# **Model Card - Multiple Sclerosis Disease Predictors**

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### **Model Details**

- Created by Jeffrey Kong, Noah Lee, and Jacob Ventura with methods taught by Adam Loy in STATTAT 270 at Carleton College.
- Employed K-nearest neighbors, Naive Bayes, and a Random Forest model.
- Finalized the model on 11/25/2024.

### **Intended Use**

- The model was designed as a capstone project for STAT 270 at Carleton College.
- Goal is to accurately predict if a patient diagnosed with CIS will develop Multiple Sclerosis.
- Intended for educational purposes, and should not be used as the sole basis for conclusions.

#### **Factors**

- Demographic: Age, Gender
- Medical History: Initial\_Symtpoms.
   Mono\_or\_Polysymptomatic, Breastfeeding, Varicella
- Instrumentation: Periventricular\_MRI, Cortical\_MRI, Infratentorial\_MRI, Spinal Cord MRI
- Environments: Schooling
- Potential Future Variable: Neurological Imaging

## **Metrics**

- Accuracy is the primary metric used to compare models, while sensitivity, specificity, and ROC-AUC were also considered.
- The validation dataset was used to test performance metrics.

## **Training Data**

• 70% of the data was randomly split and assigned as the training data, stratified by group.

### **Evaluation Data**

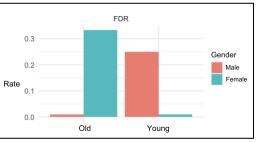
- 15% of the data was randomly assigned to testing data, and the remaining 15% was used as the validation data, also stratified by group.
- Data was pre-processed to omit NA or unknown values.

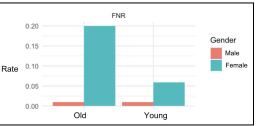
## **Ethical Considerations**

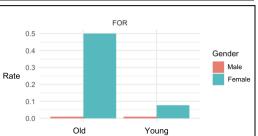
 Data was collected through clinical evaluations, diagnostic tests, and follow-ups of CIS patients at the National Institute of Neurology and Neurosurgery in Mexico City. Individuals presumably agreed to their anonymous information being collected.

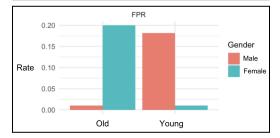
## **Quantitative Analysis**

Gender	Age Group	False Positive Rate	False Negative Rate	False Discovery Rate	False Omission Rate
Male	Old	0	0	0	0
Male	Young	0.18	0	0.25	0
Female	Old	0.20	0.20	0.33	0.50
Female	Young	0	0.06	0	0.08









False Positive Rate @ 0.5

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0.00 0.02 0.04 0.06 0.08 0.10 0.12 0.14

False Negative Rate @ 0.5

Quantitative Analyses

old-male

old-female young-female

young-male

old

voung

male female

Model Cards for Model Reporting

## **Model Card - Smiling Detection in Images**

#### **Model Details**

- Developed by researchers at Google and the University of Toronto, 2018, v1.
- Convolutional Neural Net.
- Pretrained for face recognition then fine-tuned with cross-entropy loss for binary smiling classification.

#### Intended Use

- Intended to be used for fun applications, such as creating cartoon smiles on real images; augmentative applications, such as providing details for people who are blind; or assisting applications such as automatically finding smiling photos.
- · Particularly intended for younger audiences.
- Not suitable for emotion detection or determining affect; smiles were annotated based on physical appearance, and not underlying emotions.

#### old-male old-female · Based on known problems with computer vision face technology, potential relyoung-female -0evant factors include groups for gender, age, race, and Fitzpatrick skin type; voung-male -0 hardware factors of camera type and lens type; and environmental factors of old lighting and humidity. young 0 $\bullet\;$ Evaluation factors are gender and age group, as annotated in the publicly available male dataset CelebA [36]. Further possible factors not currently available in a public female smiling dataset. Gender and age determined by third-party annotators based all 0 on visual presentation, following a set of examples of male/female gender and $0.00\,0.02\,0.04\,0.06\,0.08\,0.10\,0.12\,0.14$ young/old age. Further details available in [36]. False Discovery Rate @ 0.5 old-male old-female • Evaluation metrics include False Positive Rate and False Negative Rate to young-female measure disproportionate model performance errors across subgroups. False young-male Discovery Rate and False Omission Rate, which measure the fraction of negaold tive (not smiling) and positive (smiling) predictions that are incorrectly predicted voung to be positive and negative, respectively, are also reported. [48] male • Together, these four metrics provide values for different errors that can be calcufemale lated from the confusion matrix for binary classification systems. • These also correspond to metrics in recent definitions of "fairness" in machine 0.00 0.02 0.04 0.06 0.08 0.10 0.12 0.14 learning (cf. [6, 26]), where parity across subgroups for different metrics corre-False Omission Rate @ 0.5 spond to different fairness criteria. old-male 0 95% confidence intervals calculated with bootstrap resampling. old-female · All metrics reported at the .5 decision threshold, where all error types (FPR, FNR, young-female 10 FDR, FOR) are within the same range (0.04 - 0.14). young-male **Training Data** old -0-**Evaluation Data** vouna -0-• CelebA [36], training data split. • CelebA [36], test data split. • Chosen as a basic proof-of-concept. female **Ethical Considerations** 0 • Faces and annotations based on public figures (celebrities). No new information $0.00\,0.02\,0.04\,0.06\,0.08\,0.10\,0.12\,0.14$ is inferred or annotated. **Caveats and Recommendations** • Does not capture race or skin type, which has been reported as a source of disproportionate errors [5]. • Given gender classes are binary (male/not male), which we include as male/female. Further work needed to evaluate across a spectrum of genders. • An ideal evaluation dataset would additionally include annotations for Fitzpatrick skin type, camera details, and environment (lighting/humidity) details. Figure 2: Example Model Card for a smile detector trained and evaluated on the CelebA dataset.

## **Example**

Gender	Age Group	False Positive Rate	False Negative Rate	False Discovery Rate	False Omission Rate
Male	Old	0	0	0	0
Male	Young	0.18	0	0.25	0
Female	Old	0.20	0.20	0.33	0.50
Female	Young	0	0.06	0	0.08