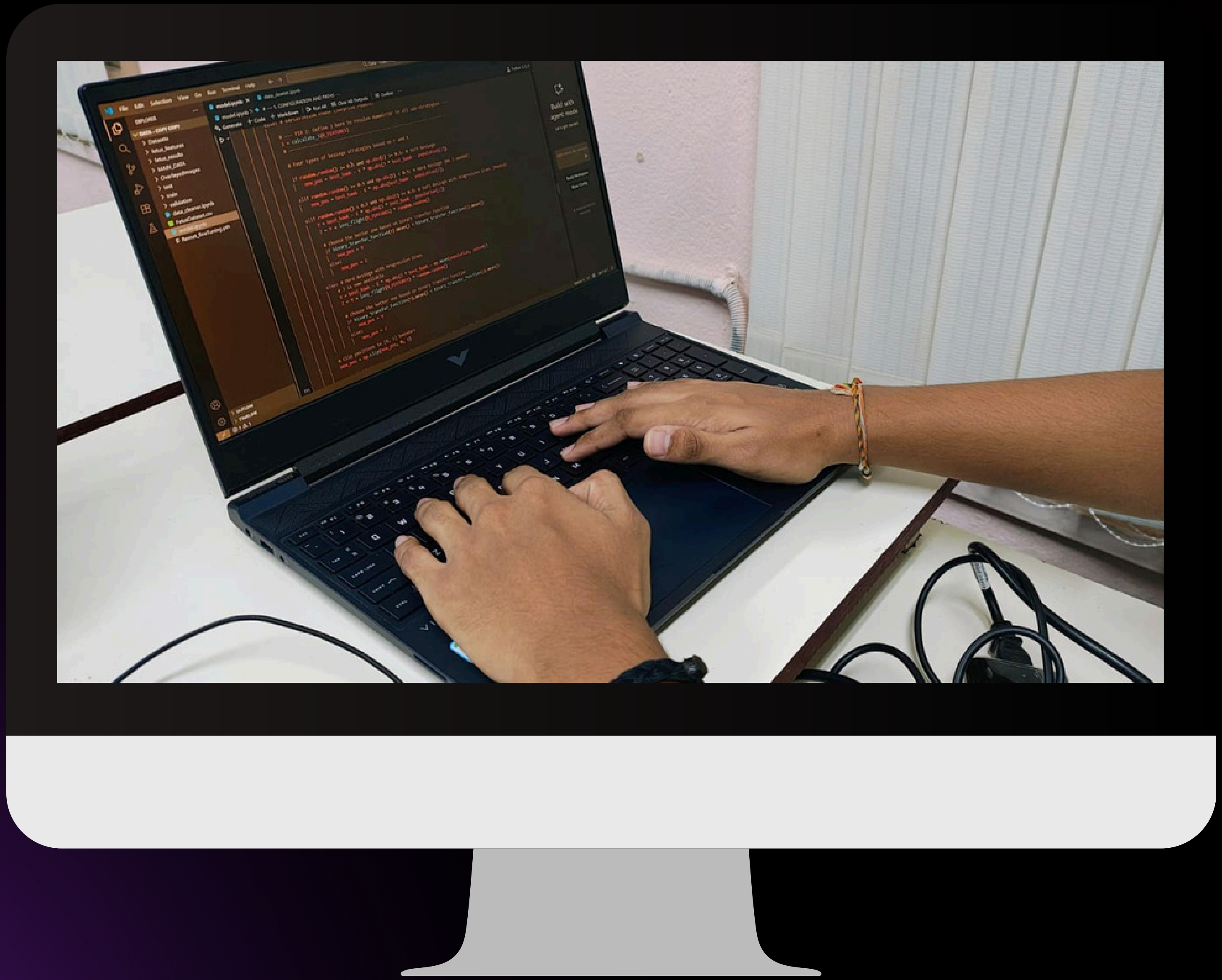
Python Project

2025

Team No. 3

CSE (AI&DS)

Next Slide



Members:

Pranav Umbarkar - 24CSB1A50
Mistry Ritik - 24CSB1A37
V. Sriram - 24CSB1A71

Data set chosen :

1) Medical-Waste-4.0-Dataset: v0.1
2) UC Merced Land Use Dataset
3) AID: A scene classification dataset

Harris Hawk Optimization with simmulated Annealing

This hybrid algorithm combines the exploration power of Harris Hawk Optimization with the exploitation and local search refinement of Simulated Annealing.

- Harris Hawk Optimization (HHO): Inspired by the cooperative hunting behavior of Harris hawks, HHO mimics the surprise pounce strategy to balance exploration (searching new areas) and exploitation (attacking promising areas).

- Simulated Annealing (SA) : Based on the annealing process in metallurgy, SA probabilistically accepts worse solutions to escape local minima, enhancing convergence to a global optimum.

- Hybrid Approach : SA is integrated into HHO's exploitation phase to refine the best solutions and prevent premature convergence.

- This improves solution accuracy, convergence speed, and robustness for complex optimization problems.

How we are approaching :

1) Feature Extraction:

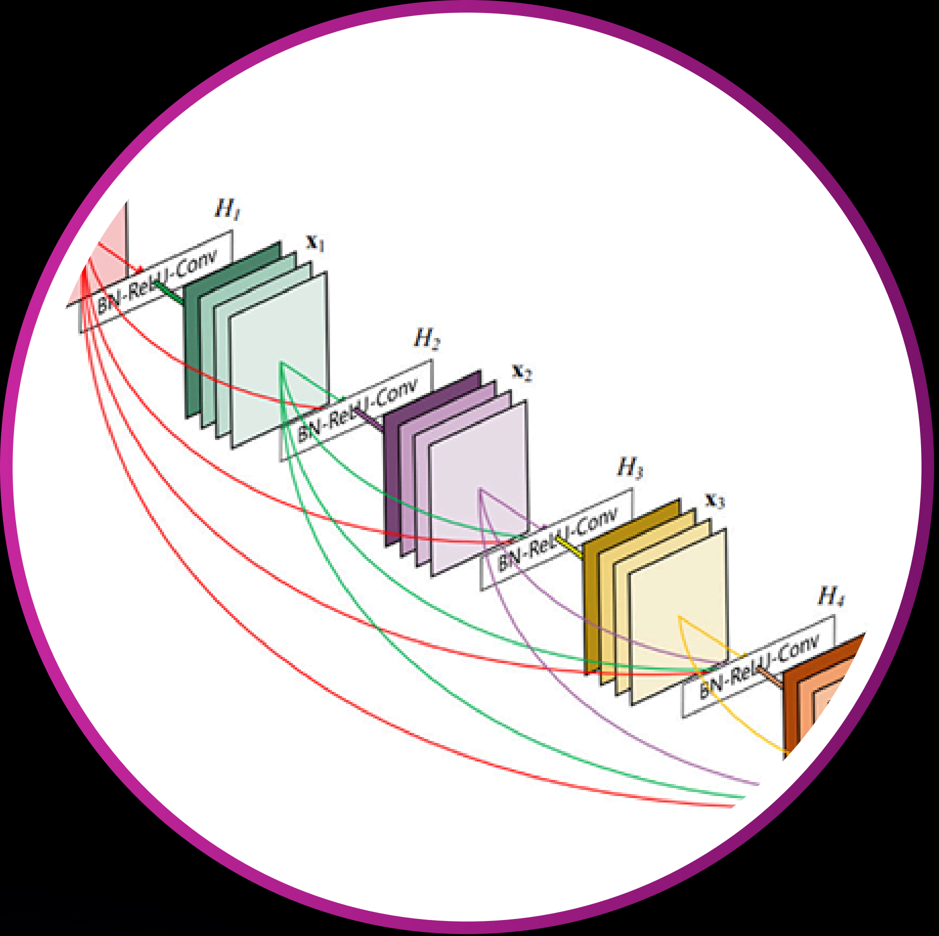
- Deep features are extracted from input images using ResNet-50, a pre-trained Convolutional Neural Network (CNN) known for its residual learning and strong feature representation capabilities.
-

2) Feature Selection & Optimization:

- Extracted features are optimized using a hybrid Harris Hawk Optimization with Simulated Annealing (HHO-SA) algorithm.
- HHO performs global exploration to identify promising feature subsets.
- SA enhances local exploitation, refining the feature selection to avoid local minima and improve convergence.
- This hybrid ensures dimensionality reduction, removes redundant features, and improves model generalization.
-

3) Classification:

- The optimized feature set is passed to a machine learning classifier (e.g., SVM, Random Forest, or CNN-based classifier) to perform accurate image category prediction.



Initialisation

Chaotic initialisation is done when assigning values to the vectors initially. The first feature vector is initialised randomly and the other feature vectors are derived from the first one by using the Sine Chaotic map.

Exploration

$$P(i+1) = \begin{cases} P_{rand}(i) - f_1 |P_{rand}(i) - 2f_2 P(i)|, \\ when\ r \geq 0.5 \\ (P_{prey}(i) - P_m(i)) - f_3(LL + f_4(UL - LL)), \\ when\ r < 0.5 \end{cases}$$

$$P_m = \frac{1}{M} \sum_{j=1}^{M} P_j(i)$$

Pm stands for average position of the current generation of hawks. And the formula for Pm

Exploitation

$$P(i+1) = \Delta P(i) - X|JS\ P_{prey} - P(i)|$$

$$\Delta P(i) = P_{prey} - P(i)$$

$$JS = 2(1 - f_5)$$

Exploitation (local attack): HHO focuses search around the current best feature subset Xbest Xbest, updating candidate positions by shrinking steps (using escape energy E and jump strength delata to intensify sampling of high-quality feature combinations.

Simulated Annealing (SA) Refinement:

Here delata f is change in fitness and T is Temprature parameter.

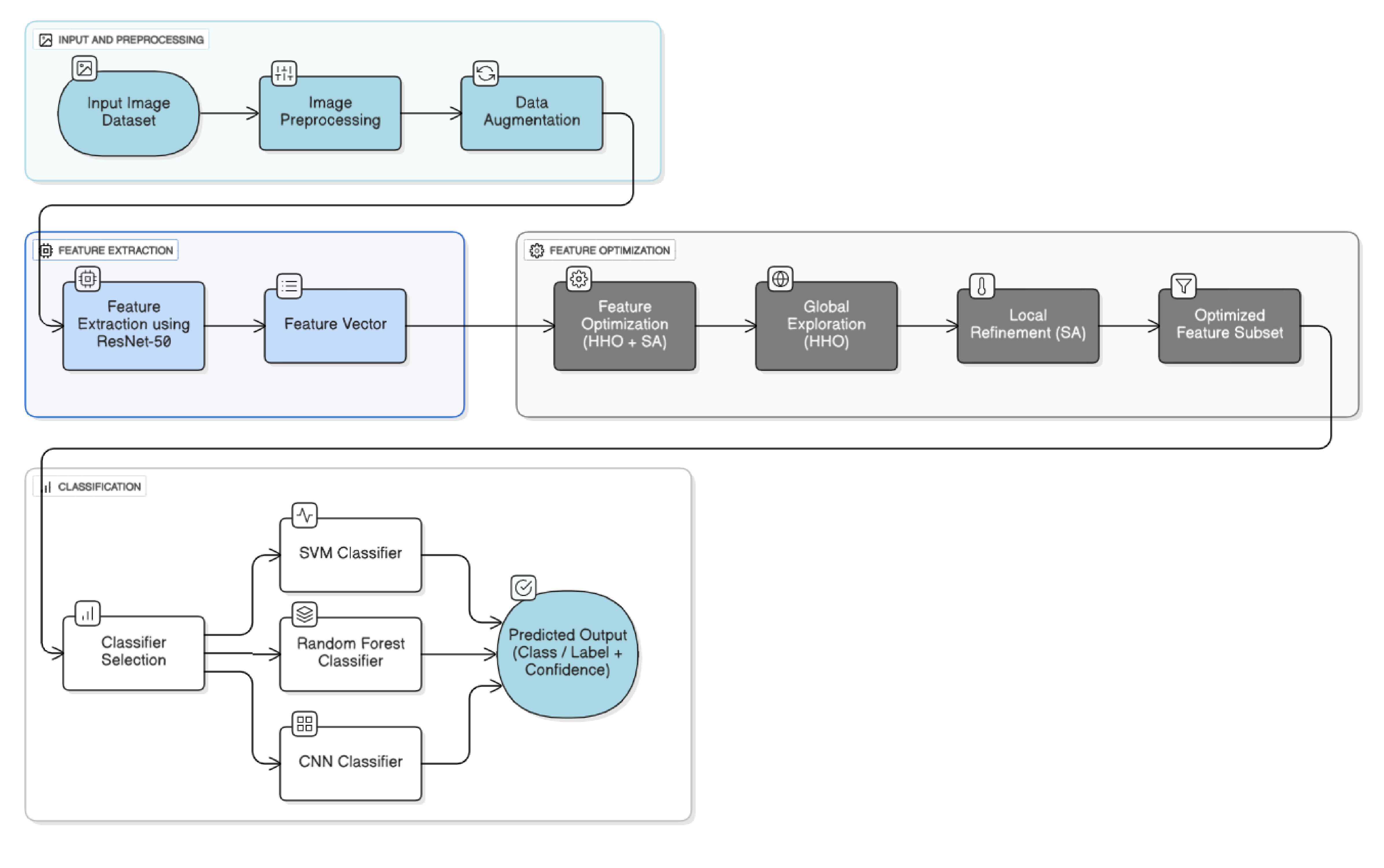
$$P(\Delta f) = \begin{cases} 1, & \Delta f < 0 \\ e^{-\Delta f / T}, & \Delta f \geq 0 \end{cases}$$

$$fitness = \alpha \frac{q}{Q} + (1 - \alpha)\frac{e}{E}$$

Final Fitness Function

Where is e = selected feature and E = Total Feature

Block Diagram



DataSet Summary & key insight :

1) Medical Waste Dataset:

Focuses on categorizing different types of medical waste generated in healthcare facilities.
Features describe chemical, physical, or visual properties of waste materials.
Supports research in smart waste management systems for healthcare environments.
Useful for developing AI models that aid in environmental safety and biomedical waste monitoring.

2) UC Merced Land Use Dataset

The images were manually extracted from large images from the USGS National Map Urban Area Imagery collection for various urban areas around the country. The pixel resolution of this public domain imagery is 1 foot.
This is a 21 class land use image dataset meant for research purposes.

3) AID Land Dataset

The AID dataset has 30 different scene classes and about 200 to 400 samples of size 600x600 in each class. AID is a new large-scale aerial image dataset, by collecting sample images from Google Earth imagery.

1) Meidcal Waste 4.0

data set : https://zenodo.org/records/7643417

Collab Link : https://colab.research.google.com/drive/1ujDR-h-onVM95N_TYzLE0jBRdu3yWQ2f?usp=sharing#scrollTo=YJSSuct8hYM6

Total Features : 2048
Selected Features : 932
Train : 72%, Test : 20%, Validation : 8%
Total Feature Reduction : 54.49%
Final Test Accuracy (HHO-SA SVM): 96.7%

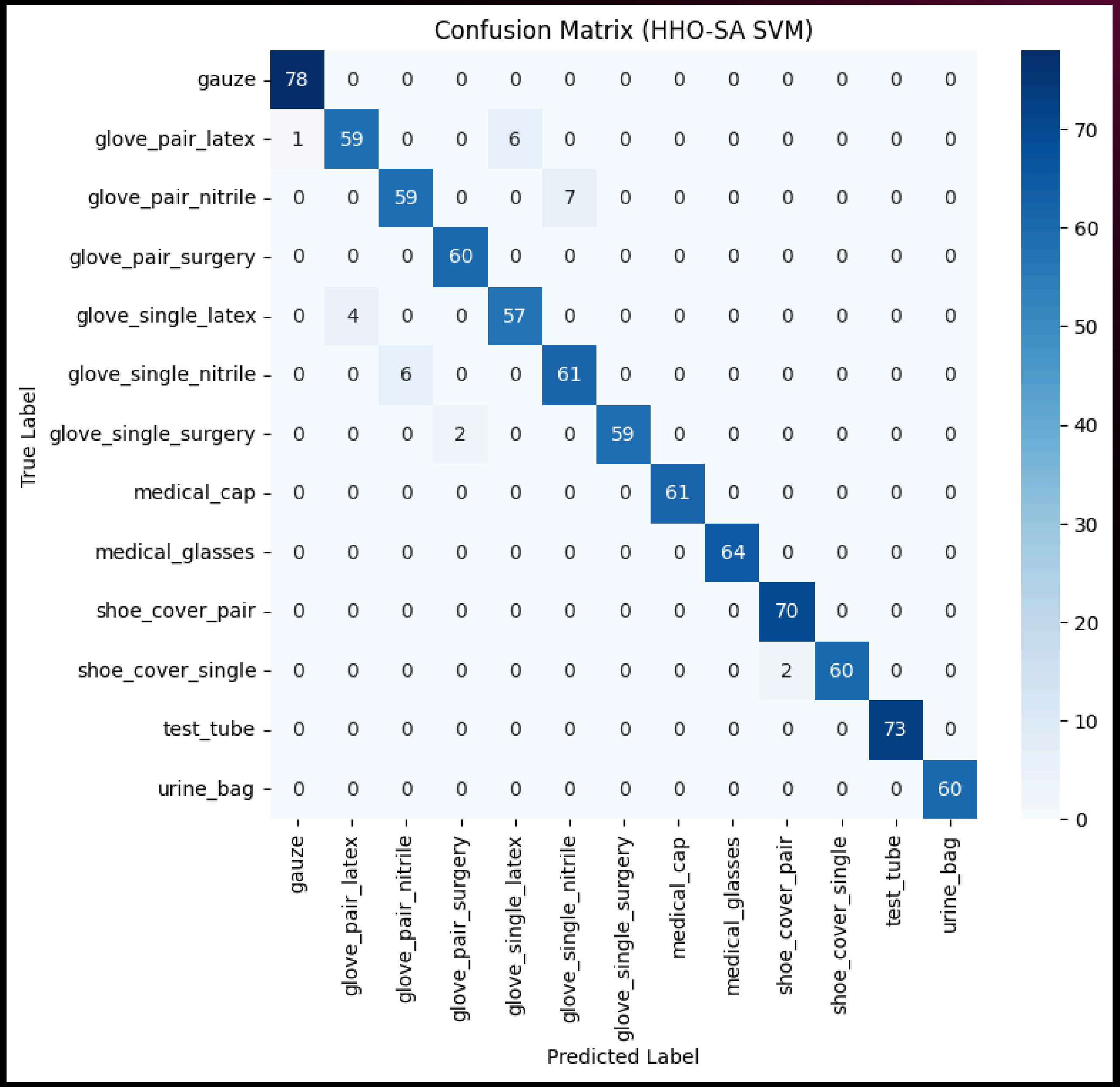
Classification Report :

```
Classification Report:
                      precision    recall  f1-score   support

               gauze     0.9873    1.0000    0.9936        78
    glove_pair_latex     0.9365    0.8939    0.9147        66
  glove_pair_nitrile     0.9077    0.8939    0.9008        66
  glove_pair_surgery     0.9677    1.0000    0.9836        60
  glove_single_latex     0.9048    0.9344    0.9194        61
glove_single_nitrile     0.8971    0.9104    0.9037        67
glove_single_surgery     1.0000    0.9672    0.9833        61
         medical_cap     1.0000    1.0000    1.0000        61
     medical_glasses     1.0000    1.0000    1.0000        64
     shoe_cover_pair     0.9722    1.0000    0.9859        70
   shoe_cover_single     1.0000    0.9677    0.9836        62
           test_tube     1.0000    1.0000    1.0000        73
           urine_bag     1.0000    1.0000    1.0000        60

            accuracy                         0.9670       849
           macro avg     0.9672    0.9667    0.9668       849
        weighted avg     0.9672    0.9670    0.9670       849
```

Confusion Matrix



2) UC Merced Land Use Dataset

data set : https://www.kaggle.com/datasets/abdulhasibuddin/uc-merced-land-use-dataset

Collab Link :
https://colab.research.google.com/drive/1cp1GNbleHNK3rz6IfBsDQ5Ugiw8A-E3K?usp=sharing

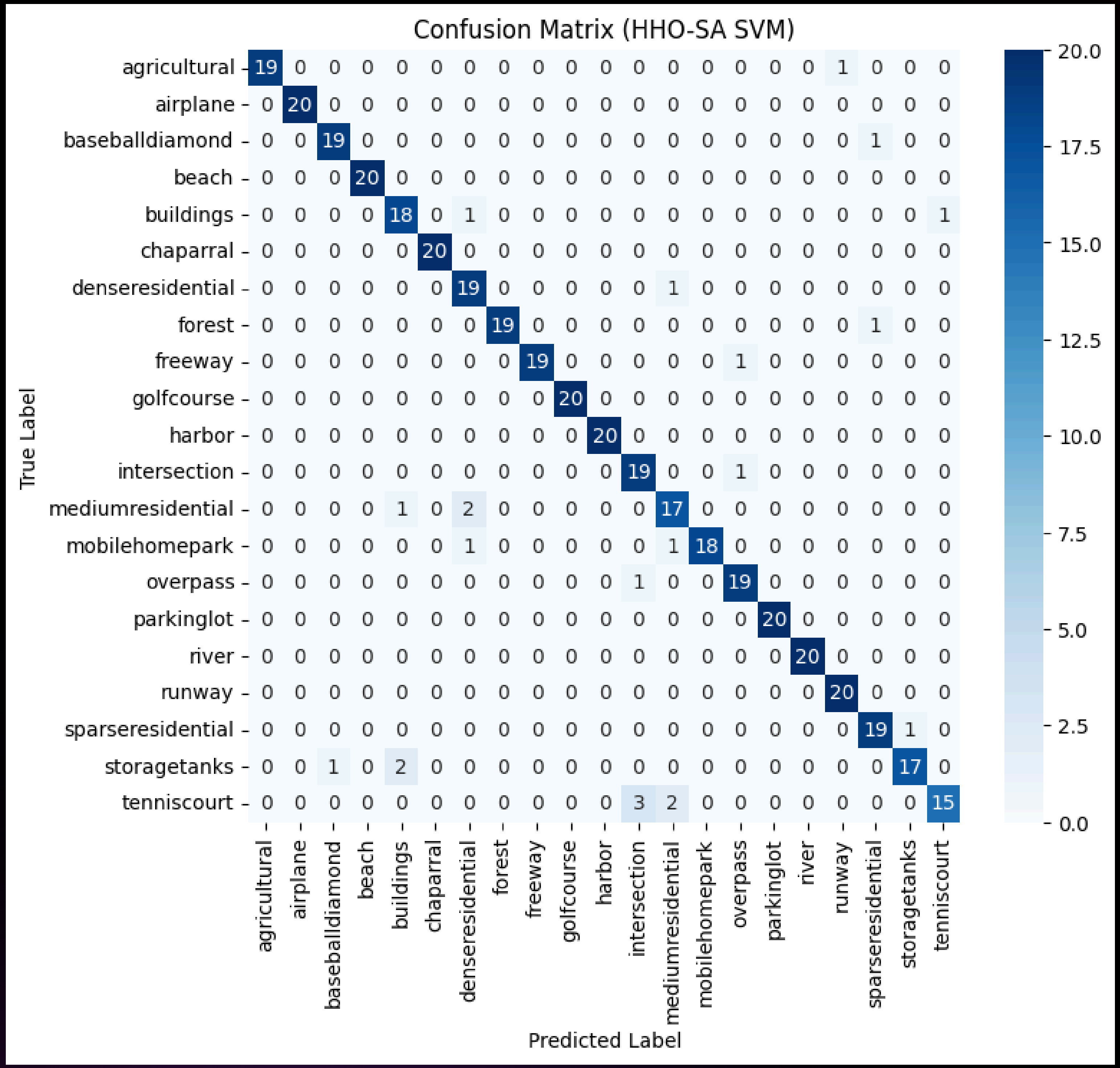
Total Features : 2048
Selected Features : 536
Train : 72%, Test : 20%, Validation : 8%
Total Feature Reduction : 73.83%
Final Test Accuracy (HHO-SA SVM): 94.52%

Classification Report :

Classification Report:

	precision	recall	f1-score	support
agricultural	1.0000	0.9500	0.9744	20
airplane	1.0000	1.0000	1.0000	20
baseballdiamond	0.9500	0.9500	0.9500	20
beach	1.0000	1.0000	1.0000	20
buildings	0.8571	0.9000	0.8780	20
chaparral	1.0000	1.0000	1.0000	20
denseresidential	0.8261	0.9500	0.8837	20
forest	1.0000	0.9500	0.9744	20
freeway	1.0000	0.9500	0.9744	20
golfcourse	1.0000	1.0000	1.0000	20
harbor	1.0000	1.0000	1.0000	20
intersection	0.8261	0.9500	0.8837	20
mediumresidential	0.8095	0.8500	0.8293	20
mobilehomepark	1.0000	0.9000	0.9474	20
overpass	0.9048	0.9500	0.9268	20
parkinglot	1.0000	1.0000	1.0000	20
river	1.0000	1.0000	1.0000	20
runway	0.9524	1.0000	0.9756	20
sparseresidential	0.9048	0.9500	0.9268	20
storagetanks	0.9444	0.8500	0.8947	20
tenniscourt	0.9375	0.7500	0.8333	20
accuracy			0.9452	420
macro avg	0.9482	0.9452	0.9454	420
weighted avg	0.9482	0.9452	0.9454	420

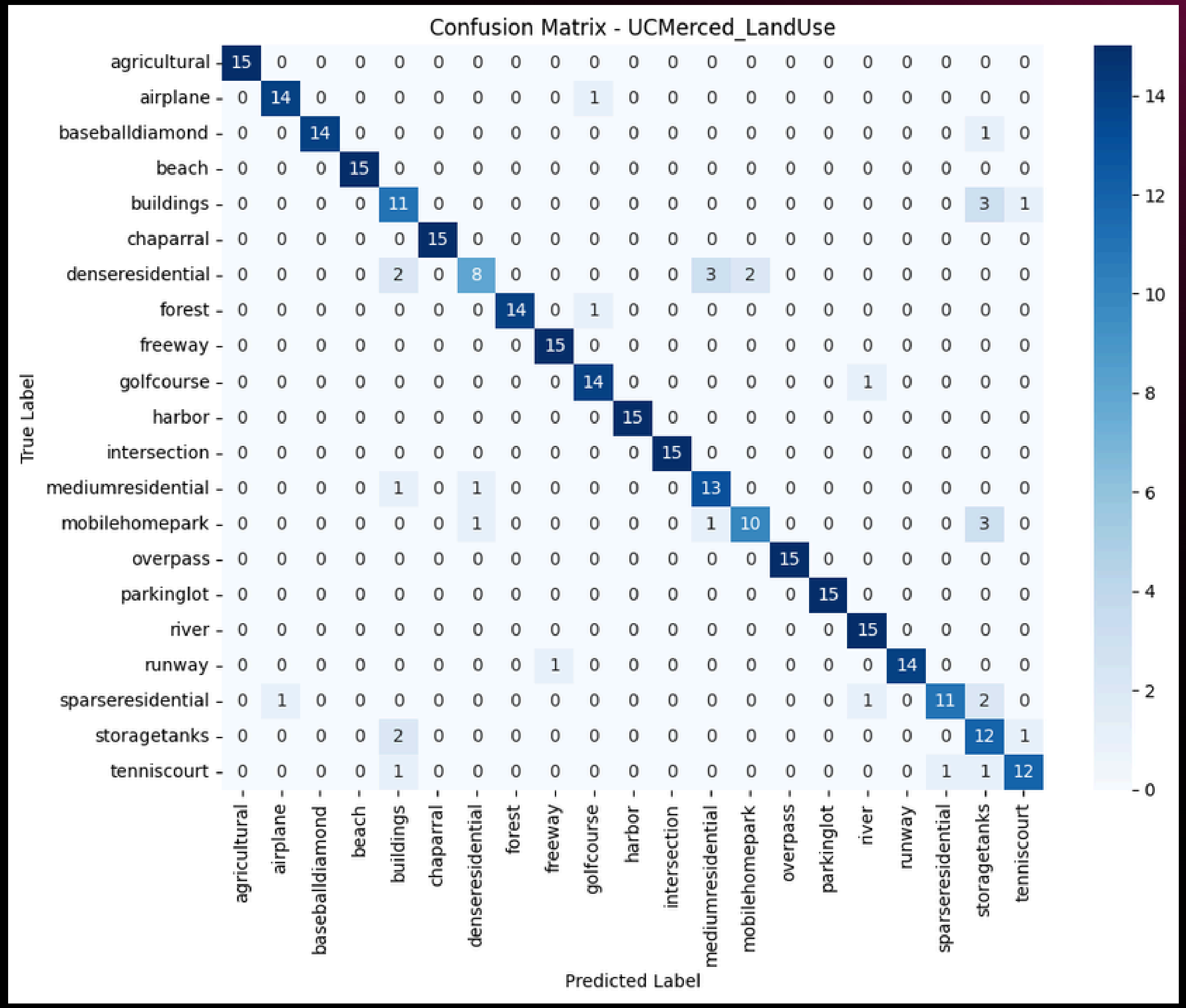
Confusion Matrix UC Merced :



3) AID Land Dataset

data set : https://www.kaggle.com/datasets/jiayuanchengala/aid-scene-classification-datasets

Confusion Matrix :



Total Features :25088
Selected Features : 1470
Train : 70%, Test : 15%, Validation : 15%
Total Feature Reduction : 54.49%
Final Test Accuracy (HHO-SA SVM): 89.5%

Classification Report :

Comparative Study :

1) Medical Waste 4.0

	Our Model	Base Line Model

Classification Report :

Our Model

Classification Report:

	precision	recall	f1-score	support
gauze	0.9873	1.0000	0.9936	78
glove_pair_latex	0.9365	0.8939	0.9147	66
glove_pair_nitrile	0.9077	0.8939	0.9008	66
glove_pair_surgery	0.9677	1.0000	0.9836	60
glove_single_latex	0.9048	0.9344	0.9194	61
glove_single_nitrile	0.8971	0.9104	0.9037	67
glove_single_surgery	1.0000	0.9672	0.9833	61
medical_cap	1.0000	1.0000	1.0000	61
medical_glasses	1.0000	1.0000	1.0000	64
shoe_cover_pair	0.9722	1.0000	0.9859	70
shoe_cover_single	1.0000	0.9677	0.9836	62
test_tube	1.0000	1.0000	1.0000	73
urine_bag	1.0000	1.0000	1.0000	60
accuracy			0.9670	849
macro avg	0.9672	0.9667	0.9668	849
weighted avg	0.9672	0.9670	0.9670	849

Base Line Model

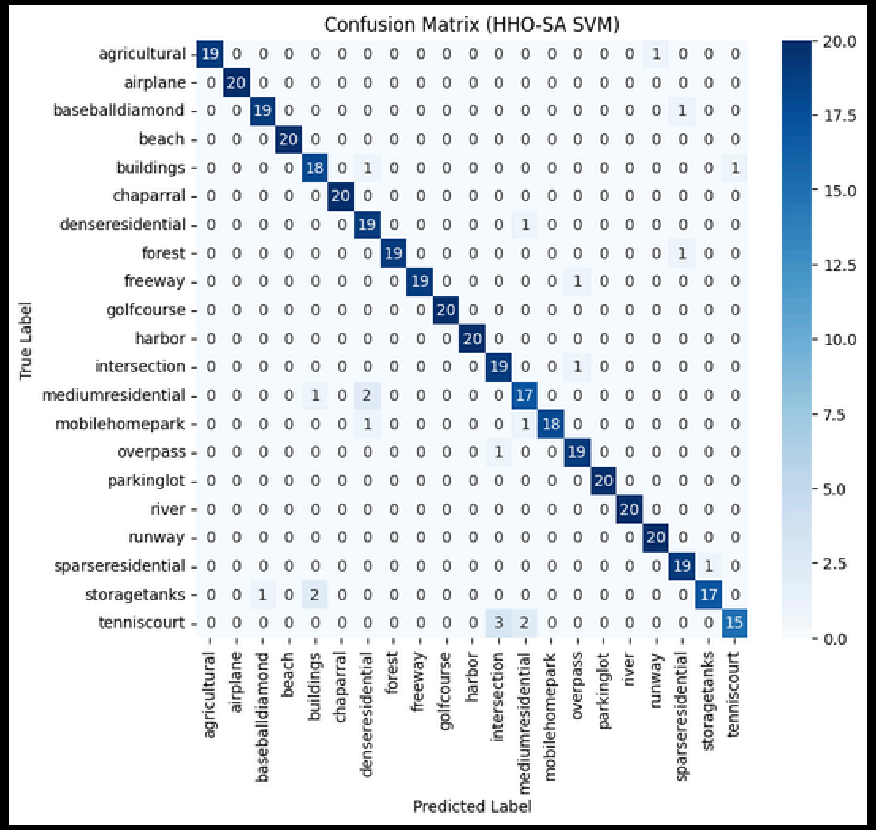
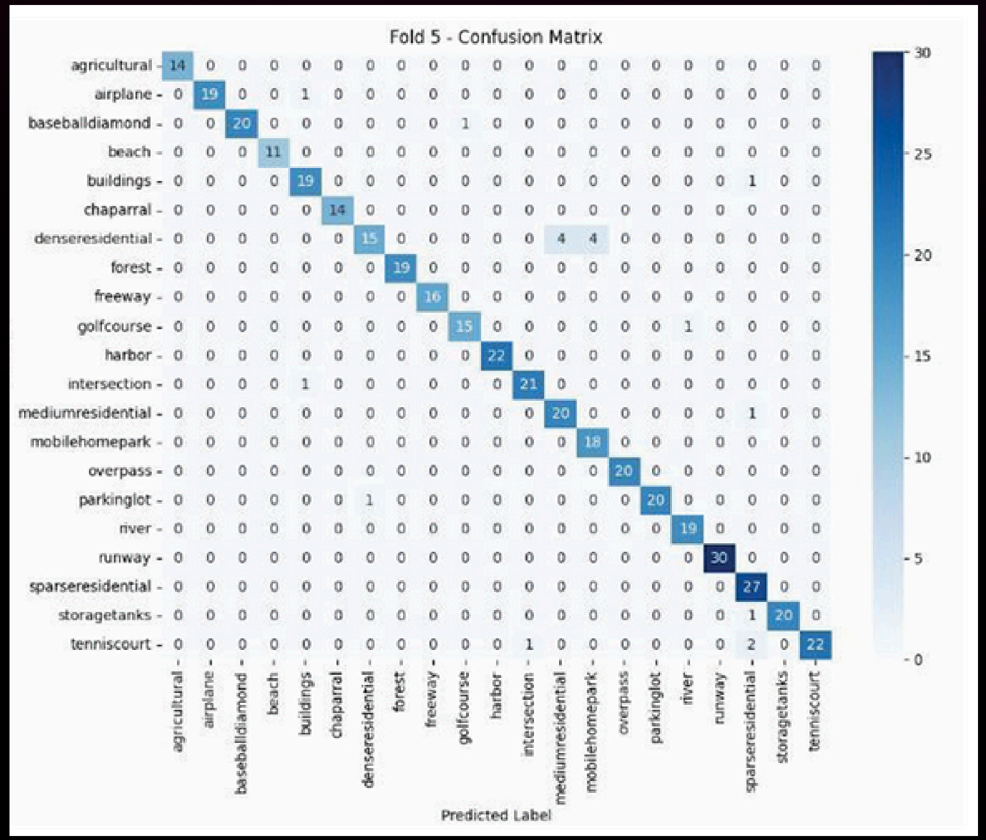
	Precision		Recall		F1-score	
	Pretrain	Fine-tune	Pretrain	Fine-tune	Pretrain	Fine-tune
Gloves	0.90	0.93	0.94	0.88	0.92	0.90
Gauze	0.95	0.98	1.00	1.00	0.98	0.99
Apparatus	0.94	0.93	0.84	0.94	0.89	0.94
Bottle	0.84	0.98	0.75	1.00	0.79	0.99
Bag	0.79	1.00	0.98	0.98	0.88	0.99
Needles	0.91	1.00	0.83	0.98	0.87	0.99
Tweezers	1.00	0.98	0.90	1.00	0.95	0.99
Syringe	0.91	0.98	0.98	1.00	0.94	0.99
Averaged	0.91	**0.97**	0.90	**0.97**	0.90	**0.97**

Accuracy :

	Our Model	Base Line Model
Accuracy :	96.7%	~97%

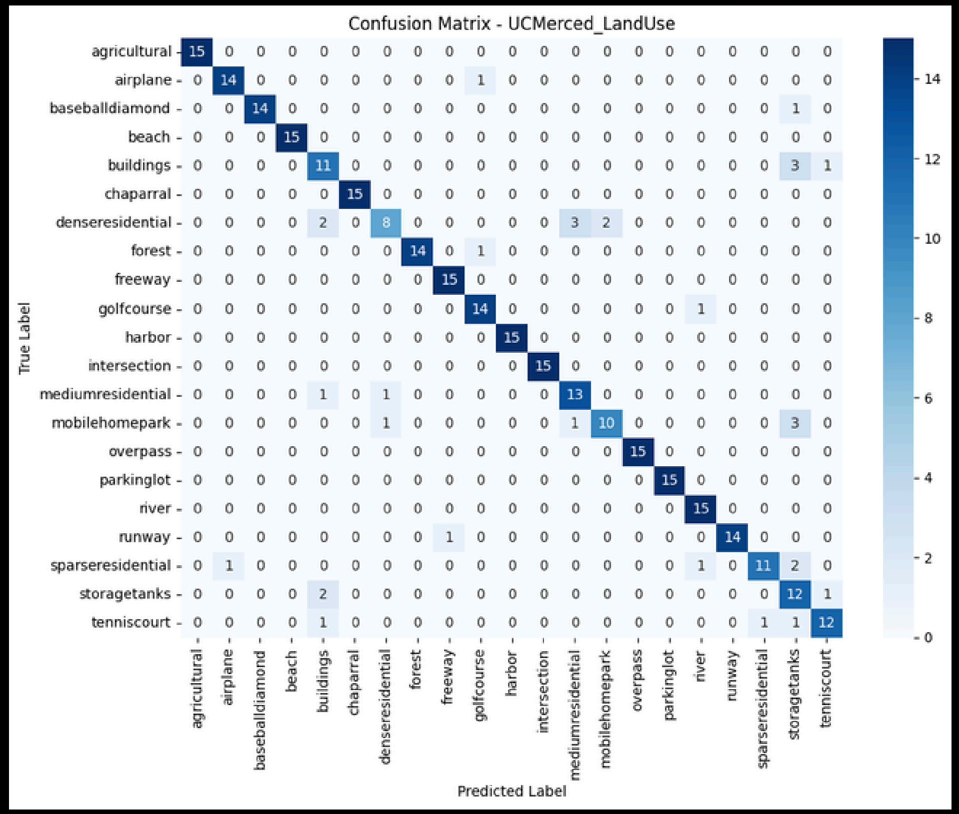
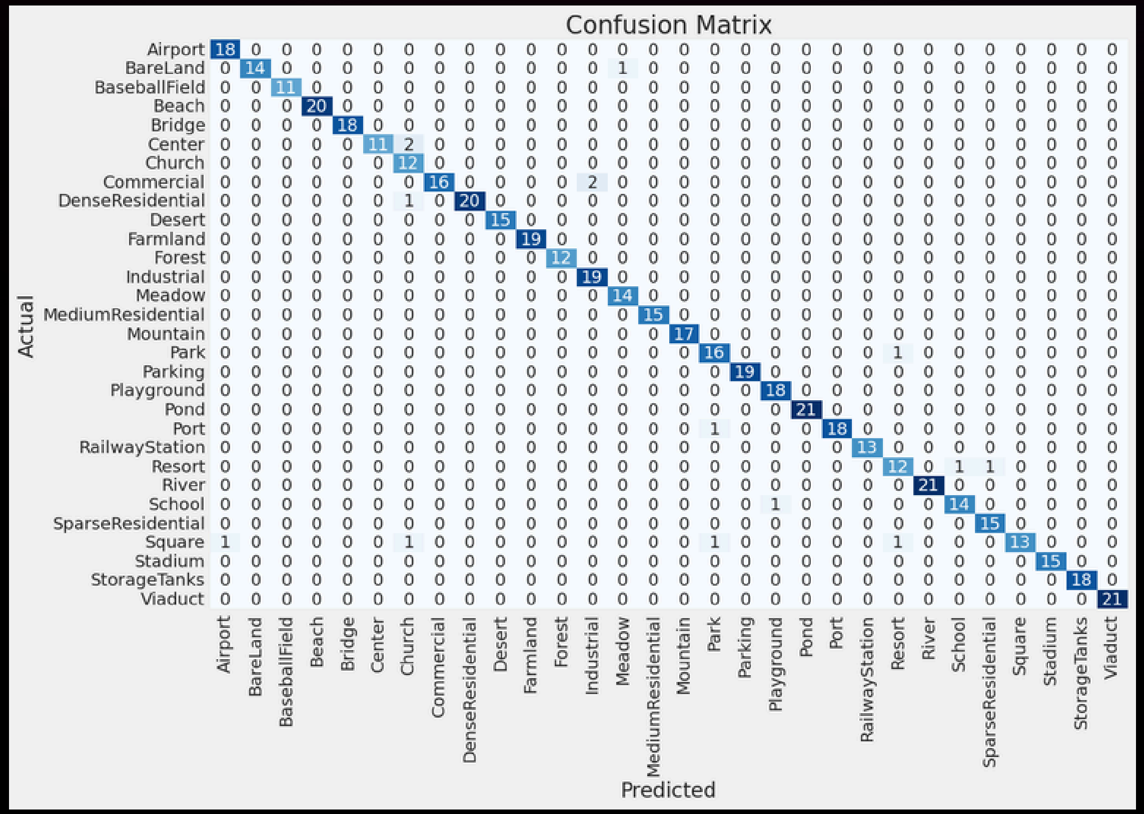
Comparative Study :

2) UC Merced Land Use Dataset

<table>
<tr><th></th><th>Our Model</th><th>Base Line Model</th></tr>
<tr><td>Confusion Matrix :</td><td>
</td><td>
</td></tr>
<tr><td>Accuracy :</td><td>94.52%</td><td>~95%</td></tr>
</table>

Comparative Study :

3) AID Land Dataset

<table>
<tr><th></th><th>Our Model</th><th>Base Line Model</th></tr>
<tr><td>Classification Report :</td><td>
</td><td>
</td></tr>
<tr><td>Accuracy :</td><td>89.5%</td><td>97%</td></tr>
</table>

Novelty :

- Introduces a hybrid feature optimization framework combining Harris Hawk Optimization (HHO) with Simulated Annealing (SA) for improved convergence and global–local balance.

- Unlike conventional models that rely only on deep features, our approach selects the most discriminative subset of features from ResNet-50 outputs, reducing redundancy and dimensionality.

- The integration of metaheuristic optimization with deep learning enhances classification accuracy and robustness on complex image datasets.

- Provides an adaptive optimization mechanism capable of escaping local minima and achieving faster, more reliable feature selection compared to standard evolutionary algorithms.

Contribution :

Pranav Umbarkar : Feature Optimization (HHO + SA Hybrid Model)

- Designed and implemented the Harris Hawk Optimization (HHO) algorithm integrated with Simulated Annealing (SA).
- Tuned algorithm parameters for effective exploration and exploitation.
- Selected the optimal feature subset to enhance model performance and reduce dimensionality.
- Creation of Video presentation.

Mistry Ritik : Data Handling & Feature Extraction

- Collected, cleaned, and preprocessed the image dataset.
- Implemented data augmentation and normalization techniques.
- Used ResNet-50 for deep feature extraction and prepared the feature dataset for optimization
- Performed result analysis, visualizations, and compiled the final report and presentation.

V. Sri Ram : Classification & Model Evaluation

- Trained and tested machine learning classifiers (e.g., SVM, Random Forest, CNN).
- Evaluated performance using metrics such as Accuracy, Precision, Recall, and F1-score.

Thank You!