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# Autism Spectrum Disorder Prediction Using Deep Neural Network

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**ABSTRACT:** Autism Spectrum Disorder (ASD) manifests as a complex neurodevelopmental challenge, characterized by hurdles in social interaction, communication, and repetitive actions. Identifying these signs swiftly and intervening promptly hold pivotal significance in improving the prospects of individuals contending with ASD. Within this landscape, machine learning techniques, especially deep neural networks (DNNs), stand out as promising tools for predictive modeling and the timely detection of ASD. In our investigation, we propose a sophisticated DNN architecture comprising 5 dense layers to forecast autism spectrum disorder predicated on behavioral and clinical attributes. Our model is designed to harness the inherent power of deep learning, adept at discerning intricate patterns from heterogeneous data streams. These encompass a varied array of inputs, including demographic details, medical histories, and behavioral evaluations, drawn from a diverse cohort encompassing both ASD-positive and ASD-negative individuals. The architectural blueprint of our DNN entails an initial input layer succeeded by 3 concealed layers, each teeming with densely interconnected neurons activated by rectified linear units (ReLUs). Culminating the neural cascade is the output layer, employing a sigmoid activation function to prognosticate the probability of an ASD diagnosis. The model's training regimen is facilitated by the Adam optimizer, optimizing parameters via binary cross-entropy loss function. Furthermore, to avert overfitting, we implement early stopping mechanisms and conduct meticulous hyperparameter tuning to enhance predictive accuracy. Our empirical findings underscore the efficacy of our proposed DNN model in accurately discerning ASD diagnoses from diverse data substrates. Evidenced by competitive performance metrics, our model holds promise as a valuable tool for expedited ASD detection and intervention, thereby advocating for improved outcomes in managing autism spectrum disorder.

**KEYWORDS:** Demographic information, Heterogeneous data sources, Competitive performance metrics, Intervention.

## I. INTRODUCTION

Medical, genetic and environmental causes have been linked to ASD but a more detailed etiology is not known. However, some genetic mutations and prenatal exposures have been implicated. Nonetheless, its precise etiology remains unknown. Nevertheless, the cause of this condition is yet unknown. But what exactly causes it still remains mysterious. Comprehensive evaluation by a multidisciplinary team involving behavioral assessments, developmental screening and medical evaluations is used for diagnosis. A child with autism requires the development of an individualized education plan (IEP) as well as a team of professionals who will facilitate his or her access to these services. This plan must be developed based on the unique needs of each student with autism spectrum disorder because they require highly specialized services that cannot be provided by general special education programs. Moreover, when autistic persons are offered proper support and intervention at very early ages they stand chances of developing strategies that are appropriate for their situation thereby optimizing future results. By maintaining awareness about ASD we can identify the symptoms early enough concerning this condition hence preventing it from getting worse. The phrase “no two people with Autism Spectrum Disorder are alike” was stated above because it encompasses people affected by autism as individuals. ASD defines such people as individuals for whom no two alike exist.

## II. LITERATURE SURVEY

The DSM helps doctors and psychologists spot mental health issues like autism. It's like a guidebook listing the signs of autism. It's a useful tool for figuring out who might have autism and how to help them. But the DSM sees autism as



either "yes" or "no," like flicking a light switch. Autism is more like a mix of different shades, so it's hard for the DSM to catch all the ways it shows up, especially if symptoms are mild or unusual. The field of autism research is continually evolving, with ongoing discoveries about the underlying biology, genetics, and presentation of ASD. The DSM requires periodic updates to reflect advances in knowledge and understanding, highlighting the need for ongoing revision and refinement of diagnostic criteria. Logistic regression models the probability of a binary outcome (presence or absence of ASD) based on one or more predictor variables (features). Features could include demographic information, behavioral assessments, medical history, genetic markers, and other relevant factors. Logistic regression estimates the coefficients of the predictor variables to calculate the log-odds of the outcome, which are then transformed into probabilities using the logistic function. The model can be trained using labeled data (individuals with and without ASD) and evaluated using general metrics. Logistic regression is good at finding simple connections between variables, but ASD is complicated with diverse symptoms and presentations. Logistic regression may struggle to account for the complexity and heterogeneity of ASD.

### III. PROBLEM STATEMENT

Autism Spectrum Disorder (ASD) presents a multifaceted neurodevelopmental challenge, marked by hurdles in social interaction, communication, and behavior. Timely identification and intervention play pivotal roles in shaping outcomes and providing tailored support to those affected. Yet, ASD diagnosis frequently faces delays owing to the diverse nature of symptomatology, restricted accessibility to specialized assessments, and the subjective nature of clinical evaluations. Consequently, there emerges a pressing demand for diagnostic methodologies that are not only precise and effective but also scalable, facilitating early detection and intervention strategies tailored to ASD.

### IV. DATASET

The dataset is divided into three subsets for different purposes:

#### Training Data:

Size: 2575 entries

Percentage of Total: Approximately 70%

Purpose: Used to train machine learning models. This subset is the largest portion of the dataset, providing ample data for model learning.

#### Testing Data:

Size: 552 entries

Percentage of Total: Approximately 15%

Purpose: Reserved for evaluating the performance of trained models. Models are tested on this subset to assess how well they generalize to unseen data.

#### Validation Data:

Size: 552 entries

Percentage of Total: Approximately 15%

Purpose: Similar to testing data, this subset is used for evaluating model performance. It helps in tuning hyperparameters and assessing model robustness.

### V. PROPOSED METHODOLOGY

A deep neural network (DNN) constructed entirely from dense layers, also referred to as fully connected layers, serves as a foundational architecture in the realm of deep learning. Dense layers establish connections between every neuron in one layer and every neuron in the subsequent layer, enabling the acquisition of intricate interactions and representations from input data. Here's an outline of a DNN featuring solely dense layers:

**Input Layer:** The inaugural stratum of the neural network, known as the input layer, encompasses 64 neurons, aligning with the dimensional aspects of the input data. Each neuron symbolizes a distinct feature from the input data ensemble. Within this layer, the rectified linear unit (ReLU) activation function is deployed, denoted by `activation="relu"`.

**Hidden Layers:** Within the architecture, three concealed layers play a pivotal role, each exhibiting a distinct neuron count and utilizing the ReLU activation function. The initial hidden layer boasts 128 neurons, endowing the model with the capability to decipher intricate patterns latent within the data. Subsequently, the second hidden layer accommodates 256 neurons, thereby augmenting the model's potential for assimilating representation learning. Lastly, the third hidden layer embraces 64 neurons, thereby contributing to the model's prowess in extrapolating hierarchical features.

**Output Layer:** Serving as the terminal layer of the neural network, the output layer features a solitary neuron, emblematic of the binary classification task at hand (ASD detection). Herein lies the model's endeavor to prognosticate the likelihood of a sample belonging to the positive class (ASD-positive). The sigmoid activation function is enlisted in the output layer (`activation="sigmoid"`) to engender a probability score spanning from 0 to 1, denoting the probability of a sample being ASD-positive.

**Compilation:** The model undergoes compilation utilizing the Adam optimizer (`optimizer="Adam"`) to facilitate gradient descent optimization. Furthermore, the binary cross-entropy loss function (`loss="binary_crossentropy"`) is selected, ideally suited for binary classification undertakings. The evaluation metric specified is accuracy (`metrics=["accuracy"]`), quantifying the proportion of accurately classified samples.

**Early Stopping Callback:** An EarlyStopping callback is enlisted to oversee the trajectory of the validation loss (`monitor="val_loss"`) throughout the training process. Training culminates if there's no discernible enhancement in validation loss over a stipulated number of epochs (`patience=10`). Notably, the model's weights are restored to the configuration delivering optimal performance (`restore_best_weights=True`).

### VI. Data Flow Diagram

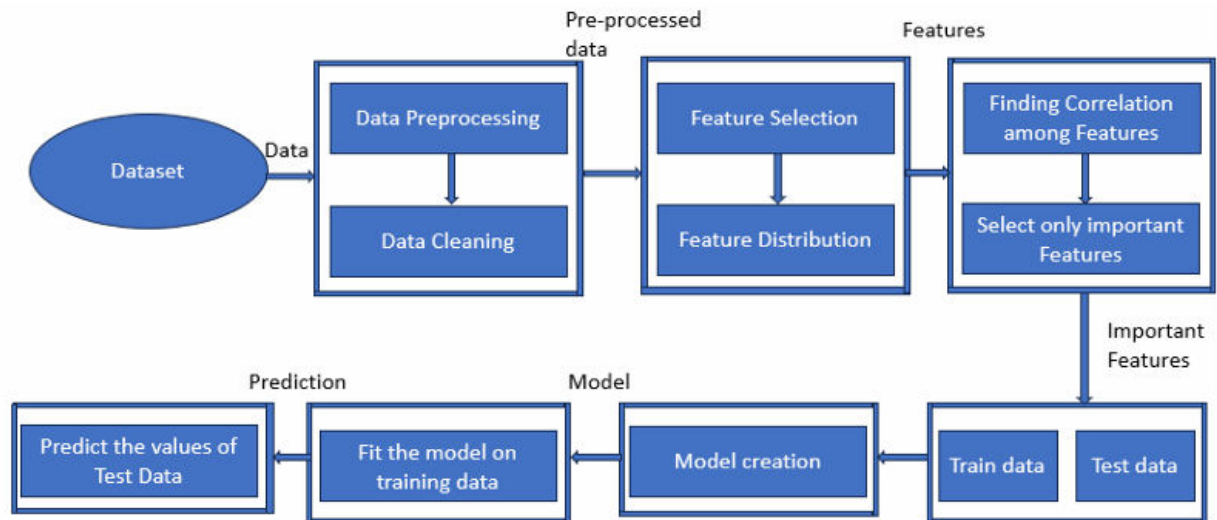


Figure: Data Flow Diagram

**Data Collection :** We've gathered all the necessary data from different sources.

**Data Cleaning and Preprocessing:** We've cleaned up our data, getting rid of any mistakes or missing parts. We've also made sure everything looks the same and is easy to work with.



**Feature Selection :** We've picked out the important things from our data and ignored the things that don't really matter. This helps keep our model simple and makes sure it doesn't learn too much from the tiny details.

**Feature Distribution :** We've understood the distribution of features in our dataset, helping us identify any skewed or imbalanced data.

**Correlation Analysis :** Relationships between different features have been identified through correlation analysis, aiding our understanding of the data's dynamics.

**Important Features Selection:** We've pinpointed the most impactful features, considering both correlation analysis results and domain expertise.

**Dataset Split:** Our dataset has been divided into training, Validation and testing subsets, allowing us to proceed with model development and evaluation.

**Model Creation :** Our neural network architecture, consisting of densely connected layers, has been designed and built.

**Model Training :** The model has been trained on the training data, learning the underlying patterns and relationships.

**Testing and Evaluation :** We've used the trained model to make predictions on the test data and evaluated its performance using appropriate metrics.

## VII. EXPERIMENTAL ANALYSIS

**Training Accuracy:** This tells us how well our model is doing on the data it's been taught with. It's like checking how well a student remembers what they studied for a test. As the model learns more, this accuracy usually goes up because it gets better at fitting the training data.

**Validation Accuracy:** Think of this as a test to see if the model really understands the material or if it's just good at repeating what it was taught. We use a separate set of data that the model hasn't seen before to check this. At first, this accuracy might increase as the model learns more about the important stuff from the training data.

**Generalization Performance:** A model with good generalization can do just that. It's not just about acing the training material; it's about being able to handle new challenges that come its way.

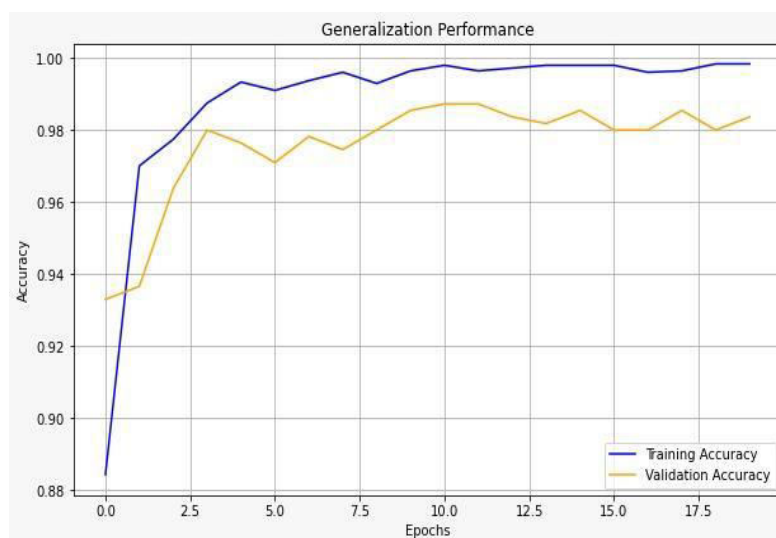


Figure: Generalization Performance

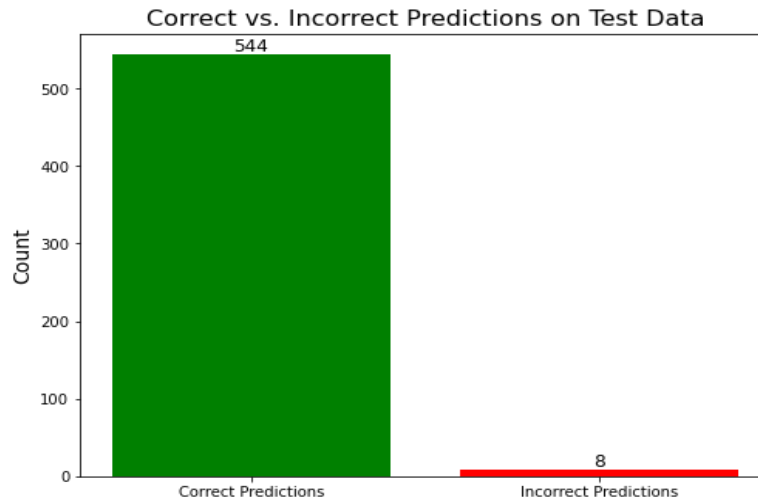


Figure: Correct vs Incorrect Predictions on the Test Data

### VIII. RESULTS

The output written to the Excel file could contain the actual labels and predicted labels for each instance in the test set. Here's how the output might look in the Excel file.

Actual_Label	Predicted_Label
1	1
0	0
1	1
1	1
0	0
0	0
0	0
0	0
0	0
0	0
0	0
0	0
1	1
1	1
0	0
0	0
0	0
0	0
0	0
0	0
0	0
1	1
0	0
0	0

1	1
1	1
1	1
1	1
1	1
0	0
1	1
0	0
0	0
0	0
0	0
1	1
0	0
0	0
0	0
0	0
0	0
1	1
1	1
0	0
0	0

Figure: Actual Label and Predictability



The "Actual\_Label" column contains the actual labels from the test set. The "Predicted\_Label" column contains the predicted labels generated by the model. Each row corresponds to one instance in the test set, with the actual and predicted labels aligned accordingly.

## IX. CONCLUSION

Our study presents a robust Deep neural network architecture to predict autism spectrum disorder (ASD) with remarkable accuracy of 98.5%, demonstrating its potential for aiding early detection and intervention. The model's satisfactory generalization performance, as indicated by the convergence of training and validation losses, underscores its ability to mitigate overfitting or underfitting issues. This advancement holds significant promise for optimizing healthcare resource allocation, enabling personalized care and support tailored to individual needs, and informing public health policies to address ASD effectively. By integrating Deep learning into ASD detection, our findings contribute to enhancing healthcare outcomes and the quality of life for affected individuals, fostering a future where timely interventions can lead to improved developmental trajectories and greater societal inclusion. Continued research efforts and interdisciplinary collaboration are vital for refining these models and ensuring their ethical and equitable implementation in clinical practice

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