MACHINE LEARNING AND PATTERN RECOGNITION
AI3011

PLAKSHAVISTA

A FUTURISTIC APPROACH TO CAMPUS LOCALIZATION AND INFORMATION

KAUSTUBH SINGH, SHIVAM KUMAR, VIKAS KUMAR 1

CONTENT

PROBLEM STATEMENT

The problem at hand is to develop a mobile-image based system that enables individuals to accurately determine their location within Plaksha University's campus and retrieve relevant information about buildings, artwork and other points of interest.

This system should be capable of providing users with a seamless and intuitive way to navigate the campus and access vital information.

MOTIVATION

Observing guests arriving at Plaksha University frequently seeking informatiom about buildings, artwork, and other points of interest from guards, students and others, we, as students of a tech-oriented institution, were inspired to bring technology to the rescue. The motivation for this project stems from our desire to streamline the process of helping visitors find their way within the campus.

By implementing a ML model for information retrieval, we aim to provide a user-friendly solution that will make navigating the university campus a more efficient and enjoyable experience for all.

LITERATURE REVIEW

LOCATION RECOGNITION USING DETECTED OBJECTS IN AN IMAGE

Aris Faryanto and Iping Supryana, 2011

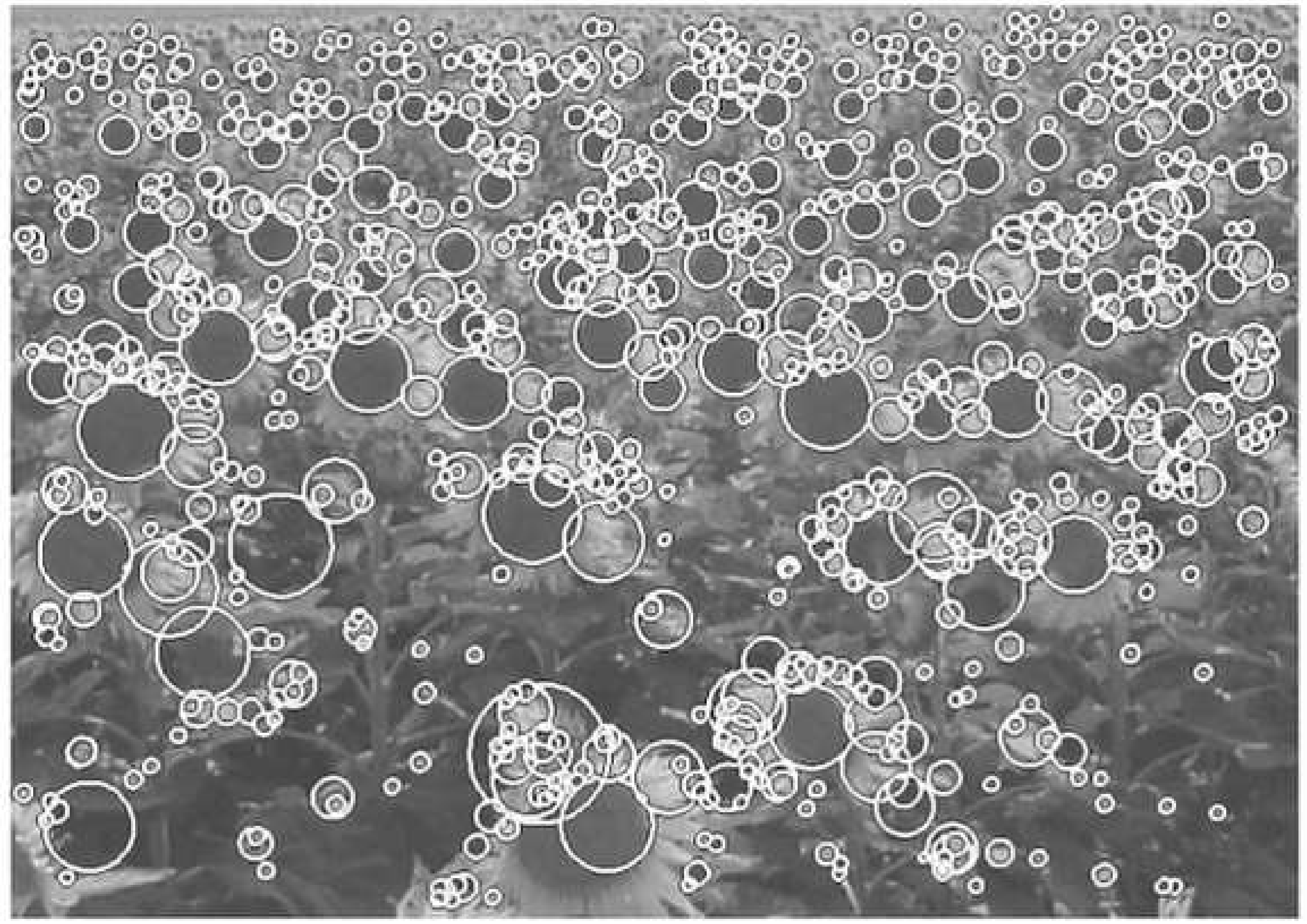


Fig. 1 Sample of detected interest points using Hessian-based detectors

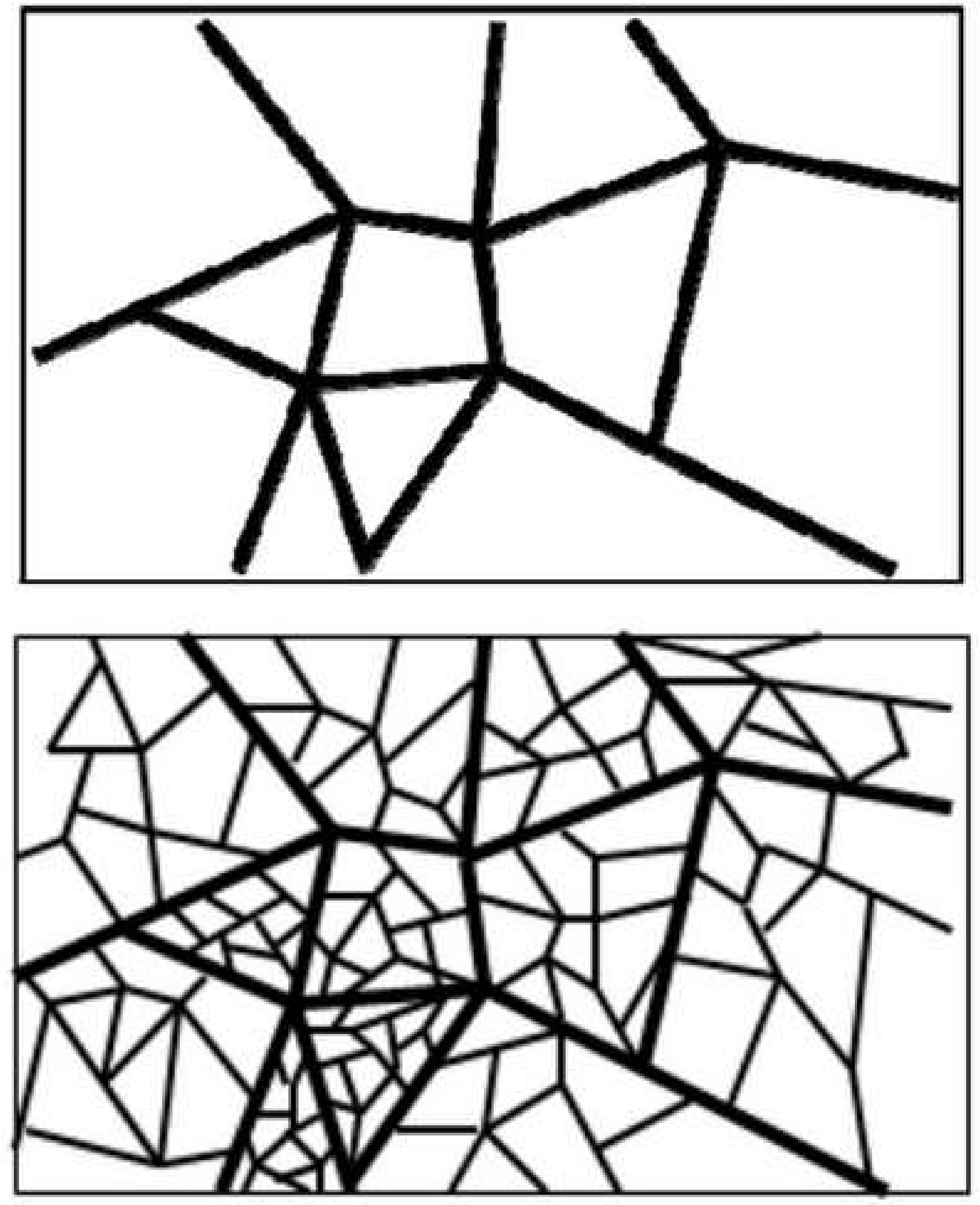
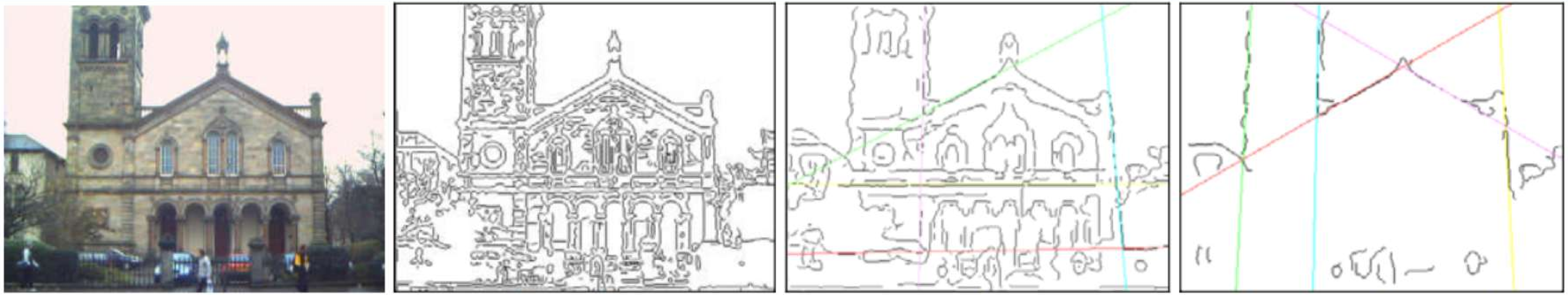
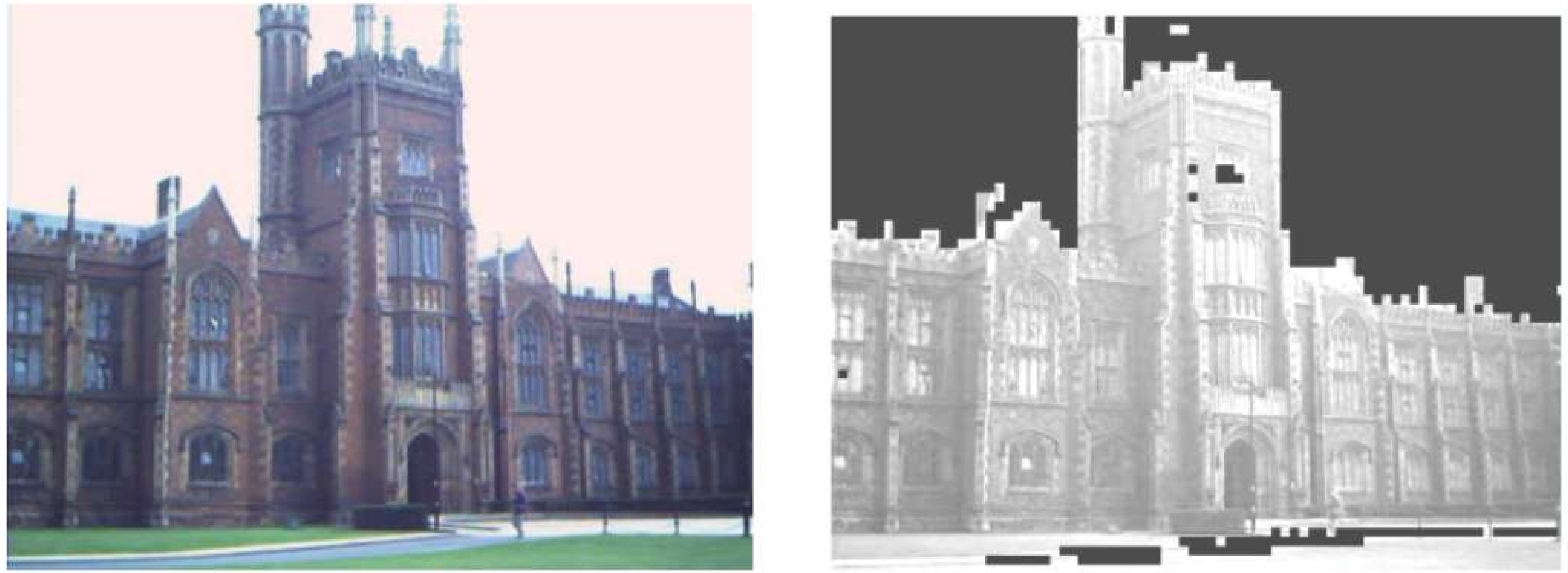


Fig. 2 Clustering visualization in first level (top) and second level (bottom)



(a) original image (b) direct detection (c) median filter (d) threshold control



(a) original image (b) detection in black

BUILDING IDENTIFICATION FROM LOW-RESOLUTION MOBILE IMAGES

Wanji Mai, Chris Tweed and Peter Hung, 2007

Table .4: A general Inception v3 Model

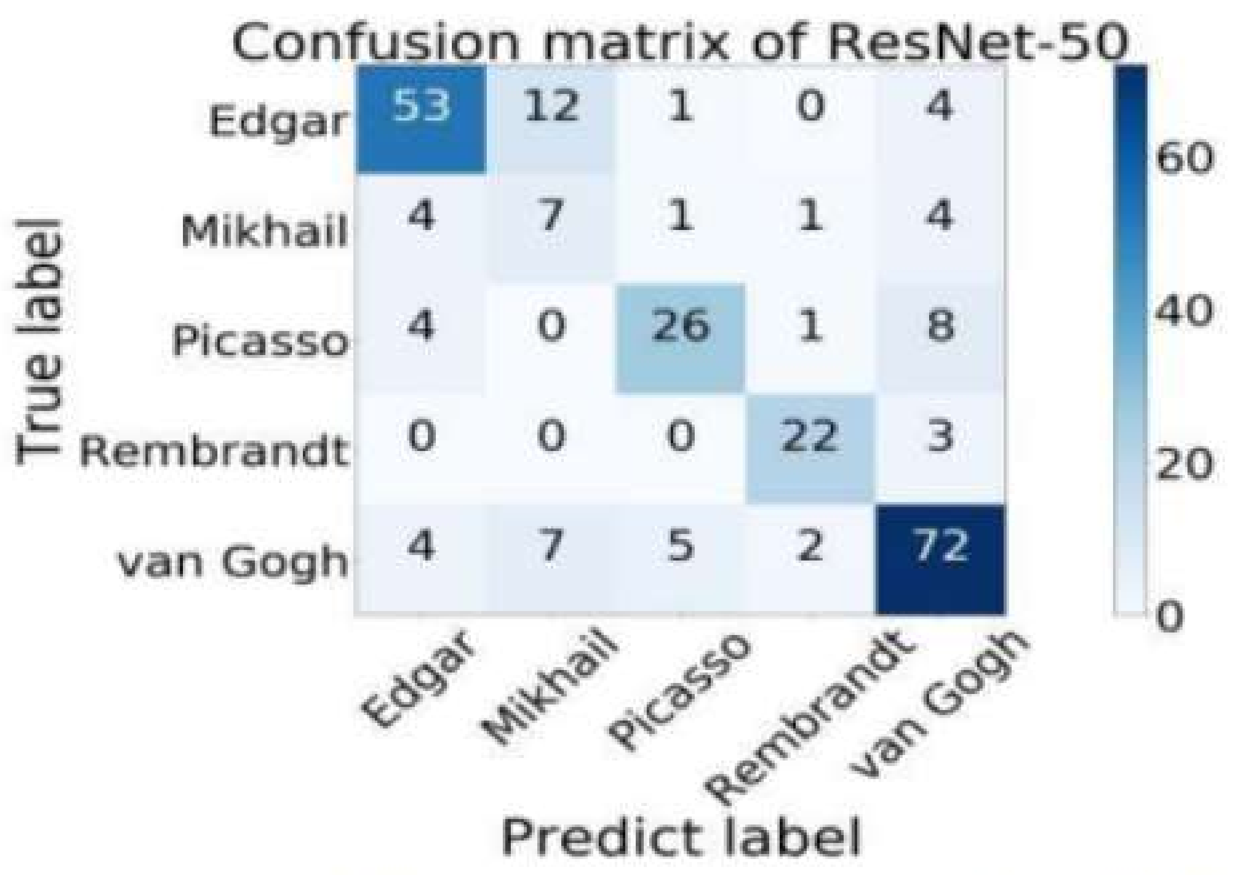
5x Inception Module A
Grid Size Reduction (with some modifications)
4x Inception Module B
[Auxiliary Classifier]
Grid Size Reduction
2x Inception Module C
Final Output Module

Table. 5: Binary classification result of one artist with other artists' artworks

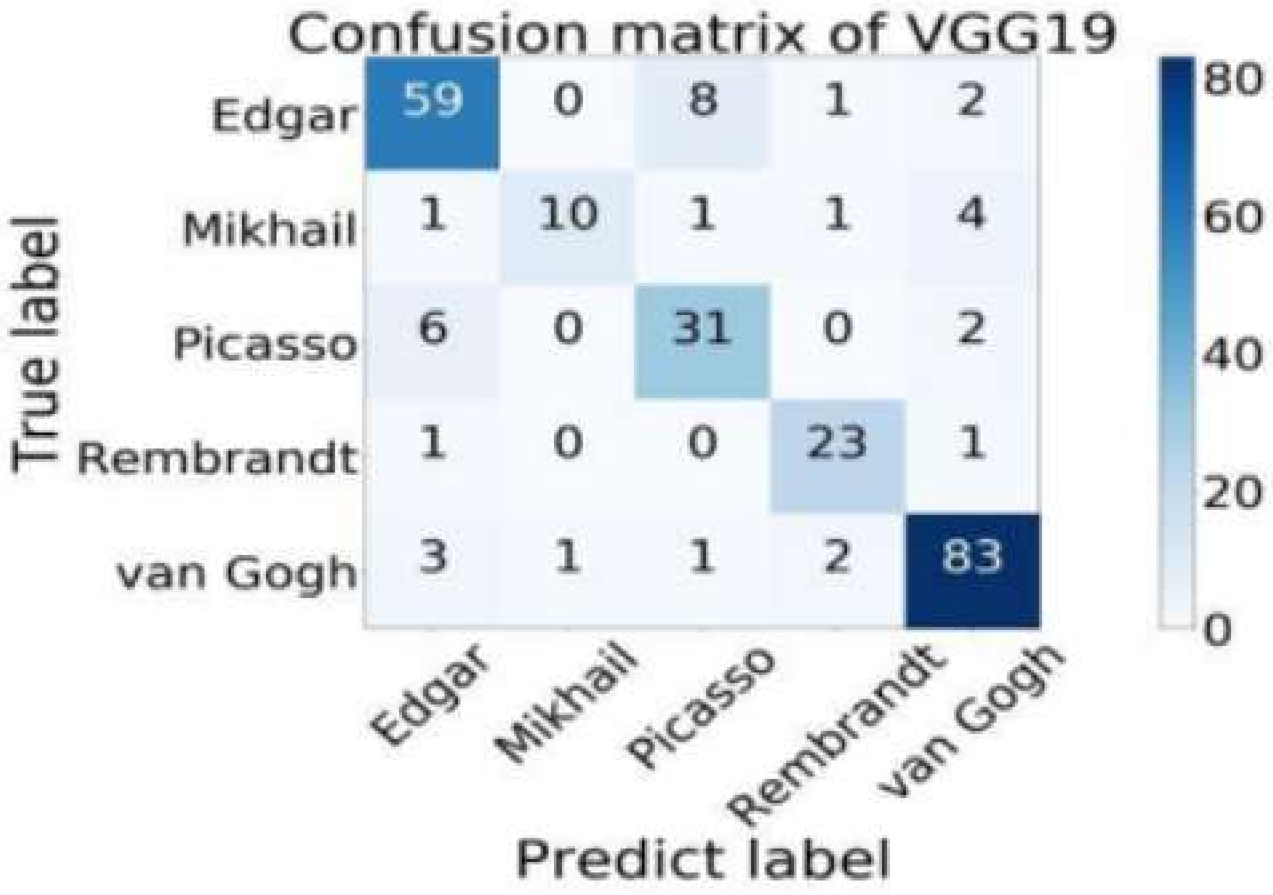
Classes	Average Accuracy
Claude Monet artworks and Other painters artworks	81.05 %
Eugene Boudin artworks and Other painters artworks	90.50 %
Nicholas Roerich artworks and Other painters artworks	87.60 %
Pablo Picasso artworks and Other painters artworks	81.00 %
Rembrandt artworks and Other painters artworks	86.65 %
Salvador Dali artworks and Other painters artworks	79.60 %
Vincent van Gogh artworks and Other painters artworks	74.85 %

CATEGORIZATION OF ARTWORK IMAGES BASED ON PAINTERS USING CNN

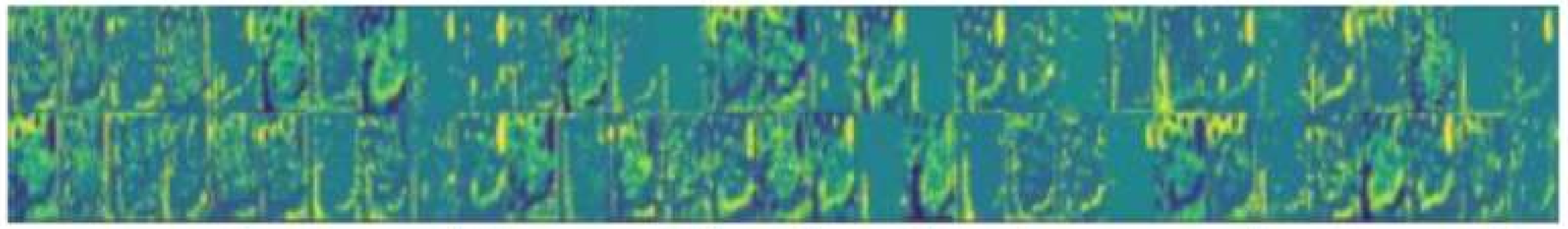
Kaustav Mondal , Anita H.B



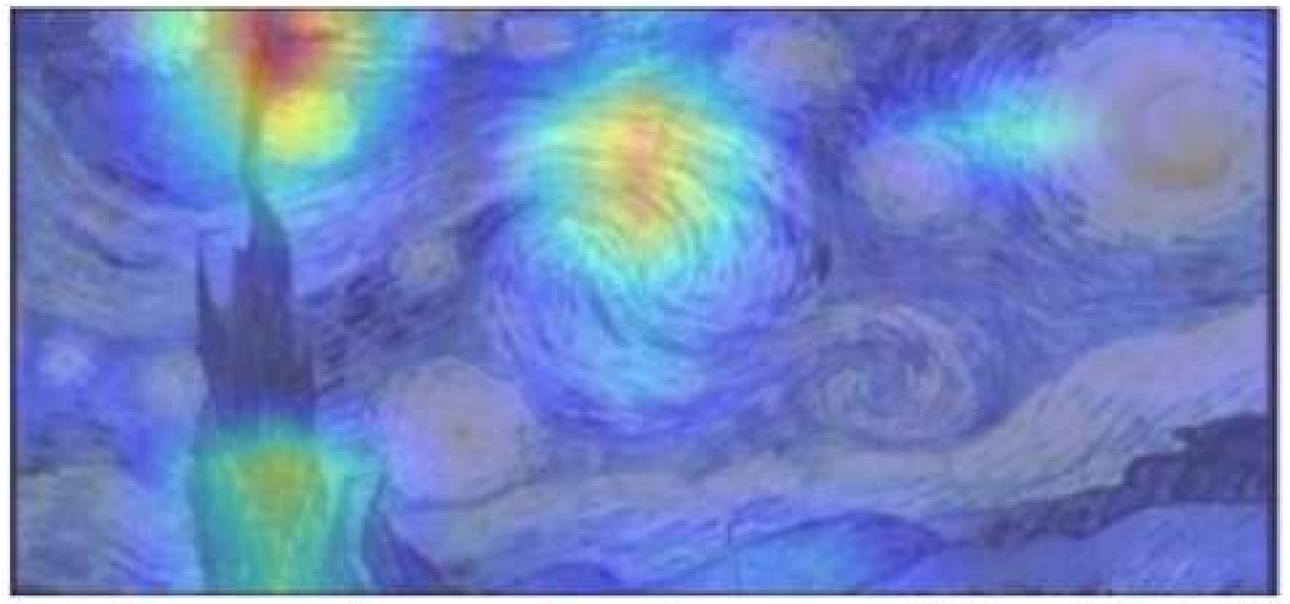
(a) the confusion matrix of ResNet-50



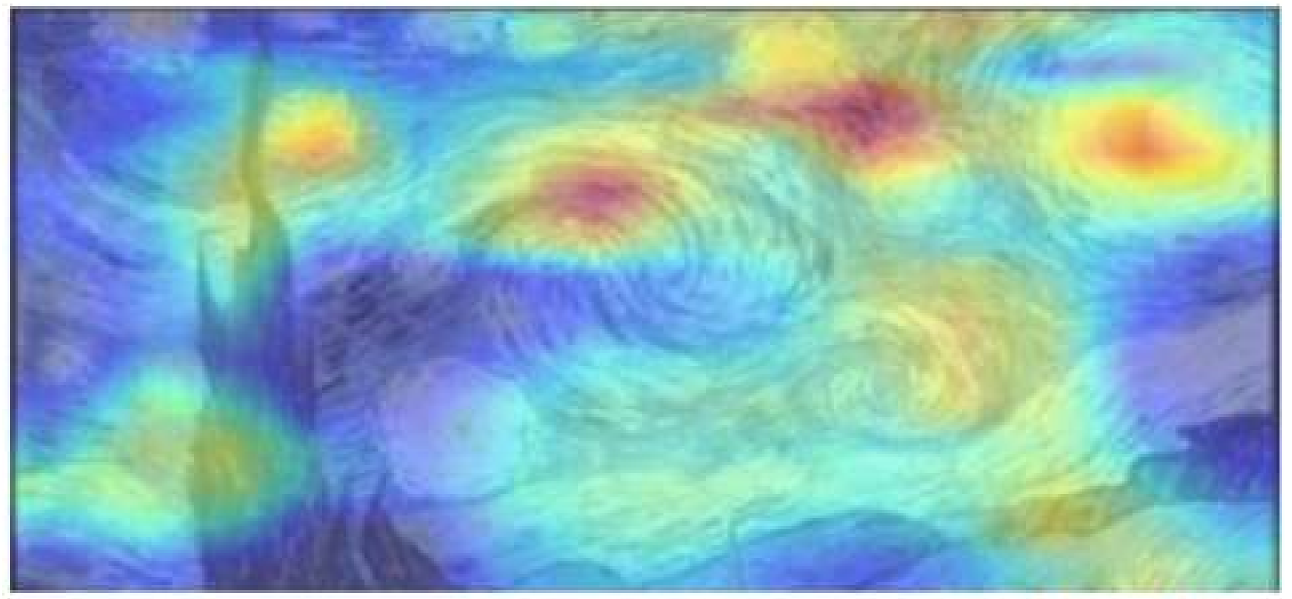
(b) the confusion matrix of VGG19



(a) the convolutional kernel in the third convolutional layer of ResNet-50



(a) the grad-cam heat-map of ResNet-50



(b) the grad-cam heat-map of VGG19

Figure 11: the grad-cam heat-map of ResNet-50 and VGG19

THE PERFORMANCE OF TWO CNN METHODS IN ARTWORKS AESTHETIC FEATURE RECOGNITION

Jipeng Gao, Haolin Zhou, Yicheng Zhang

A CNN-LSTM FRAMEWORK FOR AUTHORSHIP CLASSIFICATION OF PAINTINGS

Kevin Alfianto Jangtjik, Trang-Thi Ho, Mei-Chen Yeh, Kai-Lung Hua

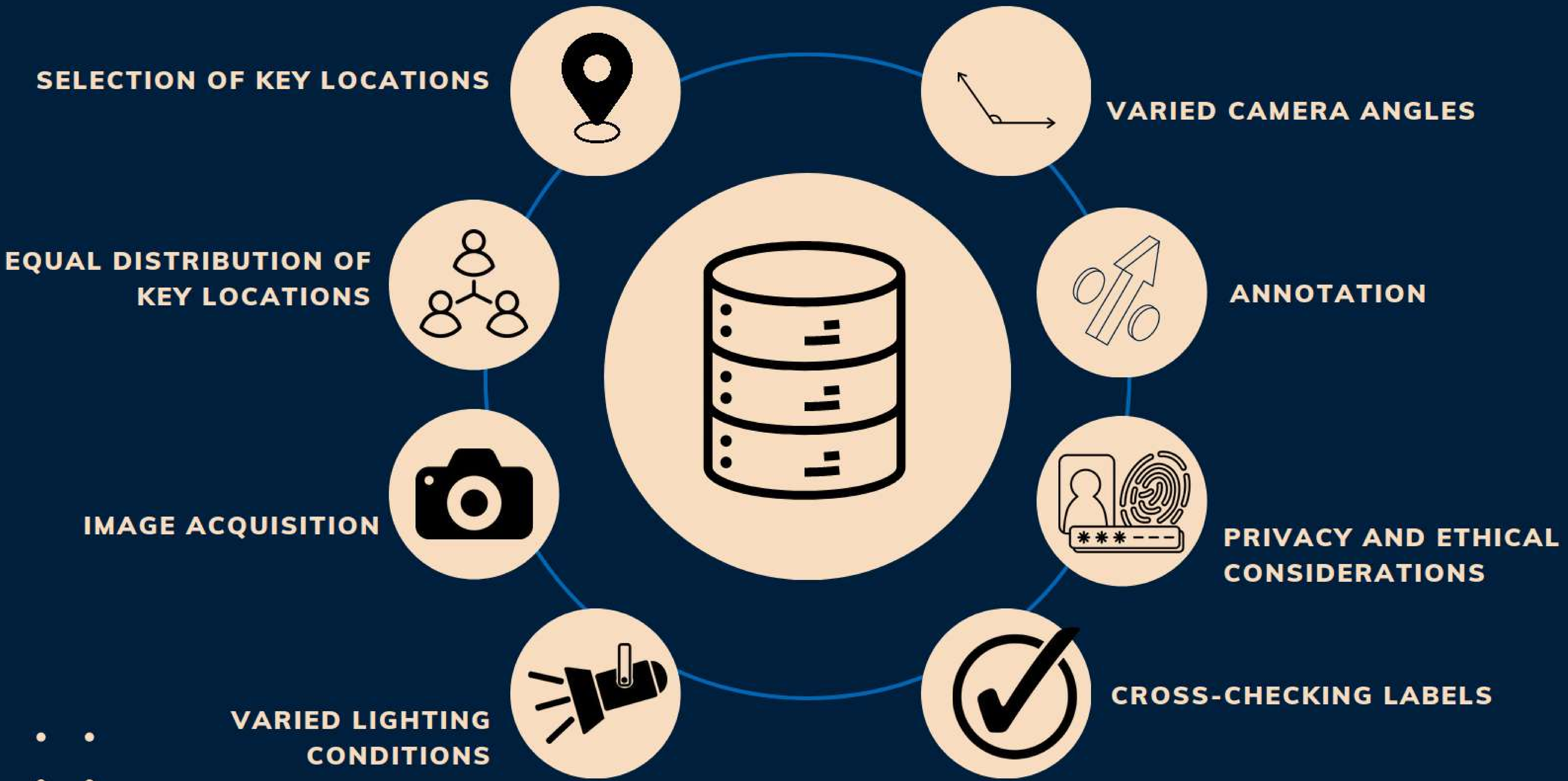
Table 1. Performance evaluation of classification result

Top-1			
	Precision	Recall	F Score
Pre-trained model [9]	65.26%	66.15%	65.7%
Multi-scale pyramid [5]	71.22%	72.30%	71.7%
Ours	73.71%	74.23%	73.97%

Predicted Class / Actual Class

	1	2	3	4	5	6	7	8	9	10	11	12	13
1	50	0	5	0	15	0	0	10	10	5	5	0	0
2	0	95	0	0	0	0	0	0	0	0	5	0	0
3	10	0	40	0	0	20	10	10	0	0	5	0	5
4	0	0	0	80	0	0	0	0	0	5	0	10	5
5	5	5	0	0	55	0	5	0	20	0	10	0	0
6	0	0	0	5	0	90	0	5	0	0	0	0	0
7	5	0	5	0	0	0	85	0	0	0	0	5	0
8	0	0	5	0	0	0	0	95	0	0	0	0	0
9	0	0	0	0	0	5	0	0	80	0	0	5	10
10	10	0	5	0	0	0	0	0	0	80	5	0	0
11	0	0	10	0	0	0	0	0	0	10	80	0	0
12	0	0	0	0	0	0	0	0	0	0	0	100	0
13	0	10	5	0	10	0	0	0	10	0	30	0	35

DATA COLLECTION



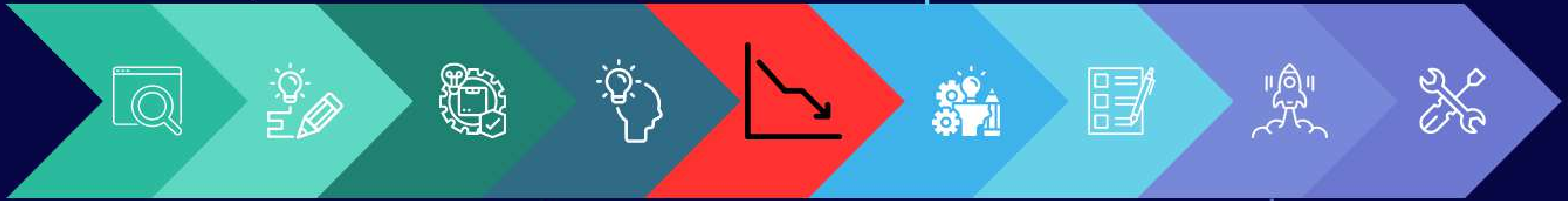
WORKFLOW

We used a shared Google Drive to store and organize data images accessible to all team members

CENTRALIZED DATA STORAGE

Now, we are storing all the data on the local device to avoid data loss

DATA STORAGE ON LOCAL SYSTEM



COLLABORATIVE DATA ANALYSIS

We worked together on the dataset using Google Colab for real-time collaboration and code sharing.

REMOTE ACCESS

Maintaining the ability to monitor and support remotely using tools like AnyDesk

DATA PRE-PROCESSING

IMAGE AUGMENTATION

Original Image

Augmented Images

MODEL SELECTION

Possible Applicable Approaches

SURF

- Robust to scale and orientation
- High number of feature points
- Does not handle lighting and patterns

ORB

- Faster than SURF
- Rotation-invariant and resistant to noise

CNN

- Translation Invariance
- Spatial Hierarchies

SHAPE & TEXTURE

- Robustness to image resolution
- Invariance to Lighting Conditions
- Specific Object Recognition

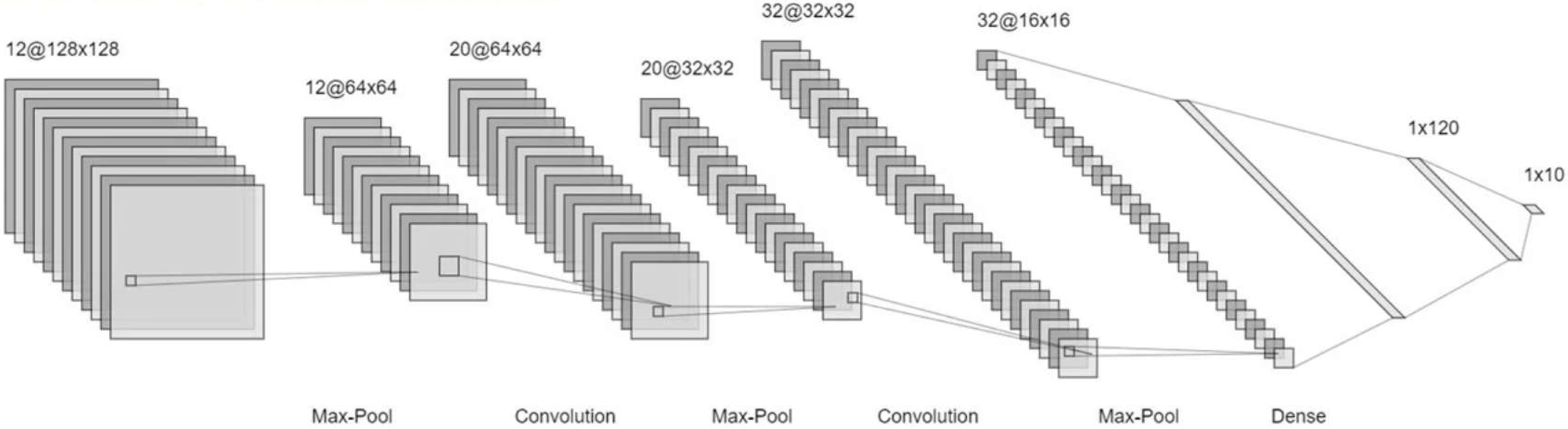
Approach	Pros	Cons
CNNs	• Identification of hierarchial features and spatial relations • Data availability and color detection. • Train once, use anytime	• Need for high-performance GPUs • Lack of interpretability • Adversarial attacks
Shape and Texture Matching	• Robustness to image resolution • Specific Object Recognition	• Sensitive to variations in lighting, scale, and rotation • Focus on local features
GAN Based Segmentation	• Great performance against adversarial attacks.	• Computationally intensive • Continuous time-scale data for segmentation • Segmentation errors
SURF/ORB	• Robust to scale and orientation • High number of feature points • Noise resistant	• Not good for unique/complex pattern recognition • Not robust to occlusions • Not invariant to changes in viewpoint or perspective
GNP Based Classification	• Exploits use of vocabulary trees • For top 10-15 best matches, the accuracy can be as high as 80%. This is good as we have many samples that are similar	• Large time-series dataset required • Video dataset over the constraint volume available • Extremely high dimensional search space

ARTNET

Image Details

Title: On The Brink

Description: 'On the Brink' by Martand Khosla is a sculpture encapsulating the theme of regeneration amid urban upheaval. In the flux of city transformations, the artwork symbolizes the collective struggle to reconcile the past with the dynamic present. Khosla's creation serves as a visual metaphor for the interplay of thoughts shaping new futures. The sculpture's form embodies the fluid exchange of ideas, mirroring the evolving urban landscape. 'On the Brink' masterfully captures the perpetual state of flux in both thoughts and cities, offering a profound reflection on the transformative nature of human existence and the ever-renewing spirit amidst societal change.

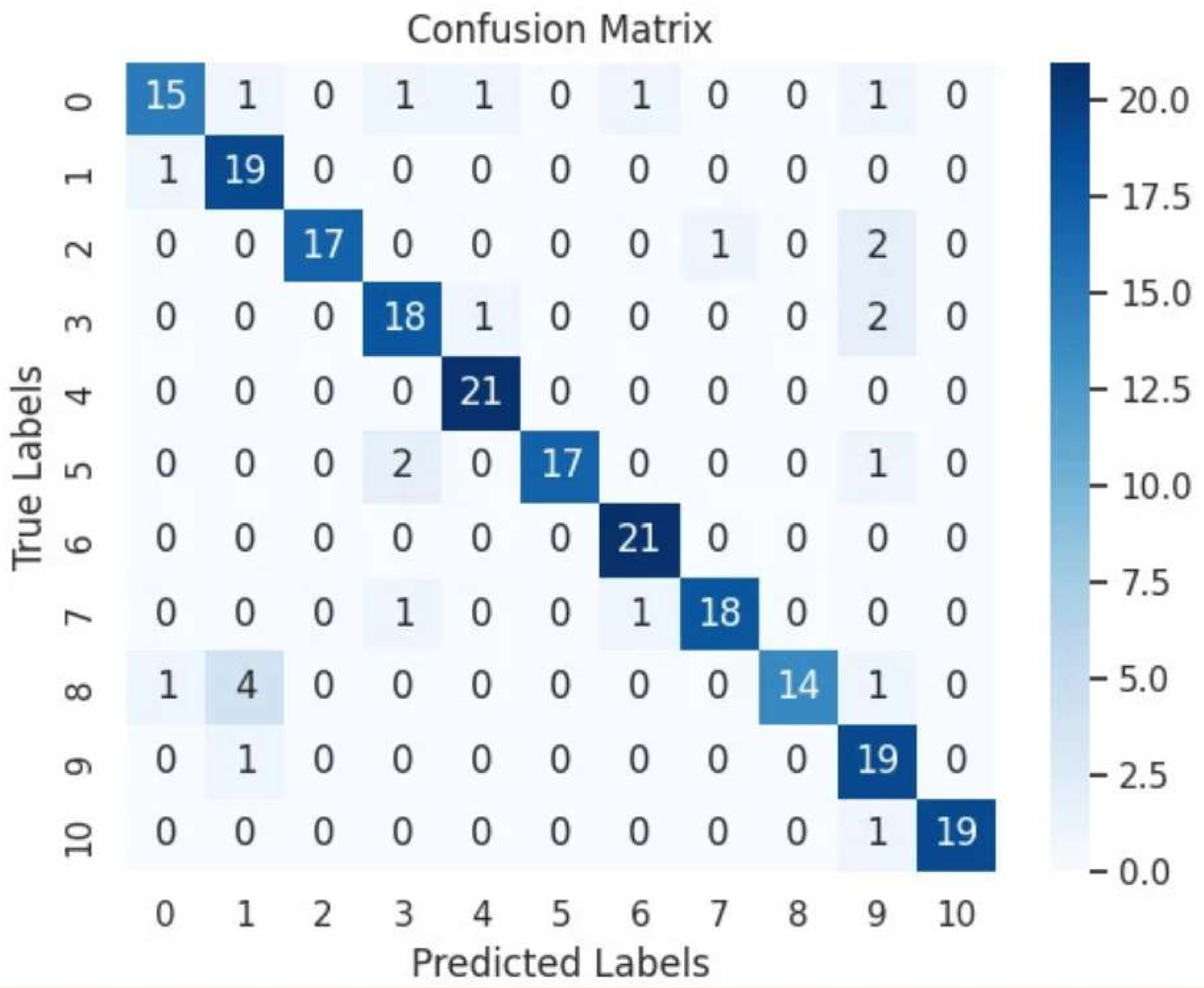


```
Training Starts...

Epoch: 1      Train Loss: 2.35      Train Accuracy: 0.38    Test Accuracy: 0.43
Epoch: 2      Train Loss: 1.25      Train Accuracy: 0.62    Test Accuracy: 0.71
Epoch: 3      Train Loss: 0.78      Train Accuracy: 0.75    Test Accuracy: 0.75
Epoch: 4      Train Loss: 0.71      Train Accuracy: 0.77    Test Accuracy: 0.78
Epoch: 5      Train Loss: 0.47      Train Accuracy: 0.85    Test Accuracy: 0.76
Epoch: 6      Train Loss: 0.39      Train Accuracy: 0.88    Test Accuracy: 0.82
Epoch: 7      Train Loss: 0.35      Train Accuracy: 0.89    Test Accuracy: 0.87
Epoch: 8      Train Loss: 0.25      Train Accuracy: 0.92    Test Accuracy: 0.83
Epoch: 9      Train Loss: 0.32      Train Accuracy: 0.90    Test Accuracy: 0.88
Epoch: 10     Train Loss: 0.26      Train Accuracy: 0.92    Test Accuracy: 0.90
```

The accuracy of the model is 89%

		precision	recall	f1-score	support
0.	Faculty Floor Bharti Academic Block	0.88	0.75	0.81	20
1.	Faculty Floor Bharti Academic Block	0.76	0.95	0.84	20
2.	Central Campus	1.00	0.85	0.92	20
3.	Community Discs	0.82	0.86	0.84	21
4.	On The Brink	0.91	1.00	0.95	21
5.	Spring of Construction	1.00	0.85	0.92	20
6.	Penumbra	0.91	1.00	0.95	21
7.	Faculty Floor Havells Research Block	0.95	0.90	0.92	20
8.	Memory of the Land of Five Rivers	1.00	0.70	0.82	20
9.	Uncle Tonnies Food Joint	0.70	0.95	0.81	20
10.	Plaksha University Utility Block	1.00	0.95	0.97	20
	accuracy			0.89	223
	macro avg	0.90	0.89	0.89	223
	weighted avg	0.90	0.89	0.89	223




```
The classes in the dataset are:
0.      Faculty Floor Bharti Academic Block
1.      Faculty Floor Bharti Academic Block
2.      Central Campus
3.      Community Discs
4.      On The Brink
5.      Spring of Construction
6.      Penumbra
7.      Faculty Floor Havells Research Block
8.      Memory of the Land of Five Rivers
9.      Uncle Tonnies Food Joint
10.     Plaksha University Utility Block

Size of Training Dataset: 1604
Size of Testing Dataset: 223
```

DEMONSTRATION

POSSIBLE IMPROVEMENTS

- Data can be collected at different saturation values or augmented in ways that vary the saturation and hue.
- A mobile app can be developed that serves similar purpose as the web version of the classifier and describer.

THANK YOU!