



QuantDiagnose

Combining “Quantum” and “Diagnosis”

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PROBLEM



PROBLEM STATEMENTS...

Understanding Autism Spectrum Disorder (ASD)

What is Autism Spectrum Disorder?

A developmental disorder characterized by challenges with social interaction, communication, and repetitive behaviors. Affects individuals differently and to varying degrees.

Importance of Early Detection:

Early diagnosis can lead to better intervention strategies. Improves outcomes and quality of life for individuals with ASD.

Project's Relevance:

Developing an automated, accurate, and efficient tool for early detection of ASD. Leveraging machine learning to assist healthcare professionals in diagnosis.





Autism



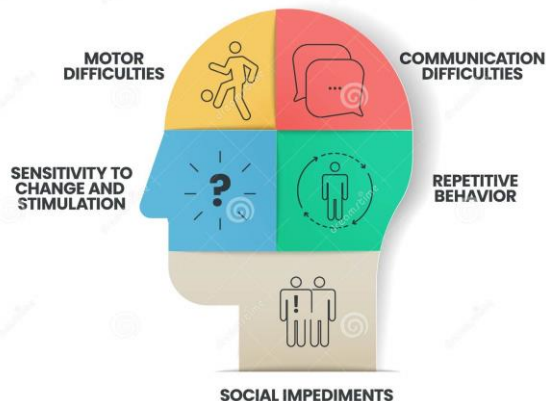
Normal





AUTISM

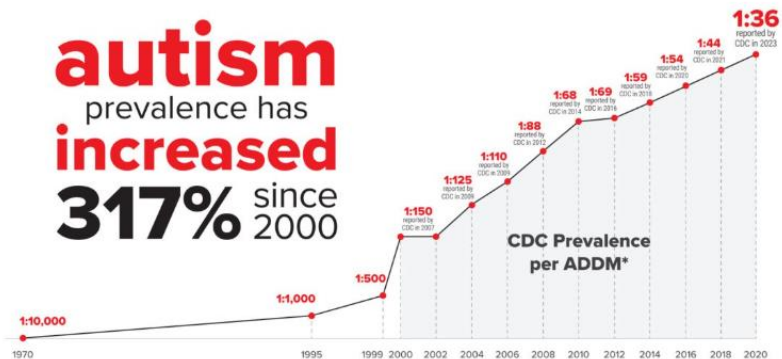
SPECTRUM DISORDER



dreamstime.com

ID 260255137 © Joebite

autism
prevalence has
increased
317% since 2000



*ADDM (Autism and Developmental Disabilities Monitoring Network)

TACA
THE AUTISM COMMUNITY IN ACTION





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SOLUTION APPROCH



Hybrid Quantum-Classical Machine Learning

Hybrid Quantum-Classical Model:

Combines classical machine learning algorithms with quantum computing techniques. Aims to enhance model performance by exploiting quantum properties.

Simplified Explanation:

Classical ML:

Traditional algorithms that learn from data patterns.

Quantum ML:

Utilizes quantum bits and circuits to process information in novel ways.

Hybrid Approach:

Integrates both to leverage strengths of each, potentially improving accuracy and efficiency.





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Progress Overview



Project Progress So Far

Data Collection and Preprocessing:

Collected datasets with features related to ASD indicators.
Performed data augmentation to enhance model training.

Model Development:

Implemented classical models: Random Forest, Gradient Boosting, SVM.
Developed a Hybrid Quantum-Classical model using PennyLane and TensorFlow.

Hyperparameter Optimization:

Utilized Genetic Algorithms to optimize model parameters.
Evaluation: Achieved ~73% accuracy with Random Forest.
Developing and testing hybrid models.





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Unique Selling Points (USPs)



What Sets Our Project Apart

Quantum Advantage:

Potential to process complex data patterns more efficiently than classical models alone.

Hybrid Model Integration:

Combining best of both classical and quantum machine learning.

Early Detection Focus:

Targeting early diagnosis to improve intervention outcomes.

Innovative Approach:

Utilizing cutting-edge quantum computing technologies in healthcare.





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Libraries and Modules Used



Tools and Technologies



Quantum Libraries:

PennyLane: For building and training quantum-classical models.

Qiskit (IBM): Quantum computing framework for circuit simulations.

Classical ML Libraries:

TensorFlow: Deep learning framework.

Scikit-learn: Traditional machine learning algorithms.

Optimization Tools:

DEAP: For implementing genetic algorithms.

Visualization:

Matplotlib & Seaborn: For plotting performance metrics.

Others:

Numpy, Pandas: Data manipulation.

Pickle: Model serialization.





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Why Quantum Machine Learning?



Advantages of Quantum ML over Traditional ML

Enhanced Computational Power:

Quantum computers can handle large-scale computations more efficiently.

Better Pattern Recognition:

Quantum algorithms can identify complex patterns that classical algorithms might miss.

Potential for Improved Accuracy:

Hybrid models may achieve higher accuracy by leveraging quantum properties.

Future-Proofing:

Positioning the project at the forefront of emerging technologies in AI and healthcare.





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How Our Code Works



How Our Code Works



Data Preprocessing:

Loading and augmenting data to improve model training.

Classical Models:

Implementing Random Forest, Gradient Boosting, and SVM for baseline comparisons.

Hybrid Model:

Dense Layers: Classical neural network layers processing input data.

Quantum Circuit: Quantum layer processing transformed data.

Aggregation Layer: Combining quantum outputs to make a final prediction.

Training Process:

Compilation: Defining loss functions and optimizers.

Fitting: Training the model on augmented data.

Evaluation: Assessing model performance using metrics like accuracy, precision, recall.

Saving Models:

Storing trained models for future use.





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Difficulties Faced



✦ Challenges and How We Overcame Them



Shape Mismatches:

Issue: Incompatible tensor shapes leading to training errors.

Solution: Adjusted model architecture to aggregate quantum outputs correctly.

Model Saving Errors:

Issue: Subclassed models not saving in HDF5 format.

Solution: Switched to TensorFlow's SavedModel format.

Quantum Circuit Complexity:

Issue: Integrating multiple qubits increased model complexity.

Solution: Modified aggregation layers and ensured proper alignment between quantum outputs and labels.





Challenges and How We Overcame Them



AutoGraph Warnings:

Issue: TensorFlow attempting to transform quantum circuit functions.

Solution: Used decorators to prevent AutoGraph conversion.

Limited Quantum Resources:

Issue: Simulating quantum circuits can be computationally intensive.

Solution: Optimized circuit design and limited the number of qubits initially.





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Future Impact





Long-Term Impact and Future Directions



Enhanced Diagnosis Tools:

Developing more accurate and efficient models for early autism detection.

Integration into Healthcare Systems:

Implementing models into clinical workflows to assist healthcare professionals.

Advancements in Quantum ML:

Pioneering the use of quantum computing in healthcare applications.

Scalability:

Scaling models with more qubits and larger datasets for better performance.





Thank You