

COVID-19:

Which Factors Impact Mortality?

By Nick Wawee, Connor MacMillan, Kshitij Saxena,
& Grant Ferrell

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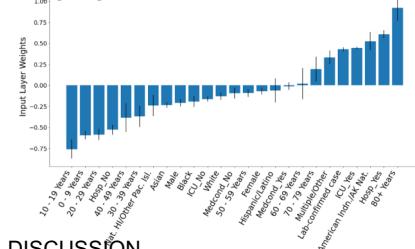
INTRO

- COVID-19 is a deadly pandemic.
 Which demographic factors increase that deadliness
- Factors that increase mortality should show up in fatal cases

METHODS

1. Use the CDC Public Use data
2. Focus only on relevant inputs. Final data shape: (328,977 x 8)
3. Find correlations
4. Use Logistic Regression with 5 K-Folds.
5. Use GridSearchCV and MLPClassifier with 5 K-Folds
6. Compare each model's metrics
7. Use weights and coefficients to find each feature's impact

RESULTS



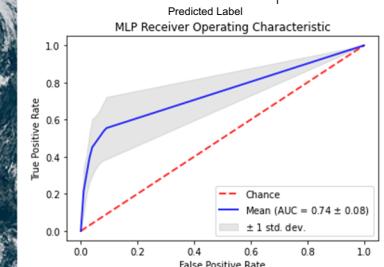
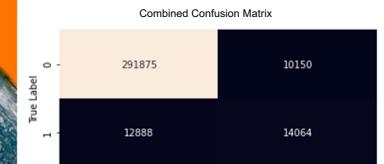
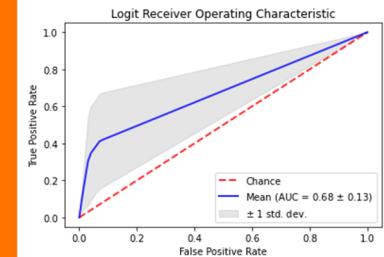
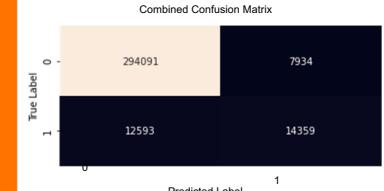
DISCUSSION

Both models performed similarly, but the MLP was more consistent. The closer the weight is to 0, the less important to mortality it is. Being 80+ has the highest impact, and some races/ethnicities are more vulnerable.

Age has a higher impact on the

mortality rate of COVID-19 than

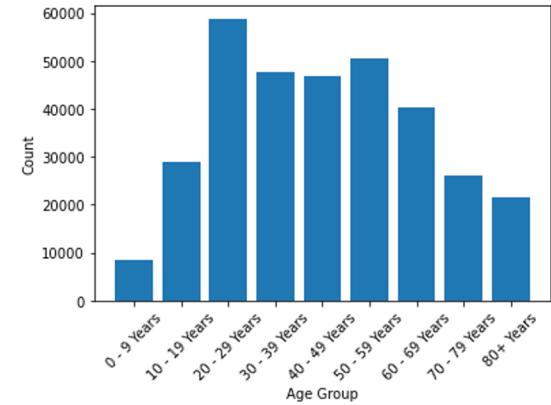
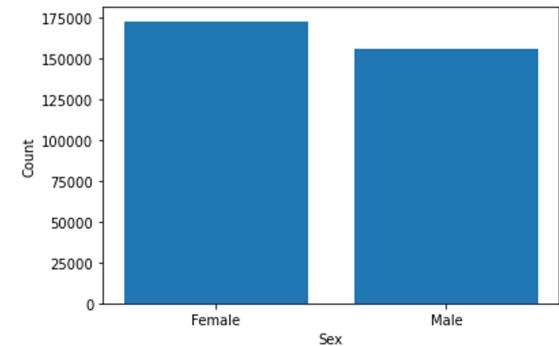
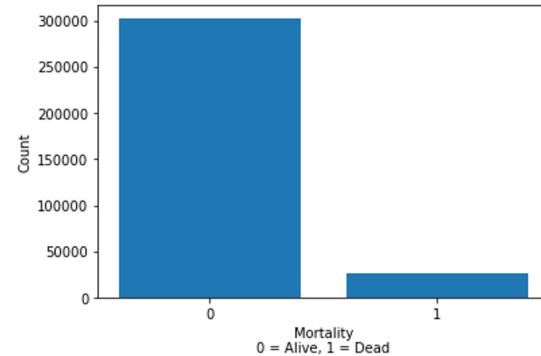
pre-existing medical conditions

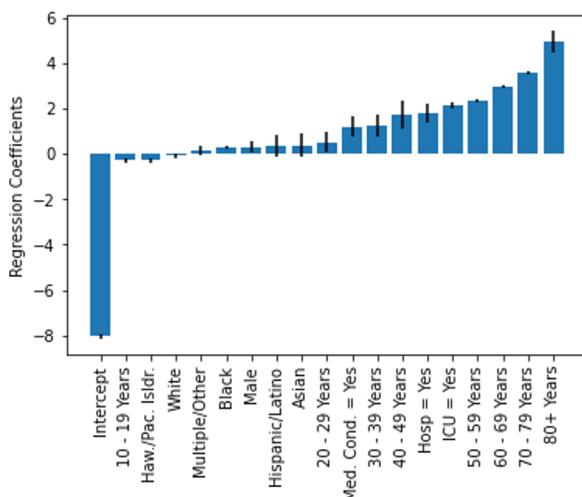
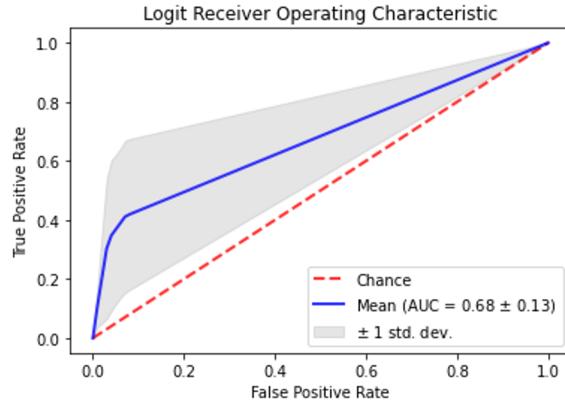


Introduction

- Covid-19 Case Dataset from the CDC
- We removed rows with missing and unknown values
- What Raises Mortality Rate?
- Mortality Calculator?
- ethnicity, sex, med-condition, and age

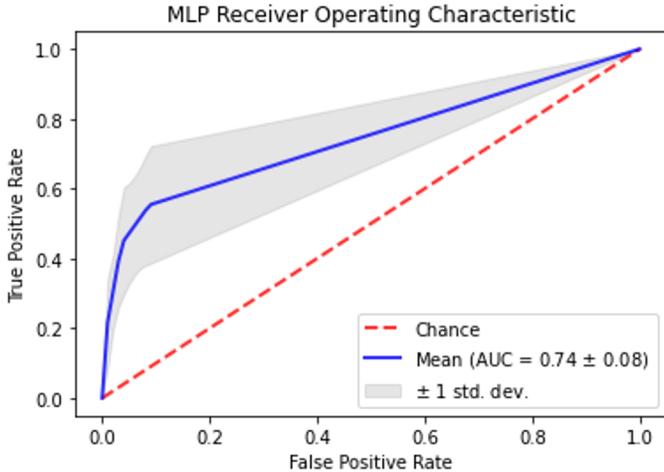
Age 23	Temperature 100 °F	Heart Rate 95
Gender Male	Do you have the value for SpO ₂ or SaO ₂ ? No	Do you have shortness of breath? No
Comorbidities Select...		
The mortality risk score is: 3%		





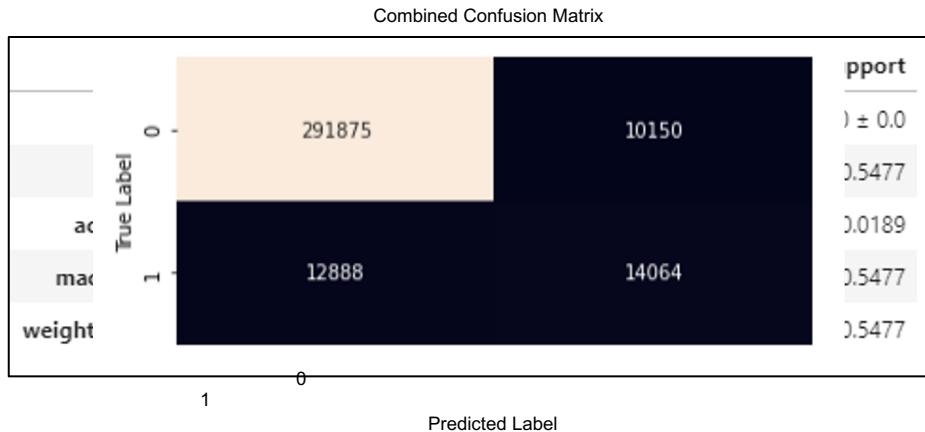
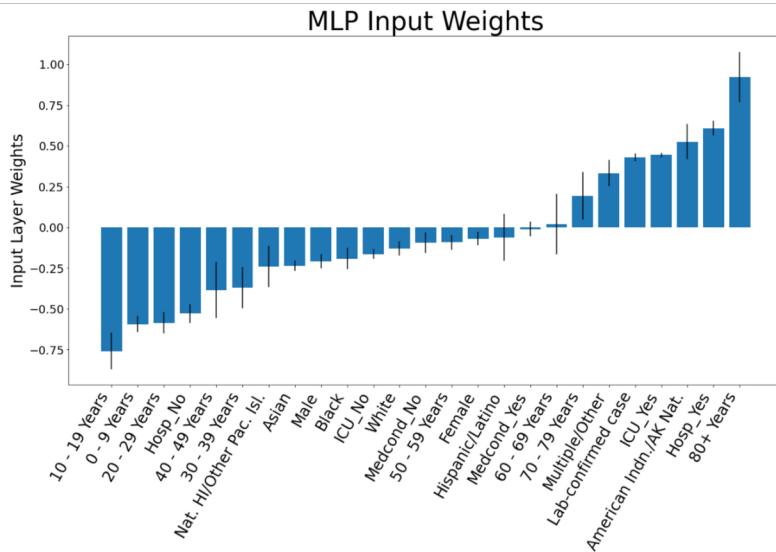
● Logistic Regression

- Probabilities calculated using logit model \Rightarrow dead if $p \geq 0.5$
- K=5 Folds, ~330,000 records
- Key Classification Metrics:
 - $F1 = 0.683 \pm 0.132$,
 - $AUC = 0.676 \pm 0.149$
- Odds of mortality changes:
 - 0-9 yrs \Rightarrow 80+ years : **143**
 - ICU? \Rightarrow **8.59**
 - Hospitalized? \Rightarrow **6.21**
 - Medical Condition? \Rightarrow **3.36**
 - Race Comparisons
 - American Indian/Alaskan \Rightarrow Asian: **1.47**
 - Female \Rightarrow Male: **1.39**



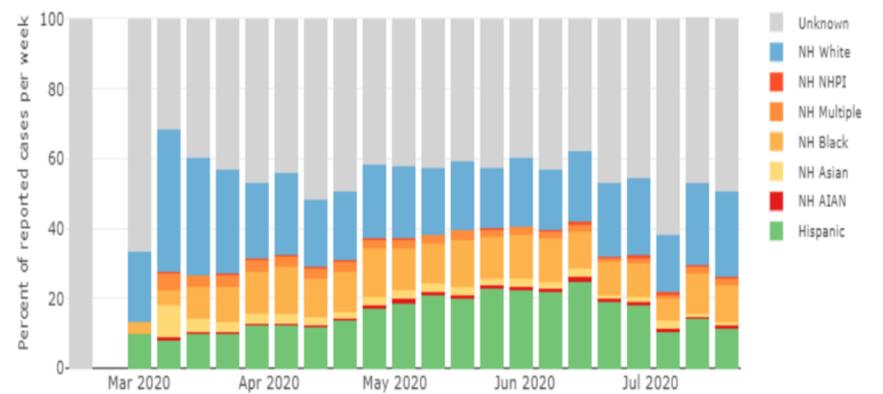
- **MLP Classifier**

- GridSearchCV used to find optimal parameters
- Stratified K-Fold for Cross-Validation
- Input Layer Weights for Feature Impact

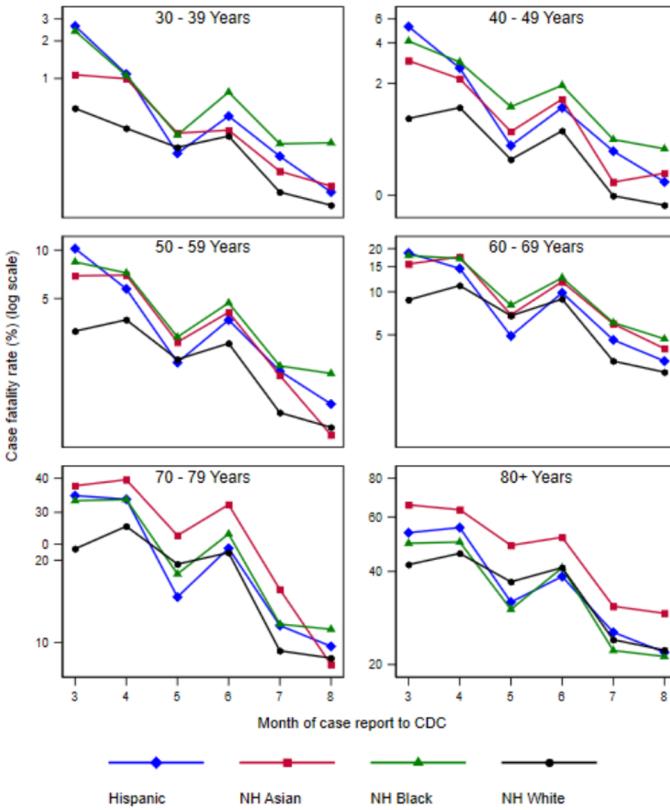


Background

- Many articles also analyze the same dataset from CDC, results are mostly consistent with ours
- 80+ year old had highest case fatality
- Contrary results to many studies for different ethnic groups



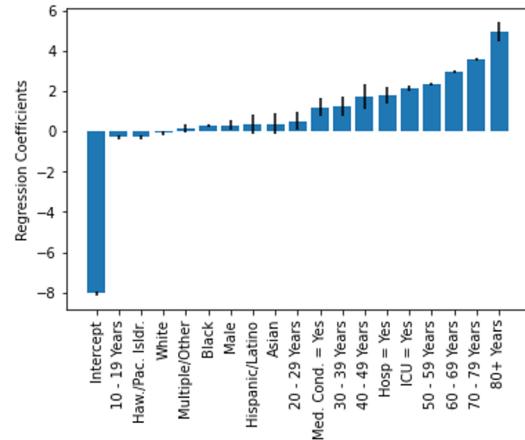
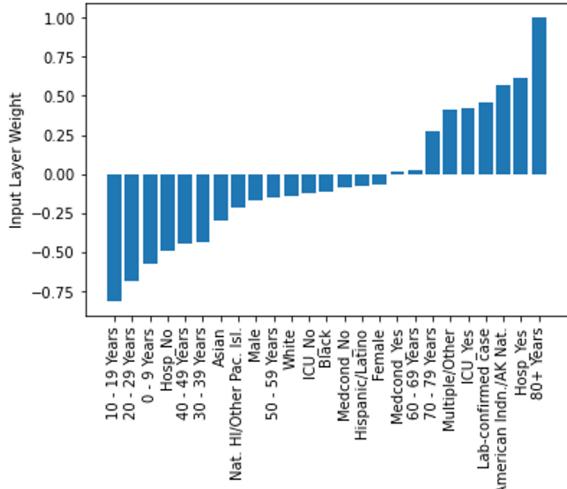
[2] Distribution of Covid-19 cases in the U.S.



[1] Age adjusted data showing case fatality for certain age groups

Conclusion

- Case surveillance data from CDC was analyzed
 - Data sized from 1,048,576 to just 328,977 rows
- Logistic regression and MLP Classifier considered but they didn't agree with every single feature
- -Age is the biggest factor in for predicting low and high chance of death
- -Another interesting find is that males have lower mortality than females in MLP model, but higher mortality in logit
- - Being admitted to the hospital and ICU both increased your chances of dying.



Any
Questions?

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