



#### Problem Statement 5: AI/ML Thunderstorms & Gale force Wind Prediction & Alert System for Airfields

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#### Introduction



Predict the Storm, Protect the Flight.

Traditional forecasts are often too slow and miss local events.

Airfields face sudden thunderstorms & strong winds that risk flights & safety.

We built an AI/ML system to predict severe weather in real-time.

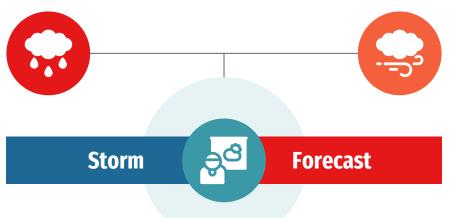


Goal: Enable air traffic & ground staff to act early and reduce risks.



#### Severe weather risks flight safety.

Delays, cancellations, and costly disruptions.



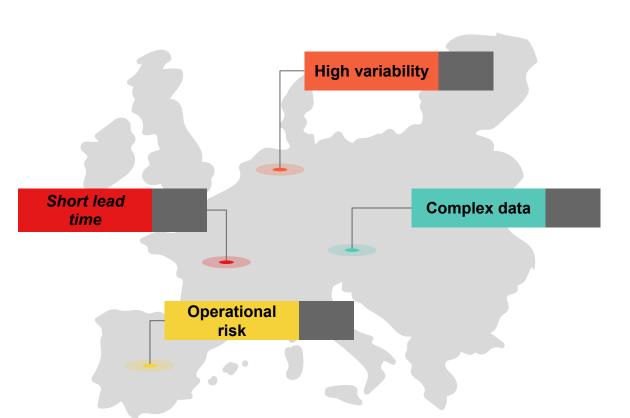
Storms change quickly & are hard to predict.

Traditional forecasts often miss local, short events.



Sudden wind gusts risk aircraft & ground crew.

### **Key Challenges**





Storms & winds are very localized and change rapidly.



Forecasts don't give enough early warning.



Multiple sources (radar, satellite, sensors) are hard to process manually.



Missed forecasts cause delays, equipment loss, or safety hazards.

### **Real-Time Storm & Wind Prediction System**



Collects data from real time API's



Generates real-time alerts with confidence scores

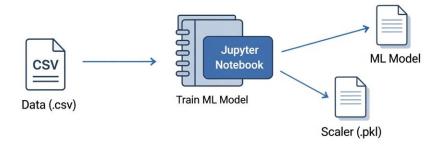


Predicts storms & wind gusts using ML models (LSTM, Logistic, Random Forest)



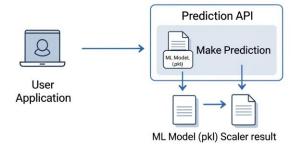
Responsive UI for whether and Storm Prediction

**Phase 1: Offline Model Training** 

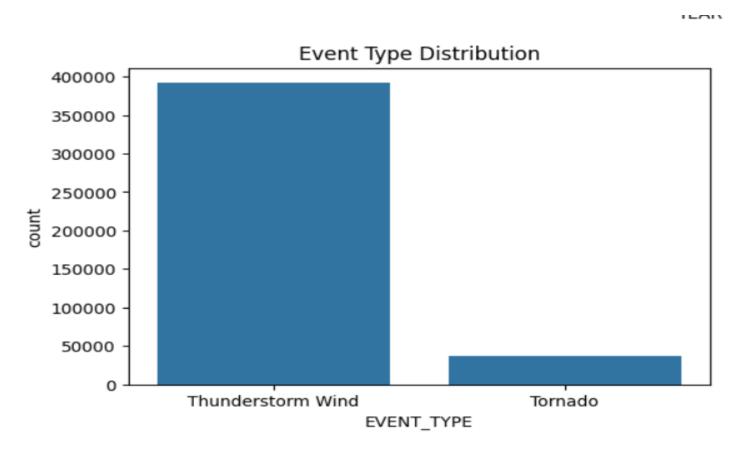


### **Architecture**

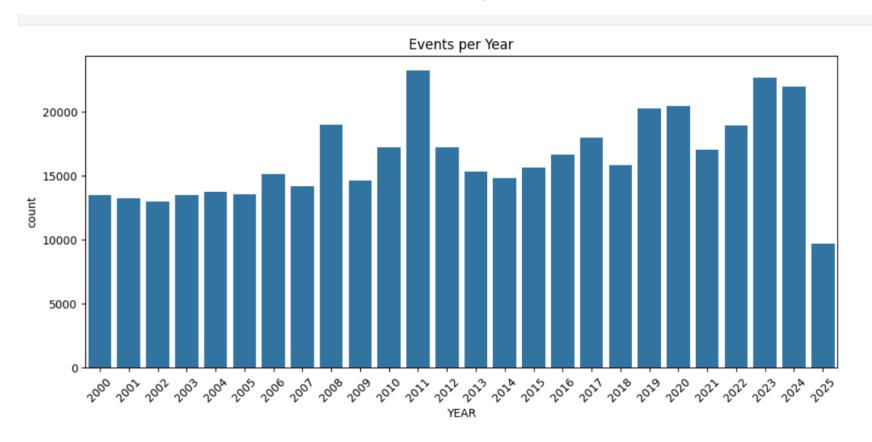
#### **Phase 2: Live Prediction**



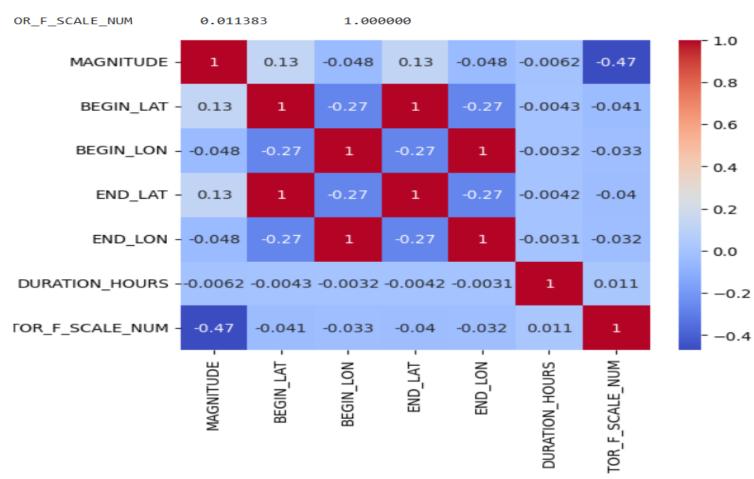
#### **Occurrence of Thunderstorm and Tornado (2000-2025)**



#### **Bar Graph**



### **Heat Map**



### **Data Cleaning , Encoding & Decoding Data**

								wind_gust_kt	altim_in_hg	sea_level_pressure_mb	wx_string	١
							4933	20.0	29.76	1015.7	-RA	
	wind_dir_degrees	wind speed kt	wind gust kt		maxT24hr c	minT24hr c	4930	20.0	29.79	1015.7	BR	
					_	_	4932	20.0	29.85	1015.7	HZ	
0	140	3.0	IVAIN	• • • •	NaN	NaN	4931	20.0	30.06	1015.7	BR	
1	0	0.0	NaN		NaN	NaN	4929	20.0	30.03	1015.7	BR	
2	0	0.0	NaN		NaN	NaN	4928	20.0	30.18	1015.7	BR	
3	0	0.0				NaN	4927	20.0	29.85	1015.7	BR	
_							4926	20.0	30.05	1017.5	BR	
4	310	5.0	NaN		NaN	NaN	4925	20.0	30.16	1015.7	BR	
							4924	20.0	29.84	1015.7	BR	
	precip_in pcp3hr	in non6hr in r	ocn21hr in snow	in	vant vic ft	matar tuna \						
			. –	_				cloud_base_ft_	_agl flight_c	ategory		
0	NaN	NaN NaN	NaN	NaN	NaN	SPECI	4933	120	0.0	MVFR		
1	NaN	NaN NaN	NaN	NaN	NaN	SPECI	4930	200	0.0	MVFR		
2	NaN	NaN NaN	NaN	NaN	200.0	SPECI	4932	100	0.0	IFR		
							4931	256	0.0	VFR		
3	NaN	NaN NaN	NaN	NaN	NaN	SPECI	4929	260	0.0	VFR		
4	NaN	NaN NaN	NaN	NaN	NaN	SPECI	4928	900	0.0	VFR		
							4927	150	0.0	VFR		
							4926	260	0.0	VFR		
							4925	808	0.0	MVFR		

# **Models Selection**

```
Logistic Regression Results:
Accuracy: 1.0
Precision: 1.0
Recall: 1.0
F1 Score: 1.0
Confusion Matrix:
[[986 0]
[ 0 1]]
```

```
XGBoost Results:
Accuracy: 1.0
Precision: 1.0
Recall: 1.0
F1 Score: 1.0
Confusion Matrix:
[[986 0]
[ 0 1]]
```

#### **Train LSTM**

```
# Define LSTM models
class LSTMClass(nn.Module):
   def init (self, input size=6, hidden=50, num classes=3):
        super(). init ()
        self.lstm = nn.LSTM(input_size, hidden, batch_first=True)
        self.fc = nn.Linear(hidden, num classes)
   def forward(self, x):
        _, (hn, _) = self.lstm(x)
        return self.fc(hn[-1])
class LSTMReg(nn.Module):
   def init (self, input size=6, hidden=50):
        super(). init ()
        self.lstm = nn.LSTM(input size, hidden, batch first=True)
        self.fc = nn.Linear(hidden, 1)
   def forward(self, x):
        , (hn, ) = self.lstm(x)
        return self.fc(hn[-1])
# Load models
model c = LSTMClass()
model c.load state dict(torch.load('lstm class multi.pth'))
model c.eval()
model r = LSTMReg()
model r.load state dict(torch.load('lstm reg multi.pth'))
model r.eval()
```

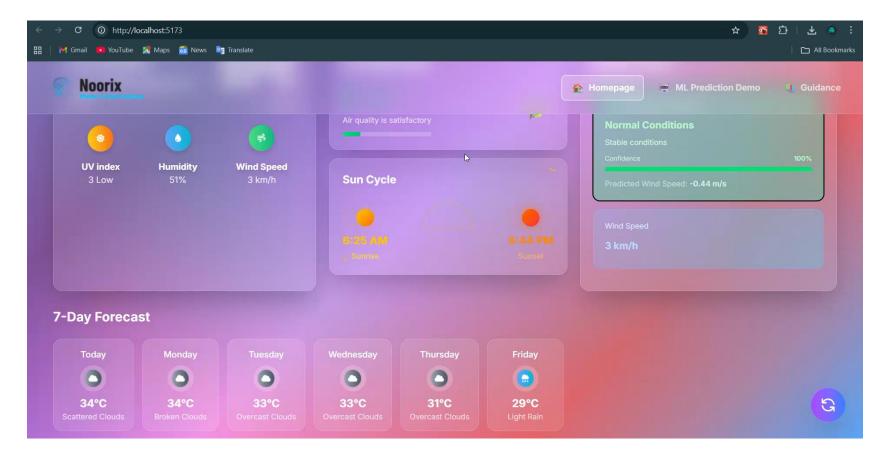
```
# Load test data
X test = np.load('X test.npy')
y class test = np.load('y class test.npy')
y reg test = np.load('y reg test.npy')
X test t = torch.tensor(X test, dtvpe=torch.float32)
y class test t = torch.tensor(y class test, dtype=torch.long)
y reg test t = torch.tensor(y reg test, dtype=torch.float32)
# Predict
with torch.no grad():
    probs = torch.softmax(model c(X test t), dim=1).numpv()
    class preds = np.argmax(probs, axis=1)
    reg preds = model r(X test t).numpy().flatten()
# Metrics
class accuracy = accuracy score(y class test, class preds)
reg mse = mean squared error(y reg test, reg preds)
print(f"Classification Accuracy: {class accuracy:.4f}")
print(f"Wind Speed MSE: {reg mse:.4f}")
# Sample predictions
event map = {0: 'normal', 1: 'wind', 2: 'thunderstorm'}
sample preds = pd.DataFrame({
    'True Event': [event map[y] for y in y class test[:5]],
    'Pred Event': [event map[y] for y in class preds[:5]],
    'Probabilities': [probs[i].round(3).tolist() for i in range(5)],
    'True Wind Speed': v reg test[:5].round(2),
    'Pred Wind Speed': reg preds[:5].round(2)
print("\nSample Predictions:")
print(sample preds)
```

## **Long Short Term Memory (LSTM) Accuracy**

```
# Confusion matrix
from sklearn.metrics import confusion_matrix
cm = confusion_matrix(y_class_test, class_preds)
plt.figure(figsize=(6, 4))
sns.heatmap(cm, annot=True, fmt='d', cmap='Blues', xticklabels=event_map.values(), yticklabels=event_map.values())
plt.title('Confusion Matrix')
plt.xlabel('Predicted')
plt.ylabel('True')
plt.show()
```

Classification Accuracy: 0.9912 Wind Speed MSE: 0.1679

#### **Output**



#### **Conclusion**



Thunderstorms & winds are serious risks for airfields

Real-time alerts empower safer, faster decisions

Our AI/ML system predicts them with speed & accuracy

Scalable solution with global impact potential

## **Scalability**



#### References

- Jupyter : <a href="https://jupyter.org/">https://jupyter.org/</a>
- Py torch : <a href="https://pypi.org/project/torch/">https://pypi.org/project/torch/</a>
- Git Hub : <a href="https://github.com/">https://github.com/</a>
- Kaggle : <a href="https://www.kaggle.com/">https://www.kaggle.com/</a>

#### **Data Source**

- https://www.ncei.noaa.gov/pub/data/swdi/stormevents/csvfiles/
- <a href="https://archive-api.open-meteo.com/v1/archive">https://archive-api.open-meteo.com/v1/archive</a>
- https://www.kaggle.com/datasets/developerghost/climate-in-india-dailyweather-data-2000-2024





