Autism Classification Using Support Vector Machine Model and the AQ-10 Survey

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For this project I will be using data collected from a ten-question survey called the Autism Quotient - 10 Questions (AQ-10) to create a binary support vector machine (SVM) classification model that can determine whether an adult should be referred to a professional clinician for the possible diagnosis of autism spectrum disorder. This investigation can be used to determine whether this short questionnaire is adequate in identifying such adults or whether a more thorough approach is needed.

The autism spectrum, also known as autism spectrum disorder (ASD) or autism spectrum condition (ASC), is a “loosely defined cluster of neurodevelopmental disorders characterized by challenges in social interaction, verbal and nonverbal communication, and often repetitive behaviors and restricted interests.” (Autism spectrum, 2023) Autism is a lifelong condition and can be diagnosed during childhood, adolescence, and adulthood. However, diagnosis for adults is much more difficult to obtain as there are fewer clinicians who specialize in adult diagnosis. Furthermore, “autism is difficult to identify in adults due to lack of validated self-report questionnaires.” (Brugha et al., 2020) The use of self-questionnaires has been researched in this discipline and an analysis of some of the current questionnaires used in identifying adult autism showed that “these tests correctly identified autism spectrum disorder patients in almost 80% of the referred cases.” (Sizoo et al., 2015)

The data consists of 20 variables including some demographic information, the responses to the 10 questions on the survey, and the binary target feature. The demographic features consist of age, age description, gender (binary), country of residence, and the relation of the person filling out the form to the person being referenced on the form. The demographic information was used during the exploratory analysis to better understand which populations may be underrepresented in the study.

However, when it came time to train the model these features were dropped and only the 10 features that were responses to the questionnaire were included in the training features. These were also the only training features to contain missing information so when they were dropped, we simultaneously cleaned the dataset if missing values. The target feature is a binary categorical variable that has just over 500 instances of non-ASD (identified with the binary value 0) and just under 200 of ASD (identified with the binary value 1) as shown in Figure 1.

Since all the training features were integer values, and the target feature was a binary categorical variable, I decided to use Pearson’s correlation coefficient to estimate the predictive strength of the training features. All the training features had some predictive power with Pearson’s correlation scores between 0.24 and 0.64 as can be seen in the correlation heat map in Figure 2.

Figure 1

Distribution of Target Variable

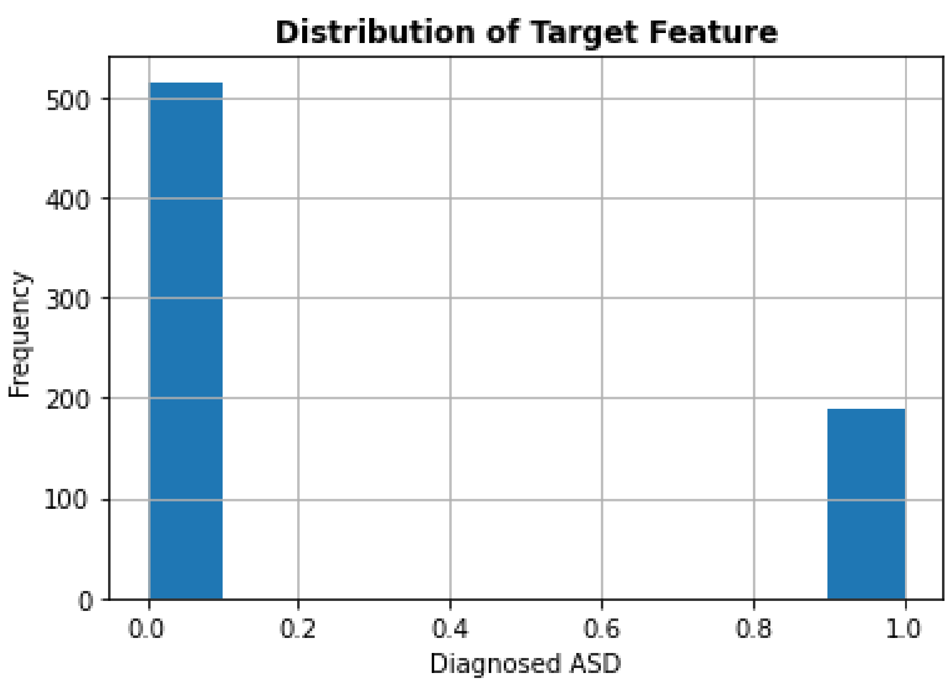
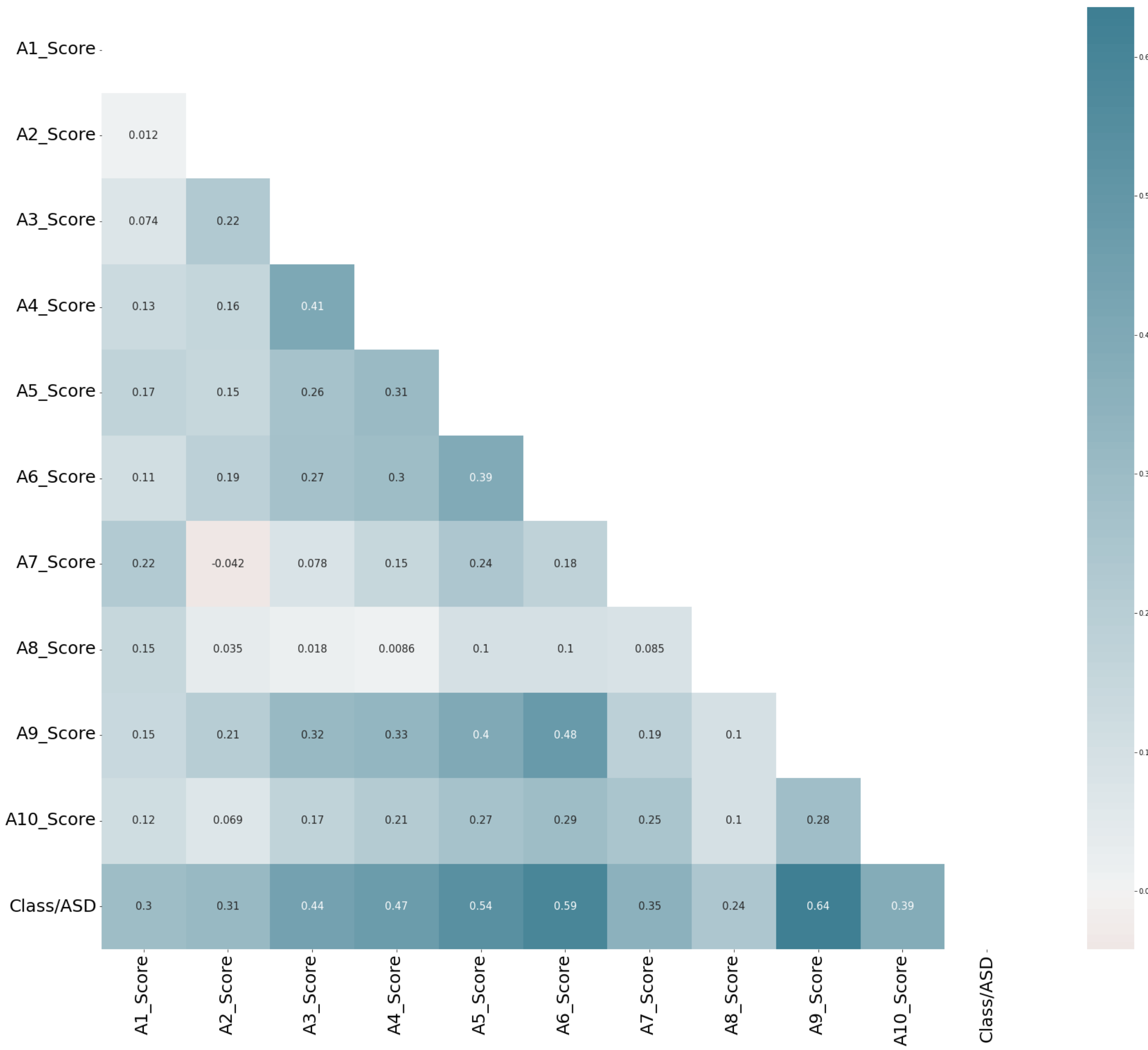


Figure 2

Correlation Heat Map



The data was split into 70% training data and 30% testing data. It was unnecessary to scale the data, as all the responses consisted of an identical range of integer outcomes. For the SVM model I did hyperparameter tuning on the hyperparameters of C, gamma, and kernel to find the best parameters to optimize the accuracy of the model.

Hyperparameter tuning yielded the best parameters for this model to be C=10, gamma=0.1, and an RBF kernel. I used cross-fold validation to evaluate the accuracy of the model. After hyperparameter tuning, the model averaged an accuracy of 99.4% when split over 5 folds. We can compare the accuracy to that of a null model where we simply predict the most common category for each instance. This model has a remarkably high accuracy, especially when compared to the accuracy of the null model accuracy which would be approximately 70%.

In conclusion, we can consider this model a success. This model may even be accurate enough to deploy in the field to help adults decide if their situation warrants further investigation from their medical professionals. Since autism is not a life-threatening condition, the small number of errors that this model makes should not be catastrophic for an individual who uses this model.

There are some assumptions to address when discussing this model. First, it should be noted that this test was designed for adults (age 16+) with suspected autism who do not have a learning disability. Thus, we must assume people taking this survey fall within those parameters. Furthermore, this model relies upon the previous diagnosis of individuals taking the survey. We must assume that those individuals labeled ASD are correctly diagnosed and that those labeled as non-ASD are not undiagnosed autistics themselves. Given the substantial number of undiagnosed autistic adults this assumption may not be valid. Our final assumption is that it is beneficial for adults to learn they are autistic and therefore beneficial to provide resources for those who may seek diagnosis, such as surveys like the AQ-10.

These sorts of questionnaires rely on the ability of the individual to reflect on their own behavior and experiences and to contextualize those experiences within the framework of what is ‘normal.’ For example, the survey asks the individual to make comparisons between their own behavior and the behavior they see in others around them. This can be challenging for autistic individuals and thus is a limitation of this survey.

The greatest challenge I faced when creating this model was the remarkably high accuracy, I got on my first attempt at the model. Before doing cross-fold validation I happened to get an accuracy score of 100%. This was concerning to me, and I spent a great deal of time making sure that testing data had not somehow bled into training. Seeing the average of the cross-fold validation bring the accuracy down to 99.4% brought me some relief that the model was performing exceptionally well rather than being a mistake.

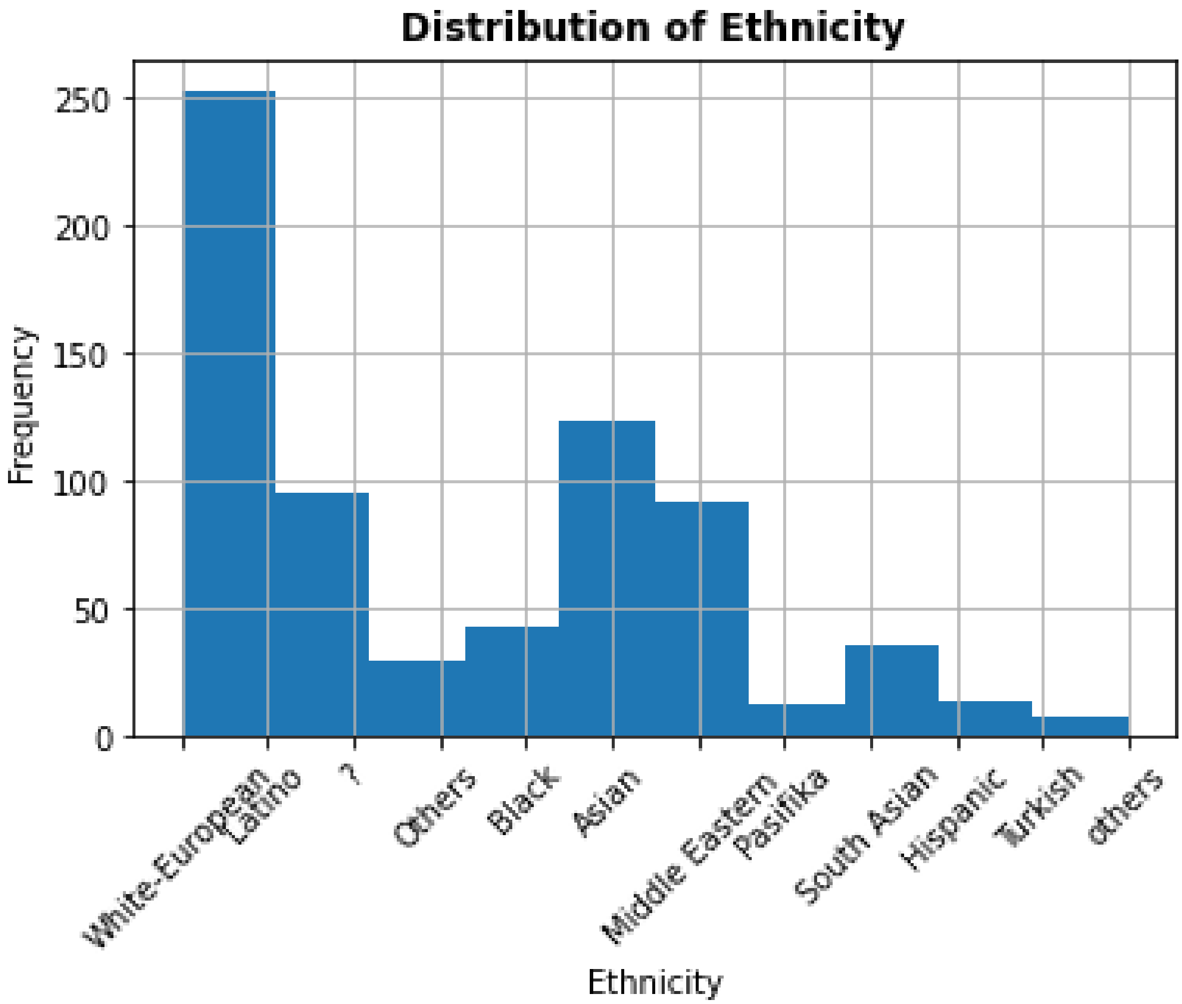
In the future I would like to see an SVM model trained on other autism questionnaires such as the Autism Quotient (AQ), the Camouflaging Autistic Traits Quiz (CAT-Q) and the Ritvo Autism Asperger Diagnostic Scale–Revised (RAADS–R) which all vary in their approach to detecting autism in adults. I think this model could also be used to improve the AQ-10 and its current implementation. For example, the questions on the survey with the lowest predictive power may be replaced by questions that do have more predictive power. Also, currently, the AQ-10 is measuring the sum of the scores of each question and comparing the total to a benchmark. This weights the importance of each question equally, which we can see from the correlation heat map, is not appropriate.

Regarding the implementation of this model, I think it would be best suited as a replacement to the self-scoring questionnaires available online for people who are questioning whether they may be autistic. This should not replace the clinical assessment by a professional, but rather serve as an indicator of whether an individual should seek further testing. The current method for scoring this questionnaire has a lower accuracy than the SVM model created here so replacing the self-scoring method with the SVM model would create a more trustworthy approach to self-assessment online.

There is a large ethical issue in this study regarding the number and type of respondents that are in this dataset. As can be seen in Figure 3, this dataset consists primarily of white and young individuals, which can lead to underrepresentation in the data for people of color as well as the elderly. Furthermore, young, white, wealthy people are already more likely to be diagnosed with ASD because of cultural biases in the medical community that put people of color and poor people at higher risk of misdiagnosis. The fact that this study overrepresents white and young individuals may exacerbate these biases in practice.

Figure 3

Distributions of Age and Race



10 Questions from the Audience

- How is creating this model different from just summing up the score and comparing it to the benchmark?
  - This model is more accurate than simply comparing a total to a benchmark because each question is not weighted equally in the creation of the model like it is in a total.
- What resources would be needed to make this available for public use?
  - There would need to be dedicated server space to host and platform this model.
- Is there any group who could benefit monetarily from such an expenditure?
  - I do not believe it is possible to profit from this endeavor unless one is charged for access to the model. This could be considered unethical.
- How can autism diagnosis help an adult who evaded diagnosis as a child?
  - An adult who learns they are autistic can then choose to accommodate sensory needs and avoid sensory overload, leading to an increased quality of life. Also, diagnosis allows an individual in the US to receive disability accommodations at work.
- How can autism diagnosis hurt an adult who evaded diagnosis as a child?
  - Folks who are diagnosed autistic may be subject to the biases of people who hold power over them. For example, autistic people are more likely to lose custody of their child or may be rejected from jobs because of their diagnosis.
- Why did I choose to use the SVM classifier over other classification models?
  - I chose the SVM classifier because I was inspired by the fact that a simple adding of scores and comparing the total to a benchmark was already so accurate. I

figured if I could extend this process into 10 dimensions it might be possible to find a dividing line that evenly separated the two groups.

- Why a 70/30 split for training and testing?
    - I tried many different ratios, and none made a substantial difference on my model.
- Why should models like this not replace the clinical assessment by a professional?
    - Models like this may amplify biases found in the medical community that already put underrepresented groups at a higher likelihood of misdiagnosis. A professional may be able to see past these biases and provide an accurate diagnosis for an individual.
- How can we minimize the impact of the ethical issues raised in the paper?
    - If we extended our dataset to include a wider range of individuals, we could mitigate some of the model's impacts.
- Why is it important that online self-testing resources for autistic adults be accurate and trustworthy?
    - Because diagnosis is so hard for adults to access, self-testing resources often become a first stop for people who are considering the possibility of autism. If these resources are not trustworthy it undermines the entire process.

References

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