

## INTRODUCTION

Fire is a natural disaster that can be caused by many different reasons. An innovative sound wave fire-extinguishing system was created and firefighting tests were performed. Machine learning algorithms were applied to data crated by performing several tests for classification of extinction and non-extinction states of the flame.

The acoustic extinguisher works by using sound waves—a type of pressure wave—to push oxygen away from the source of a flame and spread it over a larger surface area. These actions break the fire combustion triangle made up of heat, fuel, and oxygen, the three elements required for a fire to burn. The acoustic fire extinguisher puts out flames using low frequency bass (30 to 60Hz) without relying on water or chemicals.[1]

By hitting fire with the low-frequency sound waves in the 30 to 60 hertz range, the device separates oxygen from fuel. The pressure wave is going back and forth, and that agitates where the air is. That specific space is enough to keep the fire from reigniting.[2]

Dataset information:- Acoustic\_Extinguisher\_Fire\_Dataset.csv

The dataset consists of 6 predictors and a response variable, STATUS. It is formulated as a binary classification problem.

The dataset was obtained as a result of the extinguishing tests of four different fuel flames with a sound wave extinguishing system.

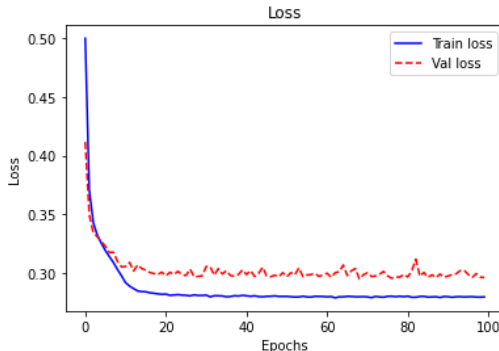
Throughout the flame extinguishing experiments, the data obtained from each measurement device was recorded and a dataset was created. The dataset includes the features of fuel container size representing the flame size, fuel type, frequency, decibel, distance, airflow and flame extinction. Accordingly, 6 input features and 1 output feature will be used in models.

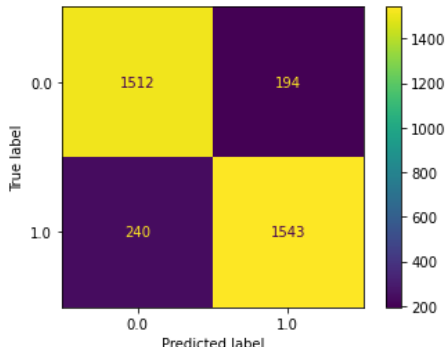
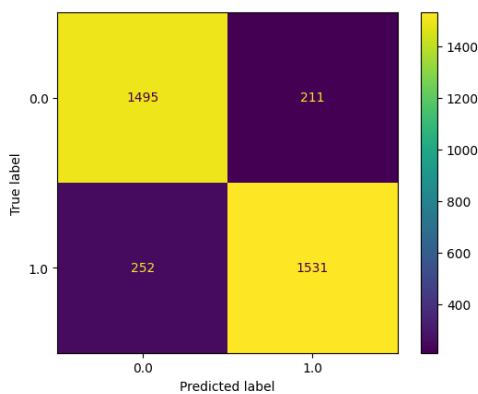
The status property (flame extinction or non-extinction states) can be predicted by using six features in the dataset. Status and fuel features are categorical, while other features are numerical. 8,759 of the 17,442 test results are the non-extinguishing state of the flame. 8,683 of them are the extinction state of the flame. According to these numbers, it can be said that the class distribution of the dataset is almost equal.[3]

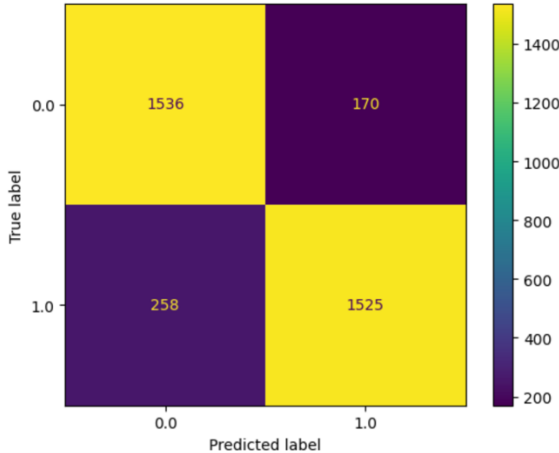
## OBSERVATION TABLE

Observation number	Output	Remark\ Interpretation
	<b>Part 1: Baseline Model</b>	
1	Task Description: The given task is of binary classification. We have been data from fires caused by different sources i.e. fuels and whether synthesized sound waves generated from a	If the fire is extinguished, that data instance is added to class 1, else added to class 0. Hence the given task is of <b>Binary</b>

	computer would extinguish the fire.	Classification.																																																
2	<p>Type of data and description: The variable, df is of type: &lt;class 'pandas.core.frame.DataFrame'&gt; (17442, 7)</p> <table><thead><tr><th></th><th>SIZE</th><th>FUEL</th><th>DISTANCE</th><th>DESIBEL</th><th>AIRFLOW</th><th>FREQUENCY</th><th>STATUS</th></tr></thead><tbody><tr><td>0</td><td>1</td><td>gasoline</td><td>10</td><td>96</td><td>0.0</td><td>75</td><td>0</td></tr><tr><td>1</td><td>1</td><td>gasoline</td><td>10</td><td>96</td><td>0.0</td><td>72</td><td>1</td></tr><tr><td>2</td><td>1</td><td>gasoline</td><td>10</td><td>96</td><td>2.6</td><td>70</td><td>1</td></tr><tr><td>3</td><td>1</td><td>gasoline</td><td>10</td><td>96</td><td>3.2</td><td>68</td><td>1</td></tr><tr><td>4</td><td>1</td><td>gasoline</td><td>10</td><td>109</td><td>4.5</td><td>67</td><td>1</td></tr></tbody></table>		SIZE	FUEL	DISTANCE	DESIBEL	AIRFLOW	FREQUENCY	STATUS	0	1	gasoline	10	96	0.0	75	0	1	1	gasoline	10	96	0.0	72	1	2	1	gasoline	10	96	2.6	70	1	3	1	gasoline	10	96	3.2	68	1	4	1	gasoline	10	109	4.5	67	1	<p>The data given is extracted from a CSV file in the form of a Pandas Data frame.</p> <p>There are 17442 data instances with 7 columns.</p>
	SIZE	FUEL	DISTANCE	DESIBEL	AIRFLOW	FREQUENCY	STATUS																																											
0	1	gasoline	10	96	0.0	75	0																																											
1	1	gasoline	10	96	0.0	72	1																																											
2	1	gasoline	10	96	2.6	70	1																																											
3	1	gasoline	10	96	3.2	68	1																																											
4	1	gasoline	10	109	4.5	67	1																																											
3	<p>Column names and predictor values: Index(['SIZE', 'FUEL', 'DISTANCE', 'DESIBEL', 'AIRFLOW', 'FREQUENCY', 'STATUS'],</p>																																																	
4	<p>Missing Values:</p> <table><tbody><tr><td>SIZE</td><td>False</td></tr><tr><td>FUEL</td><td>False</td></tr><tr><td>DISTANCE</td><td>False</td></tr><tr><td>DESIBEL</td><td>False</td></tr><tr><td>AIRFLOW</td><td>False</td></tr><tr><td>FREQUENCY</td><td>False</td></tr><tr><td>STATUS</td><td>False</td></tr></tbody></table> <p>dtype: bool</p>	SIZE	False	FUEL	False	DISTANCE	False	DESIBEL	False	AIRFLOW	False	FREQUENCY	False	STATUS	False	<p>No missing or NAN values which shows that the data provided is cleaned and little to no pre-processing is required.</p>																																		
SIZE	False																																																	
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5	<p>Type of Data predictors: &lt;class 'pandas.core.frame.DataFrame'&gt; RangeIndex: 17442 entries, 0 to 17441 Data columns (total 7 columns):</p> <table><thead><tr><th>#</th><th>Column</th><th>Non-Null Count</th><th>Dtype</th></tr></thead><tbody><tr><td>0</td><td>SIZE</td><td>17442 non-null</td><td>int64</td></tr><tr><td>1</td><td>FUEL</td><td>17442 non-null</td><td>object</td></tr><tr><td>2</td><td>DISTANCE</td><td>17442 non-null</td><td>int64</td></tr><tr><td>3</td><td>DESIBEL</td><td>17442 non-null</td><td>int64</td></tr><tr><td>4</td><td>AIRFLOW</td><td>17442 non-null</td><td>float64</td></tr><tr><td>5</td><td>FREQUENCY</td><td>17442 non-null</td><td>int64</td></tr><tr><td>6</td><td>STATUS</td><td>17442 non-null</td><td>int64</td></tr></tbody></table> <p>dtypes: float64(1), int64(5), object(1) memory usage: 954.0+ KB</p>	#	Column	Non-Null Count	Dtype	0	SIZE	17442 non-null	int64	1	FUEL	17442 non-null	object	2	DISTANCE	17442 non-null	int64	3	DESIBEL	17442 non-null	int64	4	AIRFLOW	17442 non-null	float64	5	FREQUENCY	17442 non-null	int64	6	STATUS	17442 non-null	int64	<p>The FUEL type and STATUS are categorical and the rest of the predictors and integer or floating-point values.</p>																
#	Column	Non-Null Count	Dtype																																															
0	SIZE	17442 non-null	int64																																															
1	FUEL	17442 non-null	object																																															
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6	<p>Balancing the dataset:</p> <table><tbody><tr><td>gasoline</td><td>5130</td></tr><tr><td>thinner</td><td>5130</td></tr><tr><td>kerosene</td><td>5130</td></tr><tr><td>lpg</td><td>2052</td></tr></tbody></table> <p>Name: FUEL, dtype: int64</p>	gasoline	5130	thinner	5130	kerosene	5130	lpg	2052	<p>The given dataset is balanced as it has equal entries of all types of fuels and thus the results will not be biased towards one specific type of fuel.</p>																																								
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7	<p>Converting Categorical Columns into Numeric Form</p> <table><tbody><tr><td>0</td><td>0</td></tr><tr><td>1</td><td>0</td></tr><tr><td>2</td><td>0</td></tr><tr><td>3</td><td>0</td></tr><tr><td>4</td><td>0</td></tr><tr><td>..</td><td></td></tr><tr><td>17437</td><td>2</td></tr><tr><td>17438</td><td>2</td></tr><tr><td>17439</td><td>2</td></tr><tr><td>17440</td><td>2</td></tr><tr><td>17441</td><td>2</td></tr></tbody></table> <p>Name: FUEL, Length: 17442, dtype: int8</p>	0	0	1	0	2	0	3	0	4	0	..		17437	2	17438	2	17439	2	17440	2	17441	2	<p>We have used One-Hot-Encoding to convert the categorical columns into Numeric form to further process the data.</p> <p>Each Fuel type has been replaced by its equivalent number.</p>																										
0	0																																																	
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17441	2																																																	

8	The predictor input and response output have been split into an 80-20 Test and Train subset.														
9	Choosing the model and network architecture: We have implemented a hidden layer of 4 neurons containing the RELU activation function and an output layer of 1 neuron with the SIGMOID activation function	As the given task is of binary classification, we have deployed only <b>one neuron in the output layer using the sigmoidal activation function</b> . Both layers are dense and fully connected.													
10	Number of trainable parameters: Model: "sequential" <table><thead><tr><th>Layer (type)</th><th>Output Shape</th><th>Param #</th></tr></thead><tbody><tr><td>dense (Dense)</td><td>(None, 4)</td><td>28</td></tr><tr><td>dense_1 (Dense)</td><td>(None, 1)</td><td>5</td></tr></tbody></table> Total params: 33 (132.00 Byte) Trainable params: 33 (132.00 Byte) Non-trainable params: 0 (0.00 Byte)	Layer (type)	Output Shape	Param #	dense (Dense)	(None, 4)	28	dense_1 (Dense)	(None, 1)	5	There are a total of 33 trainable parameters.				
Layer (type)	Output Shape	Param #													
dense (Dense)	(None, 4)	28													
dense_1 (Dense)	(None, 1)	5													
11	Initiating the Model: Optimizer: Adam Loss: Binary Cross Entropy Batch size: 8 Epochs: 100	In the current state, <b>The Adam optimizer</b> provides the best efficiency in terms of locating the global minima. We have used a batch size of 8 and have used 100 iterations.													
12	Loss vs Epochs: 	The plot shows how the loss has reduced over multiple epochs and has settled at <b>0.30</b> for the training set and <b>0.32</b> for the validation set.													
13	Train Accuracy : <b>0.90</b> Test Accuracy : <b>0.90</b>	We have obtained an accuracy of <b>90 percent</b> on both the test and validation set.													
14	Confusion Matrix:	<table><tr><td colspan="2" rowspan="2"></td><td colspan="2">Predicted</td></tr><tr><td>Negative (N) -</td><td>Positive (P) +</td></tr><tr><td rowspan="2">Actual</td><td>Negative -</td><td>True Negative (TN)</td><td>False Positive (FP) Type I Error</td></tr><tr><td>Positive +</td><td>False Negative (FN) Type II Error</td><td>True Positive (TP)</td></tr></table> <p>The confusion matrix is a plot as depicted above. Our values are as follows:</p>			Predicted		Negative (N) -	Positive (P) +	Actual	Negative -	True Negative (TN)	False Positive (FP) Type I Error	Positive +	False Negative (FN) Type II Error	True Positive (TP)
		Predicted													
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		TN: 1512 FP: 194 FN:240 TP:1543													
	<b>PART 2:</b> <b>Hyperparameter Tuning using KerasClassifier from scikeras and GridSearch from Sklearn</b>														
15	<b>Batch Size Optimization:</b> <pre>#Observation21:Note hyperparameters setting that gave the best #result along with the best accuracy score  print("Best: %f using %s" % (grid_result.best_score_, grid_result.best_params_)) means = grid_result.cv_results_['mean_test_score'] stds = grid_result.cv_results_['std_test_score'] params = grid_result.cv_results_['params']  #Compute predictions on Test data  Y_preds = grid.predict(X_test)  Best: 0.872429 using {'batch_size': 10, 'epochs': 5} 349/349 [=====] - 1s 1ms/step</pre>	By using Grid Search on the test data, we have found that the best batch size is 10 with epochs 5													
16	<b>Model Test and Train Accuracy:</b> 349/349 [=====] - 1s 1ms/step Test Accuracy : 0.87 1396/1396 [=====] - 2s 1ms/step Train Accuracy : 0.87	Applying the Ideal Batch Parameters and epochs to the test and training dataset.													
17	<b>Confusion Matrix with Grid Search:</b> 	<table><tr><th colspan="2" rowspan="2"></th><th colspan="2">Predicted</th></tr><tr><th>Negative (N) -</th><th>Positive (P) +</th></tr><tr><th rowspan="2">Actual</th><th>Negative -</th><td>True Negative (TN)</td><td>False Positive (FP) Type I Error</td></tr><tr><th>Positive +</th><td>False Negative (FN) Type II Error</td><td>True Positive (TP)</td></tr></table> TN: 1495 FP: 211 FN:252 TP:1531			Predicted		Negative (N) -	Positive (P) +	Actual	Negative -	True Negative (TN)	False Positive (FP) Type I Error	Positive +	False Negative (FN) Type II Error	True Positive (TP)
		Predicted													
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	<b>PART 3: Using Grid Search to find ideal Optimizer.</b>														
18	In this sub part, we have used GridSearch from Sklearn to obtain the model optimizer.														
19	<b>Ideal Optimizer:</b> Best: 0.867389 using {'optimizer': 'Adam'} 0.740798 (0.168747) with: {'optimizer': 'SGD'} 0.858044 (0.002517) with: {'optimizer': 'RMSprop'} 0.867389 (0.003673) with: {'optimizer': 'Adam'}	From a list of 3 optimizers, SGD, RMSProp and Adam, after using Grid Search to obtain model parameters, we have inferred that Adam is the best optimizer for													

		our dataset.													
20	Test and training accuracy with Adam: Test Accuracy : 0.88 Train Accuracy : 0.88														
21	Confusion Matrix: 	<table><tr><th colspan="2" rowspan="2"></th><th colspan="2">Predicted</th></tr><tr><th>Negative (N) -</th><th>Positive (P) +</th></tr><tr><th rowspan="2">Actual</th><th>Negative -</th><td>True Negative (TN)</td><td>False Positive (FP) Type I Error</td></tr><tr><th>Positive +</th><td>False Negative (FN) Type II Error</td><td>True Positive (TP)</td></tr></table> TN: 1536 FP: 170 FN: 258 TP: 1525			Predicted		Negative (N) -	Positive (P) +	Actual	Negative -	True Negative (TN)	False Positive (FP) Type I Error	Positive +	False Negative (FN) Type II Error	True Positive (TP)
		Predicted													
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Actual	Negative -	True Negative (TN)	False Positive (FP) Type I Error												
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## CONCLUSION

In this assignment, we have been provided with a dataset which contains the details of acoustic fire extinguishing. The given task is of Binary Classification. The fire has been lighted using different fuels and we have classified binary 1 if the sound waves produced have extinguished the fire or binary 0 if the fire has not been extinguished.

In Part 1, we have performed the baseline modelling. As the given data was already preprocessed, we have directly started modelling the dataset.

We have deployed an 80-20 data split and used one hidden layer with 4 neurons and RELU activation function. In the output layer we have used the sigmoidal activation function.

We obtained an accuracy of 90% in both the training and test sets. The confusion matrix states that we have obtained TN: 1512, FP: 194, FN: 240, TP: 1543

In part 2, we have used Grid Search from Sci-Kit learn to find the ideal model parameters. We have found the model batch parameters along with the model epochs.

We have obtained an accuracy of 87% accuracy in both the training and test sets. The confusion matrix states that we have obtained TN: 1495, FP: 211, FN: 252, TP: 1531

In part 3, we have used Grid Search from Sci-Kit learn to find the ideal model parameters. We have found the model optimizer function.

We have obtained an accuracy of 88% accuracy in both the training and test sets. The confusion matrix states that we have obtained TN: 1536, FP: 170, FN: 258, TP: 1525.

## CITATIONS

[1] <https://www.dell.com/en-us/perspectives/fighting-fire-with-bass-using-sound-waves-to-drown-flames/>

[2] <http://ir.aiktclibrary.org:8080/xmlui/bitstream/handle/123456789/3057/GRP25-%20Fire%20Extinguisher.pdf?sequence=1&isAllowed=y#:~:text=By%20hitting%20fire%20with%20the,keep%20the%20fire%20from%20reigniting.>

[3] Research Paper provided.