



# Predicting Fentanyl Presence In Accidental Drug Overdose Deaths In Connecticut, USA

DSI-23: Capstone Project

Ray Tan

# Outline



**1**

**Introduction**

**2**

**Data  
Source**

**3**

**Exploration &  
Visualisation**

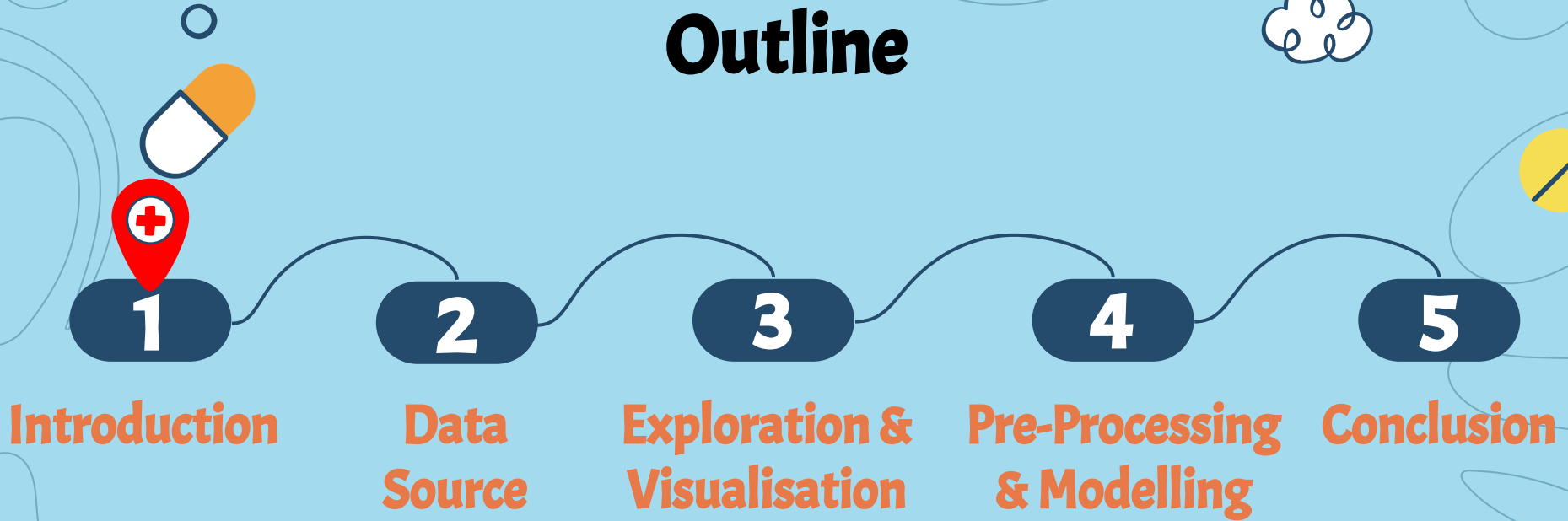
**4**

**Pre-Processing  
& Modelling**

**5**

**Conclusion**

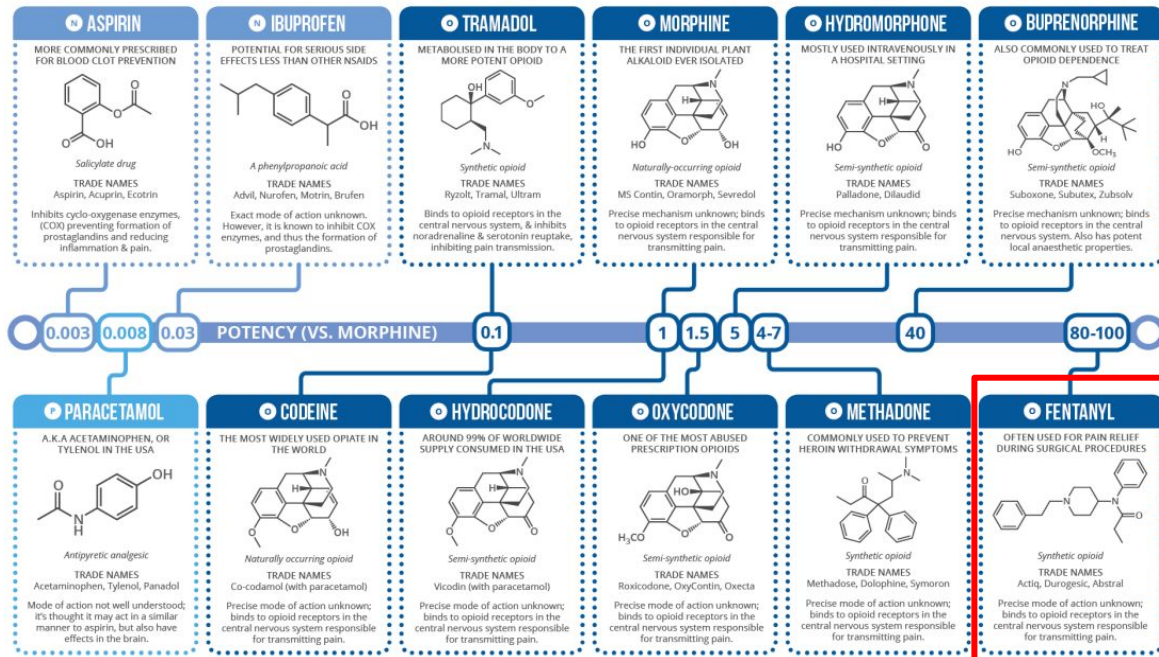
# Outline



# Background

## A BRIEF GUIDE TO SELECTED COMMON PAINKILLERS

THERE ARE TWO MAIN CLASSES OF PAINKILLERS - PARACETAMOL IS AN EXCEPTION. **Key:** **N** NON-STEROIDAL ANTI-INFLAMMATORY DRUGS **P** PARACETAMOL **O** OPIOID ANALGESICS



**Note:** Potency values are for oral administration. Numeric measures of potency are variable; the figures given are merely general approximations, and can be affected by a number of factors.



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### Opioids

#### Opiates

Opium  
Morphine  
Codeine

#### Semi-Synthetic

Heroin  
Hydrocodone  
Hydromorphone  
Oxycodone  
Oxymorphone  
Buprenorphine

#### Synthetic

**Fentanyl**  
Methadone  
Tramadol

## OPIOIDS FROM STRONGEST TO WEAK

### • Fentanyl

- Buprenorphine
- Levorphanol
- Oxymorphone
- Hydromorphone
- Phenazocine
- Methadone
- Oxycodone
- Morphine
- Hydrocodone
- Tapentadol
- Dihydrocodeine
- Tramadol
- Codeine

POTENT

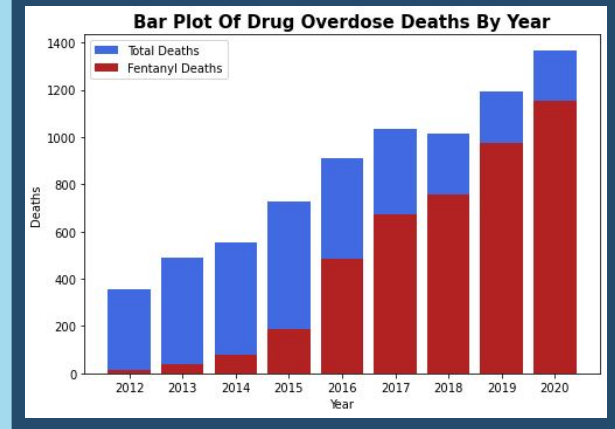
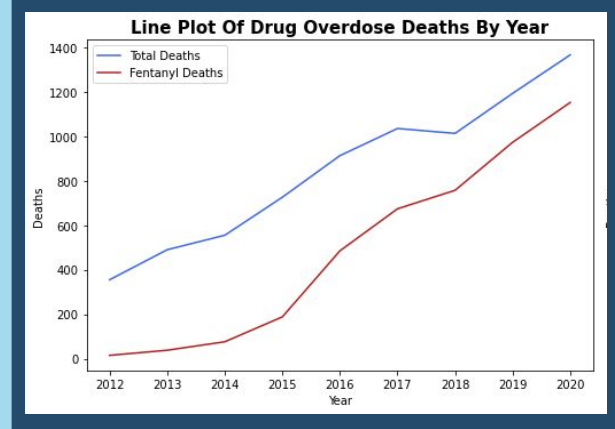
WEAK



<https://anrclinic.com/>

# Background

- 2013 marks the **year of emergence** of fentanyl in the illicit drug market
- Fentanyl-related overdose deaths have **skyrocketed in recent years**
- Connecticut has **surpassed** the national death rate for fentanyl-related overdoses since 2013
- 2020 alone has been a **record-breaking year** for fentanyl-related overdose deaths in Connecticut

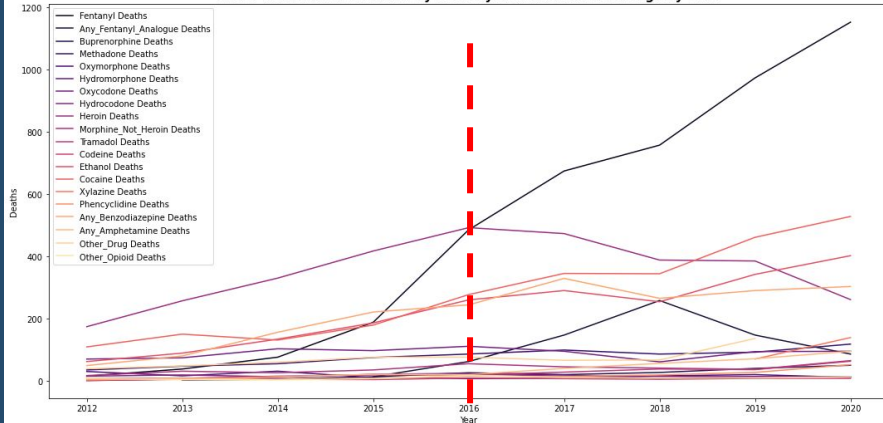


*The number of fentanyl deaths has been increasing much faster than the number of total deaths.*

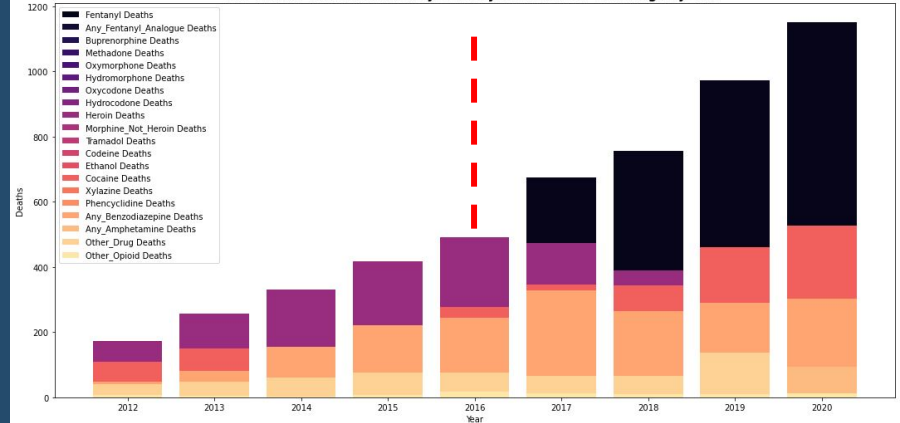
# Background

- Fentanyl has been implicated in **more overdose deaths** in Connecticut at present as compared to other drugs
- Fentanyl is now the **number one drug** found in overdose deaths in Connecticut

Line Plot Of Deaths Caused By Fentanyl And Rest Of The Drugs By Year



Bar Plot Of Deaths Caused By Fentanyl And Rest Of The Drugs By Year



*Pre-2016, heroin was responsible for the most number of deaths each year. Post-2016, fentanyl surpassed heroin to be the number one cause of deaths each year.*

# Problem Statement

- Accidental drug overdose death problem is expected to **continue to worsen** in the coming year
- Fentanyl is the **dominant drug** seen in overdose deaths today
- There is an urgent need for **effective harm-reduction strategies** to tackle the escalating fentanyl crisis and stop deaths from occurring
- As a start, it would be beneficial to know what are some of the **main factors or drivers** causing the surge in fentanyl-related overdose deaths in recent years

# Target Audience

## Connecticut State Officials

### Better Understand



Circumstances surrounding  
fentanyl-related overdose  
deaths

### Better Recognise



Top features that are most  
important in explaining fentanyl  
presence in overdose deaths



# Objectives

- Develop several **classification models**
- Evaluate their individual performance based on two metrics: **Accuracy** and **Area Under Curve**
- Choose the **best-performing hyperparameter-tuned model** that achieves an accuracy closest to 1 and an area under curve closest to 1
- Identify the **top features** that are **most important** in explaining fentanyl presence in overdose deaths
- Guide Connecticut state officials on the allocation of **scarce resources** to **key areas** that influence fentanyl presence in overdose deaths

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# Data Source

## About this Dataset

Source: <https://data.ct.gov/>

Locale: **Connecticut**

Period: **2012-2020**

## What is in this Dataset?

Rows	Columns	Each row is a
<b>7,679</b>	<b>42</b>	<b>Death</b>

## Columns in this Dataset

- Age
- Sex
- Race
- Location of Death
- Cause of Death
- Other Significant Conditions
- Overdosed Drugs (e.g. Fentanyl)

## Engineered Columns

- Covid Pandemic
- Number of Drugs
- Number of Conditions

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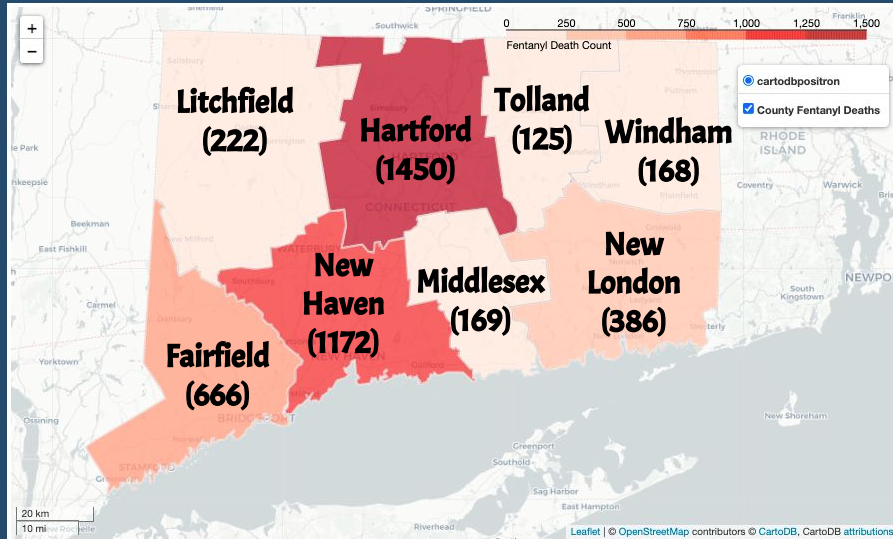
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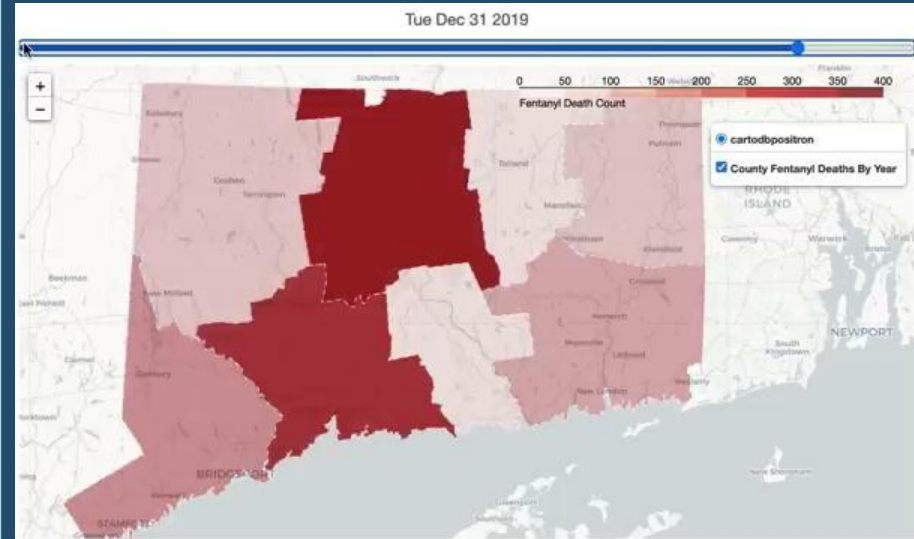
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# Choropleth Maps Of Fentanyl Deaths

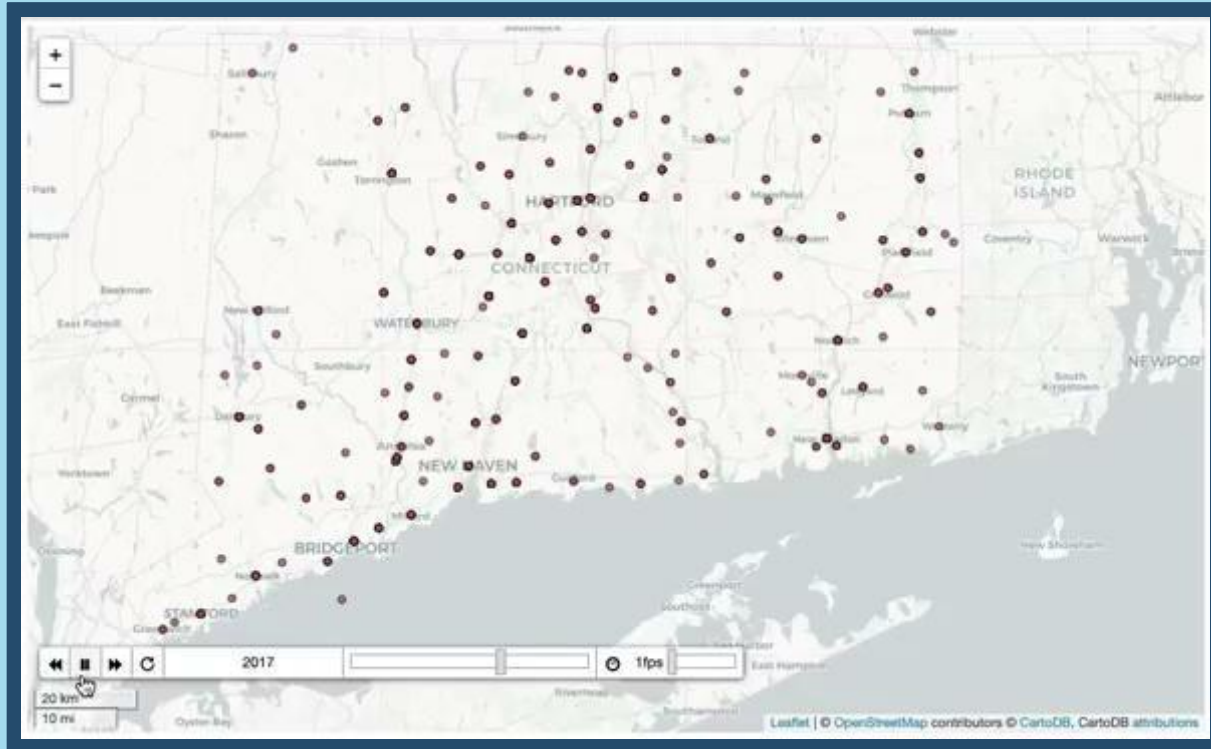


*From 2012 to 2020, Hartford County recorded the highest number of fentanyl deaths at 1450 whereas Tolland County recorded the lowest at 125.*



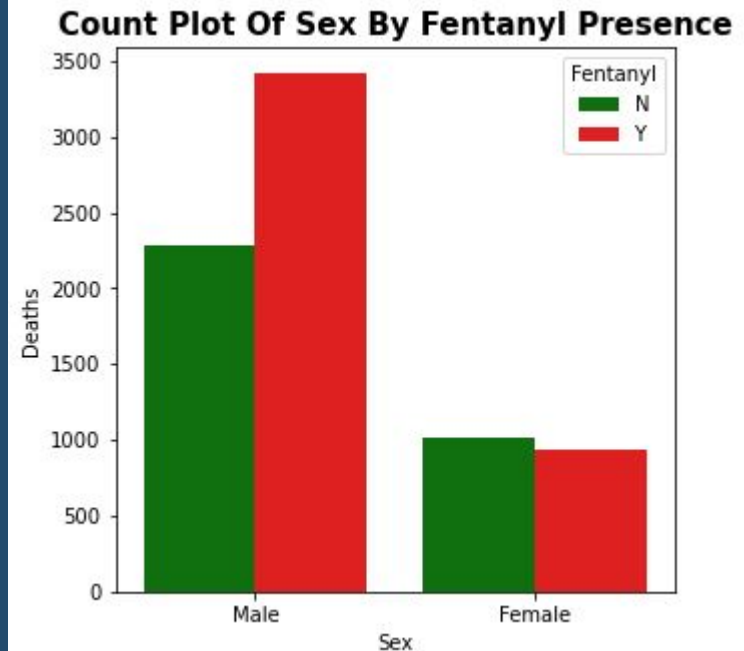
*From 2012 to 2020, all counties have been experiencing a rising trend in the number of fentanyl deaths.*

# Point Map Of Fentanyl Deaths

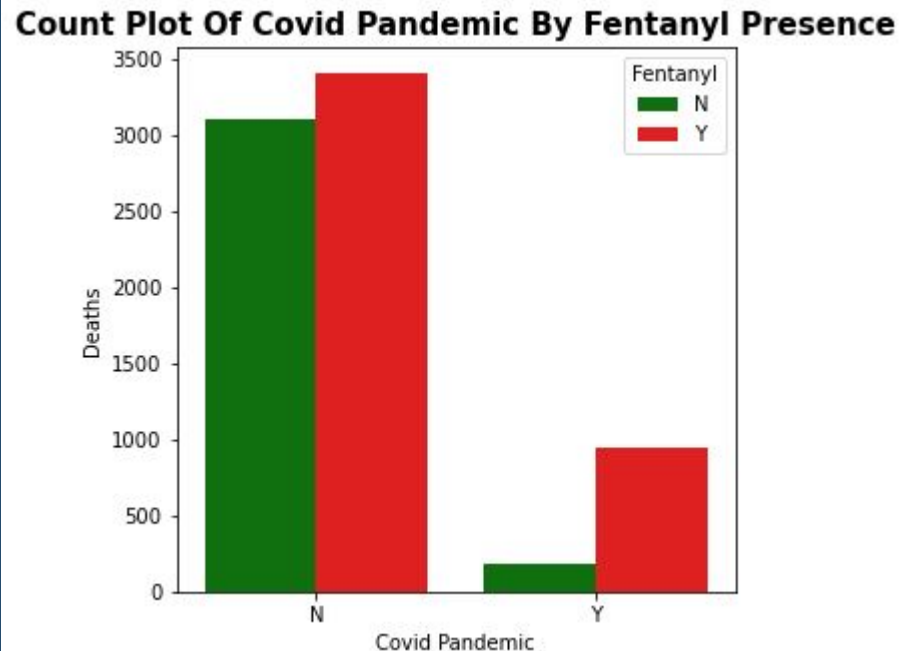


*From 2012 to 2020, the number of cities recording at least 1 fentanyl death each year has been on the rise.*

# Plots Of Sex & Covid Pandemic

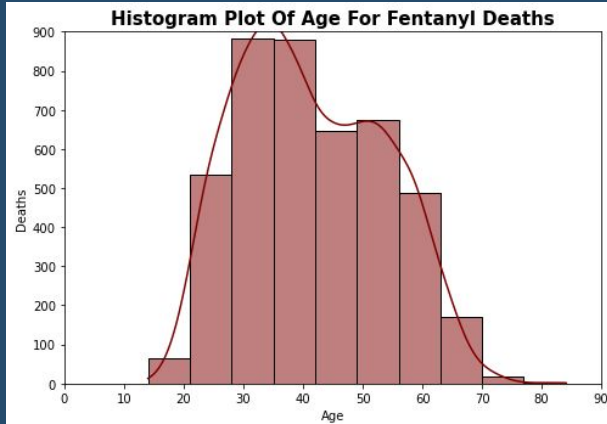
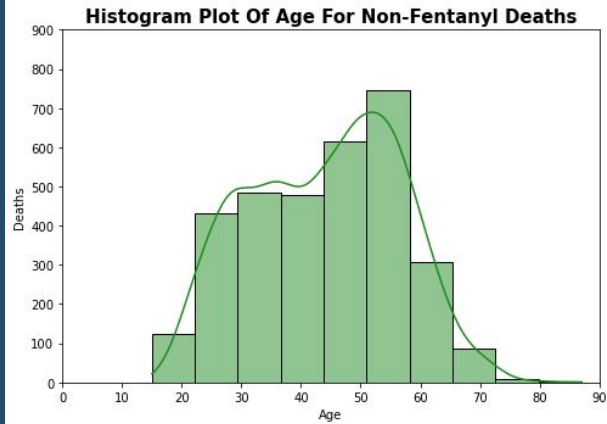


*In females, the number of fentanyl deaths and non-fentanyl deaths are comparable. In males, the number of fentanyl deaths far outnumbers that of non-fentanyl deaths.*

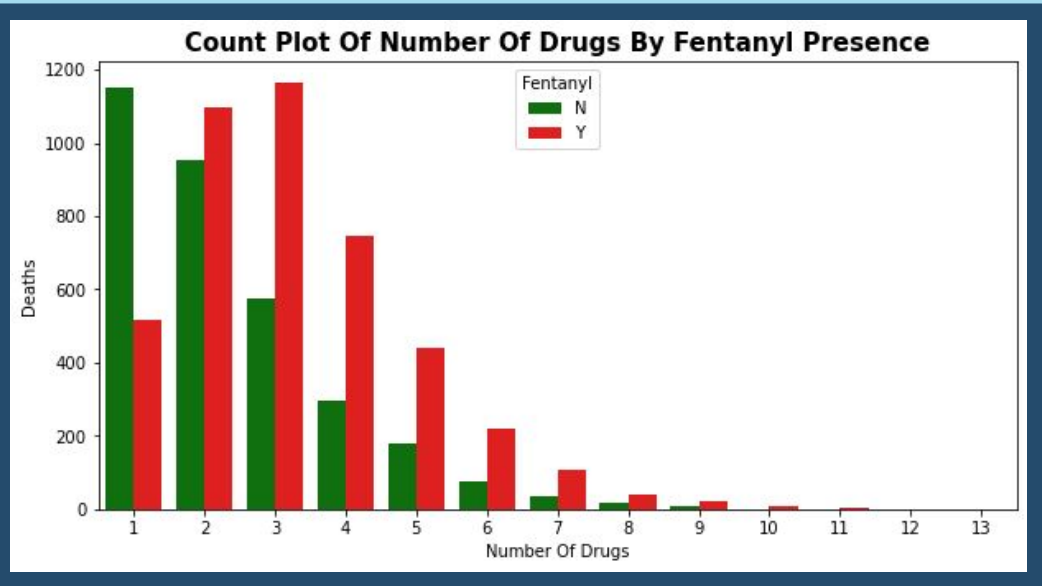


*Before Covid-19 was declared a pandemic, there were slightly more fentanyl deaths than non-fentanyl deaths. After Covid-19 was declared a pandemic, there were significantly more fentanyl deaths than non-fentanyl deaths.*

# Plots Of Age & Number Of Drugs



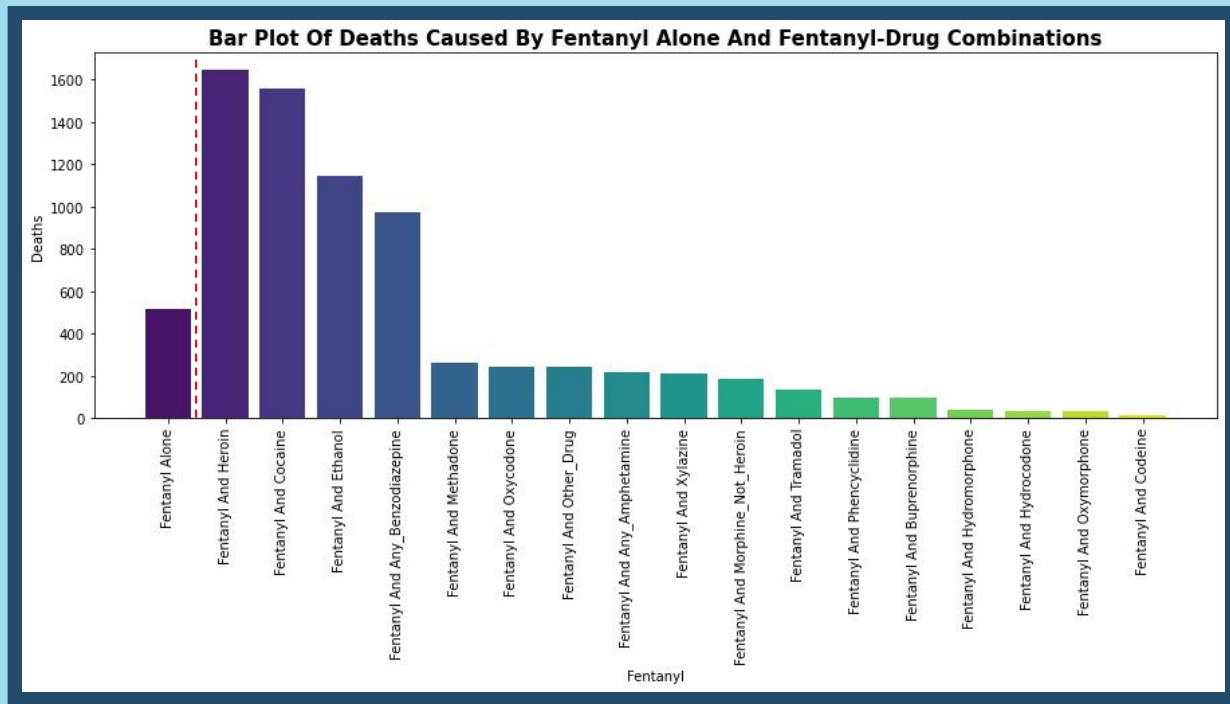
*In non-fentanyl deaths, the distribution of age has a peak number of deaths at 50-60 years. In fentanyl deaths, the distribution of age has a peak number of deaths at 30-40 years.*



*In non-fentanyl deaths, the highest number of deaths is seen among single drug users. In fentanyl deaths, the highest number of deaths is seen among triple drug users, followed by double drug users, and then single drug users.*



# Plot Of Fentanyl Alone Vs Fentanyl-Drug Combinations



*Fentanyl alone has been responsible for 515 deaths. The following drugs with fentanyl - heroin, cocaine, ethanol, or any benzodiazepine - have each resulted in more deaths than fentanyl alone. The most lethal duo is a fentanyl-heroin combination which has been responsible for 1644 deaths.*

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# Workflow

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Pre-Processing  
& Modelling

A

Set Up Environment

B

Compare Models

C

Tune Models

D

Evaluate Models

# Workflow

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Pre-Processing  
& Modelling



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Set Up Environment

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Compare Models

C

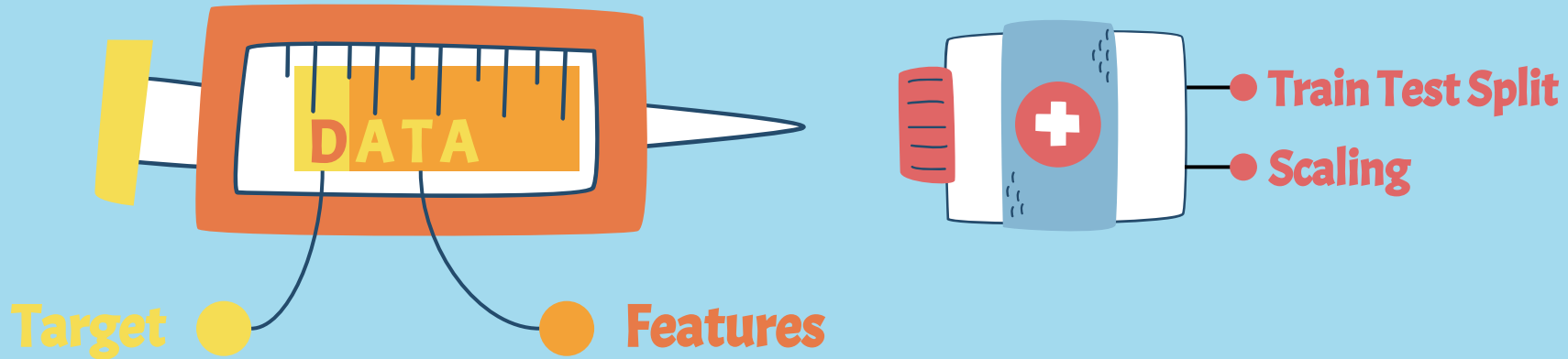
Tune Models

D

Evaluate Models

# Set Up Environment

## Pre-Processing Pipeline



# Workflow

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& Modelling



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# Compare Models

14

Classification Models  
Compared With Default  
Hyperparameters

3

Models Shortlisted For  
Hyperparameter Tuning

- Light Gradient Boosting Machine Classifier
- Gradient Boosting Classifier
- Extreme Gradient Boosting Classifier

Cross Validation on Train Dataset

TOP3	Model	Accuracy	AUC
lightgbm	Light Gradient Boosting Machine	0.7820	0.8479
gbc	Gradient Boosting Classifier	0.7786	0.8429
xgboost	Extreme Gradient Boosting	0.7745	0.8402
rf	Random Forest Classifier	0.7521	0.8109
et	Extra Trees Classifier	0.7311	0.7745
lr	Logistic Regression	0.7274	0.7818
ridge	Ridge Classifier	0.7246	0.0000
lda	Linear Discriminant Analysis	0.7237	0.7788
ada	Ada Boost Classifier	0.7186	0.7855
svm	SVM - Linear Kernel	0.7156	0.0000
knn	K Neighbors Classifier	0.7037	0.7490
dt	Decision Tree Classifier	0.7005	0.7012
nb	Naive Bayes	0.6026	0.6807
qda	Quadratic Discriminant Analysis	0.5293	0.4944

Test Dataset

TOP3	Model	Accuracy	AUC
lightgbm	Light Gradient Boosting Machine	0.7899	0.8538
gbc	Gradient Boosting Classifier	0.7847	0.8456
xgboost	Extreme Gradient Boosting	0.7781	0.8391
rf	Random Forest Classifier	0.7585	0.8176
lr	Logistic Regression	0.7328	0.7817
lda	Linear Discriminant Analysis	0.7328	0.7785
et	Extra Trees Classifier	0.7328	0.7782
ridge	Ridge Classifier	0.7323	0.7229
ada	Ada Boost Classifier	0.7280	0.7926
dt	Decision Tree Classifier	0.7110	0.7114
knn	K Neighbors Classifier	0.6922	0.7382
svm	SVM - Linear Kernel	0.6539	0.6763
nb	Naive Bayes	0.6046	0.6794
qda	Quadratic Discriminant Analysis	0.4651	0.4979

# Workflow

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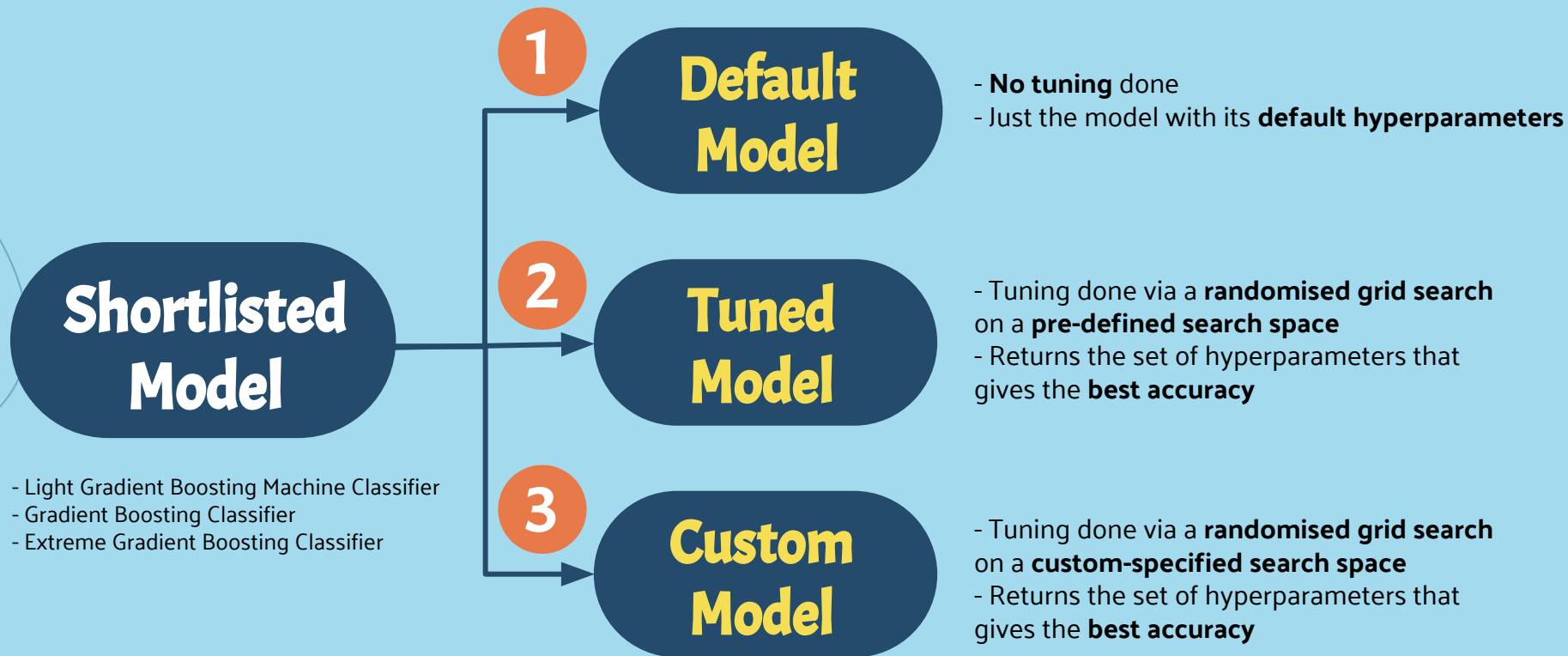
D

Evaluate Models





# Tune Models



# Workflow

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Compare Models

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Tune Models

D

Evaluate Models



# Evaluate Models:

## Light Gradient Boosting Machine Classifier

	Train CV Accuracy	Test Accuracy	Train CV AUC	Test AUC
--	-------------------	---------------	--------------	----------

Default LGBMC	0.7820	0.7899	0.8479	0.8538
------------------	--------	--------	--------	--------


Tuned LGBMC	0.7724	0.7746	0.8360	0.8411
----------------	--------	--------	--------	--------



Custom LGBMC	0.7928	0.7908	0.8533	0.8563
-----------------	--------	--------	--------	--------

# Evaluate Models:

## Gradient Boosting Classifier

	Train CV Accuracy	Test Accuracy	Train CV AUC	Test AUC
 Default GBC	0.7786	0.7847	0.8429	0.8456
Tuned GBC	0.7713	0.7781	0.8325	0.8420
Custom GBC	0.7799	0.7794	0.8422	0.8453

# Evaluate Models:

## Extreme Gradient Boosting Classifier

	Train CV Accuracy	Test Accuracy	Train CV AUC	Test AUC
--	-------------------	---------------	--------------	----------

Default XGBC	0.7745	0.7781	0.8402	0.8391
--------------	--------	--------	--------	--------


Tuned XGBC	0.7569	0.7677	0.8309	0.8363
------------	--------	--------	--------	--------



Custom XGBC	0.7930	0.7895	0.8538	0.8555
-------------	--------	--------	--------	--------

# Evaluate Models:

## Best Of Each

	Train CV Accuracy	Test Accuracy	Train CV AUC	Test AUC
 Custom LGBMC	0.7928	0.7908	0.8533	0.8563
Default GBC	0.7786	0.7847	0.8429	0.8456
Custom XGBC	0.7930	0.7895	0.8538	0.8555

# Chosen Model Vs Null Model

**0.7908**

Test Accuracy



**0.5699**

Baseline Accuracy

**0.8563**

Test AUC



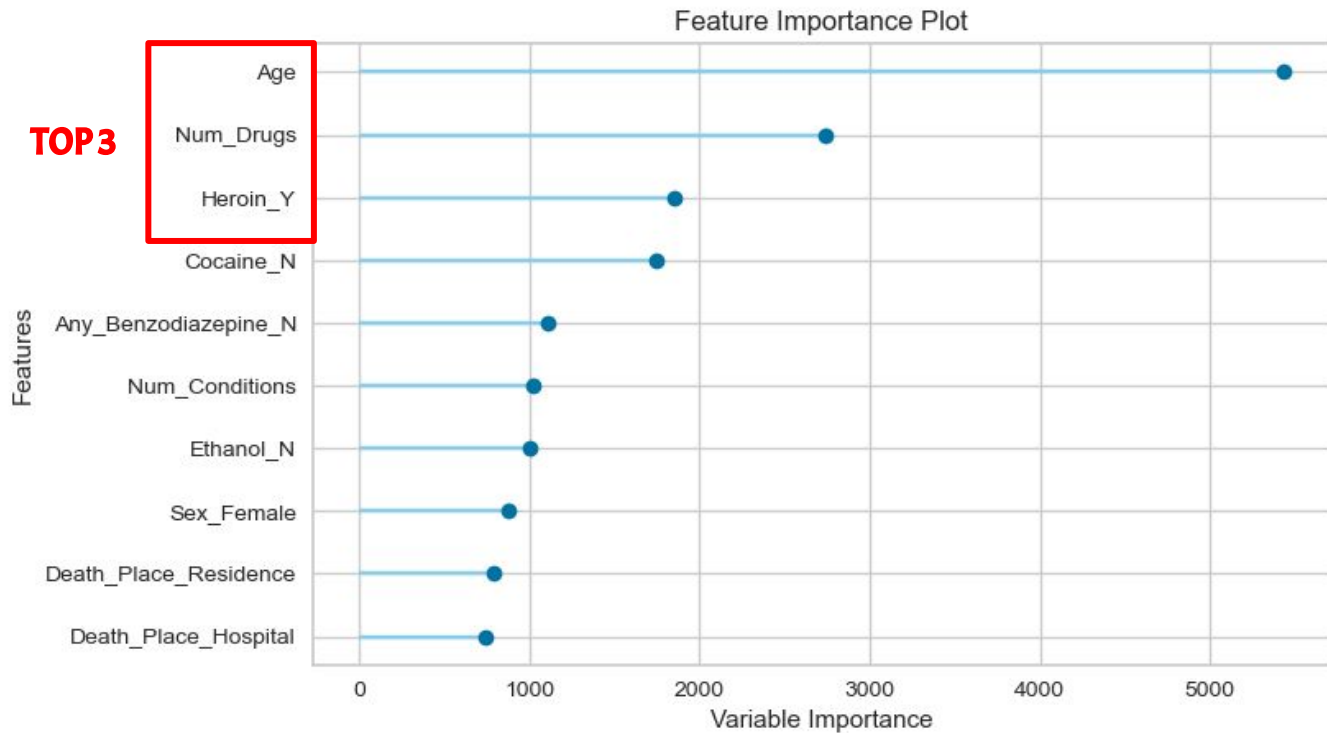
**0.5000**

Baseline AUC

**Custom  
LGBMC**

**Null  
Model**

# Feature Importances





# Recommendations

- Initiate **education campaigns** in schools and colleges to teach young kids and adults about the **dangers** of using drugs on the illicit drug market, especially on the **overdose risks** and **widespread availability of illegally manufactured fentanyl**
- Pass **stricter laws** that deal out **harsher penalties** to individuals involved in the **purchase and supply of several illicit drugs**, given the high likelihood of finding **illegally manufactured fentanyl laced into the supplies of other illicit drugs**
- Work with doctors to promote the **appropriate use of opioids for pain** to reduce irrational or inappropriate opioid prescribing and dispensing, with added measures for **higher-risk opioids such as fentanyl** that would involve **statewide monitoring of all prescribing and dispensing activities**

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# Conclusion

- Fentanyl crisis is a **complex perennial problem** that presents a major challenge for **public health policy**
- Requires a **multi-pronged approach** and a **concerted effort** to overcome successfully
- **Final chosen model**, a Custom Light Gradient Boosting Machine Classifier, was able to **accurately predict 79.08%** of accidental drug overdose deaths to have either no fentanyl present or fentanyl present
- Found the three **most important** features to be **age, number of drugs, and heroin presence** → To lead and direct the implementation of **harm-reduction strategies** aimed at **reducing fentanyl-related overdose deaths**

# Conclusion

- Next steps would involve extending it to **other states of the USA** or investigating the **presence of other drugs** commonly implicated in overdose deaths
- In the context of **Southeast Asia**, while **Singapore** is not embroiled in a drug crisis today, **Myanmar** is now facing a public health disaster as more and more of its young children are getting addicted to **methamphetamine**
- Future plans could involve applying it to Myanmar as a **starting point** for understanding what are some of the **main factors or drivers** causing the surge in addiction to methamphetamine in recent years





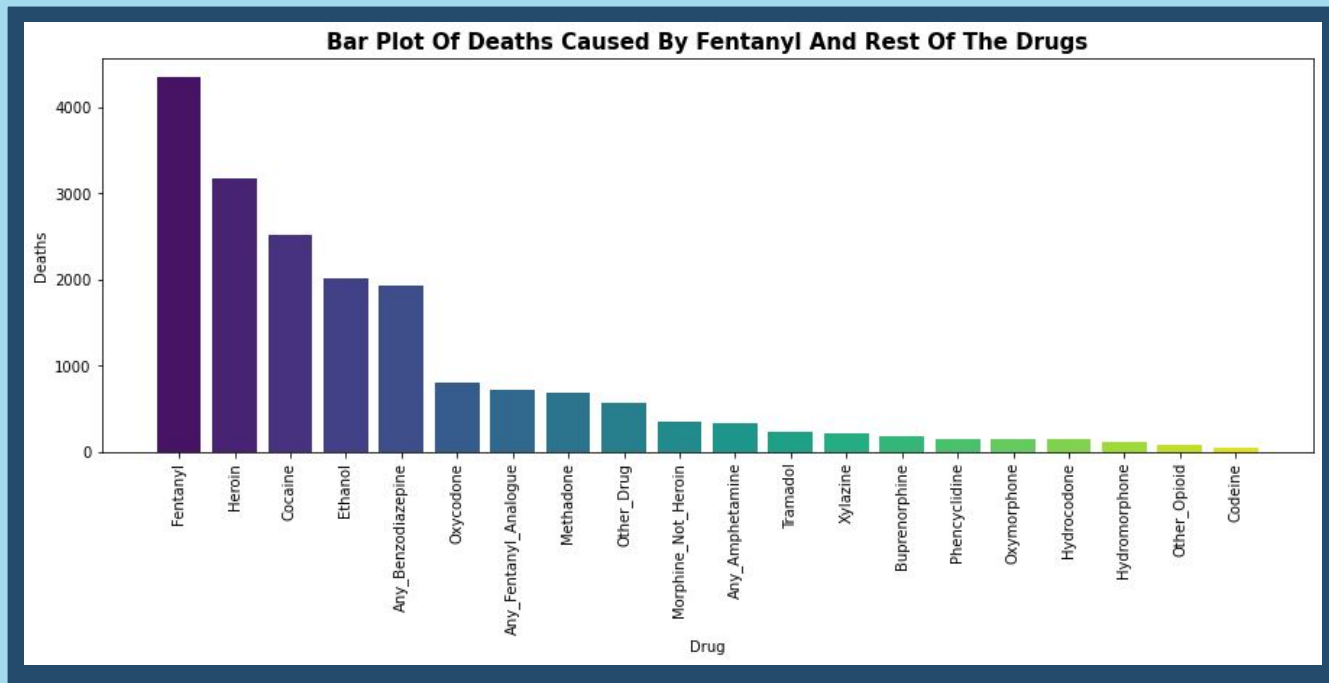
# Thank You

And Congratulations To Everyone 🎉

# Appendix



# Plot Of Fentanyl Vs Rest Of The Drugs



# Evaluate Models

## Acronyms

CV: Cross Validation

AUC: Area Under Curve

LGBMC: Light Gradient  
Boosting Machine  
Classifier

GBC: Gradient Boosting  
Classifier

XGBC: Extreme Gradient  
Boosting Classifier

## Metrics

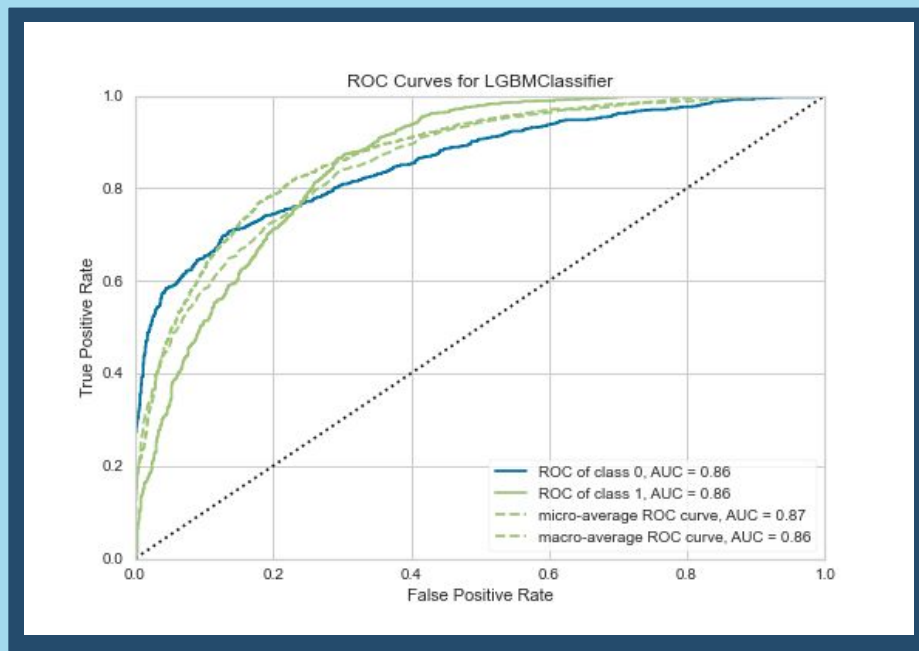
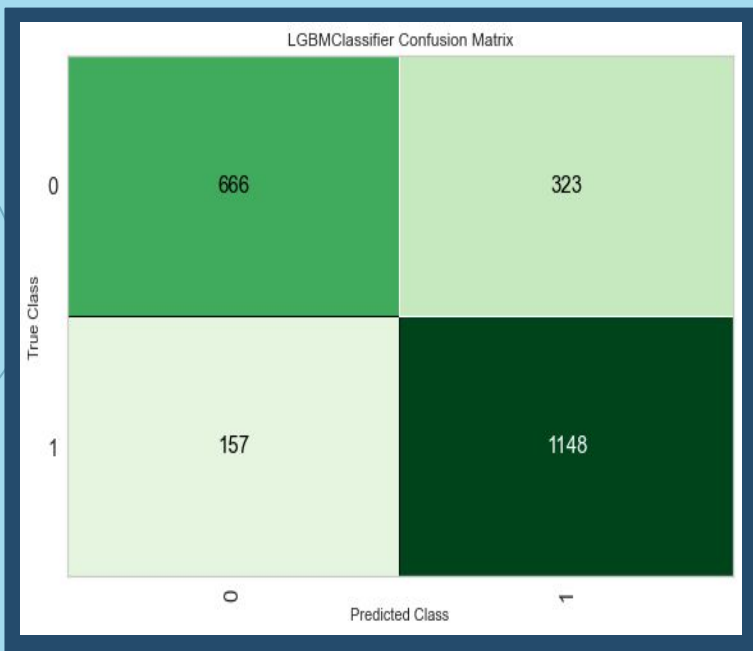
Accuracy is a metric that ranges from 0 to 1. The closer it is to 1, the better. It measures how many correct predictions the model made out of all the data points.

AUC is a metric that ranges from 0.5 to 1. The closer it is to 1, the better. It quantifies how well separated the underlying prediction distributions made by the model are.

No	Model	Train CV Accuracy	Test Accuracy	Accuracy Difference	Train CV AUC	Test AUC	AUC Difference
1	Default LGBMC	0.7820	0.7899	+0.0079	0.8479	0.8538	+0.0059
	Tuned LGBMC	0.7724	0.7746	+0.0022	0.8360	0.8411	+0.0051
	Custom LGBMC	0.7928	0.7908	-0.0020	0.8533	0.8563	+0.0030
2	Default GBC	0.7786	0.7847	+0.0061	0.8429	0.8456	+0.0027
	Tuned GBC	0.7713	0.7781	+0.0068	0.8325	0.8420	+0.0095
	Custom GBC	0.7799	0.7794	-0.0005	0.8422	0.8453	+0.0031
3	Default XGBC	0.7745	0.7781	+0.0036	0.8402	0.8391	-0.0011
	Tuned XGBC	0.7569	0.7677	+0.0108	0.8309	0.8363	+0.0054
	Custom XGBC	0.7930	0.7895	-0.0035	0.8538	0.8555	+0.0017



# Confusion Matrix & ROC Curve



# Model Inputs & All Feature Importances

	Data Type
Age	Numeric
Sex	Categorical
Race	Categorical
Death_County	Categorical
Death_Place	Categorical
Heroin	Categorical
Ethanol	Categorical
Cocaine	Categorical
Any_Benzodiazepine	Categorical
Covid_Pandemic	Categorical
Num_Drugs	Numeric
Num_Conditions	Numeric
Fentanyl	Label

