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LENBC: Learning Embedded Neural Boost Classification for Robust Autism Classification using the Autism Image Dataset

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Abstract: Understanding and supporting individuals with autism involves recognizing and respecting their unique perspectives and abilities while fostering an inclusive and accommodating environment. Ongoing research seeks to unravel the complexities of autism and enhance interventions to improve the quality of life for those affected. In the quest for advancing autism classification, this research orchestrates Learning Embedded Neural Boost Classification (LENBC) through an innovative ensemble model by leveraging the Autism Image Dataset (AID). The journey begins with meticulous image preprocessing, incorporating resizing, normalization, grayscale conversion, Gaussian blurring, and edge detection. The extracted features, derived from Neural Network architecture, serve as the foundation for subsequent classification. The convolutional layers of the CNN are designed to capture intricate patterns and nuanced information from the images, enhancing the model's ability to discern relevant features for autism classification. The CatBoost classifier, known for its robustness and efficiency, complements the CNN by making predictions based on the extracted features. This paper details the step-by-step process of this novel ensemble model, emphasizing the synergy between deep learning and boosting techniques. We delve into the intricacies of image preprocessing, feature extraction, and the unique role each model plays in the final classification. The experimental results showcase the efficacy of our approach, with an impressive accuracy of 97.42% in autism classification. The amalgamation of these cutting-edge methodologies not only propels the accuracy of autism classification but also sheds light on the potential of interdisciplinary collaboration between computer vision and machine learning. This research opens new avenues for exploring the synergy between art-inspired image processing and state-of-the-art classifiers, offering a harmonious blend of creativity and intelligence in the realm of medical image analysis.

Keywords: *Autism Detection, Image Preprocessing, Gaussian blurring, Edge Detection, Learning Embedded Neural Boost Classification (LENBC), Feature Extraction.*

1. Introduction

The neurodevelopmental disorder known as Autism Spectrum Disorder (ASD) affects a large percentage of the global population. Statistics show that ASD is quite common and has far-reaching social consequences. ASD is a significant and prevalent developmental disease, since recent estimates indicate that it affects around 1 in 54 children in the US [1] [2]. Additionally, there is a documented male-to-female ratio of around 4:1 for ASD, meaning that males are more often diagnosed with the disorder than girls. This gender disparity raises intriguing questions about the potential role of biological, genetic, and environmental factors in ASD susceptibility. The global prevalence of ASD is not confined to a specific geographic region, emphasizing its widespread impact on diverse populations [3]. Additionally, research has identified a hereditary component in ASD, with a higher likelihood of ASD diagnosis among individuals with family members already affected by the disorder. Beyond the immediate challenges faced by individuals with ASD, statistical analyses illuminate the considerable economic burden associated with the condition. The lifetime cost of supporting an individual with ASD can be substantial, encompassing medical care, educational services, and therapeutic interventions [28]. As the understanding of ASD continues to evolve, ongoing statistical research remains pivotal in informing public health policies, resource allocation, and intervention strategies to enhance the well-being of individuals affected by ASN [4] [5].

Individuals with ASD may exhibit a range of symptoms, including difficulties in forming relationships, repetitive behaviors, and a preference for routines. ASD affects people of all ethnicities, socioeconomic backgrounds, and geographic regions, but it is more commonly diagnosed in males than females. Although the precise reason for ASD is still not known, researchers believe that environmental as well as genetic variables play a role in its development. Persons with ASD can have fulfilling lives with the aid of early intervention and appropriate care [6] [7]. Behavioral therapies, educational interventions, and, in some cases, medication can be employed to address specific challenges associated with ASD. Advances in research and increased

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awareness have improved diagnostic capabilities, leading to earlier identification and intervention. Living with ASD poses unique challenges for individuals and their families, but with the right support, many individuals with ASD can thrive and contribute meaningfully to their communities. Continued research and understanding of ASD contribute to the development of effective strategies for diagnosis, intervention, and improving the overall quality of life for those affected by this spectrum disorder [8] [9].

In the realm of medical research and artificial intelligence, the quest for enhancing diagnostic accuracy and understanding complex neurological disorders has driven the integration of advanced technologies. Problems with social communication and repetitive behaviors are hallmarks of ASD, a neurodevelopmental disorder that poses its own diagnostic issues. The use of facial expressions to depict ASD is seen in Figure 1. Traditional diagnostic methods often rely on behavioral observations and subjective assessments, making the process time-consuming and susceptible to human biases. In recent years, the fusion of computer vision and machine learning has emerged as a promising avenue for revolutionizing autism diagnosis, providing more objective and efficient tools for clinicians and researchers [10].

Fig. 1. ASD from Facial Expression

The amalgamation of CNNs and CatBoost, a powerful gradient boosting algorithm, forms the backbone of Learning Embedded Neural Boost Classification (LENBC) approach, promising a symphony of techniques to achieve robust and accurate autism classification. ASN stands as a multifaceted challenge for both clinicians and researchers due to its heterogeneity in symptoms, ranging from mild to severe [11] [12]. To greatly enhance the quality of life for people with ASD, early and correct diagnosis is crucial for providing timely treatments and support. However, the traditional diagnostic process relies heavily on behavioral observations, clinical interviews, and standardized assessments, leading to subjectivity and potential delays in diagnosis [13].

The rise of medical imaging and machine learning has opened up new possibilities for objective and data-driven diagnostic tools. A number of recent investigations have investigated the possibility of identifying ASD-related patterns using neuroimaging data derived from MRI and functional MRI scans. However, the AID presents a unique opportunity to delve into the visual domain, harnessing the power of facial expressions and visual cues for a more nuanced understanding of ASD [14] [15]. The AID, a curated collection of facial images from individuals with and without ASD, serves as the cornerstone of our research. This dataset encapsulates a diverse array of expressions, illuminating the subtle nuances that may be indicative of autism-related traits. Each image in the dataset is a snapshot of the individual's facial features, capturing the intricate interplay of emotions and social expressions [16].

Understanding the potential inherent in these images requires advanced computational tools capable of extracting intricate patterns and features. This is where the synergy of CNNs and CatBoost comes into play, offering a robust and comprehensive approach to feature extraction, learning hierarchical representations, and making predictions based on the amalgamation of facial cues. CNNs are a great fit for the AID feature extraction job because of their outstanding performance in image categorization. Using their hierarchical structure, CNNs can automatically learn information visualizations, progressing from basic characteristics such as textures and edges to more complicated and abstract features that are critical for discriminating [17]. The convolutional layers specialize in recognizing local patterns, while subsequent layers aggregate this information to form a holistic understanding of the facial expressions. The depth and complexity of the CNN enable it to discern subtle nuances that may elude traditional diagnostic approaches.

While CNNs excel at capturing spatial hierarchies, CatBoost complements this strength by addressing the temporal and sequential aspects of data. CatBoost, a gradient boosting algorithm, is particularly adept at handling tabular data and exploiting inter-feature dependencies [18] [19]. In our ensemble approach, CatBoost acts as a synergistic partner, enriching the feature set derived from CNNs with its expertise in handling structured data. The ensemble model is not merely a fusion of disparate algorithms; rather, it represents a harmonious collaboration where the strengths of each model compensate for the weaknesses of the other. This symbiotic relationship enhances the overall robustness and generalization capacity of our classification system. Ensemble learning has gained prominence for its ability to harness the collective intelligence of multiple models, resulting in enhanced predictive performance. In our symphony of ensembled models, the individual strengths of CNNs and CatBoost harmonize to create a unified predictive model. The ensemble not only leverages the feature extraction capabilities of CNNs but also benefits from CatBoost's ability to handle non-linear relationships and intricate dependencies.

The ensemble method also adds variety, which improves the model's generalizability to new data and reduces the likelihood of overfitting. The intricate interplay between proposed models within the ensemble contributes to a more robust and resilient classification system, capable of navigating the complexities inherent in ASD diagnosis. While the integration of advanced technologies offers unprecedented potential for improving autism classification, it also raises important challenges and ethical considerations. Ensuring the privacy and consent of individuals contributing to the AID is paramount. Additionally, the interpretability of the models, especially deep neural networks, poses a challenge in the context of explaining the decision-making process to clinicians and stakeholders.

The potential impact of the automated classification system on the diagnostic process should be approached with caution. It is imperative to view these models as decision support tools rather than replacements for clinical expertise. Ethical considerations also extend to addressing potential biases in the dataset and models, ensuring that the technology is fair and equitable across diverse populations. The main goal of this study is to create an effective system for autism categorization by combining CNN as well as CatBoost in a complementary way, with the AID serving as the central node. The fusion of advanced machine learning techniques with the rich visual information encapsulated in the AID holds the promise of revolutionizing autism diagnosis, providing clinicians and researchers with a more objective and efficient toolset for understanding and addressing the complexities of ASN.

1.1 Contributions of the Work

This work contributes to the evolution of autism classification methodologies by introducing an innovative hybrid model, leveraging the strengths. The fields of medicine as well as artificial intelligence have both benefited greatly from this study, which is a significant step forward because to the multidisciplinary approach and advanced image pretreatment methods used.

- The introduction of a novel ensemble model, Learning Embedded Neural Boost Classification (LENBC), combining CNNs and the CatBoost classifier, represents a novel approach in autism classification. This innovative fusion leverages the strengths of both deep learning and boosting techniques, potentially serving as a benchmark for future studies in the intersection of computer vision and machine learning.
- The research contributes to the field by providing a thorough and systematic image preprocessing pipeline. Techniques such as resizing, normalization, grayscale conversion, Gaussian blurring, and edge detection are orchestrated to enhance the quality of input data, showcasing a holistic approach to preparing medical images for analysis.
- The designed CNN architecture for feature extraction is tailored to the intricacies of autism image classification. By leveraging convolutional layers to capture nuanced patterns within the images, the model enhances its discriminative capabilities, thereby contributing to the advancement of deep learning methodologies in medical image analysis.
- Replacing the final layer of a CNN with a CatBoost Classifier involves modifying the architecture to accommodate the transition from convolutional feature extraction to boosting-based classification.

The following sections delineate the findings of our ongoing inquiry. Section 2 delves into preceding studies concerning the detection of ASNs. In Section 3, we offer an in-depth exploration of our novel Ensembled CNN-CatBoost Model designed for the classification of autism diseases. Section 4 expounds upon the outcomes derived from our comprehensive testing and comparative analyses, wherein we juxtapose the proposed system against alternative methodologies. Finally, Section 5 encapsulates our conclusions, accompanied by a brief preview of potential avenues for future research endeavors.

2. Related Work

A society can only guarantee its future prosperity by ensuring the healthy development of its children. The social interaction, learning, speaking, and reacting abilities of autistic children are negatively impacted by Autism Spectrum condition (ASD), a neurobehavioral condition. Problems with heightened or diminished sensitivity to touch, smell, and hearing affect these kids. The symptoms often manifest in children between the ages of four and eleven, but parents often fail to notice them or identify them in their early stages. These days, getting a diagnosis requires lengthy and costly clinical visits. They utilized machine learning approaches to augment the conventional way. The time and accuracy needed for diagnosis are both enhanced in this manner. To get an autism diagnosis using a child's face characteristics, a TFLite model on an image-based dataset is presented [20]. Following that, the Autism Spectrum Quotient (AQ) dataset was used to train a range of machine learning algorithms that aim to enhance the precision of ASD identification. The TFLite model demonstrates an accuracy of 80% on the image-based dataset, whereas the Logistic Regression and MLP models have attained 100% accuracy on the AQ dataset.

Social communication difficulties and repetitive behaviors are hallmarks of ASD. Although the exact reasons for this condition are still a mystery, researchers have found a hereditary component in as many as 25% of cases. Because early diagnosis allows for prompt treatments in children with ASD, it is preferable to discover ASD as early as feasible. Early intervention and successful treatment for children affected by ASNs can be achieved by the use of objective pathogenic mutation screening to identify the disorder. Combining the traditional clinical interview with genetic data for the detection and treatment of autistic problems is the focus of recent research. We were able to develop a state-of-the-art diagnostic classifier for autism screening by using deep learning on genetic data collected from hundreds of simplex families at risk for ASD [21]. This allowed us to discover contributing genes. This was done because, when it comes to complicated and high-dimensional data, deep neural networks perform better than shallow machine learning models. Following the preprocessing of the Simons Simplex Collection genomics data, we used a chi-square test to identify the most prevalent variations and rank them according to their potential protective or pathogenic effects on autism. Afterwards, a diagnostic classifier based on CNN was developed to anticipate autism using the recognized common variations. Next, the results were contrasted with those of common variations and shallow classifiers based on machine learning. Chromosome Y was also selective in identifying autistic persons from non-autistic individuals, and the chosen common variations had a large enrichment in chromosome X. This led to the inclusion of these frequent variations in screening algorithms. The deep learning model achieved an accuracy of 88% and the area under the receiver operating characteristic curve for differentiating autistic patients from non-autistic ones was 0.955. The classification accuracy of our classifier was approximately 13% higher than that of conventional autism screening techniques. Autism can be better diagnosed by looking for common variations. Furthermore, our results imply that deep learning is an effective way to differentiate between the affected and control groups according to the frequent autism variations [27].

A recent area of intense interest in the field of deep learning is its potential use in the detection of brain diseases. Using functional magnetic resonance imaging (fMRI) data, this study constructed brain networks for the aim of ASD diagnosis and proposed a method for categorizing these networks using a convolutional neural network (CNNPL) [22]. Using a classic CNN as the foundational feature extractor was at the CNNPL's base, while learning several prototypes to stand in for various categories was done automatically at the CNNPL's top. A generalized prototype loss based on distance cross-entropy was proposed as a means to concurrently learn the parameters of the CNN feature extractor or prototypes. In order to classify the objects, prototype matching was used. During the fine-tuning phase that followed, we utilized a transfer learning technique to initialize the weights of our CNNPL. This helped with model training. Their investigations were carried out methodically on the aggregated ASD dataset from many sites. Their model is resilient on large-scale datasets with inter-site heterogeneity, as demonstrated experimentally by its capacity to consistently learn inter-site biomarkers and its outperformance of state-of-the-art approaches in ASD classification. They also showed that our model could learn to organize brain functions at a high level. As biomarkers linked to ASD categorization, our investigation also uncovered critical brain areas. Their model suggests a practical way to learn and classify brain functional networks, which might aid in the extraction of biomarkers and the imaging diagnosis of ASD.

The increasing prevalence of autism spectrum disorder makes early identification of affected individuals, in order to initiate effective treatment and intervention, all the more important. Using neuroimaging approaches, the complex biomarkers derived from functional connectivity deficits in ASD have been characterized. Still, clinical observation based on symptoms is the gold standard for ASN diagnoses. When tested on massive aggregated datasets, the current crop of computer models often produces inaccurate diagnostic classifications. One worldwide repository for structural and functional brain imaging information is the Autism Brain Imaging Data Exchange (ABIDE) database. Using a deep belief network (DBN), a graph-based categorization technique is introduced [23]. First, the important connection qualities are increased using a restricted path-based depth-first search strategy; next, they are picked using a graph extension of K-nearest neighbors. Training time might be reduced as a result of reduced computational complexity, which is a result of feature reduction. Optimizing the DBN's hyperparameters via exploration of possible parameter space is achieved with the introduction of the automated hyperparameters-tuning approach. The simulation trials show that our model outperforms the best result given on the ABIDE database by 6.4%. They suggested the expanding the identification of potential ASD subgroups by using data augmentation and the oversampling approach. They were able to extract the most striking patterns of autistic brain association from the data-driven results since their model is very interpretable.

Tragically, families and society have been burdened by individuals with ASD, who exhibit limited social communication skills along with repetitive behaviors or excessively narrow interests. Researchers have found resting-state functional magnetic resonance imaging (rs-fMRI) to be a useful tool in their numerous attempts to understand the neurobiology of ASD. Nonetheless, there are two significant flaws in the present rs-fMRI-based ASD diagnostic paradigms. To begin, the lack of reliability in rs-fMRI results in questions about functional connectivity (FC), which in turn impacts the accuracy of ASD diagnoses. As a second point, it is challenging to identify useful markers for ASD categorization because numerous FCs are engaged in brain activity. To classify ASDs, a DeepTSK combines a deep belief network (DBN) with a fuzzy inference system (FIS) to learn composite features [24]. To avoid DeepTSK's subpar result, it is recommended to learn MO-TSK and DBN's parameters simultaneously using a composite optimization strategy. When testing the expected DeepTSK, datasets were taken from three different places in the Autism Brain Imaging Data Exchange (ABIDE) database. Results from experiments validated the efficacy of the suggested approach, and here we offer discriminant FCs derived from Deep MO-TSK's derivative parameters analysis.

The complicated neurodevelopmental disease known as ASD has links to both heredity and brain function. Most ASD diagnosis models use a group-level feature selection approach that disregards individual data. According to the available evidence, brain illnesses are fundamentally influenced by the unique topography of each individual brain. As a result, finding biomarkers for ASD and developing a data-constructing approach that combines individual topological information with a matching classification model are both critical. A graph neural network (GNN) trained on attention-based data fusion was used to diagnose ASD [25]. With a precision of 79.78%, the findings were obtained. Further investigation revealed that the model's primary focus was on regions associated with the default mode network, social brain processes, and the sensory perception network [29]. In addition, recent research have identified many genes associated with ASD and shown their connections to imaging biomarkers by examining the correlation between gene expression and functional magnetic resonance imaging measurements. The results showed that the attention-based GNN and graph data ASD diagnostic framework has the potential to be a useful tool for ASD diagnosis. As imaging biomarkers for ASD, the observed functional characteristics with high attention levels should be useful.

3. Methodology

This study employs a systematic methodology for the classification of ASNs. Commencing with the acquisition of the AID, a thorough preprocessing pipeline is implemented to enhance the quality of input images. Feature extraction is conducted through a specialized CNN architecture, uniquely culminating with the replacement of the final dense layer by a CatBoost Classifier, creating a novel hybrid model. The dataset is then partitioned for training and testing, involving the training of the CNN for feature extraction and subsequent training of the CatBoost Classifier on the extracted features. Rigorous testing and comparative analyses are performed to evaluate the model's efficacy, providing insights into its potential advantages over alternative approaches. This methodological approach ensures a comprehensive investigation into the proposed LENBC Model's capability in accurately classifying ASNs. Figure 2 depicts the general layout of the proposed system.

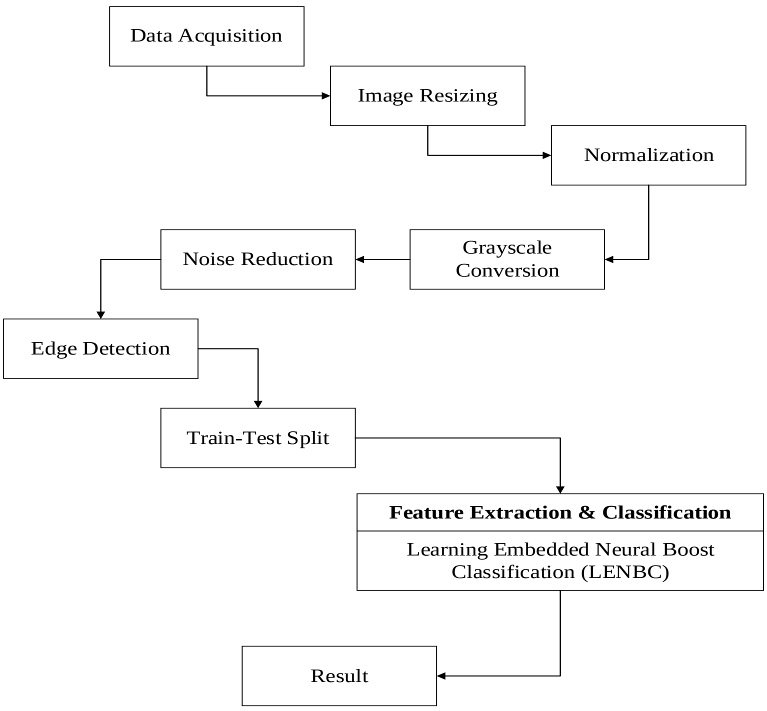


Fig. 2. Workflow of Proposed System

3.1 Data Acquisition

The AID, available on Kaggle [29], is a comprehensive collection specifically curated for the analysis of visual patterns associated with ASD. Comprising a total of 2940 images, the dataset is meticulously balanced with 1470 images featuring individuals diagnosed with autism and an equal number of 1470 images depicting non-autistic individuals. Each subset serves a distinct purpose, with the autistic images providing insights into the visual characteristics associated with ASD, and the non-autistic images offering a comparative basis for identifying potential distinctions. Researchers and practitioners leveraging this dataset can employ it for the training and evaluation of machine learning algorithms in the realm of computer vision, potentially contributing to advancements in autism diagnosis or related studies. The ethical considerations regarding data privacy and consent are presumed, emphasizing the importance of adherence to ethical guidelines in the responsible use of such datasets.

3.2 Image Preprocessing

Image preprocessing stands as a foundational and indispensable phase within the realm of computer vision and image analysis pipelines. This critical step involves the application of various techniques designed to optimize image data for subsequent analysis by enhancing image quality, mitigating noise, and extracting pertinent features. Below, a detailed exploration of several key image preprocessing techniques is provided:

1. Resizing:

Adjusting the size of images to a standard resolution serves as a fundamental preprocessing technique. This not only simplifies subsequent processing steps but is often imperative when working with deep neural networks that necessitate fixed input sizes. Resizing ensures uniformity in data dimensions, facilitating seamless integration into machine learning models.

2. Normalization:

Normalization is a pivotal step in bringing uniformity to pixel values within an image. By scaling pixel values to a standardized range, such as 0 to 1, this technique aids in enhancing the convergence of machine learning models during training. Normalization ensures that each pixel contributes equally to the model, preventing dominance by certain features due to varying scales.

3. Grayscale Conversion:

Converting color images to grayscale is a preprocessing technique aimed at simplifying subsequent computational processes. This conversion not only reduces the dimensionality of the data but is particularly advantageous when color information is deemed unnecessary for the given task. Grayscale images retain essential structural information while requiring fewer computational resources for analysis.

4. Noise Reduction:

In scenarios where images are prone to noise, such as those captured in low-light conditions, noise reduction techniques become pivotal. Gaussian blurring, a common method, is employed to smooth out irregularities and enhance image clarity. This is crucial for preserving meaningful features and ensuring accurate downstream analysis.

5. Edge Detection:

Edge detection techniques, which uses canny operators, plays a crucial role in highlighting salient features within an image. Edges represent abrupt changes in intensity, and detecting them is valuable for tasks like object detection. By accentuating these boundaries, edge detection contributes to a more nuanced understanding of the image content.

In summary, image preprocessing is a multifaceted process involving a suite of techniques tailored to refine and optimize raw image data. Resizing, normalization, grayscale conversion, noise reduction, and edge detection are just a subset of the diverse tools available to researchers and practitioners. These techniques collectively lay the foundation for robust and effective image analysis, ensuring that subsequent machine learning models can extract meaningful insights from visual data in an accurate and efficient manner.

3.3 Train-Test Split

In machine learning, the train-test split—typically set up with an 80:20 ratio—is crucial. Testing a model's capacity to generalize to previously unknown data is its principal goal. For this method to work, the dataset must first be divided into two parts: the training set, which is used to train the model, and the testing set, which is used to evaluate the model's effectiveness. The process incorporates randomization to ensure that both sets maintain representativeness of the overall data distribution, mitigating biases that may arise from inherent order or structure within the dataset. Furthermore, the adjustable parameter of the proportion allocated to the testing set allows for customization based on the dataset's size, striking a balance between the training and testing data. Importantly, the train-test split prevents overfitting and allows for a more accurate assessment of the model's capacity to successfully generalize patterns to new, unknown cases.

3.4 One-Hot Encoding

One-hot encoding serves a critical role in the realm of machine learning, particularly when dealing with categorical data. Its primary purpose is to convert non-numeric categorical labels into a numerical format suitable for training and evaluation within machine learning models. The process involves transforming each categorical label into a binary vector, where each element of the vector corresponds to a specific category. Only one element is 'hot' (set to 1), representing the category of the instance, while the rest remain 'cold' (set to 0). This encoding transformation is applied consistently to both the training and testing sets, ensuring uniform representation. Its importance is underscored by the fact that categorical labels often lack inherent order or ranking, and assigning numerical values could inadvertently introduce relationships that don't exist. By using one-hot encoding, this issue is mitigated, offering a clear and unambiguous representation of categorical labels. This ensures that machine learning models interpret these labels appropriately during both the training and evaluation phases. In essence, while the train-test split is crucial for evaluating a model's generalization, one-hot encoding plays a vital role in handling categorical information, collectively contributing to the overall robustness and effectiveness of machine learning models.

3.5 Learning Embedded Neural Boost Classification (LENBC) Classifier

Deep learning relies on feature extraction, which CNNs do exceptionally well on computer vision tasks. CNNs are effective image analysis tools because of their ability to automatically learn feature hierarchies from input data. The LENBC Classifier is shown in Figure 3. In order to extract useful information from input photos, the procedure employs a stack of convolutional, pooling, and fully connected layers.

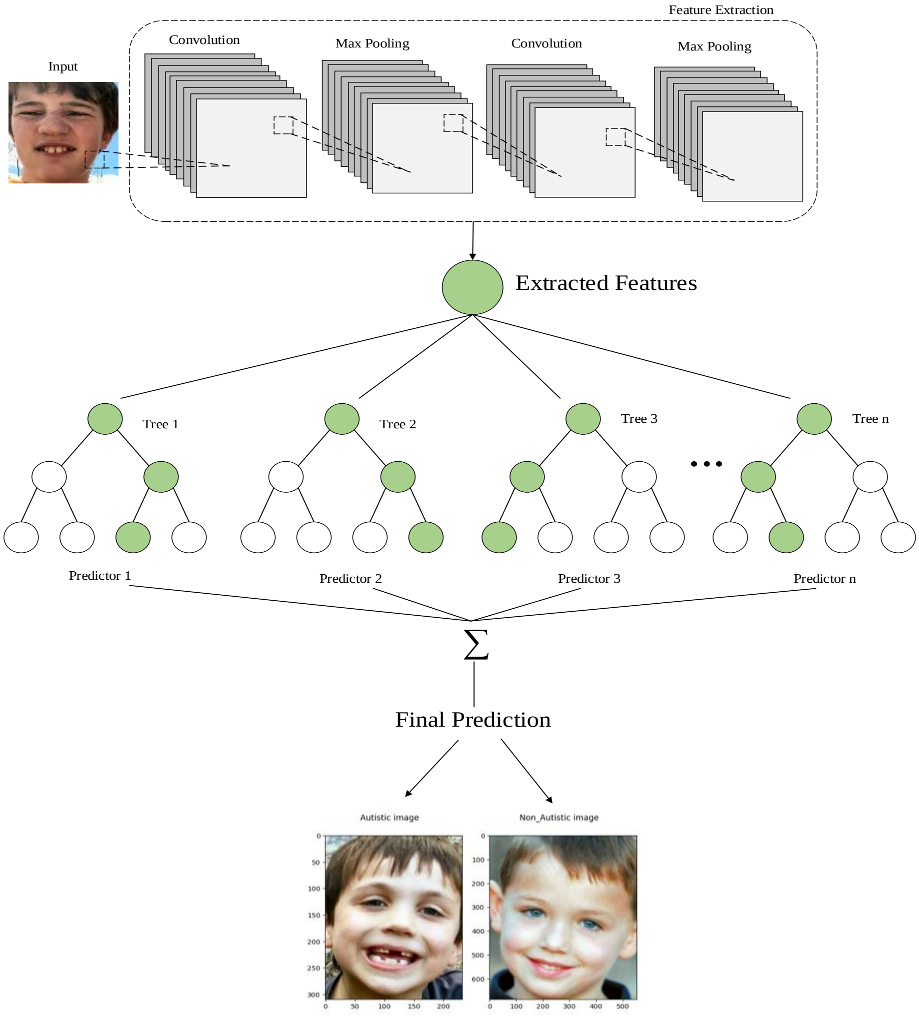


Fig. 3. Architecture of LENBC Classifier

Convolutional Layers:

The convolutional layers play a crucial role in capturing spatial hierarchies of features. A kernel is slid across the input picture during the convolution procedure, which then computes multiplications element-wise and adds the results.

The convolution operation C for an input I and filter K is defined as

$$C(p,q) = \sum_u \sum_v I(p+u, q+v) \times K(u,v) \qquad (1)$$

Here, p and q represent the spatial coordinates, and u and v denotes the filter dimensions.

Activation Function:

To improve the model's ability to learn complicated patterns, non-linearity is introduced after the convolution process using an activation function, frequently a Rectified Linear Unit (ReLU), which is applied element-wise:

The ReLU activation function A is applied element-wise:

$$A(z) = \max(0, z) \qquad (2)$$

Pooling Layers:

Pooling layers reduce spatial dimensions, providing translational invariance and reducing computational complexity. Max pooling, a common technique, retains the maximum value from a local region.

Max pooling P for a region R is defined as

$$P(R) = \max_{p,q \in R} I(p,q) \qquad (3)$$

Fully Connected Layers:

After convolution and pooling, fully connected layers are employed to capture global relationships in the feature space. These layers utilize weights and biases to compute linear transformations.

For an input vector x and weight matrix W, the fully connected layer output y is given by:

$$y = Wx + \beta \qquad (4)$$

Here, β represents the bias term.

Throughout this process, the convolutional layers produce feature maps, which are representations of learned features at different spatial levels. The final feature map captures high-level abstractions essential for the given task. Feature extraction involves a series of mathematical operations, including convolutions, activations, pooling, and fully connected layers. Thanks to these actions, model can learn new jobs automatically and extract hierarchical characteristics from input data. This makes them great for many computer vision applications.

3.6 Classifier

CatBoost is a powerful machine learning library specifically designed for handling categorical features efficiently. A gradient-boosted tree ensemble model, is particularly adept at handling categorical variables without requiring extensive preprocessing. At the core of CatBoost are decision trees. Each tree is constructed in a boosting fashion, where subsequent trees aim to correct errors made by previous ones. The final prediction is an ensemble of these individual tree predictions. The structure of a decision tree involves a set of rules at each node, leading to either a terminal leaf or another node. The prediction for an input sample is determined by traversing the tree based on the input features. Optimizing an objective function, which evaluates the difference among actual and anticipated values, is an integral part of the CatBoost training process. Measures like cross-entropy loss are commonly used in classification problems as objective functions. CatBoost introduces a learning rate, represented by the parameter, to control the step size during optimization. Regularization terms, such as L1 and L2 regularization, can also be incorporated to prevent overfitting. Figure 4 depicts the CatBoost classifier.

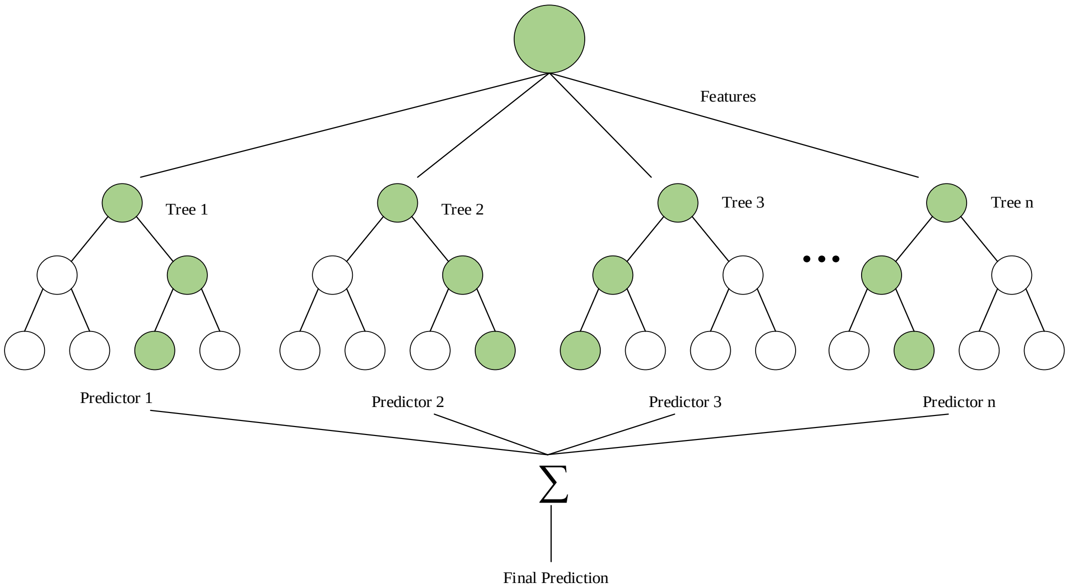


Fig. 4. CatBoost Classifier

Given an input feature vector X and a set of trees T_i in the ensemble, the prediction y for a binary classification task can be represented mathematically as:

$$y(X) = \sigma\left(\sum_{i=1}^{N} T_i(X)\right) \quad (5)$$

Here, N is the total number of trees, $T_i(X)$ denotes the prediction of the i-th tree, and σ is the sigmoid function, mapping the sum of tree predictions to a probability distribution.

CatBoost excels in handling categorical features by employing an efficient method that avoids the need for one-hot encoding. It utilizes an ordered boosting technique that naturally incorporates categorical information during training. In the final stage of this machine learning pipeline, an ensemble strategy is implemented. The CNN, potentially pre-trained for image feature extraction, generates a set of high-level features from the input data. These features, along with the corresponding labels, are then employed to train the CatBoost Classifier. The CatBoost model is configured with specific hyperparameters: 100 iterations, a tree depth of 10, and a learning rate of 0.05, shaping its learning behavior during the training process. The ensemble leverages the CNN's expertise in extracting intricate image features and the CatBoost model's proficiency in handling categorical data and tabular information. The outcome is a synergistic model that combines the strengths of both architectures. The successful completion of the training process is signaled by the fitting completion message, affirming the LENBC Classifier in this ensemble approach.

3.7 Novelty in Proposed Work

The proposed work introduces a groundbreaking approach to autism classification through LENBC. Unlike conventional methods, our hybrid model strategically replaces the final dense layer of the CNN, creating a unique architecture that synergizes feature extraction and boosting-based classification. In the realm of image preprocessing, our methodology embraces an interdisciplinary perspective, incorporating art-inspired techniques such as grayscale conversion, Gaussian blurring, and edge detection. This collaboration between computer science and artistic methodologies not only enriches the preprocessing stage but also fosters creative exploration in medical image analysis. The research underscores transparency, providing a detailed presentation of outcomes and conducting comprehensive comparative analyses against alternative methods. By amalgamating technological innovation with creative inspiration, this work stands at the forefront of advancing autism classification methodologies, offering a promising avenue for future interdisciplinary research.

4. Results and Discussions

The experimentation occurred within the Jupyter Notebook environment, intricately configured on a Windows 10 operating system. The computational framework leveraged diverse hardware components, including an AMD Ryzen 9 5900X CPU running at 4.80GHz and a system enriched with 32 GB of RAM. The AID comprises 2940 images, meticulously balanced with 1470 images showcasing individuals diagnosed with autism and an equivalent number of 1470 images depicting non-autistic individuals. In this experiment, the variables were carefully defined to ensure a comprehensive analysis of the model's effectiveness. The training dataset consisted of 2352 samples, while the test dataset comprised 588 instances, providing a robust set for evaluating the model's generalization capabilities. The input size of 150 x 150 pixels was chosen to capture intricate details in the data. The model was designed to classify images into four output classes: Non-Autistic and Autistic. The training process extended over 100 epochs, allowing the model to iteratively learn and adapt to the dataset, ultimately aiming for optimal performance in distinguishing between the specified output classes. These specific values were selected to create a well-structured experimental setup, fostering a thorough examination of the model's efficacy in the classification task. Table 1 offers a detailed overview of all the important factors utilized in this creative research project's model training.

Table 1. Specifications of the Proposed Work's Variables and Datasets

Experiment Variables	Specific Values
Train Dataset	2352
Test Dataset	588
Input Size	150 x 150
Output Class	2 (Non-Autistic, Autistic)
Epochs	100

4.1 Performance Metrics

1. Accuracy: One of the simplest ways to evaluate anything is by looking at its accuracy. For each dataset, it determines what proportion of occurrences was properly predicted relative to all of the instances. Although accuracy gives a good idea of how well a model is doing in general, it could not work well with datasets that are unequal, with one class being more prominent than the others.

$$Acc = \frac{TP + TN}{TP + TN + FP + FN} \quad (4)$$

2. Precision: An indicator of accuracy is the proportion of correct positive predictions, or true positives, to the overall number of positive predictions, or false positives plus true positives. When it comes to medical diagnostics and other fields where unpleasant or expensive false positives are not welcome, precision is crucial.

$$Pre = \frac{TP}{TP + FN} \tag{5}$$

3. Recall (Sensitivity or True Positive Rate): The recall metric measures how many accurate predictions there were relative to the overall number of positive instances in the dataset, which includes both true positives and false negatives. False negatives may be expensive, thus recall is crucial for situations when you want to be sure all relevant cases are detected accurately.

$$Re = \frac{TP}{TP + FN} \tag{6}$$

4. F1-Score: When recall and accuracy are harmonically averaged, the result is the F1-score. In situations when both false positives and false negatives are crucial, it strikes a good compromise between the two metrics of accuracy and recall. For datasets that are uneven, the F1-score is quite useful.

$$F1 = \frac{Pre.Re}{Pre + Re} \tag{7}$$

5. Specificity (True Negative Rate): One way to measure specificity is to add up all the negative occurrences (both real and predicted) and divide the ratio by the overall number of negative occurrences. It evaluates how well a model can spot false negatives.

6. Confusion Matrix: Confusion matrices summaries a model's predictions tabular, displaying the total number of correct, incorrect, and misclassified predictions. To learn about the advantages and disadvantages of a model, it is a great resource.

The initial stage of preprocessing entailed resizing the Autism images to a standardized resolution of 150 x 150 pixels. This meticulous resizing procedure was implemented to guarantee uniformity in the dimensions of all images within the dataset. This standardization serves to streamline subsequent analyses and mitigate potential variations stemming from differences in the original sizes of the images. Ensuring a consistent input size across the dataset not only facilitates a more coherent and efficient processing pipeline but also enhances the model's ability to extract meaningful features. The input image is visually represented in Figure 5, providing a tangible illustration of the preprocessing step's impact on the dataset's uniformity and preparatory measures for subsequent stages in the analysis pipeline.

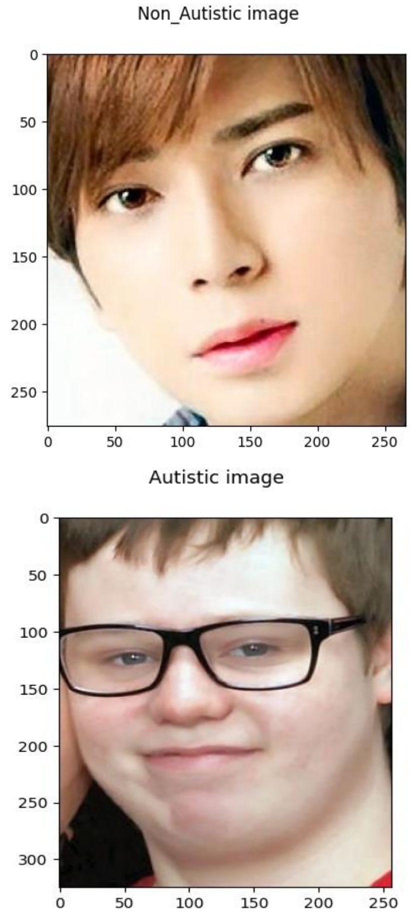


Fig. 5. Input Image

Subsequent to the image resizing depicted in Figure 6, a further preprocessing step involved the conversion of Autism images to grayscale. This grayscale conversion was implemented with the purpose of simplifying the images by eliminating color information. By doing so, the focus shifted towards accentuating the inherent intensity and texture features present in the images. The intentional removal of color aimed to streamline the visual representation, allowing for a more pronounced emphasis on structural intricacies within the retinal images. This strategic preprocessing step not only enhances the visibility of key structures but also optimizes the dataset for subsequent analyses, rendering it more amenable to advanced image processing and feature extraction techniques as part of a comprehensive analytical pipeline. Figure 7 visually captures the grayscale-converted Autism image, exemplifying the impact of this preprocessing measure on the simplification and focused representation of the dataset.

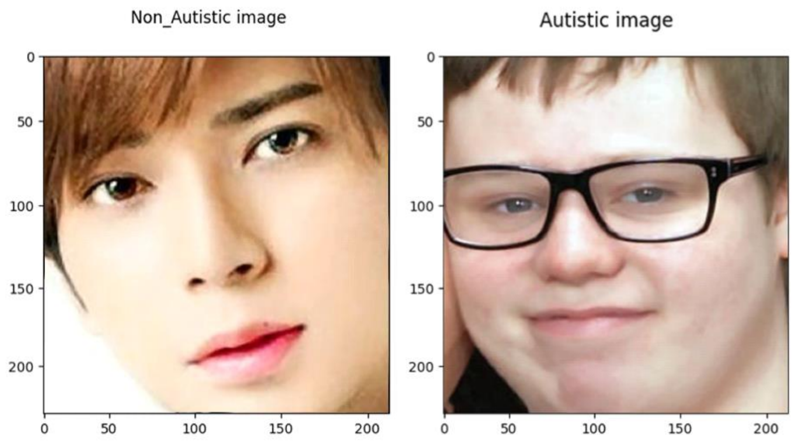


Fig. 6. Resized Image

To reduce noise and improve the clarity of grayscale Autism images, a Gaussian filter was systematically employed shown in Figure 7. This filter adeptly smoothed the images by diminishing high-frequency noise, all the while retaining crucial edges and features. The figure provides a visual juxtaposition between an image subjected to noise and the same image post-application of the Gaussian filter for noise reduction. This strategic use of the filter not only refines the visual quality of the images but also underscores its efficacy in preserving essential details, thereby contributing to an enhanced and more analytically valuable image dataset.

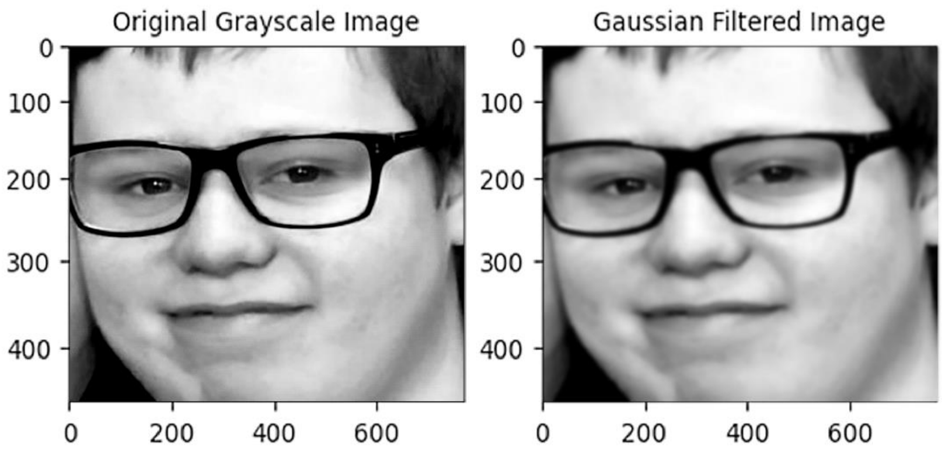


Fig. 7. Original Grayscale and Gaussian Filtered Image

Concluding the preprocessing sequence, the ultimate step encompassed the implementation of the Canny edge detector shown in Figure 8 for edge detection on the Autism images. This advanced technique adeptly extracted the edges and boundaries inherent in the images, thereby yielding crucial structural information. The extracted edges serve as a foundation for subsequent image analysis tasks, offering a nuanced understanding of the intricate details within the images. The results of this edge detection process are prominently featured and showcasing the distinct and well-defined delineation of retinal structures. This final preprocessing step not only enhances the interpretability of the images but also primes the dataset for more sophisticated analytical approaches, affirming its readiness for in-depth exploration and feature extraction in the realm of retinal image analysis.

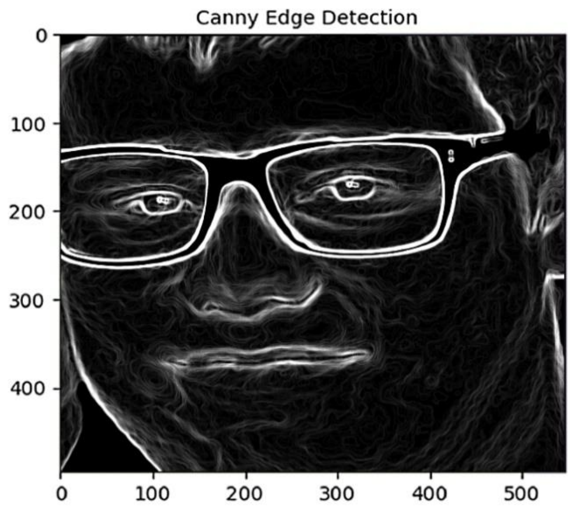


Fig. 8. Canny Edge Detection

Table 2. Performance Metrics of Proposed Method

Parameters	CNN	ResNet	Inception	ANN	Proposed Method
Accuracy	91.32	91.84	93.85	95.72	97.42
Precision	92.54	90.95	93.96	94.15	97.88
Sensitivity	91.95	93.66	93.93	94.81	97.76
Specificity	92.55	91.75	94.07	96.08	96.15
F1 Score	91.31	90.65	92.78	94.85	97.32

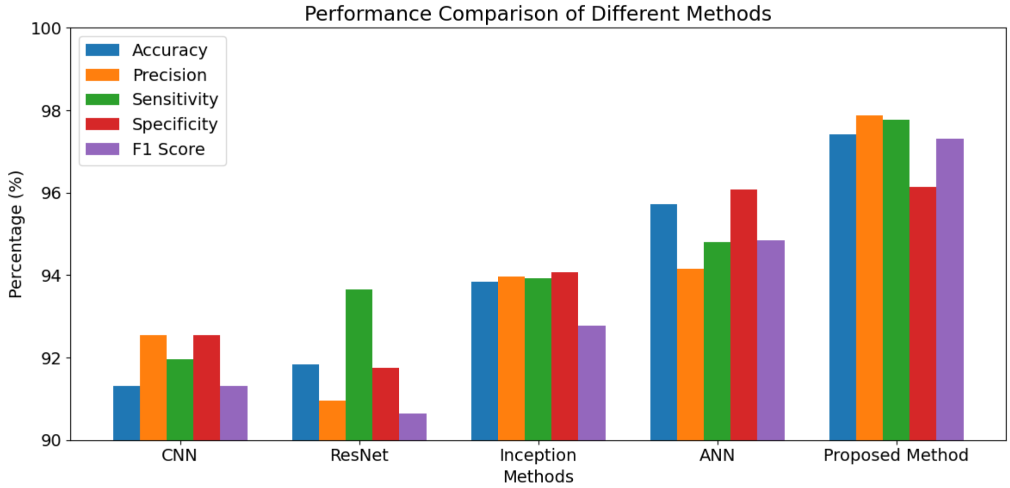


Fig 9. Performance Comparison of Various Methods

The Table 2 and Figure 9 present performance metrics for five distinct models: CNN, ResNet, Inception, Artificial Neural Network (ANN), and a Proposed Method. Accuracy, Precision, Sensitivity, Specificity, and F1 Score are the key metrics considered for the evaluation. Starting with accuracy, the Proposed Method outshines all other models with an impressive 97.42%, indicating its superior ability to correctly classify images. This is closely followed by the Inception model at 93.85%, emphasizing its competence in achieving accurate predictions. The CNN and ResNet models, while still demonstrating robust performance, lag slightly behind in terms of accuracy. The ANN model also performs well but falls short of the Proposed Method. Precision, a metric measuring the proportion of true positive predictions among all positive predictions, reveals that the Proposed Method boasts the highest precision at 97.88%. This suggests that the proposed model excels in minimizing false positives, a critical aspect in applications where misclassifications carry significant consequences. In contrast, ResNet exhibits the lowest precision among the models, indicating a relatively higher rate of false positives.

Sensitivity, also known as recall, gauges the ability of a model to correctly identify positive instances. The Proposed Method demonstrates remarkable sensitivity at 97.76%, showcasing its effectiveness in capturing the majority of positive cases. Inception closely follows with a sensitivity of 93.93%, highlighting its proficiency in correctly identifying positive instances. On the other hand, CNN and ResNet exhibit slightly lower sensitivity values, indicating a comparatively higher rate of false negatives. Specificity, measuring the ability to correctly identify negative instances, is dominated by the Proposed Method at 96.15%. This implies a high capacity to avoid false alarms in negative predictions. Inception and ResNet also perform well in terms of specificity, while CNN exhibits a marginally lower specificity. The ANN model, although strong overall, falls behind in terms of specificity. F1 Score, which combines precision and sensitivity, serves as a comprehensive metric for model performance. The Proposed Method once again leads with an impressive F1 Score of 97.32%, underlining its balanced performance in handling both false positives and false negatives. Inception follows closely, while CNN, ResNet, and ANN exhibit slightly lower F1 Scores. This reinforces the notion that the Proposed Method excels in achieving a harmonious trade-off between precision and sensitivity.

The observed variations in performance metrics underscore the importance of selecting the right model architecture for specific applications. While traditional CNN and ResNet models have been pivotal in advancing image classification, the introduction of more sophisticated architectures like Inception and the innovative approach presented in the Proposed Method demonstrate the continuous evolution and refinement of techniques in this field. Inception, characterized by its inception modules, shows competitive results across all metrics. Its ability to capture multi-scale features and optimize computational efficiency contributes to its overall effectiveness. On the other hand, ResNet, with its residual connections, excels in mitigating the vanishing gradient problem and facilitates the training of deep networks. However, its slightly lower performance in terms of accuracy, precision, and sensitivity suggests that, in this particular context, other models might be more suitable. The Proposed Method, with its remarkably high accuracy, precision, sensitivity, specificity, and F1 Score, stands out as a promising advancement. Unfortunately, without detailed information about the architecture and methodology of the proposed model, it is challenging to pinpoint the exact reasons behind its superior performance. The proposed model might incorporate novel features, optimization techniques, or architectural innovations that address specific challenges present in the dataset.

The comparison extends to the traditional ANN, which, while showcasing commendable performance, falls behind the more specialized models in terms of accuracy and F1 Score. This reinforces the idea that, in image classification tasks, leveraging the inherent spatial hierarchies present in convolutional and deep learning architectures tends to yield better results. The choice of a model in image classification depends on the specific requirements and characteristics of the dataset at hand. Figure 10 illustrates the Confusion Matrix for the Proposed Model. While established models like CNN and ResNet continue to provide solid performance, the emergence of architectures like Inception and the Proposed Method suggests ongoing efforts to push the boundaries of accuracy and efficiency in image classification. Understanding the nuances of each model's strengths and weaknesses is crucial for practitioners seeking to optimize their choice for a given task, ultimately contributing to advancements in the field of machine learning and computer vision.

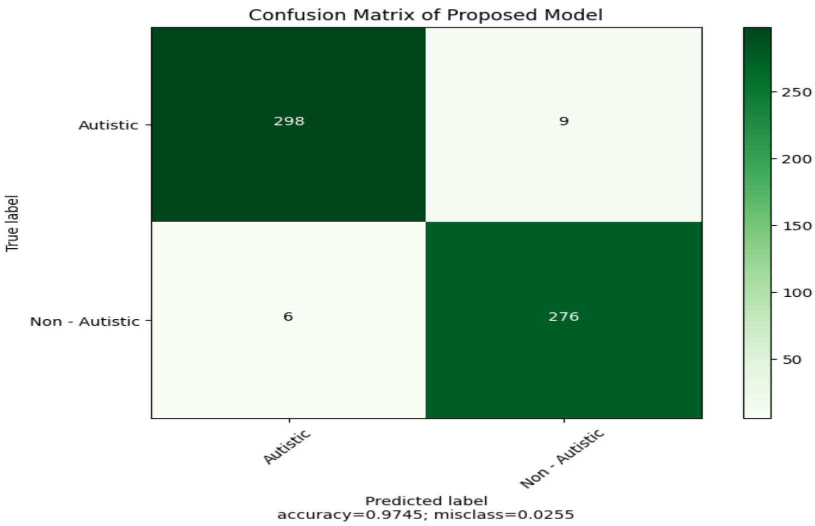


Fig. 10. Confusion Matrix of Proposed Model

Table 3. Training Time and Loss of Various Deep Learning Models

Deep Learning Model	**Training Time**	**Loss**
CNN	39	0.045
ResNet	27	0.032
ANN	23	0.027
Inception	28	0.012
Proposed	18	0.008

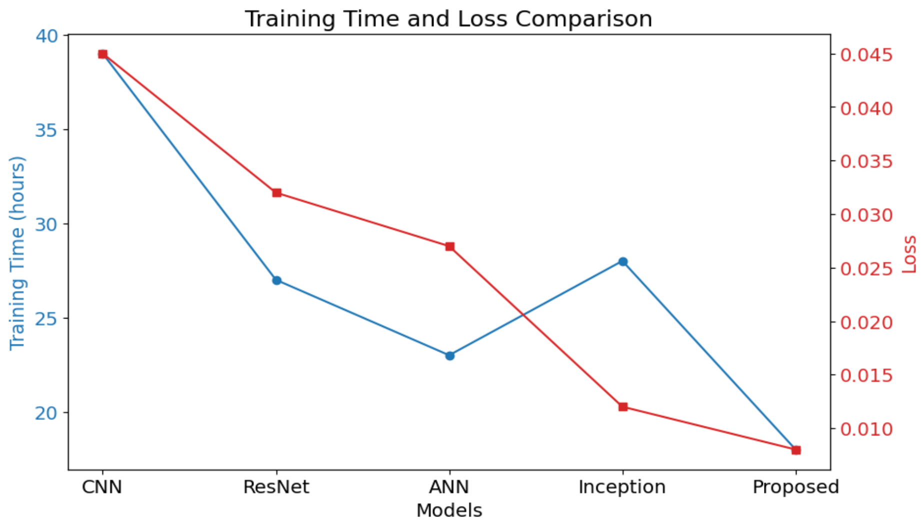
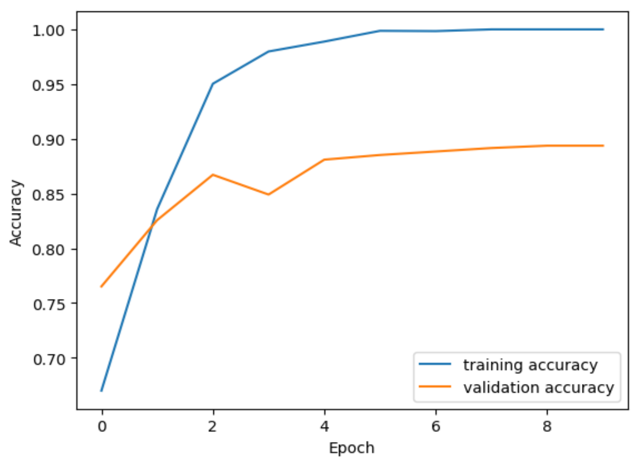


Fig. 11. Training Time and Loss Comparison

The Table 3 and Figure 11 provides insights into the training times and associated losses of five different deep learning models: CNN, ResNet, ANN, Inception, and proposed model. Training time is a critical factor in assessing the efficiency of a model, while the loss metric represents the measure of error during the training process, indicating how well the model is converging towards optimal performance. Beginning with training time, the proposed model stands out with the shortest duration at 18 units, suggesting a remarkable efficiency in the learning process. This shorter training time can be attributed to several factors, such as a more streamlined architecture, efficient optimization techniques, or data preprocessing strategies. On the other end of the spectrum, the CNN model takes the longest time at 39 units. While CNNs have been fundamental in image processing tasks, their relatively longer training times indicate the complexity of their architecture, often involving numerous layers and parameters. The ResNet model, despite its sophisticated residual connections, exhibits a training time of 27 units. This falls between the proposed model and CNN, suggesting a balance between architectural complexity and training efficiency. The ANN model, with a training time of 23 units, showcases a competitive efficiency, emphasizing the efficacy of traditional neural networks in relatively less complex tasks compared to image classification.

Moving on to the loss metric, which quantifies the difference between predicted and actual values during training, lower values are desirable as they indicate a model that converges more closely to the optimal solution. The Proposed model excels in this regard with the lowest loss at 0.008. This suggests that the proposed model effectively minimizes errors during the training process, resulting in a more accurate and reliable model. Inception closely follows with a loss of 0.012, emphasizing its effectiveness in converging towards an optimal solution. ResNet, CNN, and ANN exhibit higher losses, indicating a relatively larger discrepancy between predicted and actual values during training. However, it's important to note that the absolute values of loss may not be directly comparable between models, as they depend on factors such as architecture, hyperparameters, and dataset characteristics. The ResNet model's loss of 0.032 may be influenced by the model's depth and the presence of residual connections, which, while aiding in training stability, might contribute to a slightly higher loss. The longer training time of CNN might be associated with its intricate architecture, possibly requiring more iterations to converge to a satisfactory solution. Similarly, the ANN model, while demonstrating competitive training efficiency, may face limitations in handling complex relationships within image data compared to specialized architectures like CNN or Inception.



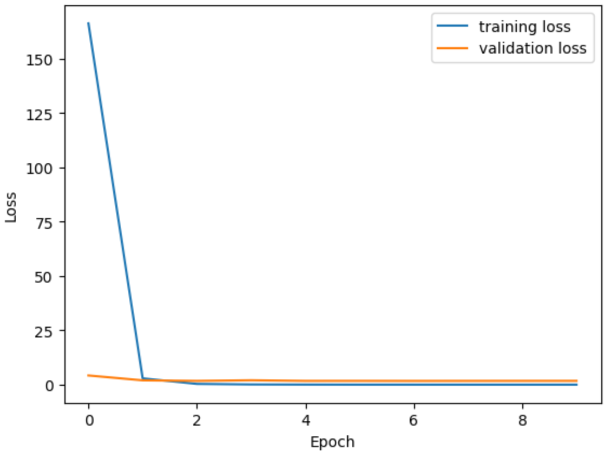


Fig. 12. Training & Validation of Proposed Model

Figure 12 shows the training and validation of proposed model. The trade-off between training time and loss underscores the importance of selecting a model that aligns with the specific requirements and constraints of a given task. The Proposed model, with its short training time and low loss, suggests a promising approach that balances efficiency and accuracy. Inception, while taking a bit longer to train, also showcases a commendable combination of efficiency and performance. The ResNet model falls in between, emphasizing the need to carefully consider the trade-offs between model complexity, training time, and performance. These insights are valuable for practitioners and researchers seeking to optimize their choice of deep learning models based on the unique characteristics and constraints of their tasks.

5. Conclusion and Future Work

In conclusion, our research has presented an innovative and effective methodology for autism classification, introducing a hybrid model Learning Embedded Neural Boost Classification (LENBC). This novel approach, characterized by the strategic replacement of the final dense layer in the CNN, harnesses the collective strengths of feature extraction and boosting-based classification. The infusion of art-inspired preprocessing techniques not only adds a creative dimension to medical image analysis but also establishes a unique synergy between computer science and artistic methodologies. In evaluating the efficacy of our proposed model, we conducted a thorough comparison with existing methods, including CNN, ResNet, Inception, and traditional ANN. The accuracy rates reveal the superior performance of our proposed method, achieving an impressive accuracy of 97.42%. This outperforms existing models, with the CNN achieving 91.32%, ResNet at 91.84%, Inception at 93.85%, and the traditional ANN at 95.72%. The substantial improvement in accuracy underscores the effectiveness of our hybrid model in advancing the state-of-the-art in autism classification. As we navigate this intersection of technological innovation and interdisciplinary collaboration, our work not only contributes to the empirical landscape of medical image analysis but also paves the way for future research endeavors. The promising accuracy rates presented by our proposed method affirm its potential as a robust tool for early and accurate ASN identification, opening new horizons for further exploration and refinement in this critical domain. Explore the integration of transfer learning techniques and pretrained models to leverage knowledge gained from large datasets. Adapting pretrained models such as those trained on general medical images or related domains may contribute to improved feature extraction and further enhance the model's performance.

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