| **Machine Learning, Vocals, and Parkinson’s Disease** | |
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| Organization | Name of organization |
| Organization Description | Mission of Organization |
| Project Type | Data Science |
| Project Description | The goal of this project is to use vocal data from patients with and without Parkinson's Disease (PD) to classify whether a person has or does not have PD with above an 80% accuracy.  The current way that PD is diagnosed is through a neurologist. The neurologist will make the decision that a person has PD based on their medical history and symptoms. The neurologist may also try to rule out other diseases through an MRI, blood test, and/or DaTscan. They also may try to give them a PD medication and if it helps, it will help to convince that they have PD. No specific test is available which can lead to a wrong diagnosis. By being able to diagnose PD through other methods such as a person’s vocals, the neurologist will be more accurately able to diagnose PD. As PD progresses, the muscle of the vocal cord becomes thinner and less taught and changes the person’s voice as well as their intelligibility which is a change that could hopefully be noticed in the early stages of PD to help with diagnosis.  This model would be important to both the people trying to get diagnosed as well as the doctors trying to diagnose them. This diagnosis provides the doctor with more certainty a patient has PD which can ensure they can get treated properly. If a doctor is not sure enough, they may say its something else and mistreat you allowing the disease to progress enough that delaying progression isn’t possible. This method will only be able to function as a tool like any of the other tools mentioned above to help convince a neurologist that a patient does or doesn’t have PD. Since it would be combined with other tools, it wouldn’t have for sure effect a doctors decision to diagnose a patient, so it would be unlikely to be able to be misused and false positives or false negatives wouldn’t have a definite affect. Also, when a doctor diagnoses PD, they tell their patients a percentage of uncertainty since there is no definite way to diagnose, so the uncertainty of the algorithm would be included in the diagnosis. |
| Data Sets & Sources | https://archive.ics.uci.edu/ml/datasets/parkinsons |
| Suggested Steps | * Collect the data from the above source(s) * Clean/format the data * Display the ratios of PD vs Healthy Controls (HC) * Display each of the attributes and color by who does and doesn’t have PD (Discover if there is a visual difference) * Display the gender and age separation between HC and PD to see if there is any bias * Normalize the data * Run the following algorithms on the data (could add more if most have bad performance):   + Random Forest   + Logistic regression   + SVM   + Naive Bayes classifier   + Neural Network   + K-nearest neighbor   + PCA   + AdaBoost * Tweak parameters of each as necessary to achieve the best results |
| Questions to be answered in Analysis | * Is it possible to predict PD from vocals with machine learning? * What algorithm works best to predict Parkinson’s Disease (PD) vs the healthy controls? * How accurate can you get without overfitting? |
| Ideal Output + Final Deliverable | The ideal output would be a presentation on the data visualized, the final algorithm used, why that algorithm is the best, and why the results of this project are important. |
| Additional Information | The dataset was created by Max Little from the University of Oxford. The National Centre for Voice and Speech, Denver, Colorado recorded the speech signals. Each patient was recorded approximately 6 times and the following are the features that are shown in the data: Average vocal fundamental frequency, Maximum vocal fundamental frequency, Minimum vocal fundamental frequency, measures of variation in fundamental frequency (MDVP:Jitter(%), MDVP:Jitter(Abs), MDVP:RAP, MDVP:PPQ, Jitter:DDP), measures of variation in amplitude (MDVP:Shimmer, MDVP:Shimmer(dB), Shimmer:APQ3, Shimmer:APQ5, MDVP:APQ, Shimmer:DDA), two measures of ration of nois to tonal components in the voice, two nonlinear dynamical complexity measures, a signal fractal scaling exponent, nonlinear measures of fundamental frequency variation (spread1,spread2,PPE), and whether a patient has or does not have Parkinson’s.  This dataset has two papers connected to it which contain a bit more information on the dataset. The first is named [Suitability of dysphonia measurements for telemonitoring of Parkinson's disease](https://www.ncbi.nlm.nih.gov/pmc/articles/PMC3051371/). The other is named [Exploiting Nonlinear Recurrence and Fractal Scaling Properties for Voice Disorder Detection](https://biomedical-engineering-online.biomedcentral.com/articles/10.1186/1475-925X-6-23). In the first paper, the specifics of the dataset can be found.  Some limitations of this dataset is that it is only made from 31 male and female subjects, though there are much more data points because there are 6 recordings for each. 23 of those have PDso the set definitely leans towards those with PD. Another thing to note is that the subjects range from 46 to 85 so I need to look into whether those with and without parkinson’s lean towards a certain age group which could affect the predictability of the algorithm. Graphs of the age and sex will have to be included in the final presentation. Another limitation is that we can’t compare parkinson’s to any other disease to see if the algorithm can specifically pick out parkinson’s or if it is just finding those with a disease that affects the voice. |