Industrial Fire Detection

Here, we will be using the dataset smoke_detection_iot.csv, downloaded from Kaggle. It was created by Stefan Blattmann in his project Real-time Smoke Detection with AI-based Sensor Fusion. We will be using it to explore what can be learned about the minimum information needed to determine if there is fire present. It contains over 62M rows of tested atmospheric conditions and wether or not fire was present.

In [73]:
```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
import itertools

from sklearn.model_selection import train_test_split
from sklearn.linear_model import LogisticRegression
from sklearn.metrics import recall_score, confusion_matrix
from sklearn.model_selection import cross_val_score, StratifiedKFold, GridSearchCV
from sklearn.compose import ColumnTransformer
from sklearn.ensemble import RandomForestClassifier
from sklearn.pipeline import Pipeline
from sklearn.preprocessing import MinMaxScaler
from sklearn.tree import DecisionTreeClassifier
```

In [74]:
```
# Load the dataset
df = pd.read_csv('data/smoke_detection_iot.csv')
df.head()
```

Out[74]:

	Unnamed: 0	UTC	Temperature[C]	Humidity[%]	TVOC[ppb]	eCO2[ppm]	Raw H2	Raw Ethanol
0	0	1654733331	20.000	57.36	0	400	12306	18520
1	1	1654733332	20.015	56.67	0	400	12345	18651
2	2	1654733333	20.029	55.96	0	400	12374	18764
3	3	1654733334	20.044	55.28	0	400	12390	18849
4	4	1654733335	20.059	54.69	0	400	12403	18921

Feature Description

- UTC : The time when experiment was performed.
- Temperature : Temperature of Surroundings. Measured in Celsius
- Humidity : The air humidity during the experiment.
- TVOC : Total Volatile Organic Compounds. Measured in ppb (parts per billion)
- eCo2 : CO2 equivalent concentration. Measured in ppm (parts per million)
- Raw H2 : The amount of Raw Hydrogen present in the surroundings.
- Raw Ethanol : The amount of Raw Ethanol present in the surroundings.
- Pressure : Air pressure. Measured in hPa
- PM1.0 : Paticulate matter of diameter less than 1.0 micrometer .
- PM2.5 : Paticulate matter of diameter less than 2.5 micrometer.
- NC0.5 : Concentration of particulate matter of diameter less than 0.5 micrometers.
- NC1.0 : Concentration of particulate matter of diameter less than 1.0 micrometers.
- NC2.5 : Concentration of particulate matter of diameter less than 2.5 micrometers.
- CNT : Simple Count.
- Fire Alarm : (Reality) If fire was present then value is 1 else it is 0.

In [75]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 62630 entries, 0 to 62629
Data columns (total 16 columns):
 #   Column          Non-Null Count  Dtype  
---  ------          --------------  -----  
 0   Unnamed: 0      62630 non-null  int64  
 1   UTC             62630 non-null  int64  
 2   Temperature[C]  62630 non-null  float64
 3   Humidity[%]     62630 non-null  float64
 4   TVOC[ppb]       62630 non-null  int64  
 5   eCO2[ppm]       62630 non-null  int64  
 6   Raw H2          62630 non-null  int64  
 7   Raw Ethanol     62630 non-null  int64  
 8   Pressure[hPa]   62630 non-null  float64
 9   PM1.0           62630 non-null  float64
 10  PM2.5           62630 non-null  float64
 11  NC0.5           62630 non-null  float64
 12  NC1.0           62630 non-null  float64
 13  NC2.5           62630 non-null  float64
 14  CNT             62630 non-null  int64  
 15  Fire Alarm      62630 non-null  int64  
dtypes: float64(8), int64(8)
memory usage: 7.6 MB
```

All numeric, no NaNs, great.

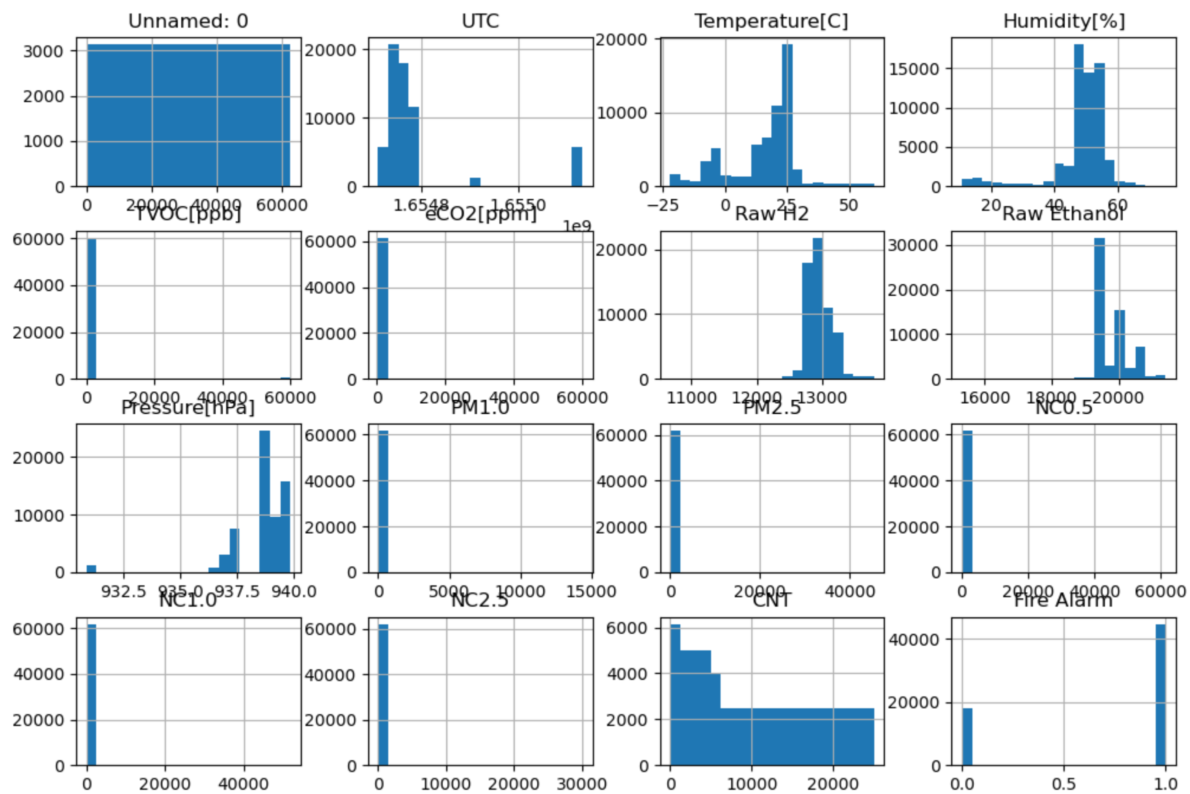
In [76]:
```
df.describe()
```

Out[76]:

	Unnamed: 0	UTC	Temperature[C]	Humidity[%]	TVOC[ppb]	eCO2[ppm]	
count	62630.000000	6.263000e+04	62630.000000	62630.000000	62630.000000	62630.000000	626
mean	31314.500000	1.654792e+09	15.970424	48.539499	1942.057528	670.021044	129
std	18079.868017	1.100025e+05	14.359576	8.865367	7811.589055	1905.885439	2
min	0.000000	1.654712e+09	-22.010000	10.740000	0.000000	400.000000	106
25%	15657.250000	1.654743e+09	10.994250	47.530000	130.000000	400.000000	128
50%	31314.500000	1.654762e+09	20.130000	50.150000	981.000000	400.000000	129
75%	46971.750000	1.654778e+09	25.409500	53.240000	1189.000000	438.000000	131
max	62629.000000	1.655130e+09	59.930000	75.200000	60000.000000	60000.000000	138

In [77]:

```
# Taking a look at distributions
df.hist(bins=20, figsize=(12, 8))
plt.show()
```



We will be modeling using atmospheric data to predict wether or not there is fire present, we will drop Unnamed, UTC, and CNT, as they have do not reflect atmospheric data.

In [78]:

```
# Drop unnecessary columns
df = df.drop(["Unnamed: 0", "UTC", "CNT"], axis=1)
```

Logically, all features will have a relationship with the target 'Fire Alarm'. Fire will affect the temperature, humidity, and pressure of the air around it. Fire will consume H2, ethanol, or VOCs. It will also create detectable VOCs in Class A fires which it will then consume. Fire will also create particulates, which is the basis of how smoke detectors work and how this dataset was created. We will create a baseline model and determine what features are most important to see what we can remove and still be reliable.

In [79]:
```
# Seperate independent and dependent data, then training and test sets, set random_
features1 = ['Temperature[C]', 'Humidity[%]', 'TVOC[ppb]', 'eCO2[ppm]', 'Raw H2', '
target1 = 'Fire Alarm'

X1 = df[features1]
y1 = df[target1]

X_train1, X_test1, y_train1, y_test1 = train_test_split(X1, y1, stratify=y1, test_s
```

In [80]:
```
# Start with a logistic regression
# We don't have to use pipelines, but we will just because I was using them while t

# Using MinMaxScaler due to a variety of distributions
numeric_transformer = Pipeline(steps=[('scaler', MinMaxScaler())])
preprocessor = ColumnTransformer(transformers=[('num', numeric_transformer, feature
lr = LogisticRegression(max_iter=1000)
pipelinelr = Pipeline(steps=[('preprocessor', preprocessor), ('classifier', lr)])
```

In [81]:
```
# Check accuracy, recall, and confusion matrix on test data

# Fit on train, predict on test
pipelinelr.fit(X_train1, y_train1)
y_pred1 = pipelinelr.predict(X_test1)

print(pipelinelr.score(X_test1, y_test1))
print(recall_score(y_test1, y_pred1))
print(confusion_matrix(y_test1, y_pred1))
```

```
0.8845601149608814
0.9572114847503073
[[2512 1063]
 [ 383 8568]]
```

We have a precision of 88.93%, meaning we have a false alarm rate of 11.07%, which is fine. However, we've missed 4.3% of actual fires. This is not acceptable. We are priotitizing recall because a false alarm is not desirable, but an unidentified fire could have dramatic consequences. We will try to improve this model by tuning hyperparameters.

In [82]:
```
# Setting hyperparameters and checking them via cross validation
param_grid = {'classifier__C': [ 0.001, 0.01, 0.1, 1, 10, 100, 1000, 10000], 'class
cv = StratifiedKFold(n_splits=5, shuffle=True, random_state=42)
grid_search = GridSearchCV(pipelinelr, param_grid=param_grid, cv=cv)
grid_search.fit(X_train1, y_train1)
```

```
c:\Users\Fagan\anaconda3\envs\learn-env4\lib\site-packages\sklearn\linear_model\_sa
g.py:350: ConvergenceWarning: The max_iter was reached which means the coef_ did no
t converge
  warnings.warn(
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g.py:350: ConvergenceWarning: The max_iter was reached which means the coef_ did no
```

```
t converge
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c:\Users\Fagan\anaconda3\envs\learn-env4\lib\site-packages\sklearn\linear_model\_sa
```

```
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t converge
  warnings.warn(
c:\Users\Fagan\anaconda3\envs\learn-env4\lib\site-packages\sklearn\model_selection\
_validation.py:378: FitFailedWarning:
40 fits failed out of a total of 240.
The score on these train-test partitions for these parameters will be set to nan.
If these failures are not expected, you can try to debug them by setting error_scor
e='raise'.

Below are more details about the failures:
--------------------------------------------------------------------------------
40 fits failed with the following error:
Traceback (most recent call last):
  File "c:\Users\Fagan\anaconda3\envs\learn-env4\lib\site-packages\sklearn\model_se
lection\_validation.py", line 686, in _fit_and_score
    estimator.fit(X_train, y_train, **fit_params)
  File "c:\Users\Fagan\anaconda3\envs\learn-env4\lib\site-packages\sklearn\pipelin
e.py", line 405, in fit
    self._final_estimator.fit(Xt, y, **fit_params_last_step)
  File "c:\Users\Fagan\anaconda3\envs\learn-env4\lib\site-packages\sklearn\linear_m
odel\_logistic.py", line 1162, in fit
    solver = _check_solver(self.solver, self.penalty, self.dual)
  File "c:\Users\Fagan\anaconda3\envs\learn-env4\lib\site-packages\sklearn\linear_m
odel\_logistic.py", line 54, in _check_solver
    raise ValueError(
ValueError: Solver lbfgs supports only 'l2' or 'none' penalties, got l1 penalty.

  warnings.warn(some_fits_failed_message, FitFailedWarning)
c:\Users\Fagan\anaconda3\envs\learn-env4\lib\site-packages\sklearn\model_selection\
_search.py:952: UserWarning: One or more of the test scores are non-finite: [
nan 0.71469344 0.71463356 0.7112406  0.70601145 0.7112406
        nan 0.87078874 0.86933177 0.79921766 0.80153286 0.79921766
        nan 0.88565779 0.88362199 0.86969102 0.87320373 0.86975089
        nan 0.89529775 0.89497842 0.88326273 0.88479957 0.88324277
        nan 0.89523787 0.89529774 0.89238383 0.89342168 0.89238382
        nan 0.89505825 0.89521791 0.89531771 0.89543746 0.89519795
        nan 0.89503829 0.8953177  0.89541749 0.89547737 0.89543745
        nan 0.89497841 0.8953177  0.89503829 0.89519795 0.89523787]
  warnings.warn(
```

Out[82]:

```
▸ GridSearchCV
▸ estimator: Pipeline
  ▸ preprocessor: ColumnTransformer
      ▸ num
      ▸ MinMaxScaler
  ▸ LogisticRegression
```

In [83]:
```
# Print the best hyperparameters
print(grid_search.best_params_)
print(grid_search.best_score_)

print(grid_search.score(X_test1, y_test1))

# Print the confusion matrix for the test data
y_pred1 = grid_search.predict(X_test1)
print(confusion_matrix(y_test1, y_pred1))

print(recall_score(y_test1, y_pred1))
```

```
{'classifier__C': 1000, 'classifier__penalty': 'l2', 'classifier__solver': 'libline
ar'}
0.8954773737626036
0.8937410186811432
[[2726  849]
 [ 482 8469]]
0.9461512680147469
```

That is worse from a false negative perspective. Let's try another model.

In [84]:
```
# Use a decision tree with default arguments, set random state for repeatablility

dt = DecisionTreeClassifier(random_state=42)
pipelinedt = Pipeline(steps=[('preprocessor', preprocessor), ('classifier', dt)])
pipelinedt.fit(X_train1, y_train1)

print(pipelinedt.score(X_test1, y_test1))
y_pred1 = pipelinedt.predict(X_test1)

print(confusion_matrix(y_test1, y_pred1))
```

```
1.0
[[3575    0]
 [   0 8951]]
```

Great, let's make sure it is not a one off result.

In [85]:
```
#Checking cross validation
cv = StratifiedKFold(n_splits=5, shuffle=True, random_state=42)
cv_scores = cross_val_score(pipelinedt, X_train1, y_train1, cv=cv)
print(cv_scores)
print(cv_scores.mean())
```

```
[0.99950105 0.99970063 0.99980042 0.99980042 0.9997006 ]
0.999700622704297
```

This works, as expected. We will go beyond a decision tree to a Random Forest for robustness.

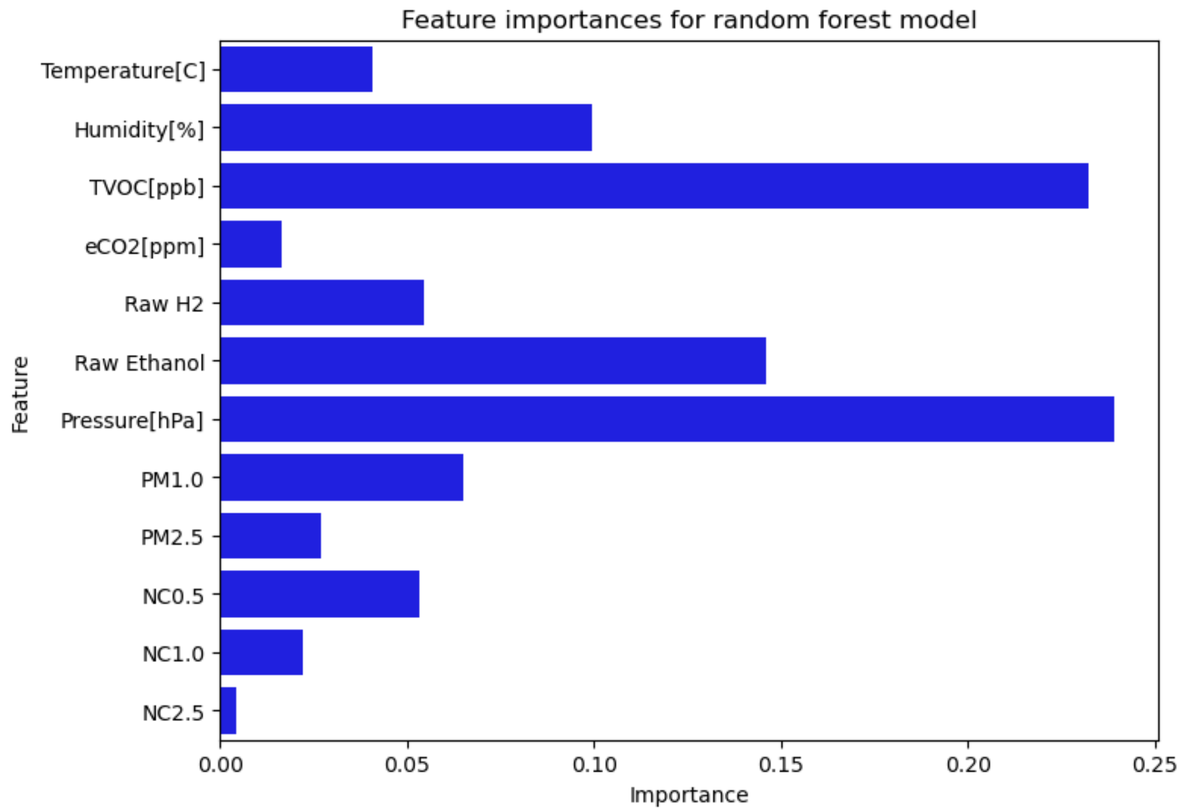
In [86]:
```
rfc = RandomForestClassifier(n_estimators=100)
pipelinerf = Pipeline(steps=[('preprocessor', preprocessor), ('classifier', rfc)])

# Cross Validate
cv = StratifiedKFold(n_splits=5, shuffle=True, random_state=42)
cv_scores = cross_val_score(pipelinerf, X_train1, y_train1, cv=cv)
print(cv_scores)
print(cv_scores.mean())

# Check accuracy
pipelinerf.fit(X_train1, y_train1)
print(pipelinerf.score(X_test1, y_test1))
print(confusion_matrix(y_test1, pipelinerf.predict(X_test1)))
```

```
[1.         0.99990021 0.99980042 0.99990021 0.9998004 ]
0.9998802474882588
1.0
[[3575    0]
 [   0 8951]]
```

In [87]:
```
feature_importances1 = pd.DataFrame({'Feature': features1, 'Importance': rfc.featur

print("Feature importances for random forest model:")
print(feature_importances1)
```

```
Feature importances for random forest model:
           Feature  Importance
0   Temperature[C]    0.040681
1      Humidity[%]    0.099575
2        TVOC[ppb]    0.232311
3        eCO2[ppm]    0.016444
4           Raw H2    0.054557
5      Raw Ethanol    0.145873
6    Pressure[hPa]    0.238974
7            PM1.0    0.065009
8            PM2.5    0.027001
9            NC0.5    0.053231
10           NC1.0    0.022168
11           NC2.5    0.004176
```

In [88]:
```
plt.figure(figsize=(8, 6))
sns.barplot(x="Importance", y="Feature", data=feature_importances1, color="b")
plt.title("Feature importances for random forest model")
plt.xlabel("Importance")
plt.ylabel("Feature")
plt.show()
```



We can see that we can use smoke detectors to detect fire. Let's see if we can do it without them.

In [101…

```
# No particulate information, train test split setting random state for repeatablil
features2 = ['Temperature[C]', 'TVOC[ppb]', 'eCO2[ppm]', 'Raw H2', 'Raw Ethanol', '
target2 = 'Fire Alarm'

X2 = df[features2]
y2 = df[target2]

X_train2, X_test2, y_train2, y_test2 = train_test_split(X2, y2, stratify=y2, test_s
```

In [102…

```
# Instantiate a new model
preprocessor2 = ColumnTransformer(transformers=[('num', numeric_transformer, featur
rfc2 = RandomForestClassifier(n_estimators=100)
pipelinerf2 = Pipeline(steps=[('preprocessor', preprocessor2), ('classifier', rfc2)
```

In [103…

```
# Cross Validate
cv2 = StratifiedKFold(n_splits=5, shuffle=True, random_state=42)
cv_scores2 = cross_val_score(pipelinerf2, X_train2, y_train2, cv=cv2)
print(cv_scores2)
print(cv_scores2.mean())

# Check accuracy, recall
pipelinerf2.fit(X_train2, y_train2)
print(pipelinerf2.score(X_test2, y_test2))
y_pred2 = pipelinerf2.predict(X_test2)
print(confusion_matrix(y_test2, y_pred2))
```

```
[0.99990021 0.99980042 0.99970063 0.99990021 0.9998004 ]
0.9998203732242132
0.9999201660546064
[[3575    0]
 [   1 8950]]
```

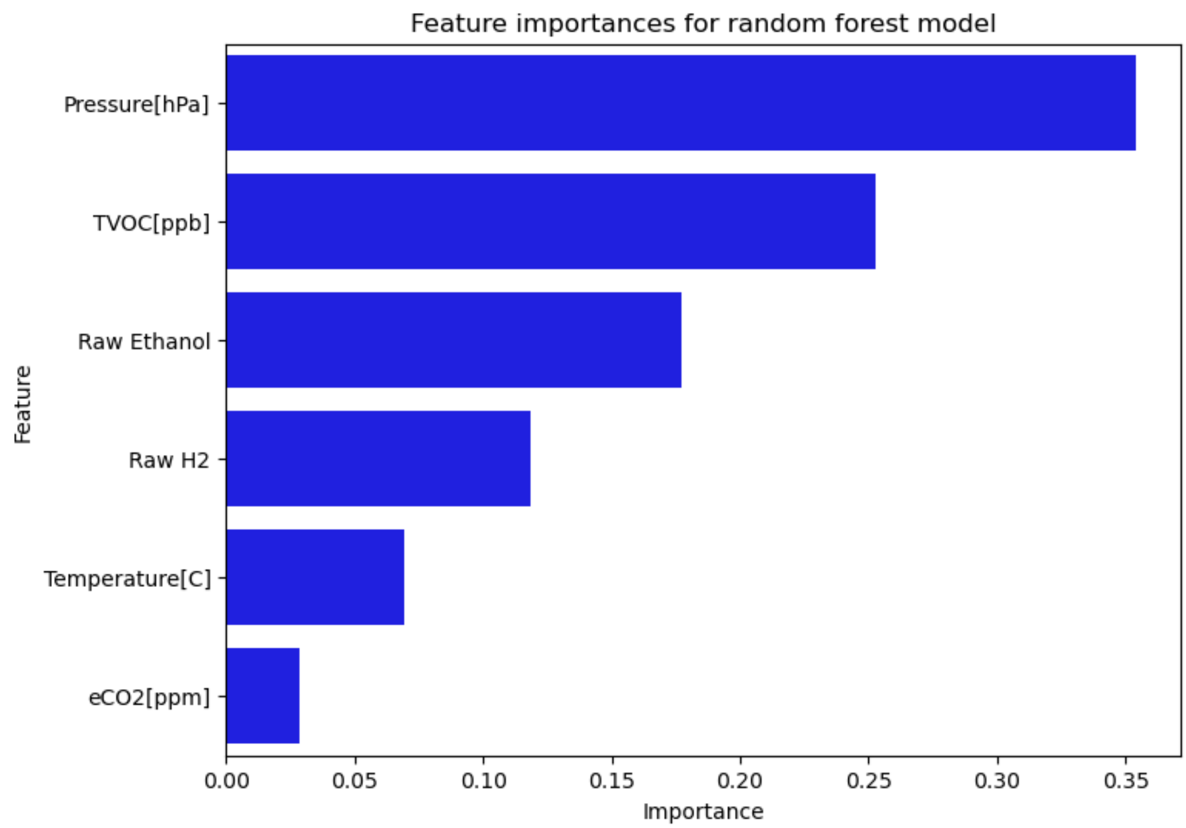
In [104…

```python
# Check Feature Importances
feature_importances2 = pd.DataFrame({'Feature': features2, 'Importance': rfc2.featu

print("Feature importances for random forest model:")
print(feature_importances2)
```

```
Feature importances for random forest model:
          Feature  Importance
0  Temperature[C]    0.069436
1       TVOC[ppb]    0.252827
2       eCO2[ppm]    0.028451
3          Raw H2    0.118487
4     Raw Ethanol    0.176938
5   Pressure[hPa]    0.353861
```

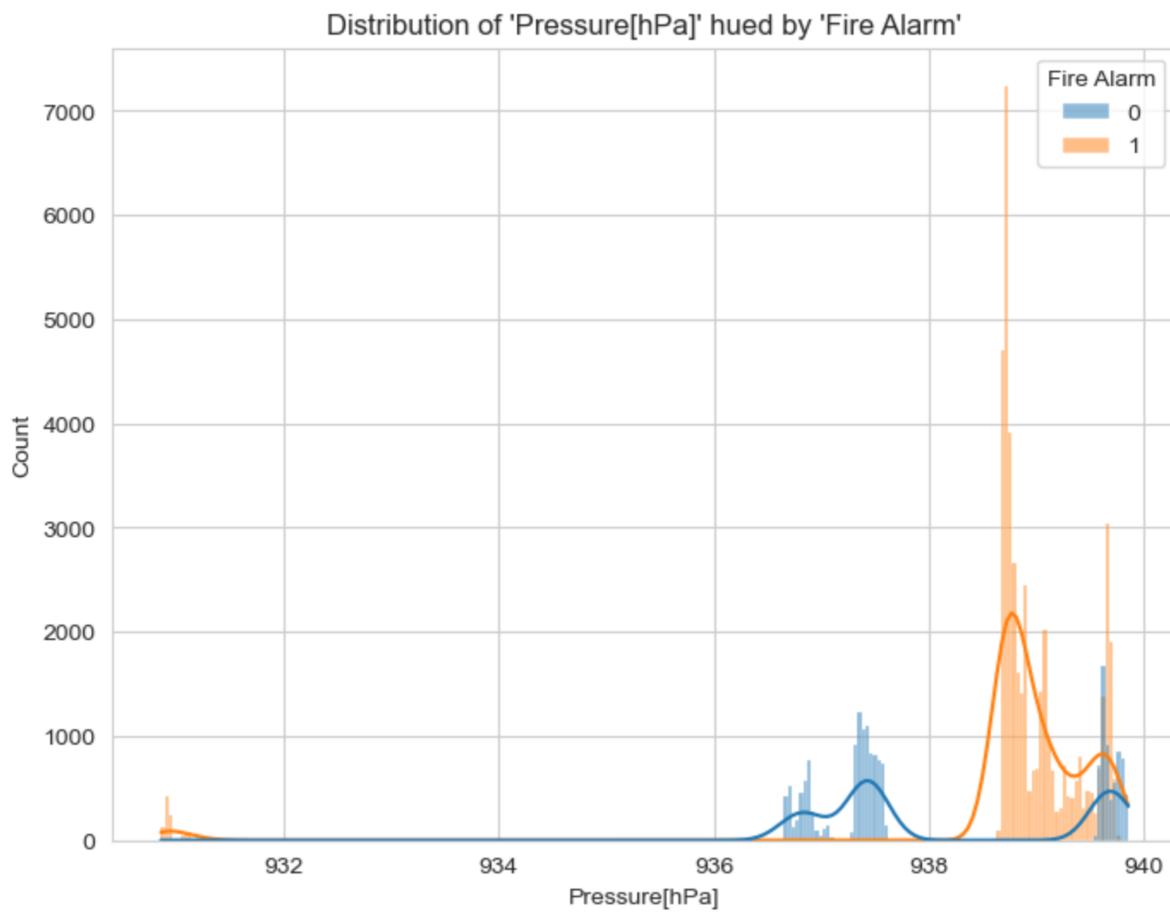
In [106…

```python
feature_importances_sorted2 = feature_importances2.sort_values('Importance', ascend

plt.figure(figsize=(8, 6))
sns.barplot(x="Importance", y="Feature", data=feature_importances_sorted2, color="b
plt.title("Feature importances for random forest model")
plt.xlabel("Importance")
plt.ylabel("Feature")
plt.show()
```



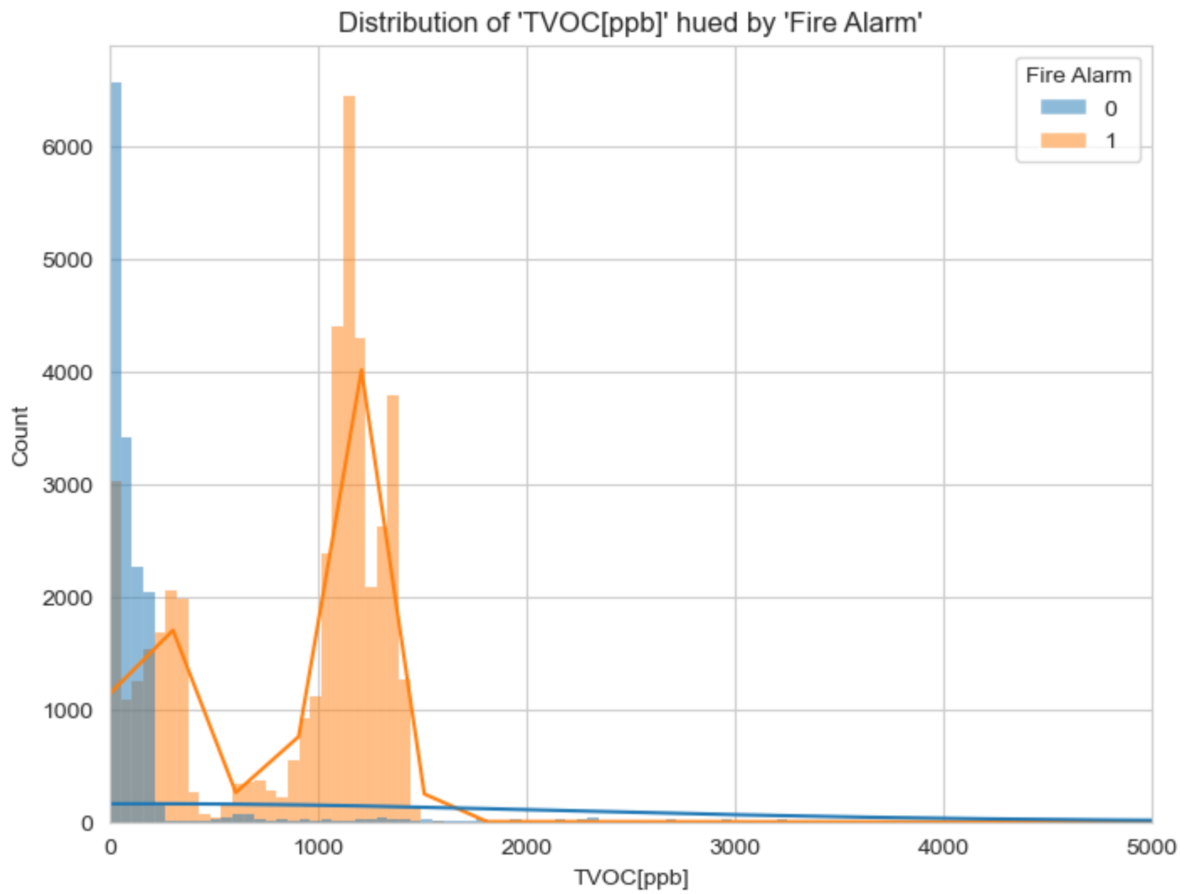
In [107…

```
# Verify that they make sense
sns.set_style("whitegrid")
plt.figure(figsize=(8, 6))
sns.histplot(data=df, x='Pressure[hPa]', hue='Fire Alarm', kde=True)
plt.title("Distribution of 'Pressure[hPa]' hued by 'Fire Alarm'")
plt.xlabel('Pressure[hPa]')
plt.ylabel('Count')
plt.show()
```



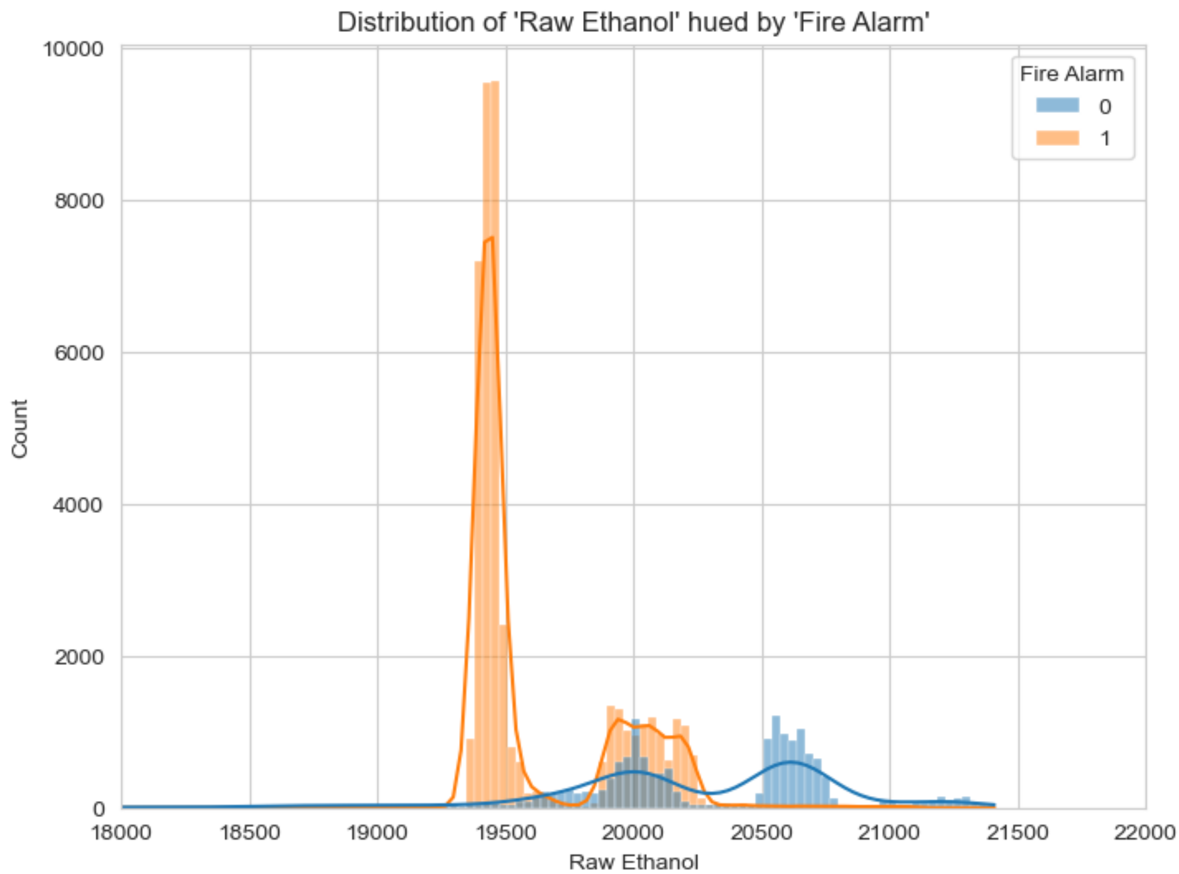
In [108…

```
sns.set_style("whitegrid")
plt.figure(figsize=(8, 6))
sns.histplot(data=df, x='TVOC[ppb]', hue='Fire Alarm', kde=True)
plt.xlim(0, 5000)
plt.title("Distribution of 'TVOC[ppb]' hued by 'Fire Alarm'")
plt.xlabel('TVOC[ppb]')
plt.ylabel('Count')
plt.show()
```



In [109…

```
sns.set_style("whitegrid")
plt.figure(figsize=(8, 6))
sns.histplot(data=df, x='Raw Ethanol', hue='Fire Alarm', kde=True)
plt.xlim(18000, 22000)
plt.title("Distribution of 'Raw Ethanol' hued by 'Fire Alarm'")
plt.xlabel('Raw Ethanol')
plt.ylabel('Count')
plt.show()
```



The most important features have clearly visible areas of fire/no fire, so our models results make sense. Let's see if we can learn more about what features combine to give us good results.

In [110…

```
combinations = []
for i in range(1, len(features2) + 1):
    combinations += itertools.combinations(features2, i)

recall_scores = {}
for combo in combinations:
    X_train_combo = X_train2[list(combo)]
    X_test_combo = X_test2[list(combo)]
    rf = RandomForestClassifier(random_state=42)
    rf.fit(X_train_combo, y_train2)
    y_pred = rf.predict(X_test_combo)
    recall = recall_score(y_test2, y_pred)
    recall_scores[combo] = recall

ranked_combinations = sorted(recall_scores.items(), key=lambda x: x[1], reverse=Tru
for i, combo in enumerate(ranked_combinations):
    print(f"Rank {i + 1}: Features: {combo[0]}, Recall score: {combo[1]}")
```

```
Rank 1: Features: ('Temperature[C]', 'TVOC[ppb]', 'eCO2[ppm]', 'Raw Ethanol'), Reca
ll score: 1.0
Rank 2: Features: ('TVOC[ppb]', 'eCO2[ppm]', 'Raw H2', 'Raw Ethanol'), Recall scor
e: 1.0
Rank 3: Features: ('TVOC[ppb]', 'eCO2[ppm]', 'Raw Ethanol', 'Pressure[hPa]'), Recal
l score: 1.0
Rank 4: Features: ('TVOC[ppb]', 'Raw H2', 'Raw Ethanol', 'Pressure[hPa]'), Recall s
core: 1.0
Rank 5: Features: ('Temperature[C]', 'TVOC[ppb]', 'eCO2[ppm]', 'Raw H2', 'Raw Ethan
ol'), Recall score: 1.0
Rank 6: Features: ('TVOC[ppb]', 'eCO2[ppm]', 'Raw H2', 'Raw Ethanol', 'Pressure[hP
a]'), Recall score: 1.0
Rank 7: Features: ('Temperature[C]', 'TVOC[ppb]', 'eCO2[ppm]', 'Raw H2', 'Raw Ethan
ol', 'Pressure[hPa]'), Recall score: 1.0
Rank 8: Features: ('TVOC[ppb]', 'Raw Ethanol', 'Pressure[hPa]'), Recall score: 0.99
98882806390348
Rank 9: Features: ('Temperature[C]', 'TVOC[ppb]', 'Raw H2', 'Pressure[hPa]'), Recal
l score: 0.9998882806390348
Rank 10: Features: ('Temperature[C]', 'TVOC[ppb]', 'Raw Ethanol', 'Pressure[hPa]'),
Recall score: 0.9998882806390348
Rank 11: Features: ('Temperature[C]', 'TVOC[ppb]', 'eCO2[ppm]', 'Raw H2', 'Pressure
[hPa]'), Recall score: 0.9998882806390348
Rank 12: Features: ('Temperature[C]', 'TVOC[ppb]', 'eCO2[ppm]', 'Raw Ethanol', 'Pre
ssure[hPa]'), Recall score: 0.9998882806390348
Rank 13: Features: ('Temperature[C]', 'TVOC[ppb]', 'Raw H2', 'Raw Ethanol', 'Pressu
re[hPa]'), Recall score: 0.9998882806390348
Rank 14: Features: ('TVOC[ppb]', 'Raw H2', 'Pressure[hPa]'), Recall score: 0.999776
5612780695
Rank 15: Features: ('TVOC[ppb]', 'eCO2[ppm]', 'Raw H2', 'Pressure[hPa]'), Recall sc
ore: 0.9997765612780695
Rank 16: Features: ('Temperature[C]', 'TVOC[ppb]', 'eCO2[ppm]', 'Raw H2'), Recall s
core: 0.9996648419171043
Rank 17: Features: ('Temperature[C]', 'TVOC[ppb]', 'Raw Ethanol'), Recall score: 0.
9995531225561389
Rank 18: Features: ('Temperature[C]', 'TVOC[ppb]', 'Raw H2', 'Raw Ethanol'), Recall
score: 0.9995531225561389
Rank 19: Features: ('Temperature[C]', 'eCO2[ppm]', 'Raw H2', 'Raw Ethanol', 'Pressu
re[hPa]'), Recall score: 0.9994414031951737
Rank 20: Features: ('TVOC[ppb]', 'eCO2[ppm]', 'Raw Ethanol'), Recall score: 0.99932
96838342085
Rank 21: Features: ('Temperature[C]', 'Raw H2', 'Raw Ethanol', 'Pressure[hPa]'), Re
call score: 0.9993296838342085
Rank 22: Features: ('eCO2[ppm]', 'Raw H2', 'Raw Ethanol', 'Pressure[hPa]'), Recall
score: 0.9993296838342085
Rank 23: Features: ('Raw H2', 'Raw Ethanol', 'Pressure[hPa]'), Recall score: 0.9992
179644732432
Rank 24: Features: ('TVOC[ppb]', 'Raw H2', 'Raw Ethanol'), Recall score: 0.99910624
5112278
Rank 25: Features: ('Temperature[C]', 'TVOC[ppb]', 'Raw H2'), Recall score: 0.99854
76483074517
Rank 26: Features: ('Temperature[C]', 'eCO2[ppm]', 'Raw H2', 'Raw Ethanol'), Recall
score: 0.9976538934197297
Rank 27: Features: ('Temperature[C]', 'Raw H2', 'Raw Ethanol'), Recall score: 0.997
5421740587643
Rank 28: Features: ('Temperature[C]', 'Raw Ethanol', 'Pressure[hPa]'), Recall scor
e: 0.9974304546977991
Rank 29: Features: ('Temperature[C]', 'eCO2[ppm]', 'Raw Ethanol', 'Pressure[hPa]'),
Recall score: 0.9974304546977991
Rank 30: Features: ('TVOC[ppb]', 'eCO2[ppm]', 'Raw H2'), Recall score: 0.9973187353
```

```
368339
Rank 31: Features: ('TVOC[ppb]', 'Raw Ethanol'), Recall score: 0.9962015417271813
Rank 32: Features: ('Temperature[C]', 'eCO2[ppm]', 'Raw H2', 'Pressure[hPa]'), Reca
ll score: 0.9958663836442856
Rank 33: Features: ('Temperature[C]', 'TVOC[ppb]', 'Pressure[hPa]'), Recall score:
0.9957546642833203
Rank 34: Features: ('Temperature[C]', 'Raw H2', 'Pressure[hPa]'), Recall score: 0.9
95642944922355
Rank 35: Features: ('Temperature[C]', 'TVOC[ppb]', 'eCO2[ppm]', 'Pressure[hPa]'), R
ecall score: 0.9955312255613898
Rank 36: Features: ('eCO2[ppm]', 'Raw Ethanol', 'Pressure[hPa]'), Recall score: 0.9
950843481175288
Rank 37: Features: ('Raw Ethanol', 'Pressure[hPa]'), Recall score: 0.99452575131270
25
Rank 38: Features: ('eCO2[ppm]', 'Raw H2', 'Raw Ethanol'), Recall score: 0.99162104
79276059
Rank 39: Features: ('Raw H2', 'Pressure[hPa]'), Recall score: 0.9906155736789185
Rank 40: Features: ('eCO2[ppm]', 'Raw H2', 'Pressure[hPa]'), Recall score: 0.990392
1349569881
Rank 41: Features: ('TVOC[ppb]', 'Raw H2'), Recall score: 0.9893866607083007
Rank 42: Features: ('Temperature[C]', 'eCO2[ppm]', 'Raw Ethanol'), Recall score: 0.
989051502625405
Rank 43: Features: ('Temperature[C]', 'Raw Ethanol'), Recall score: 0.9875991509328
567
Rank 44: Features: ('Temperature[C]', 'Pressure[hPa]'), Recall score: 0.98737571221
09261
Rank 45: Features: ('Raw H2', 'Raw Ethanol'), Recall score: 0.9873757122109261
Rank 46: Features: ('Temperature[C]', 'eCO2[ppm]', 'Pressure[hPa]'), Recall score:
0.9869288347670652
Rank 47: Features: ('Temperature[C]', 'TVOC[ppb]', 'eCO2[ppm]'), Recall score: 0.98
67053960451346
Rank 48: Features: ('TVOC[ppb]', 'Pressure[hPa]'), Recall score: 0.9865936766841694
Rank 49: Features: ('TVOC[ppb]', 'eCO2[ppm]', 'Pressure[hPa]'), Recall score: 0.986
5936766841694
Rank 50: Features: ('Temperature[C]', 'eCO2[ppm]', 'Raw H2'), Recall score: 0.98424
7570103899
Rank 51: Features: ('Temperature[C]', 'TVOC[ppb]'), Recall score: 0.981119427996871
9
Rank 52: Features: ('eCO2[ppm]',), Recall score: 0.978996760138532
Rank 53: Features: ('eCO2[ppm]', 'Raw Ethanol'), Recall score: 0.9706178080661378
Rank 54: Features: ('eCO2[ppm]', 'Raw H2'), Recall score: 0.9703943693442073
Rank 55: Features: ('Temperature[C]', 'Raw H2'), Recall score: 0.968048262763937
Rank 56: Features: ('eCO2[ppm]', 'Pressure[hPa]'), Recall score: 0.9653669981007709
Rank 57: Features: ('Pressure[hPa]',), Recall score: 0.9651435593788403
Rank 58: Features: ('Raw Ethanol',), Recall score: 0.9521841135068707
Rank 59: Features: ('TVOC[ppb]', 'eCO2[ppm]'), Recall score: 0.9267120992067925
Rank 60: Features: ('Raw H2',), Recall score: 0.9213495698804602
Rank 61: Features: ('Temperature[C]', 'eCO2[ppm]'), Recall score: 0.906267456150150
8
Rank 62: Features: ('Temperature[C]',), Recall score: 0.8785610546307675
Rank 63: Features: ('TVOC[ppb]',), Recall score: 0.8612445536811529
```

Let's try even less features.

In [111…

```
# Set new features
features3 = ['TVOC[ppb]', 'Raw Ethanol', 'Pressure[hPa]']
target3 = 'Fire Alarm'

X3 = df[features3]
y3 = df[target3]
X_train3, X_test3, y_train3, y_test3 = train_test_split(X3, y3, stratify=y3, test_s

# New Model
rf3 = RandomForestClassifier(random_state=42)
rf3.fit(X_train3, y_train3)
y_pred3 = rf3.predict(X_test3)

print("Confusion matrix for the random forest model:")
print(confusion_matrix(y_test3, y_pred3))
```

```
Confusion matrix for the random forest model:
[[3572    3]
 [   1 8950]]
```

In [112…

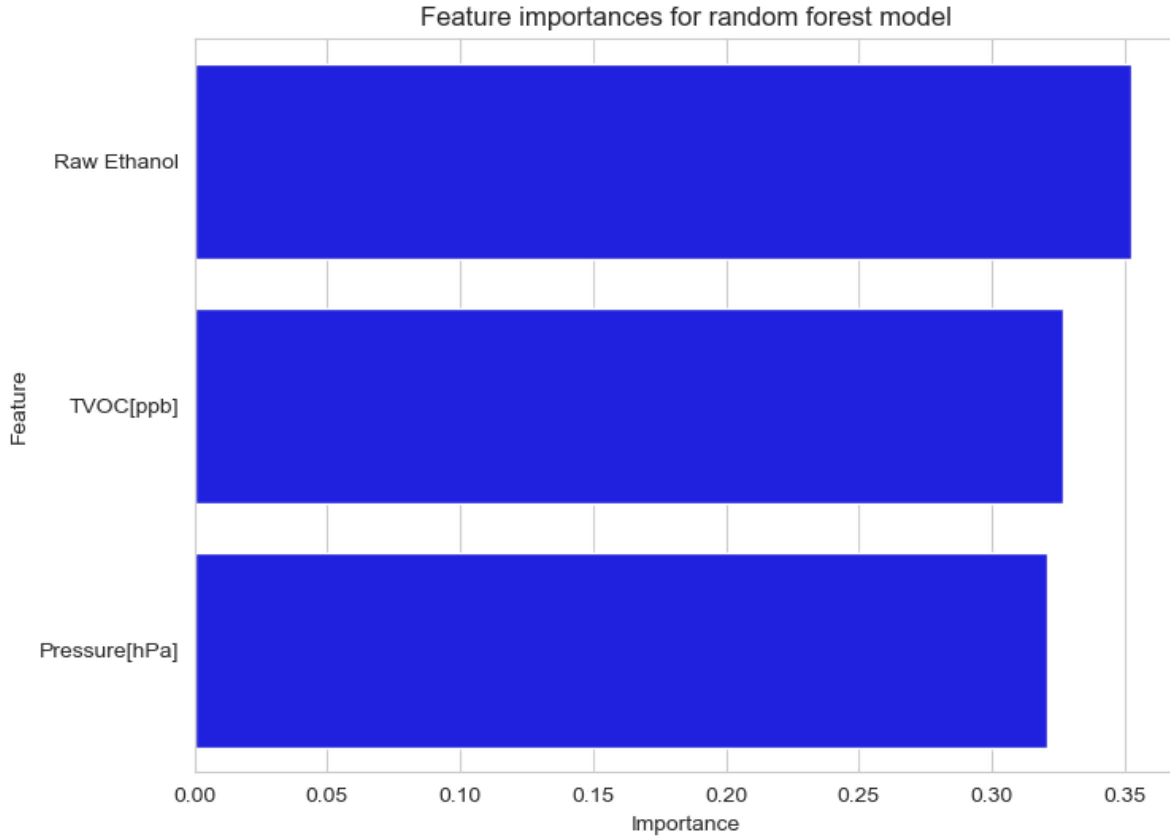
```
# Check feature importances
feature_importances3 = pd.DataFrame({'Feature': features3, 'Importance': rf3.featur

print("Feature importances for random forest model:")
print(feature_importances3)
```

```
Feature importances for random forest model:
         Feature  Importance
0      TVOC[ppb]    0.326626
1    Raw Ethanol    0.352540
2  Pressure[hPa]    0.320834
```

Fuel source has become more important than pressure.

In [113…

```
feature_importances_sorted3 = feature_importances3.sort_values('Importance', ascend


plt.figure(figsize=(8, 6))
sns.barplot(x="Importance", y="Feature", data=feature_importances_sorted3, color="b
plt.title("Feature importances for random forest model")
plt.xlabel("Importance")
plt.ylabel("Feature")
plt.show()
```



Running every combination has given us valuable insight into the minimum viable instrumentation to detect fire.