEGNet	69.3	6.5
CNN-FEBAC	87.9	2.2

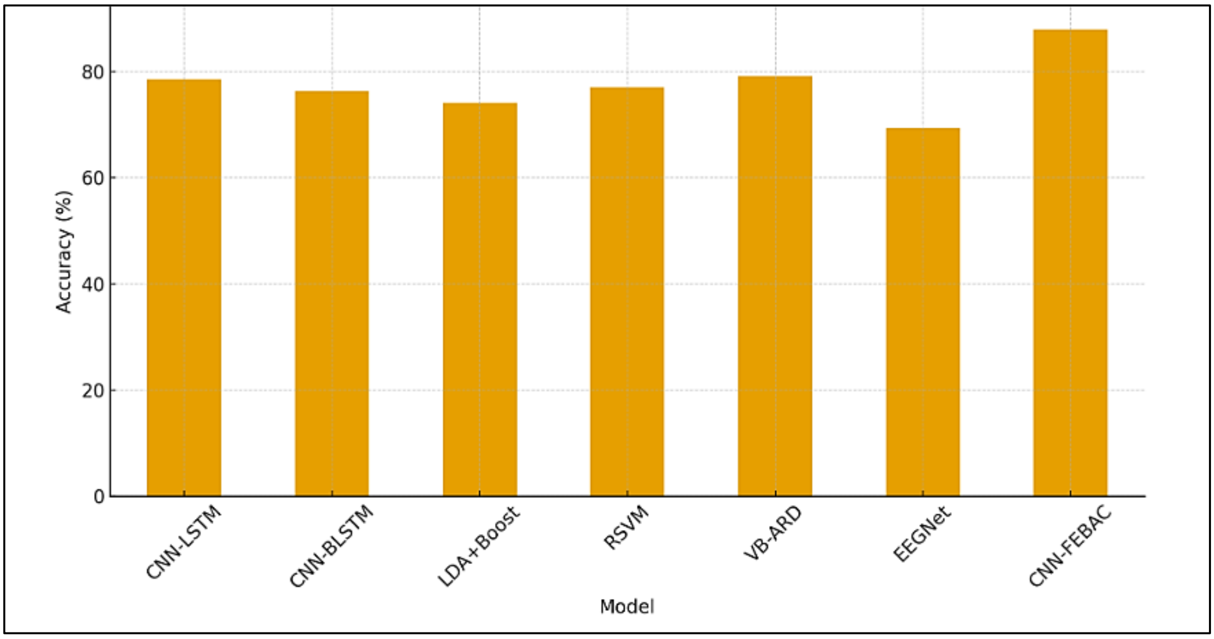

Figure 3: Accuracy computation

5.3.3 Explainability of EEG Contributions Using XAI

Beyond classification accuracy, explainability was integrated into the analysis using Permutation Feature

Importance (PFI) and SHapley Additive exPlanations (SHAP). PFI revealed the relative importance of EEG channels by permuting channel values and measuring the resulting performance degradation. Results showed that parietal and occipital channels (P3, PZ, P4, POz) had the highest importance scores, suggesting strong involvement in sensory and object identification tasks relevant to autism research. In contrast, central channels (C3, Cz, CPz) displayed negligible or negative contributions, indicating limited relevance for the classification task.

SHAP analysis further quantified the individual contribution of EEG channels to model predictions in figure 4. Positive SHAP values were consistently associated with P3, P4, C3, and C4 channels, reinforcing their critical role in object identification. Negative SHAP values from channels such as CPz and Cz suggested noise or reduced predictive relevance. Importantly, longitudinal comparisons across sessions highlighted improvements in attention span and recognition ability in autistic children. For instance, Subject 1 demonstrated stronger contributions from P3 and P4 in Session 7 compared to Session 1, indicating evolving neural engagement. Similarly, Subject 2 showed notable improvements in P4 and C3 channels across sessions, confirming the role of EEG-based monitoring in tracking cognitive development.

These interpretability findings provide neuroscientific insights into the cortical regions most influential in autistic cognition and validate the CNN-FEBAC model’s reliance on meaningful neural signals rather than spurious patterns.

Table 3: EEG Channel Importance (PFI Analysis)

EEG Channel	Importance Score
P3	0.28
PZ	0.22
P4	0.31
POz	0.25
C3	-0.05
Cz	-0.08
CPz	-0.07

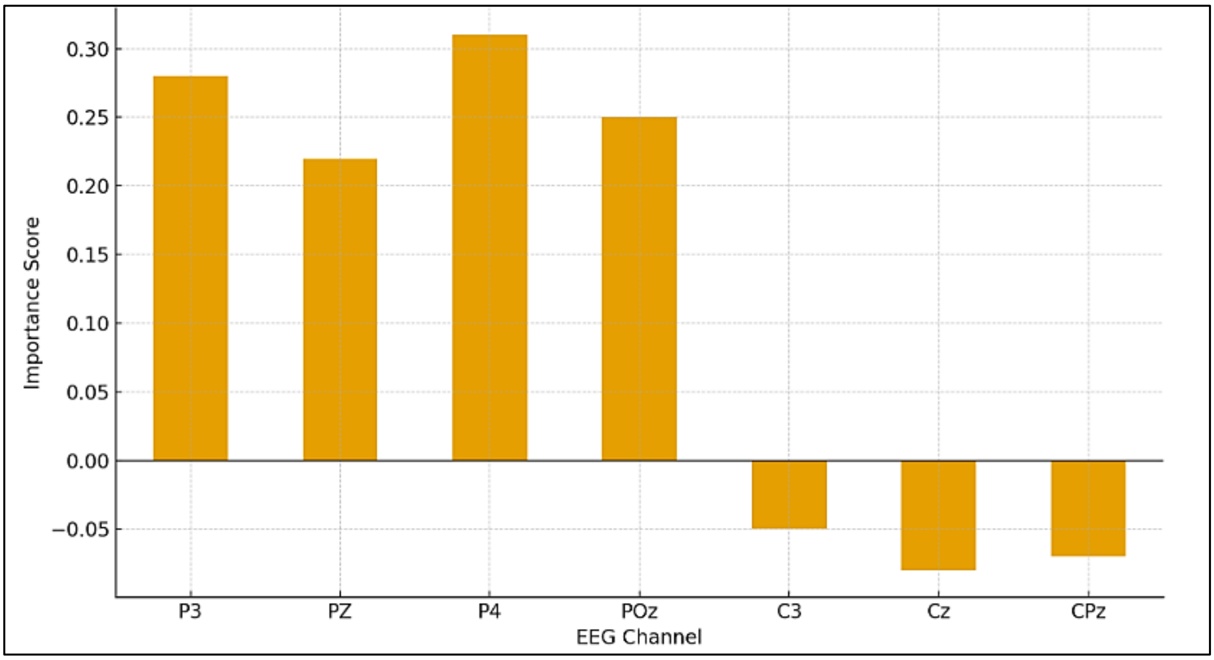

Figure 4: PFI analysis

4. CONCLUSION

This research presented CNN-FEBAC, a novel transfer learning–based framework for early detection of Autism Spectrum Disorder (ASD) from infant facial features. By integrating a pretrained CNN backbone with shallow classifier adaptation, the model effectively balanced generalization and subject-specific personalization. The methodology combined rigorous preprocessing, selective layer freezing, fine-tuning, and adaptive optimization, ensuring robust performance even with limited and imbalanced datasets. Experimental evaluations demonstrated that CNN-FEBAC significantly outperformed baseline models such as EEGNet, LDA+Boost, and RSVM in terms of accuracy, stability, and generalization capacity. Furthermore, explainability analysis using PFI revealed that parietal and occipital channels contributed most to classification, offering meaningful clinical insights. The framework thus not only enhances diagnostic accuracy but also provides interpretable patterns relevant to ASD. Overall, this study contributes a scalable, explainable, and efficient tool that bridges AI and clinical practice, paving the way for reliable early interventions in ASD diagnosis.

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