Software Engineering Department

Braude College

Capstone Project Phase B

Classification Of MRI Imaging Of ASD Using Deep Learning methods

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Table of Contents

Abstract

Autism spectrum disorder (ASD) is a brain-based disorder characterized by social deficits and repetitive behaviors, traditionally diagnosed through behavioral assessments. According to recent Centers for Disease Control data, ASD affects one in 68 children in the United States.
At the time of our study, there was no unequivocal way to detect ASD, as traditional methods were not always accurate and relied on behavioral tests.
Magnetic Resonance Imaging (MRI) had emerged as a powerful tool for investigating brain structural changes in individuals with ASD.

In this project, we investigated brain imaging data of ASD patients from a worldwide multi-site database known as ABIDE (the Autism Brain Imaging Data Exchange) to improve the accuracy and reliability of ASD diagnosis.
We classified MRI images using deep learning techniques, specifically the CNN-Inception v4 architecture. Our model successfully classified anatomical MRI scans, distinguishing ASD participants from controls using brain imaging data, and identified neural patterns that emerged from the classification.
We aimed to enhance the accuracy of ASD diagnosis and achieved over 90% accuracy in identifying ASD compared to control patients in the dataset, demonstrating substantial improvements over traditional methods based on behavioral assessments.
The detection of ASD using MRI scans, as shown in our study, has the potential to assist in early diagnosis and enable timely, appropriate interventions.

1. Introduction

Autistic disorder and related pervasive developmental disorders (PDDs) are types of neurodevelopmental conditions. The most frequently diagnosed PDD is autism, Asperger's syndrome, and PDD not otherwise specified (NOS) are collectively known as autism spectrum disorders (ASDs). ASD encompass a wide range of symptoms and severities, with common challenges in social communication, social interaction, and sensorimotor skills. The core symptoms of ASD include (1) Impaired social communication and language skills. (2) Repetitive behaviors, restricted interests, or activities. The prevalence of ASD has surged significantly, rising from 4 in 10,000 to 1 in 68 children. Studies show that autism's concordance rate in identical twins ranges from 60% to 90% [1-3].

Historically, the diagnosis of ASD and criteria for clinical trials have been guided by the Diagnostic and Statistical Manual of Mental Disorders or behavioral diagnostic scales. However, disorders like ASD, which involve many genetic and environmental influences, pose a challenge when using symptom-based criteria. The same symptoms can result from diverse underlying biological processes, and only 10% to

38% of cases have identifiable genetic causes, with no clear genetic markers for ASD [2].

To better understand the causes of mental disorders like ASD, researchers are working to identify brain activation patterns and link them to psychological and neural factors. Noninvasive brain imaging, such as MRI, has advanced this research by identifying objective biomarkers that can aid in diagnosing ASD and addressing social and communication deficits [1].

MRI is the method we decided to use to diagnose (classify) the patient. It is a non-invasive diagnostic technique that offers high spatial resolution and contrast sensitivity without the usage of ionizing radiation. MRI is a powerful tool for investigating changes in the structure, function, maturation, connectivity, and metabolism of the brain. As a result, detailed images of brain development are generated [1,3].

Functional MRI technique is helping to emphasize reduced connectivity, especially between frontal and posterior regions. This technique is helping researchers better understand the neural circuitry in autism, revealing areas of dysfunctional cortical activation and atypical cortical specialization.

Structural MRI techniques are helping researchers determine how the brain develops in autistic individuals. Various cohorts and patients benefit from it since it provides a contrast between gray matter and white matter.

Structural MRI studies found evidence of increased total brain volume, especially in the frontotemporal cortices, and early rapid brain overgrowth in affected individuals [Fig. 1]. In addition, revealed consistent abnormalities in cortical gray and white matter volume in ASDs. Diffusion tensor imaging has been further elucidate the structural integrity and orientation of white matter.
The advances in structural and functional MRI and structural MRI techniques in the past decades have helped researchers to understand neuropathological differences in ASD and helped to understand the neurobiology of autism [1-3].

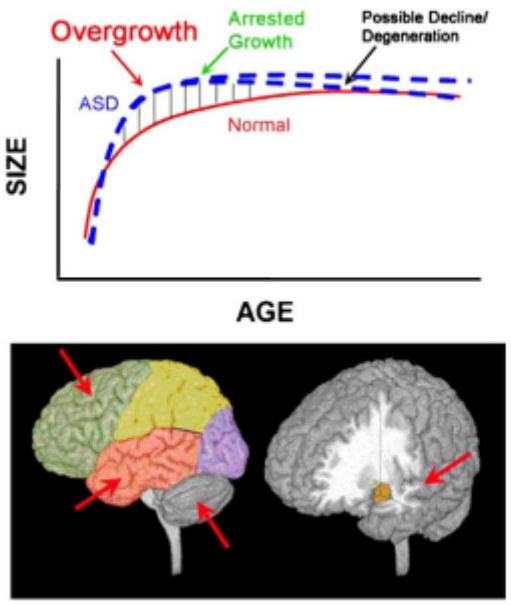

Fig. 1: Regional Early Overgrowth in ASD. (Top) This model illustrates initial rapid brain growth in ASD, depicted by blue lines, followed by a stabilization of growth. In comparison, red lines show the growth patterns of typically developing age-matched individuals. In certain cases and individuals, this plateau in growth may progress to a mild degeneration, represented by the dashed blue lines that decline slightly. (Bottom) Areas of the brain experiencing early overgrowth in ASD encompass the frontal and temporal cortices, cerebellum, and amygdala[3].

2. Literature review

Kimberly A. Stigler a b, Brenna C. McDonald c, Amit Anand b c, Andrew J. Saykin c, Christopher J. McDougle a b [3] focuses on Structural and Functional studies in ASD. Structural MRI has been crucial in identifying neuroanatomical abnormalities, such as atypical increases in brain volume at early ages and region-specific changes in gray and white matter volumes. This challenges the older view of ASD as a static condition, with recent evidence suggesting a dynamic, age-dependent development pattern. Abnormalities in gray and white matter are widespread across various brain regions, indicating broad brain involvement in ASD. However, discrepancies remain in the exact locations and directions of these volumetric changes, with factors like diagnostic criteria, participant characteristics (age, IQ, gender), imaging techniques, and the heterogeneity of autism itself potentially influencing results.

Functional MRI research in ASD has focused on understanding the neurobiological basis of social impairments, particularly related to face perception, one of the earliest social deficits in individuals with ASD. Research has shown that individuals with ASD tend to avoid the eye region when scanning faces, in contrast to typically developing individuals. Consistent findings indicate altered activation in the fusiform face area (FFA), which plays a crucial role in socioemotional functioning. Task-based and resting-state fMRI studies have revealed widespread cortical abnormalities and reduced connectivity in networks linked to ASD's core symptoms. Moreover, disruptions in the default mode network (DMN) during resting states are significant,

as the DMN is involved in higher-order social cognitive processes, such as the theory of mind. These deficits in theory of mind may be linked to early dysfunction in the mirror neuron system (MNS), essential for action observation, imitation, and emotional understanding.

Dongyun Li, Hans-Otto Karnath, and Xiu Xu [2] focus on identifying potential biomarkers for diagnosing Autism Spectrum Disorder (ASD) in children using various MRI techniques. These biomarkers are important for understanding ASD's neurobiological basis and improving early diagnosis and intervention.

Structural MRI detects neuroanatomical brain development, such as brain volume and cortex thickness. VBM and SBM analyze tissue density and features like curvature, showing consistent evidence of larger brains in children with ASD, especially in the frontal and temporal lobes.

Diffusion Tensor Imaging (DTI) assesses white matter microstructure and connectivity using measures like fractional anisotropy (FA) and mean diffusivity (MD). ASD children show reduced FA and increased MD in major white matter tracts, indicating altered connectivity and microstructural disorganization.

Resting-state functional MRI (RS-fMRI) examines functional connectivity by measuring the correlation between brain signals during rest. Studies show ASD children have reduced long-range connectivity and increased short-range connectivity, suggesting impaired information integration.

These MRI findings reveal increased brain volume, altered white matter, disrupted connectivity, and neurochemical imbalances in ASD children. These biomarkers could improve early diagnosis and intervention. Advancing neuroimaging, cross-disciplinary studies, and large-scale collaborations will be key in developing and integrating these biomarkers with genetic and phenotypic data.

Anibal Sólon Heinsfeld, Alexandre Rosa Franco, R. Cameron Craddock, Augusto Buchweitz, and Felipe Meneguzzi [1] explore the use of deep learning to identify Autism Spectrum Disorder (ASD) from brain imaging data. Using resting-state fMRI data from the ABIDE dataset [7], they combined supervised and unsupervised machine learning methods to classify ASD and control participants based on functional connectivity patterns. They created connectivity matrices using Pearson correlation coefficients and applied denoising autoencoders for unsupervised pre-training, followed by a multilayer perceptron (MLP) for classification.

The model achieved 70% classification accuracy, with 74% sensitivity and 63% specificity, outperforming the previous state-of-the-art accuracy of 67%. Key ASD-related neural patterns included underconnectivity between anterior and posterior brain regions and increased local connectivity in posterior areas. Significant

brain regions involved were the Paracingulate Gyrus, Supramarginal Gyrus, Middle Temporal Gyrus, Occipital Pole, and Lateral Occipital Cortex.

The deep learning model outperformed Support Vector Machine (SVM) and Random Forest (RF) classifiers, which achieved 65% and 63% accuracy, respectively. The model was robust in handling site-specific variability, essential for multi-site clinical datasets. However, the study noted challenges with multi-site data and emphasized the need for further refinement to meet clinical biomarker standards.

Xin Yang, Paul T. Schrader, and Ning Zhang [7] focus on using multilayer perceptrons (MLPs), a type of deep neural network (DNN), to classify Autism Spectrum Disorder (ASD) and typically developing (TD) participants based on functional connectivity from resting-state fMRI (rs-fMRI) data. The study used the Autism Brain Imaging Data Exchange (ABIDE) dataset, which includes data from over a thousand subjects. Functional connectivity features were extracted using the CC400 brain atlas and processed through the Configurable Pipeline for the Analysis of Connectomes (CPAC). The researchers employed deep neural networks in TensorFlow to handle the high-dimensional fMRI data and achieved a classification accuracy of 75.27%, with a recall of 74% and precision of 78.37%. This study demonstrates that deep learning significantly improves the accuracy of classifying ASD from TD using rs-fMRI data.

3. Background

3.1 Dataset

We're using the Autism Brain Imaging Data Exchange (ABIDE) dataset [7] for ABIDE initiative is a large-scale brain imaging data from labs worldwide that will be compiled to help understand the neural bases of Autism Spectrum Disorder (ASD). Compiling extensive functional and structural brain imaging data will facilitate discovery science and enable comparisons across diverse samples to address the complexity and heterogeneity of autism spectrum disorders.

The ABIDE dataset comprises two main collections: ABIDE I and ABIDE II. ABIDE I involved 17 international sites and included 1,112 datasets, with 539 from individuals with ASD and 573 from typical controls. The participants' ages range from 7 to 64 years old, with a median age of 14.7 years. Released in August 2012, this collection has demonstrated the feasibility of aggregating resting-state fMRI and structural MRI data across sites, making it a valuable resource for capturing whole-brain and regional properties of the brain connectome in ASD.

ABIDE II, established with support from the National Institute of Mental Health, has aggregated over 1,000 additional datasets, with enhanced phenotypic characterization. This collection includes longitudinal data from 38 individuals at two time points (1-4 year intervals) and involves 19 sites, contributing 1,114 datasets

from 521 individuals with ASD and 593 controls. The age range of participants in ABIDE II extends from 5 to 64 years. The data were released to the scientific community in June 2016.

Both ABIDE I and ABIDE II datasets are anonymized according to HIPAA guidelines and the protocols of the 1000 Functional Connectomes Project/International Neuroimaging Data-sharing Initiative (INDI), ensuring no protected health information is included. These datasets, consistent with open science principles, are made available to investigators globally.

For our project, we focused specifically on the anatomical MRI scans, working with images sized 128x128 pixels to ensure uniformity and facilitate processing. This focus allowed us to harness detailed structural brain data crucial for our ASD classification objectives. [Fig. 2]

Fig. 2 : Pictures from ABIDE data set[7] The cerebellum is marked with red rectangles. Each rectangle highlights the cerebellum's location in the respective slices. The cerebellum is positioned towards the back and lower part of the brain and is identified by its unique, foliated structure. (a) , (b) are subjects with ASD, and (c) and (d) are the Typical Controls.

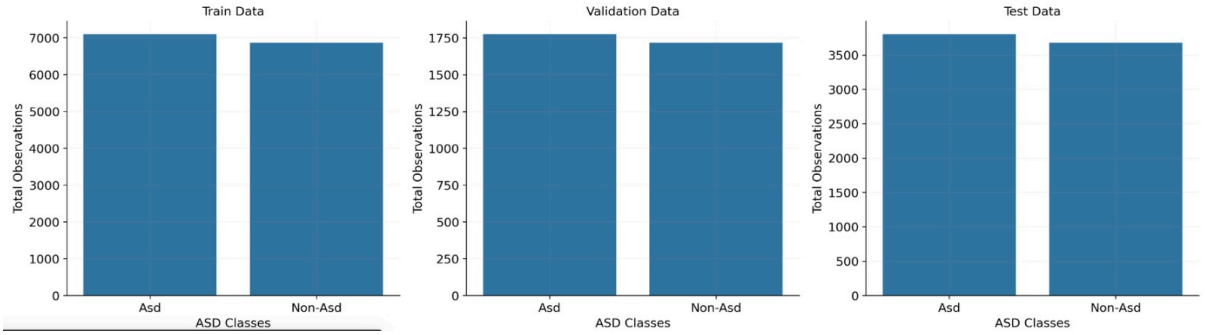

Fig. 3 : Distribution of Training/Validation/Testing Data.

3.2 CNN- Inception v3

Inception-v3 is a deep convolutional neural network designed as an improvement over earlier Inception models, particularly GoogleNet (Inception-v1). It optimizes computational efficiency and classification accuracy while reducing the number of parameters through architectural refinements. The model introduces several key innovations, including factorized convolutions, auxiliary classifiers, efficient grid size reduction, and label smoothing regularization.

To improve computational efficiency, Inception-v3 replaces large convolutions with smaller, stacked convolutions. For example, 5×5 convolutions are factorized into two consecutive 3×3 convolutions, and 3×3 convolutions are further optimized using asymmetric factorization (e.g., 1×3 followed by 3×1). This approach reduces parameter count and computational load while preserving feature extraction capabilities. Additionally, batch normalization is integrated throughout the network to stabilize and accelerate training.

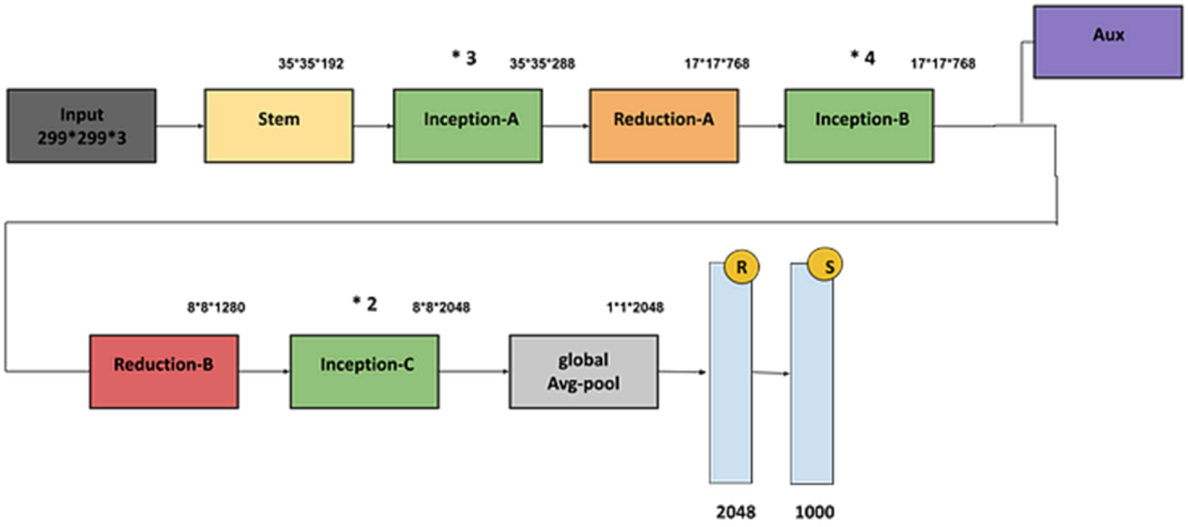

Fig .4: Inception V3 architecture.
Stem: Convolutional and pooling layers for basic feature extraction.Inception-A: Parallel convolutions (1×1, 3×3, 5×5) for multi-scale features.Reduction-A: Downsampling with convolutions and Max Pooling.Inception-B: Larger filters for capturing complex patterns.Reduction-B: Aggressive downsampling with Max Pooling.Inception-C: Wider and deeper filters for high-level features.Global Max Pooling: Reduces dimensions by keeping the most significant values.Auxiliary Classifier: Helps mitigate gradient vanishing via intermediate classification
.Fully Connected Layers: Final layers for classification.
Softmax: Outputs class probabilities.

Auxiliary classifiers are employed as intermediate supervision layers, aiding in gradient flow and acting as regularizers to improve convergence and prevent overfitting. Another major enhancement in Inception-v3 is its efficient grid size reduction technique, which replaces traditional pooling layers with parallel convolutional and pooling operations. This ensures that spatial resolution is reduced without creating representational bottlenecks, maintaining high-quality feature extraction.

To further enhance generalization, Inception-v3 applies label smoothing regularization (LSR), which prevents the model from becoming overly confident in its predictions, thereby reducing overfitting. The training process is optimized using stochastic gradient descent (SGD) with the RMSProp optimizer, employing learning rate decay and gradient clipping to stabilize training.

In performance evaluations, Inception-v3 achieves a Top-1 error rate of 21.2% and a Top-5 error rate of 5.6% on the ImageNet ILSVRC 2012 dataset, outperforming its

predecessors while maintaining computational efficiency. Through its architectural improvements and optimized training methodologies, Inception-v3 remains a benchmark model in deep learning for image classification tasks [4].

3.3 Transfer learning

Transfer learning is a technique where a model developed for one task is reused for a different, but related, task. It leverages the knowledge gained from solving one problem to improve performance on another, often requiring less data and computational resources. Commonly applied in fields like computer vision and natural language processing, transfer learning enables more efficient training by fine-tuning pre-existing models rather than building new ones from scratch. This approach is particularly valuable when data availability is limited.

TL(Transfer learning) with CNN (convolutional neural networks) is the idea that knowledge can be transferred at the parametric level. CNN models trained in the medical domain utilize the parameters of the convolutional layers to solve a new medical problem. With the use of TL with CNN for medical image classification, it is possible to learn the classification of medical images (target task) using generic features learned from natural image classification (source task), since labels are available in both domains.

There are two transfer learning approaches for utilizing CNN models: using them as feature extractors or through fine-tuning. In the feature extractor approach, the convolutional layers are kept frozen, while in the fine-tuning approach, the parameters are updated during model training.

Each approach can be further divided into two subcategories, resulting in four transfer learning methods, including the feature extractor hybrid.[Fig. 7a], in which the FC layers are removed and the machine learning algorithm is attached to the feature extractor, whereas the structure of the networks remains the same for the other types [Fig. 7b-d]. A fine-tuning process by starting from scratch is the most time-intensive approach because it involves updating the entire ensemble of parameters during the training process.

Using transfer learning accelerates the development of models for new tasks and significantly reduces the amount of data and computing resources required. Transfer learning improves the efficiency and effectiveness of deep learning applications in various domains by using already trained models, leading to more robust and generalized models [7].

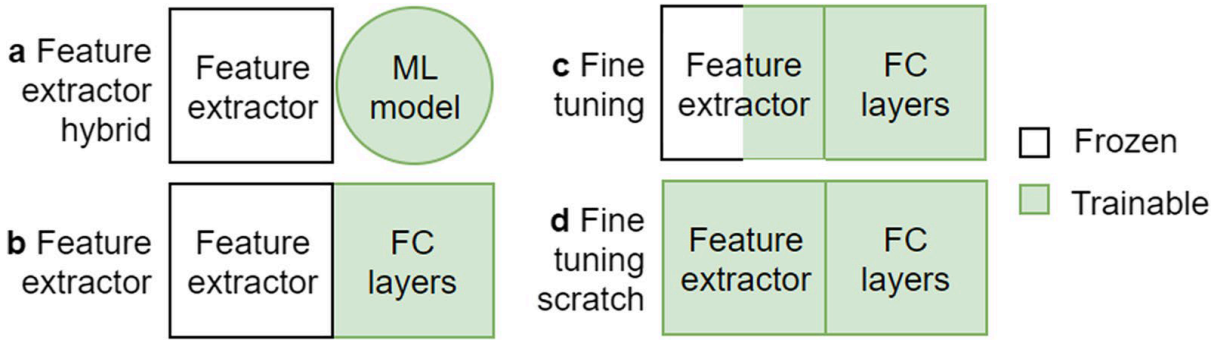

Fig. 5 : Four approaches to transfer learning with Convolutional Neural Networks (CNNs):
(a) the "Feature Extractor Hybrid" approach, where the feature extractor is frozen, and the FC layers are replaced with an external machine learning model;
(b) the "Feature Extractor" approach, where only the FC layers are trainable;
(c) the "Fine-tuning" approach, where both the feature extractor and FC layers are trainable;
(d) the "Fine-tuning from Scratch" approach, where the entire network is retrained from scratch.
Frozen parts are shown in white, while trainable parts are shown in green.[8].

4. Proposed approach

The model we presented was designed to classify MRI images as ASD or Non-ASD. Our research aimed for the model's performance to be both accurate and efficient in distinguishing between the two classes. We utilized a dataset containing anatomical MRI scans of individuals labeled as ASD or Non-ASD, ensuring a reliable foundation for model training and evaluation. Throughout our research, we explored various hyperparameters to optimize performance. We compared training loss versus validation loss, or training accuracy versus validation accuracy over epochs, to enhance accuracy while preventing overfitting. Our model was constructed using Transfer Learning, leveraging the Inception V3 architecture. This approach allowed us to extract deep feature representations from MRI scans, ensuring both efficiency and accuracy in ASD classification.

4.1 Model Architecture

The architecture of our proposed model consists of utilizing Transfer Learning with the Inception V3 framework to classify MRI images as ASD or Non-ASD, as explained earlier in our research. Inception V3 is a deep convolutional neural network known for its efficiency in feature extraction and classification, requiring no internal architectural modifications.
We preprocessed MRI images to ensure uniformity and consistency before inputting them into the model. The Inception V3 network, pretrained on large-scale datasets, was fine-tuned to recognize patterns specific to ASD-related neuroanatomical features. The model outputted a probability score for each image, determining whether it belonged to the ASD or Non-ASD class.
To optimize performance, we explored various hyperparameters and evaluated classification accuracy across training and validation sets. We compared training

loss versus validation loss and monitored training accuracy against validation accuracy over multiple epochs to prevent overfitting.
By leveraging Inception V3's robust feature extraction capabilities and Transfer Learning, we anticipated that our model would achieve high classification accuracy while maintaining computational efficiency, making it suitable for ASD diagnosis based on MRI scans.

4.2 Hyperparameters

The hyperparameters of a CNN are settings selected before training that determine how the model will learn. The hyperparameters are optimized in the validation stage and then used in the testing stage. To figure out which combination of these values works best, we'll test different combinations:

1. Learning rates - determines the magnitude of steps the model will take during gradient descent, which minimizes the loss function. If the learning rate is too low, the model can take a long time to converge.Learning rates will be tested at 5e-4, 5e-5, and 5e-6.
Loss Function evaluates how the model's predictions align with the actual data.

2. Epoch - when all the training data is used at once and is defined as the total number of iterations of all the training data in one cycle for training the model. Epoch sizes range from 50 to 150.

3. Batch size - is a technique in which the training data is divided into smaller "batches" and fed to the neural network in separate chunks, rather than all at once. The batch size is 32 vs. 64.

4. Dropout rate - A technique involving random deactivation of neurons during training can be used to avoid overfitting in deep learning models.
Overfitting occurs when the model learns not only the underlying patterns in the training data but also the noise, which results in poor performance on new, unseen data.It is caused by training data size is too small or there are not enough samples to represent all possible input data values, which leads to overfitting.
By doing this we are creating a new network architecture out of the parent network. The nodes are dropped by a dropout probability of dropout rate of 0.2 to 0.5.

Based on sensitivity, specificity, precision, and recall, we will evaluate the performance:

- True Positive (TP) - The number of instances that were correctly predicted as positive by the model.
- False Positive (FP) - The number of instances that were incorrectly predicted as positive by the model, but are actually negative.
- True Negative (TN) - The number of instances that were correctly predicted as negative by the model.

- False Negative (FN) - The number of instances that were incorrectly predicted as negative by the model, but are actually positive.
- Recall - measures the proportion of actual positive cases that are correctly = TP / (TP + FN)
- Sensitivity - is another term for recall, often used in medical testing or diagnostic fields. It refers to the model's ability to correctly identify positive instances out of the actual positives: Sensitivity = TP / (TP + FN)
- True Positive Rate (TPR) - is essentially the same as recall and sensitivity. It measures the proportion of actual positives correctly predicted by the model = TP / (TP + FN)
- False Positive Rate(FPR) - The ratio of the number of false positives to the total number of actual negatives. It quantifies how often a model incorrectly labels negative examples as positive: FPR = FP / (TN + FP)
- Accuracy - is a metric that measures how often a model correctly predicts the outcome: Accuracy = (TP + TN) / (TP + TN + FP + FN)
- Precision - the quality of a positive prediction made by the model = TP / (TP + FP)
- F1 score - is a metric used to evaluate the performance of the model: F1 score = 2 / ((1 / Precision) + (1 / Recall))
- Error Rate = 1 – accuracy or (FP + FN) / (TP + TN + FP + FN)

4.3 Product:

In this section, we describe our work process and the GUI for the system.
Figure 9 illustrates the screen a doctor will encounter upon accessing a system that utilizes our selected model. Figure 10 shows an example of our system after classification has been performed and how it will assist the doctor in detecting ASD.

Flow chart of system training process:

Before starting the training process, we prepare the dataset. The dataset includes MRI images labeled as either ASD or non-ASD.
The dataset is split, Training set 80%: Used to train the model.
Validation set 15%: Used during training to monitor the model’s performance and help prevent overfitting. The test set 5%: Used after training to evaluate the model’s final performance.
Images are padded to match the required input size (128x128 for Inception V3).
Loading Inception V3 model pre-trained on ImageNet.
The early layers of the pre-trained model capture general features, which are useful for many tasks. Therefore, these layers are frozen during training to retain their pre-trained weights. Only the deeper layers will be trained to learn task-specific features.
The final layer will have 2 output units with a softmax activation function to output probabilities for the two classes.
A batch size of 32 or 64 images per batch.

Training:
Initially, only the new layers added to the model are trained, while the early layers from Inception V3 are frozen.

Validation:
Monitor validation performance after each epoch to check for signs of overfitting or underfitting.

Testing:
To evaluate the final performance, we will measure performance metrics such as accuracy, precision, recall, F1-score, and confusion matrix on the test set to assess how well the model generalizes to completely unseen data.

Once the model performs well on the training, we will fine-tune if necessary (canceling the freeze part or all of the model and continuing training with a smaller learning rate for better performance) [fig. 6].

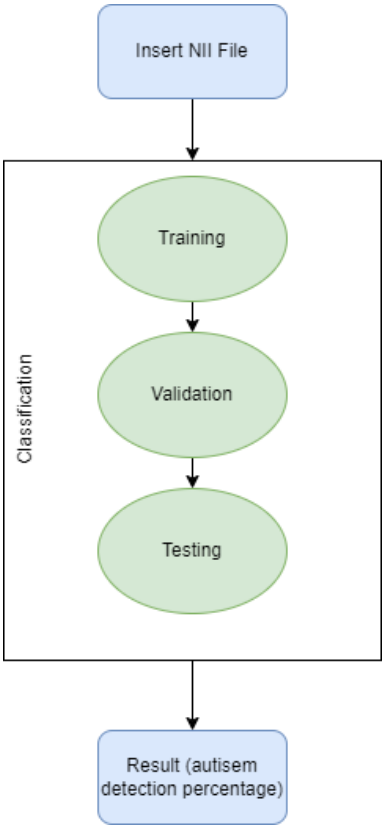

Fig. 6: ASD classification process diagram.

GUI:

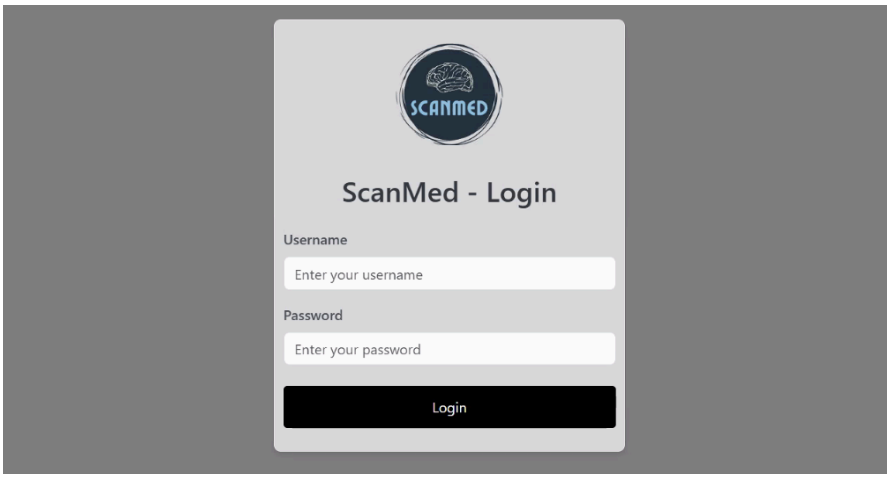

Fig. 7: The login screen for the doctor.

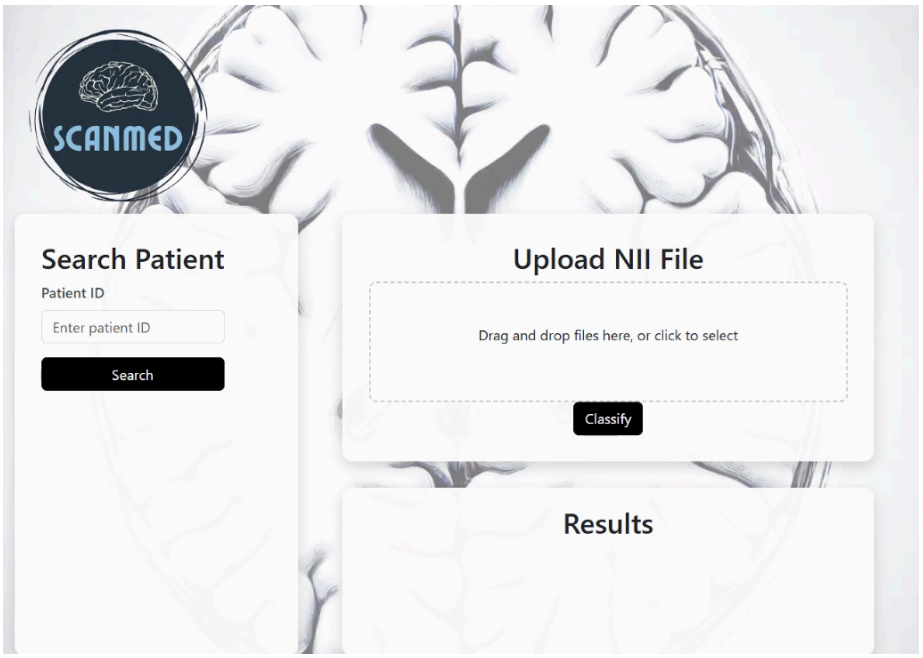

Fig. 8: The system before entering patient details and NII file.

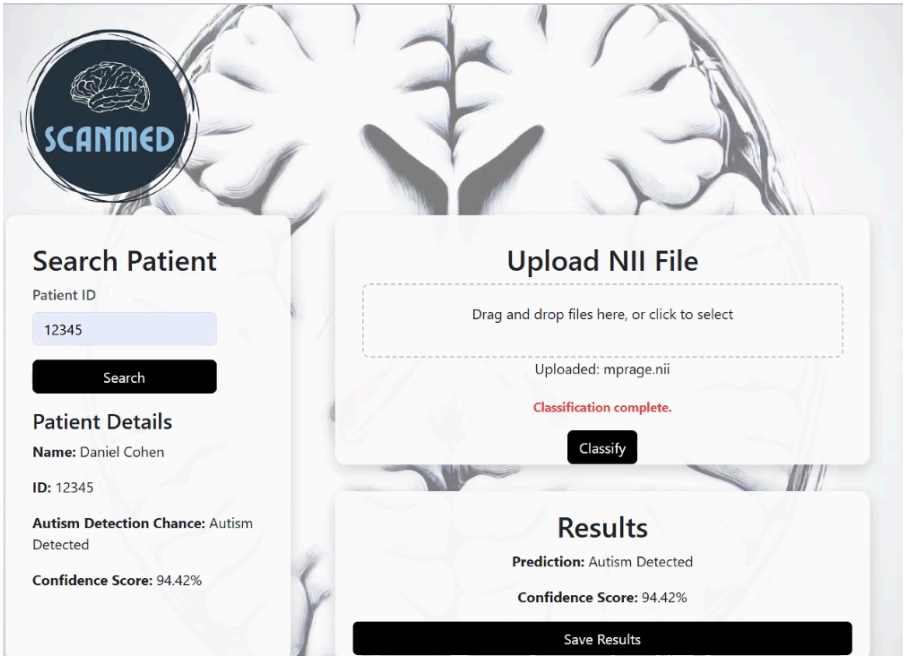

Fig. 9: The system after entering patient details and NII file.

5. Reachers Process

In the initial phase of our project, we aimed to classify ASD using MRI images by leveraging deep learning techniques, focusing on the Inception v4 architecture with transfer learning. We began by researching the model's structure, understanding its advantages, and exploring its implementation. Our initial attempts involved training Inception v4 from scratch, but the results were not satisfactory. To refine our approach, we attempted using a pre-trained version of Inception v4 from a deep learning library, hoping to enhance accuracy through transfer learning. However, this approach also failed to yield the desired results.

A significant challenge we faced was time constraints, which required us to efficiently identify an alternative model capable of delivering strong classification performance. With this in mind, we reassessed our approach and explored different architectures that could better suit our problem of MRI-based ASD classification.

After careful evaluation, we decided to implement Inception v3, which provided a more effective balance between performance and computational efficiency. Unlike Inception v4, this model produced significantly better results, allowing us to successfully classify MRI scans for ASD detection. By making this transition, we were able to overcome the obstacles we faced and achieve the level of accuracy necessary for our system to function effectively.

Following this initial work, we manually downloaded anatomical MRI images from the ABIDE website, using NII files that required conversion into image format. After

converting the files, we processed the images to remove irrelevant features such as skull parts, black backgrounds, and eye regions that do not contribute to our analysis. These cleaned images were then organized based on patient IDs into two separate folders—one for individuals diagnosed with Autism Spectrum Disorder (ASD) and another for those without (NON-ASD).

After categorizing the images into ASD and NON-ASD groups, we streamlined our directory structure by discarding individual patient folders and directly storing all images in their respective ASD and NON-ASD folders. Our code specifically manages the data by dividing it into three subsets: TRAIN, TEST, and VALIDATION. This organization facilitates a structured approach to machine learning model training and evaluation.

To enhance the effectiveness of model training through increased data variability, we applied a series of image augmentation techniques to each image in our dataset. These techniques included rescaling pixel values to a range of 0 to 1 to reduce model complexity and speed up convergence, rotating images by 15 degrees to make the model robust against orientation variations, and horizontally shifting images by 10% to improve spatial invariance. We also applied slight zoom to simulate different image scales, distorted images to represent different viewing angles, varied image brightness to accommodate different lighting conditions, and applied horizontal and vertical flips to ensure the model learns features irrespective of image orientation. All images were resized to 128x128 pixels to maintain consistency across the dataset.

Our model architecture leverages the powerful feature extraction capabilities of the Inception V3 framework.We initiated a linear stack of layers, incorporating the Inception V3 model for its efficiency in feature extraction. The subsequent steps involved transforming the 3D feature maps into 1D feature vectors to prepare for the dense layers, applying a 50% dropout to reduce overfitting by randomly omitting half of the features during training, and introducing a dense layer with 1024 units and ReLU activation to capture complex patterns. Another dropout of 30% further minimized overfitting. The final layer, using softmax activation, classifies the images into ASD and NON-ASD categories. The model is compiled with the Adam optimizer and a custom learning rate, focusing on minimizing categorical cross-entropy loss while tracking accuracy.

This approach, which combines extensive data augmentation with a sophisticated neural network architecture, is designed to significantly enhance the accuracy and reliability of ASD detection through MRI scans. By addressing the variability in brain imaging and the subtle neurological differences associated with ASD, our study aims to advance the field of medical imaging and diagnostics.

6. Result

Using MRI scans from the ABIDE (Autism Brain Imaging Data Exchange) multi-site database, we trained a Convolutional Neural Network (CNN) to improve the accuracy and reliability of ASD diagnosis.

To evaluate our results, we divided them into two cases. The first case involves analyzing the learning curves of the Inception V3 model, specifically accuracy versus epochs and loss versus epochs. We examined different learning scenarios, including both high and low accuracy trends. The second case consists of a comparative analysis of model performance under different training conditions. The results are summarized in Table 1, which presents the model's accuracy along with the hyperparameters used.

Initially, the model was trained for 50 epochs with a learning rate of 0.0001. The accuracy versus epochs and loss versus epochs graphs were analyzed to assess performance. To further investigate the effect of training duration, we conducted two additional experiments: one with 70 epochs to explore potential improvements, and another with 40 epochs to examine whether reducing training time could help avoid overfitting.

Dataset	Optimizer	Learning Rate	Epochs	Train Accuracy	Validation Accuracy	F1-Score	precision	recall
ABIDE	Adam	0.0001	40	90.27%	90%	0.75	0.8969	0.8969
ABIDE	Adam	0.0001	50	92.32%	91.21%	0.832	0.9050	0.9050
ABIDE	Adam	0.0001	70	94.56%	92.59%	0.88	0.9336	0.9336

Table 1: Performance of Inception V3 with various configurations.

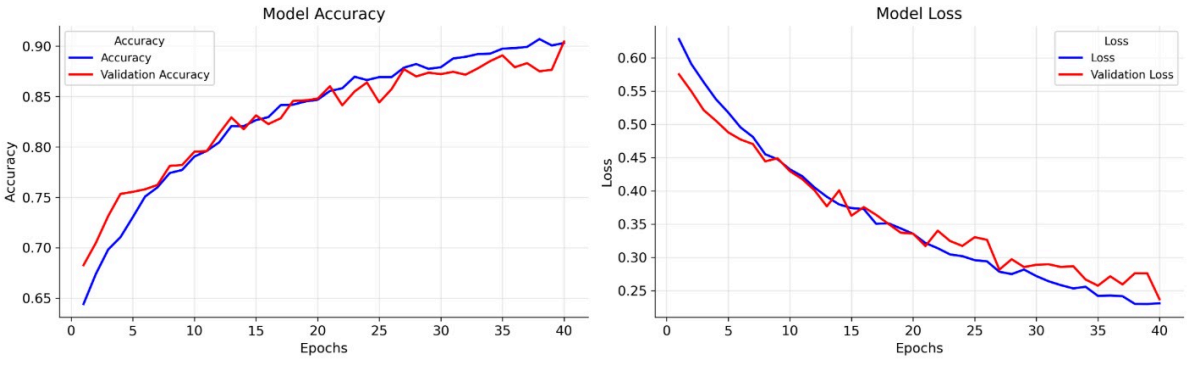

Fig. 10: 40 epochs, learning rate = 0.0001

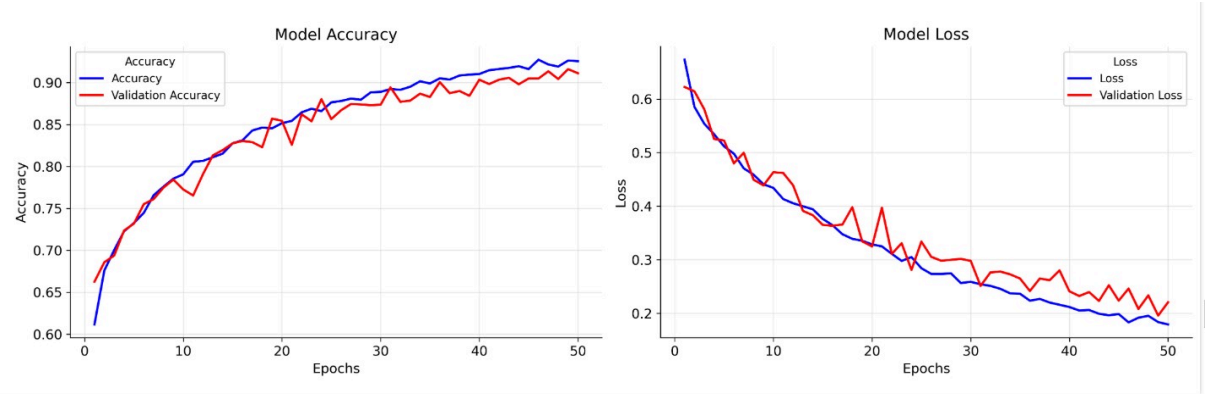

Fig. 11: 50 epochs, learning rate = 0.0001

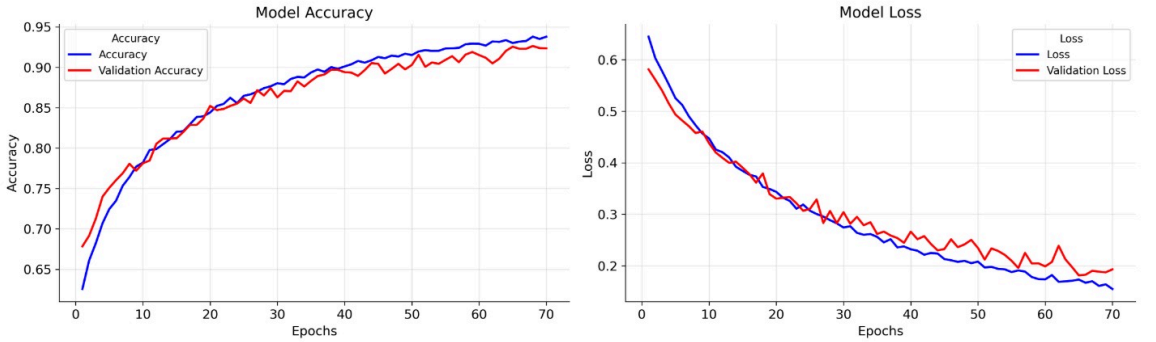

Fig. 12: 70 epochs, learning rate = 0.0001

In the first experiment, we trained the Inception V3 model with Transfer Learning using the Adam optimizer, keeping the learning rate at 0.0001 and training for 50 epochs while maintaining all other parameters. The model's performance improved, with training accuracy reaching 92.32% and validation accuracy reaching 91.21%. Additionally, the F1-score increased to 0.832, and both precision (0.9050) and recall (0.9050) improved, suggesting better generalization.

In the second experiment, we reduced the number of epochs to 40. After training, the model achieved a training accuracy of 90.27% and a validation accuracy of 90%. However, the F1-score (0.75) and classification metrics (precision: 0.8969, recall: 0.8969) indicated room for improvement, suggesting that reducing the number of epochs limited the model's ability to capture complex patterns.

In the third experiment, we extended the training to 70 epochs, keeping all other parameters unchanged. The results showed significant improvement, with training accuracy increasing to 94.56% and validation accuracy reaching 92.59%. The F1-score rose to 0.88, with precision at 0.9336 and recall at 0.9336, demonstrating higher classification accuracy.

The model leveraged pre-trained weights from ImageNet, which significantly accelerated the learning process and improved stability. Instead of training the model from scratch, we utilized an Inception V3 model pre-trained on ImageNet, a large-scale dataset containing millions of labeled images across 1,000 different categories. This pre-trained model had already learned to recognize fundamental visual patterns such as edges, textures, and shapes, which are transferable to many different image classification tasks.

When applying Transfer Learning, we retained the lower layers of the Inception V3 model, which had already learned general feature representations from ImageNet. These layers remained frozen, meaning their pre-trained weights were not updated during training, ensuring that the model preserved its ability to extract generic features. However, the final layers of the model were replaced and fine-tuned on the MRI dataset to specialize in detecting anatomical structures relevant to ASD.

Using pre-trained weights helped mitigate the risk of overfitting, as the model did not have to learn basic visual features from scratch. Instead, it focused on task-specific patterns in MRI scans, improving classification accuracy while requiring fewer training samples.

The most effective model was Inception V3 with Transfer Learning, trained for 70 epochs, achieving a validation accuracy of 92.59% and an F1-score of 0.88. These results highlight that leveraging pre-trained ImageNet weights enabled the model to generalize better, learn faster, and improve performance compared to training from scratch. The combination of Inception V3’s powerful feature extraction capabilities and fine-tuning the higher layers for ASD classification led to a stable and highly accurate model, making Transfer Learning an essential technique for MRI-based ASD detection.

7. Evaluation / Verification Plan

CASE #	Test explanation	Expected result	Checked
1	Upload Nii file.	Sends the anatomical MRI scans as input to the model to start the enhancement process.	V
2	Press->without uploading anything.	Throw error: “Error! No file has been uploaded”.	V
3	Insert the wrong file type.	Throw error: “Error! The file type is not supported”.	V
4	Insert empty file.	Throw error: “Error! The file is empty”.	V
5	Press save (after uploading the file and receiving results)	Saves the image.	V
6	Press save (before uploading the file and receiving results)	Throw error: “Please upload a file”	V

Table 2: Suggested use cases for our program validation.

8.Conclusion:

Our research focused on developing an effective classification model for ASD diagnosis using MRI images by leveraging Transfer Learning. We studied the Inception V3 architecture, exploring its structure and how it processes anatomical brain features for classification tasks. We also examined how adjusting hyperparameters affects the training process and model performance.

We found that Transfer Learning with Inception V3 provides strong classification accuracy while maintaining computational efficiency. However, we encountered challenges with our dataset, particularly variations in MRI scan quality which impacted model performance. To address this, we applied preprocessing techniques, including the removal of irrelevant MRI slices—images where the relevant brain

regions could not be identified. This ensured that the model focused only on meaningful anatomical structures, improving classification accuracy.

Additionally, Throughout our research, we monitored the learning curve, adjusted the number of epochs and we observed that performance improved when optimizing hyperparameters and fine-tuning the model on ASD-relevant brain regions.

The results showed that our deep learning system achieved an optimal performance with minimal loss, demonstrating the system's capability in identifying ASD early. This early identification can facilitate timely intervention, leading to improved skills and behaviors for children. Moreover, the system's accuracy helps in preventing incorrect diagnoses and inappropriate treatments, further enhancing the effectiveness of ASD diagnosis

9.User Guide:

This guide provides operating instructions for users, describing the operational process that supports various usage scenarios. The focus is on the successful operation of the system, without detailing error states or error handling.

1. Introduction

The system is designed to assist in classifying Autism Spectrum Disorder (ASD) using brain MRI scans, leveraging deep learning technology with the Inception V3 model. This system allows users to upload MRI images, perform classification, and quickly obtain accurate results. By utilizing these capabilities, the system aids healthcare professionals in diagnosing ASD based on MRI scans, providing valuable support in the diagnostic process.

Before seeking consultation or diagnosis, users are required to undergo an MRI scan. The system will then classify the scan to assist doctors in evaluating the presence of ASD.

2. System Requirements

Before using the system, ensure the following requirements are met:

- The system must be accessed via a supported web interface.
- The user should have an MRI scan file in .nii format for classification.

3. User Interface Overview

Once logged into the system, the user will be presented with the main dashboard, where they can access the following sections:

1. Login Page: Where users enter their username and password.

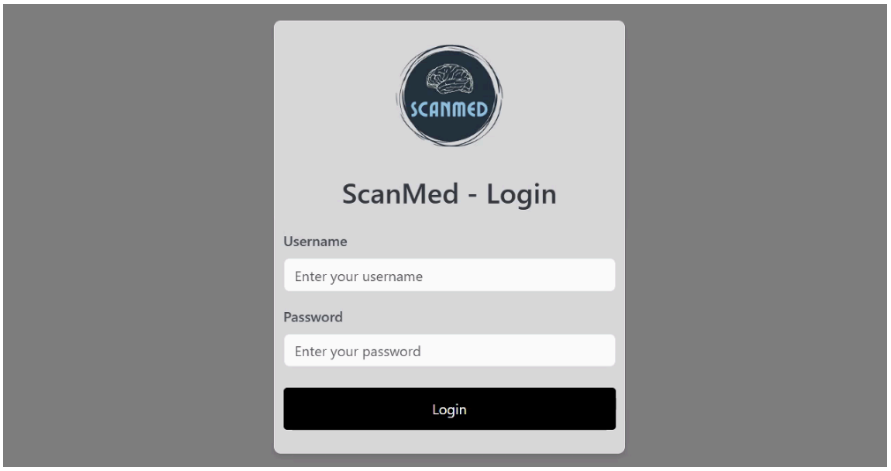

Fig. 13: Login Page.

2. Patient Information Part: After logging in, the user can input the patient ID to retrieve patient details.
3. MRI Upload and Classification Page: This page allows the user to upload a .nii file containing the MRI scan and perform the classification.

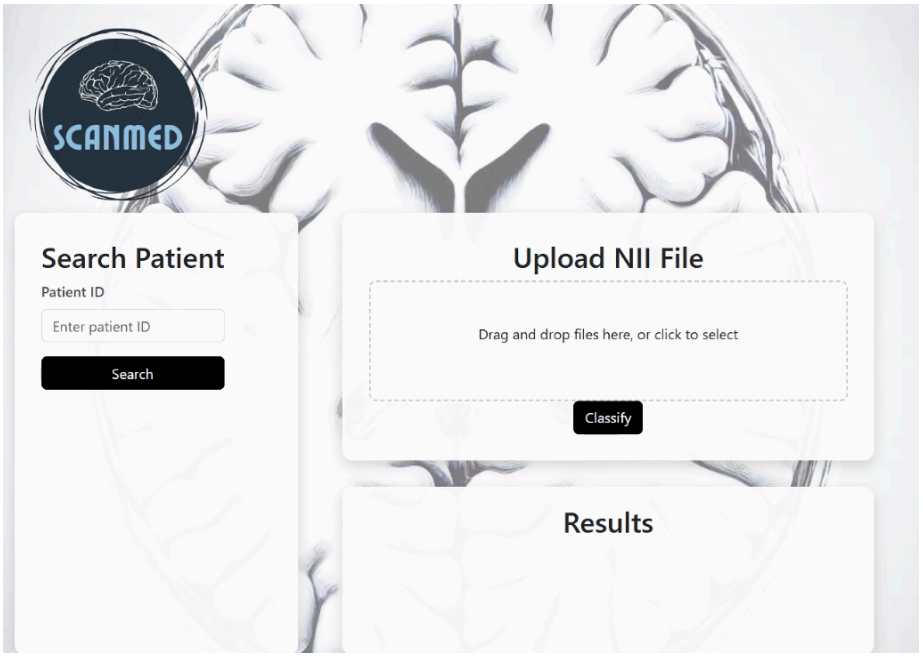

Fig. 15: MRI Upload and Classification Page with Patient Information Part.

4. Operating Instructions

Once you've logged into the system, The first thing you'll do is access the Patient Information Page, where you'll enter the patient's ID. This simple step allows the system to retrieve and display the relevant details about the patient, ensuring that all subsequent actions are tied to the correct profile.

After this, you'll navigate to the MRI Upload and Classification Page. To begin the classification process, you'll need to upload an MRI scan of the patient's brain. The scan should be in the .nii format, which is the required format for processing. You simply click the "Choose File" button, select the MRI file from your local storage, and hit "Upload." The system will now begin processing the image.

Once the file is uploaded, the system utilizes the Inception V3 model to analyze the MRI scan. The model assesses the brain structure captured in the image, comparing it with the characteristics known to be associated with Autism Spectrum Disorder (ASD). Within moments, you'll see the results displayed on the screen. The system will output the probability percentage for ASD.

The results can be saved to the patient's profile by clicking the "Save Results" button. This ensures that all information is securely stored and can be referenced later for follow-up consultations.

10.Maintenance Guide:

The purpose of this guide is to ensure the continued use and support of the system after the project is completed. This includes applying updates, improvements, and modifications to extend the system's lifecycle and maintain its functionality.

1. System Environment

The Inception V3 Autism Classification System is a web-based application designed to run in a cloud or local server environment. It uses deep learning technology for ASD classification based on MRI scans. To maintain and update the system, the following software and hardware components are required:

-
- **Software Infrastructure: Python (3.7 or higher)**: The system relies heavily on Python for its backend processing.
- **PyTorch (1.10 or higher)**: The deep learning framework used to implement the Inception V3 model.
- **Flask**: A lightweight web framework for the user interface and server-side logic.
- **TensorFlow**: An alternative to PyTorch, can be integrated for model compatibility if needed.
- **NumPy & SciPy**: For data manipulation and scientific computations.
- **scikit-learn**: For any additional machine learning techniques that may be needed.
- **NIfTI Library**: For processing MRI files in .nii format.
- **Hardware Requirements: Server (Cloud or Local)**: A machine with at least 8GB RAM, and a GPU with CUDA support (e.g., Nvidia Tesla or GeForce) for faster deep learning model inference.
- **Storage**: Sufficient disk space (at least 100GB) for storing MRI scan datasets and model checkpoints.

2. Installation Instructions

To ensure the smooth running and future updates of the system, follow these installation steps for the necessary components:

1. **Setting Up the Environment**:
    - Install Python (3.7 or higher) on your server or local machine.
    - Create a virtual environment to manage dependencies:
    - python -m venv venv

    - source venv/bin/activate # On Windows, use venv\Scripts\activate
2. **Install Required Libraries**:
    - After activating the virtual environment, install the required dependencies:
    - pip install flask torch torchvision numpy scipy scikit-learn nibabel
    - If using TensorFlow for any future adjustments, install it as follows:
    - pip install tensorflow
3. **Download Pre-trained Inception V3 Model**:
    - The Inception V3 model should be downloaded and saved in the system directory. The model should be in .h5 format for PyTorch or .h5 for TensorFlow.
    - You can download the pre-trained model from a trusted source or load a custom model that was trained specifically for ASD classification.
4. **Configure the Server**:
    - Set up Flask to run the web application.
    - Ensure that the server is running in a secure environment, using HTTPS for all data transmissions.
    - Modify the configuration files as necessary to handle the specific server setup (e.g., port configurations, logging settings, etc.).
5. **Database Configuration (Optional)**:
    - The system may need a database to store patient profiles and classification results. You can use a lightweight database like SQLite for simplicity or configure a MySQL/PostgreSQL server if scalability is needed.
    - Configure the database by updating the connection strings in the Flask app.
6. **MRI File Handling**:
    - Ensure that NIfTI (.nii) files are correctly processed. Install the nibabel library to handle these files.
    - Implement proper file storage and backup solutions for MRI data to maintain integrity and security.

3. Ongoing Maintenance and Updates

Once the system is up and running, it will require regular maintenance to ensure continued functionality and improvement:

- **Updating the Model**:
- Periodically, you may want to retrain the model with additional data to improve accuracy or adapt it to new research findings. Ensure the

latest version of the ABIDE dataset or any other relevant dataset is added to the training pipeline.

- Follow these steps to retrain the model:
    1. Prepare the updated dataset.
    2. Train the Inception V3 model using the existing training pipeline.
    3. Save the updated model to the server.
    4. Replace the old model file with the newly trained model.
- **Software Updates**:
- Regularly update the Python libraries to their latest stable versions to ensure security patches and performance improvements.
- Use the following command to update the libraries:
- pip install --upgrade <library_name>

4. Future Updates and Improvements

As part of the ongoing support for the system, the following future updates may be implemented:

Performance Optimization: Enhance the system's speed by utilizing more efficient algorithms, parallel processing, or upgrading the hardware.

User Interface Enhancements: Improve the user experience by redesigning the web interface or adding new features such as detailed result explanations or visualizations.

Integration with Other Medical Tools: Consider integrating the system with other diagnostic tools or electronic health record (EHR) systems for a more seamless workflow.

11. Reference

11.1 GitHub:

https://github.com/NitzanEz/Final-Project

11.2 Resources

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