MACHINE LEARNING / AI PROJECTS

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PREDICTIVE MAINTENANCE: PROACTIVE SAFETY IN INDUSTRIAL OPERATIONS

At Nutrien, safety means Everyone Home Safe, Every Day. Predictive Maintenance saves lifes

Why it matters:

- SIF Prevention: Early hazard detection stops major incidents.
- Environmental Protection: Prevents leaks, emissions, and hazardous releases.

Real-World Incidents

West Fertilizer (2013) - Ammonium nitrate blast; 15 dead, 200+ injured Williams Olefins (2013) - Heat exchanger rupture; 2 dead, 167 injured Clairton Coke Works (2025) - Gas explosion; 2 dead, 10+ injured

Code: https://github.com/NikhilDhiman/Artwork-Mapped-Using-ML



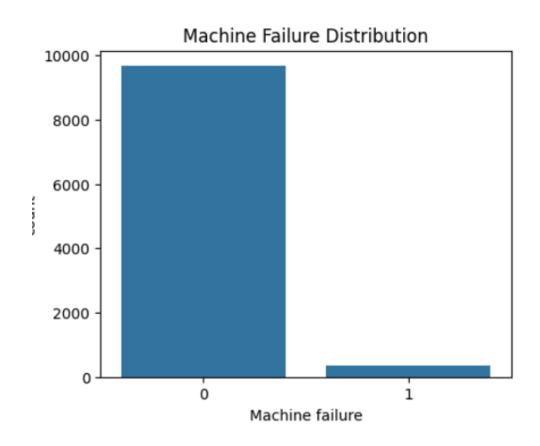
EXPLORATORY DATA ANALYSIS (EDA)

Data Source: https://archive.ics.uci.edu/ml/machine-learning-databases/00601/ai4i2020.csv

Sha	Shape: (10000, 14)													
	UDI	Product ID	Type	Air temperature [K]	Process temperature [K]	Rotational speed [rpm]	Torque [Nm]	Tool wear [min]	Machine failure	TWF	HDF	PWF	OSF	RNF
0	1	M14860	М	298.1	308.6	1551	42.8	0	0	0	0	0	0	0
1	2	L47181	L	298.2	308.7	1408	46.3	3	0	0	0	0	0	0
2	3	L47182	L	298.1	308.5	1498	49.4	5	0	0	0	0	0	0
3	4	L47183	L	298.2	308.6	1433	39.5	7	0	0	0	0	0	0
4	5	L47184	L	298.2	308.7	1408	40.0	9	0	0	0	0	0	0

Dataset Info:		Missing Values per Column:			
<class 'pandas.core.frame.dataframe'=""></class>		UDI .	0		
RangeIndex: 10000 entries, 0 to 9999			^		
Data columns (total 14 columns):		Product ID	0		
# Column Non-Null Count	Dtype	Type	0		
		Air temperature [K]	0		
0 UDI 10000 non-null					
1 Product ID 10000 non-null	object	Process temperature [K]	0		
2 Type 10000 non-null	object	Rotational speed [rpm]	0		
3 Air temperature [K] 10000 non-null	float64	Torque [Nm]	0		
4 Process temperature [K] 10000 non-null	float64				
5 Rotational speed [rpm] 10000 non-null	int64	Tool wear [min]	0		
6 Torque [Nm] 10000 non-null	float64	Machine failure	0		
7 Tool wear [min] 10000 non-null	int64	TWF	0		
8 Machine failure 10000 non-null	int64		_		
9 TWF 10000 non-null	int64	HDF	0		
10 HDF 10000 non-null	int64	PWF	0		
11 PWF 10000 non-null	int64	OSF	0		
12 OSF 10000 non-null	int64		_		
13 RNF 10000 non-null	int64	RNF	0		
dtypes: float64(3), int64(9), object(2) memory usage: 1.1+ MB dtype: int64					

FAILURE DISTRIBUTION



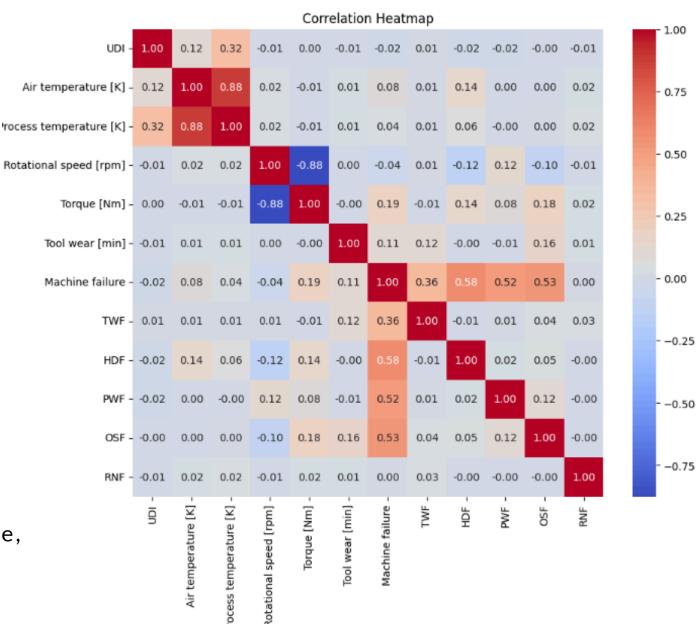


Class-weighted models: Balanced weights in Logistic Regression, Decision Tree, Random Forest.

XGBoost weighting: scale_pos_weight = #neg / #pos for minority class focus.

Stratified CV: Preserve class ratios in all folds.

Metrics: Used ROC-AUC & PR-AUC (PR-AUC for imbalance).



MODEL CHOICES

Model Choices & Rationale

- Logistic Regression Simple, interpretable baseline; fast; class_weight='balanced' for imbalance.
- Decision Tree Captures non-linear rules; handles mixed data; visualizable; balanced weights.
- Random Forest Ensemble of trees; reduces overfitting; feature importance; balanced weights.
- XGBoost High-performance boosting; handles complex patterns; scale_pos_weight for imbalance; tuned for best results.

XGBoost Fine-Tuning

Pipeline: Preprocessor + XGBClassifier.

Search: RandomizedSearchCV (80 configs, F1 score).

CV: Stratified 5-fold.

Key Params Tuned:

n_estimators, learning_rate, max_depth, min_child_weight, subsample, colsample_bytree, reg_alpha, reg_lambda.

RESULTS

Metrics:

Accuracy: How often the model is right (can be misleading if one class is much bigger).

Precision: When the model says "positive," how often it's correct.

Recall: Of all the real positives, how many the model finds.

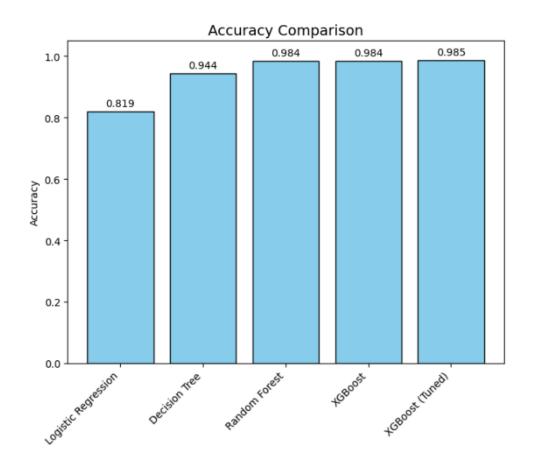
F1-score: A balance between precision and recall.

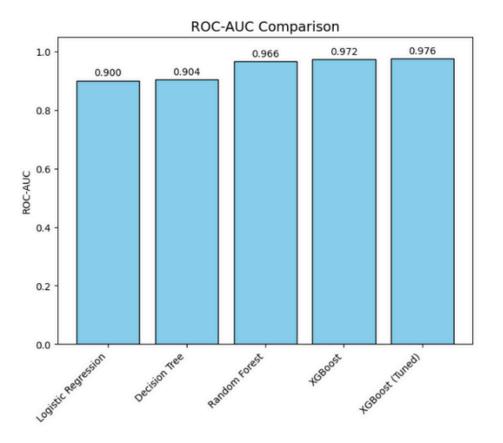
ROC-AUC: How well the model tells the two classes apart.

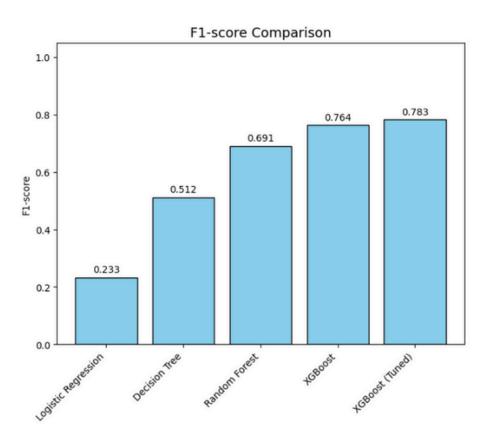
PR-AUC: Focuses on how well the model finds the important (positive) cases in imbalanced data.

	Model	Accuracy	Precision	Recall	F1-score	ROC-AUC	PR-AUC
0	Logistic Regression	0.8194	0.136120	0.808253	0.232938	0.900340	0.426264
1	Decision Tree	0.9435	0.362002	0.873222	0.511771	0.904406	0.731281
2	Random Forest	0.9836	0.949822	0.548903	0.690572	0.966190	0.818113
3	XGBoost	0.9843	0.783645	0.749342	0.763835	0.972261	0.829322
4	XGBoost (Tuned)	0.9853	0.784352	0.784723	0.783279	0.976223	0.842558

RESULTS







ARTWORK MAPPED USING ML

An interactive 3D visualization of 120K artworks mapped by visual similarity using ML and dimensionality reduction.

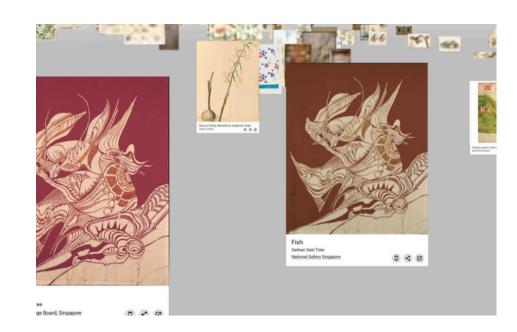
UNSUPERVISED LEARNING

FEATURE EXTRACTION

DIMENSIONALITY REDUCTION AND CLUSTERING

Live Demo: https://3d-umap-cs5660.vercel.app

Code: https://github.com/NikhilDhiman/Artwork-Mapped-Using-ML



FLOW OF PROJECT

PRE-DATA CHECKS

EXTRACT HIGH-DIMENSIONAL FEATURE

DIMENSIONALITY REDUCTION

BUILD AN INTERACTIVE 3D LANDSCAPE WHERE

- Using OpenCV
- Duplicate and corrupt image filtering
- Blurry Image Detection
- TensorFlow DatasetPipeline
- ResNet50 Model
 - HDF5 Feature Storage

- PCA
- UMAP

- HDBSCAN
- Three JS
- HTML
- CSS

PRE-DATA CHECKS

```
# Total Valid Images

# Define valid image file extensions
valid_exts = ('.jpg', '.jpeg', '.png')

# Recursively walk through IMAGES_DIR and collect paths to all valid image files
all_image_paths = [
    os.path.join(root, f)
    for root, _, files in os.walk(IMAGES_DIR)
    for f in files
    if f.lower().endswith(valid_exts) and not f.startswith(".")
]

# Print the total number of images found
print(f"Total images found: {len(all_image_paths)}")
```

Total images found: 111668

Checking for duplicates: 100% Completed No Duplicate Found

Checking for blurriness: 100% Completed No Blurriness Found

EXTRACT HIGH-DIMENSIONAL FEATURE

Goal: Turn each artwork into a 2048-number vector capturing its style & content.

Feature Extraction Pipeline

- Preprocessing: Resize to 224×224, normalize, clean corrupt images.
- Model: ResNet50 (ImageNet pretrained, Global Avg Pooling → 2048-D/image).
- Batch Processing: TF Dataset API, batch=32, parallel load & prefetch.
- Storage: Features in HDF5, filenames in NumPy, resume support (111,668 images).

Why ResNet50?

Sees fine details, captures patterns, and gives a fixed-size summary.

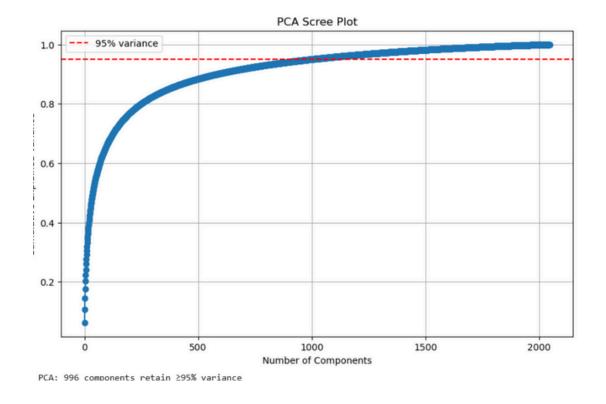
Why Pretrained CNN?

Already trained on millions of images: fast, accurate, works without labels.

DIMENSIONALITY REDUCTION

We used PCA before UMAP to compress the 2048-dimensional features down to only the components that explain most of the variance (≥95%), because:

- Speeds up UMAP
- Reduces noise



So, PCA acts as a denoising + dimensionality reduction pre-step before the more flexible, nonlinear UMAP mapping.

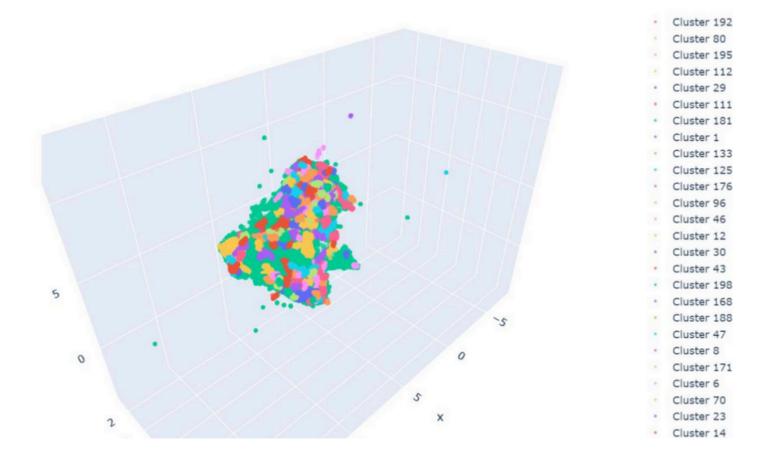
UMAP + HDBSCAN

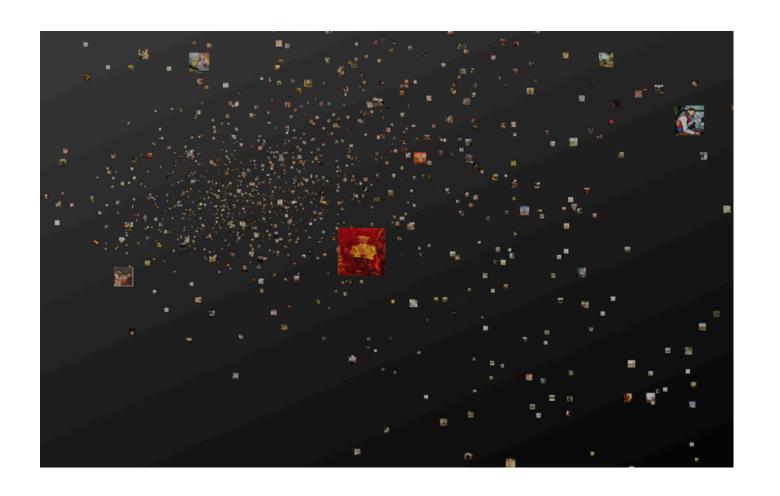
Reduce features to 3D, then cluster to find natural groupings

• Evaluate: Silhouette score for cluster quality

• Optimize: Grid search best UMAP parameters

• Visualize: Plotly 3D scatter:





Live Demo: https://3d-umap-cs5660.vercel.app

PHYSICS-GUIDED DEEP GENERATIVE MODEL FOR NEW LIGAND DISCOVERY

Generative Al Model to generate new medicine molecules

SEMI-SUPERVISED

GENERATIVE AI - DEEP LEARNING

ACTIVE LEARNING

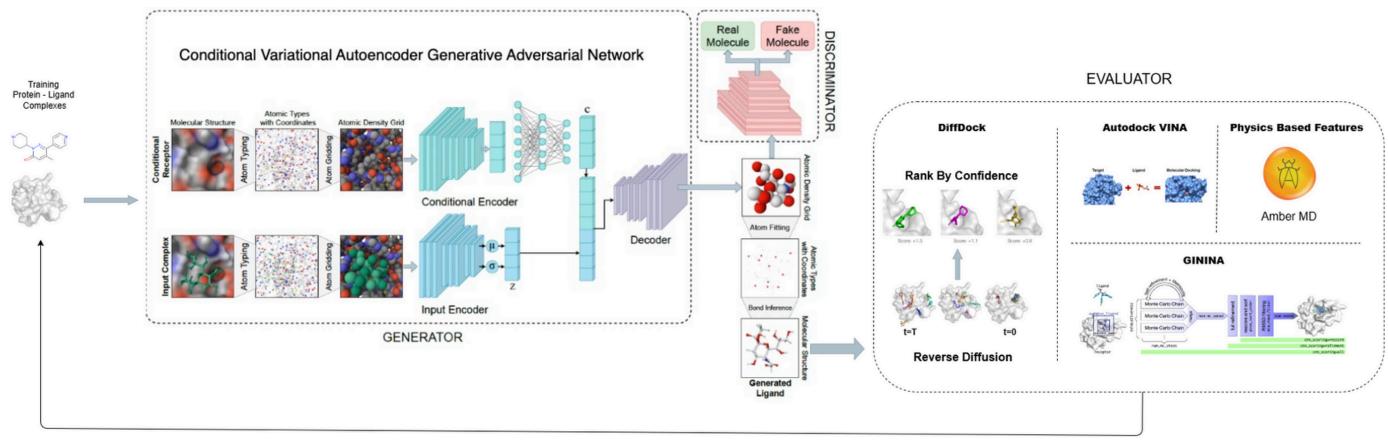
Ligand

+
Binding Site

Protein with
Binded Ligand

Publication Link: https://www.cell.com/biophysj/abstract/S0006-3495(24)02507-4

ARCHITECTURE

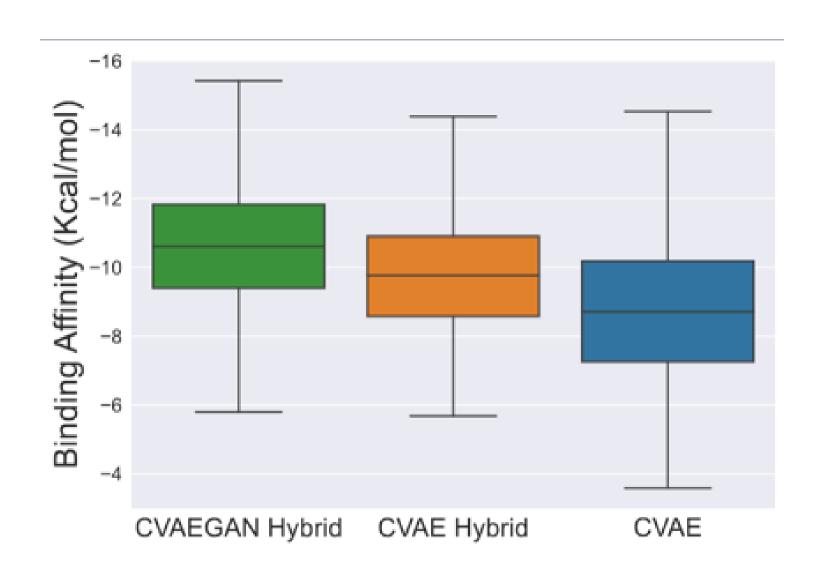


Top-ranked ligands added to training pool for next round (Active Learning Loop)

Repeat until convergence

CVAEGAN framework for active learning. Ligands are generated using the CVAEGAN model, evaluated through docking, binding free energy, and physics-based metrics, and top candidates are iteratively fed back for model retraining.

RESULTS



OTHER ML/AI DATA ANALYSIS PROEJECTS

- Early Skin Cancer Detection: Bringing Dermatology to Everyone https://github.com/NikhilDhiman/Early-Skin-Cancer-Detection-Bringing-Dermatology-to-Everyone
- Amazon Employee Access Challenge https://github.com/NikhilDhiman/Amazon-Employee-Access-Challenge
- KNN Classification using Scikit learn https://github.com/NikhilDhiman/KNN-Classification-using-Scikit-learn
- IMDb Movie Data Analysis https://github.com/NikhilDhiman/IMDb-Movie-Data-Analysis

Github: https://github.com/NikhilDhiman Portfolio Website: https://nikhildhiman.me/

THANK YOU



for the time seeing my projects