Application of Chaos Theory to Evaluate Pedestrian Behavior using Deep Learning based Video Analytics in Different Diurnal Variations

Bachelor of Science (Civil Engineering)
Thesis Presentation

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Presentation Outline

Background and Motivation

Study Objectives

Research Methodology

Data Collection and Preprocessing

Model Building and Validation

Results and Analysis

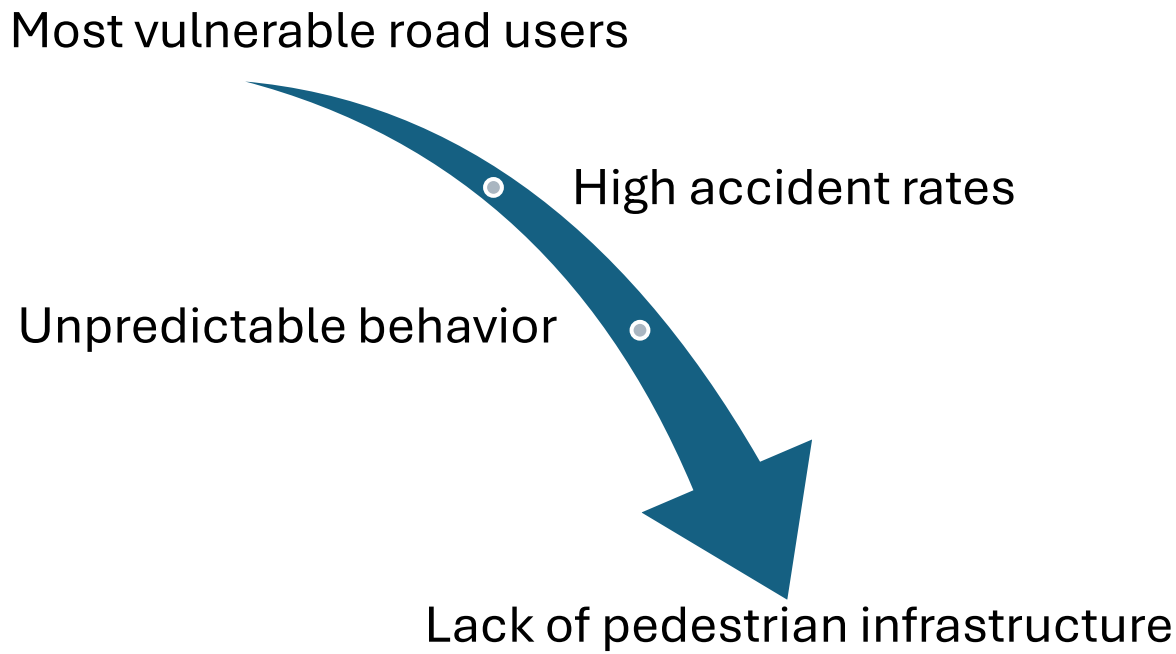
Major Findings

Study Limitations

Recommendations for Future Research

Background and Motivation

Necessity for Pedestrian Behavior Evaluation



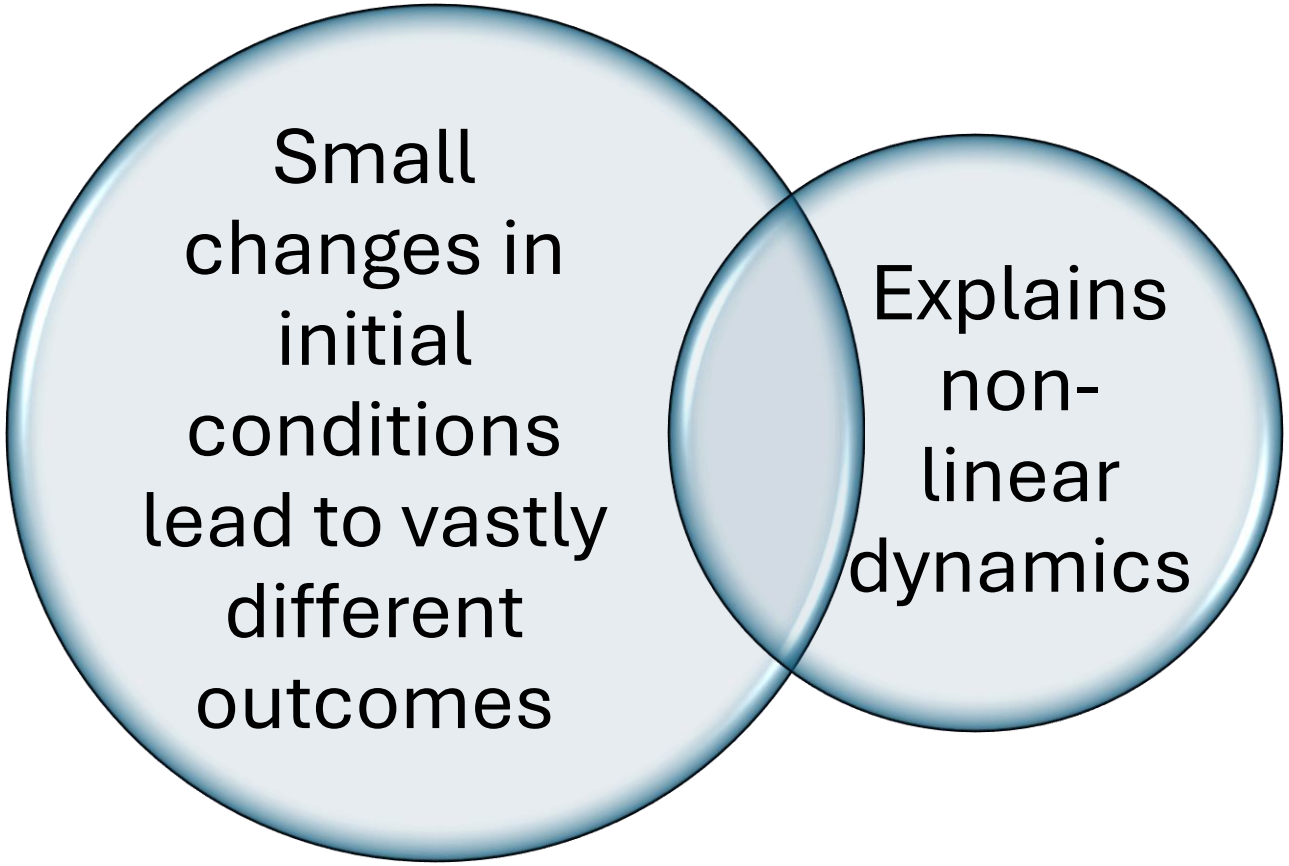
Background and Motivation

What is
Chaos Theory?

Background and Motivation

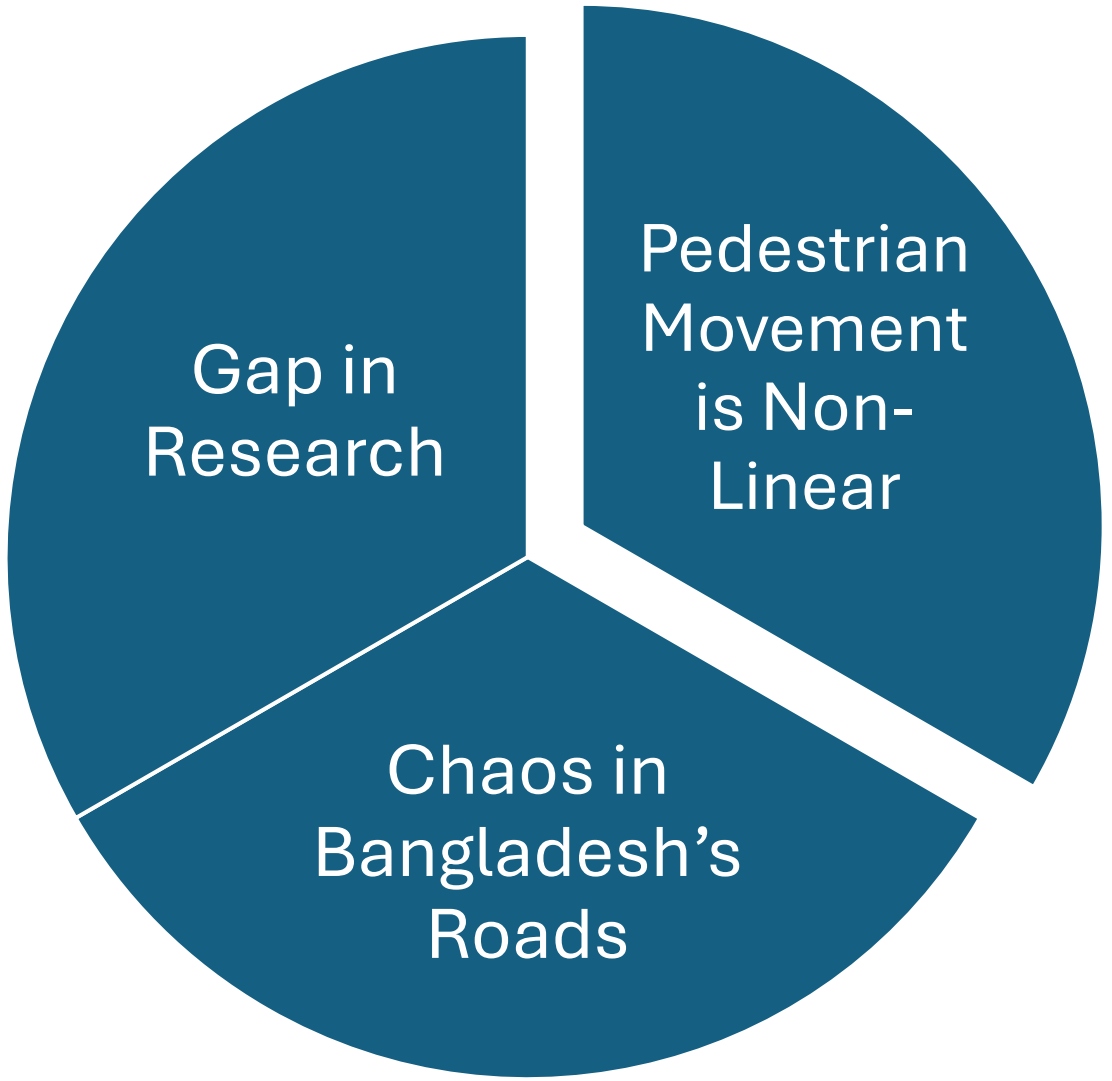
Can a butterfly's flapping in Brazil cause a tornado in Texas?

Background and Motivation



Background and Motivation

Why use Chaos Theory?



Study Objectives

Objective #1

- Develop a custom-trained YOLOv8 model using a custom dataset for nighttime road users' detection in Bangladesh and extract pedestrian trajectories using the DeepSORT algorithm.

Study Objectives

Objective #2

- Analyze nighttime and daytime pedestrian trajectories using chaos theory, focusing on Lyapunov Exponent and Approximate Entropy.

Literature Review

Author/Publication Year	Brief Review
Rahman et al. (2020)	Developed a real-time wrong-way vehicle detection system using YOLO and centroid tracking.
Shah Junayed et al. (2021)	Created a front vehicle detection system using YOLO, improving detection accuracy compared to RetinaNet, SSD, and Faster R-CNN on the DhakaAI dataset.
Saha et al. (2024)	Introduced the Bangladesh Native Vehicle Dataset (BNVD) for autonomous vehicle detection in Bangladesh. Used YOLO v5-v8 models, achieving mAP of 0.848 at 50% IoU and 0.643 across various IoUs
Guo et al. (2024)	Developed KSC-YOLOv5, an improved model for nighttime vehicle detection using SKAttention, CARAFE, and SIOU. Achieved superior accuracy in challenging conditions with mAP .91

Methodology

- Continuous video recordings capture dynamic traffic patterns and behavior
- Nighttime video datasets were collected for analysis

Real-Time Video Data Collection

Detection and Tracking of Road Users

- Developed custom-trained YOLOv8 for nighttime road user detection in urban Bangladesh
- Used DeepSORT for object tracking and ID assignment
- Extracted pedestrian trajectories for further analysis.

Methodology

Two stability checking indicator for chaos theory

- **Lyapunov Exponent**
- **Approximate Entropy**

Two indicators are used to avoid biasness

Methodology

Lyapunov Exponent

Understanding the Lyapunov Exponent

- The sensitivity of a system to small changes in initial conditions
- The rate at which nearby trajectories in a system diverge or converge
- **LE ≥ 0:** System is Chaotic
- **LE < 0:** System is Stable

Methodology

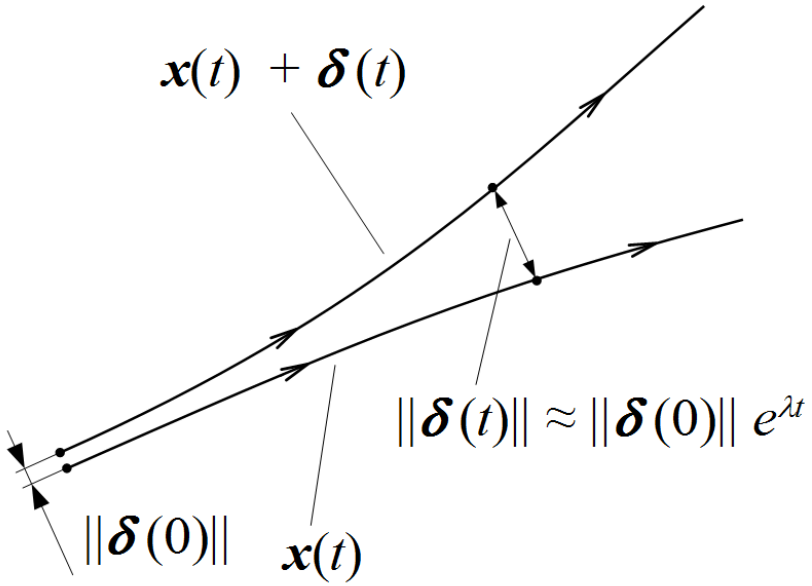
Mathematical Representation of Lyapunov Exponent

$$\lambda = \lim_{t\to\infty} \frac{1}{t} \ln \frac{||\delta X(t)||}{||\delta X(0)||}$$

here,

- δX(0) represents an initial small perturbation in the system,
- δX(t) is the perturbation after time t, and
- λ (Lyapunov exponent) quantifies the rate at which two nearby trajectories diverge over time.

If λ ≥ 0, the system is chaotic; if λ<0, the system is stable



Methodology

Applying Lyapunov Exponent to Pedestrian Movement

Pedestrian trajectories range from orderly to chaotic

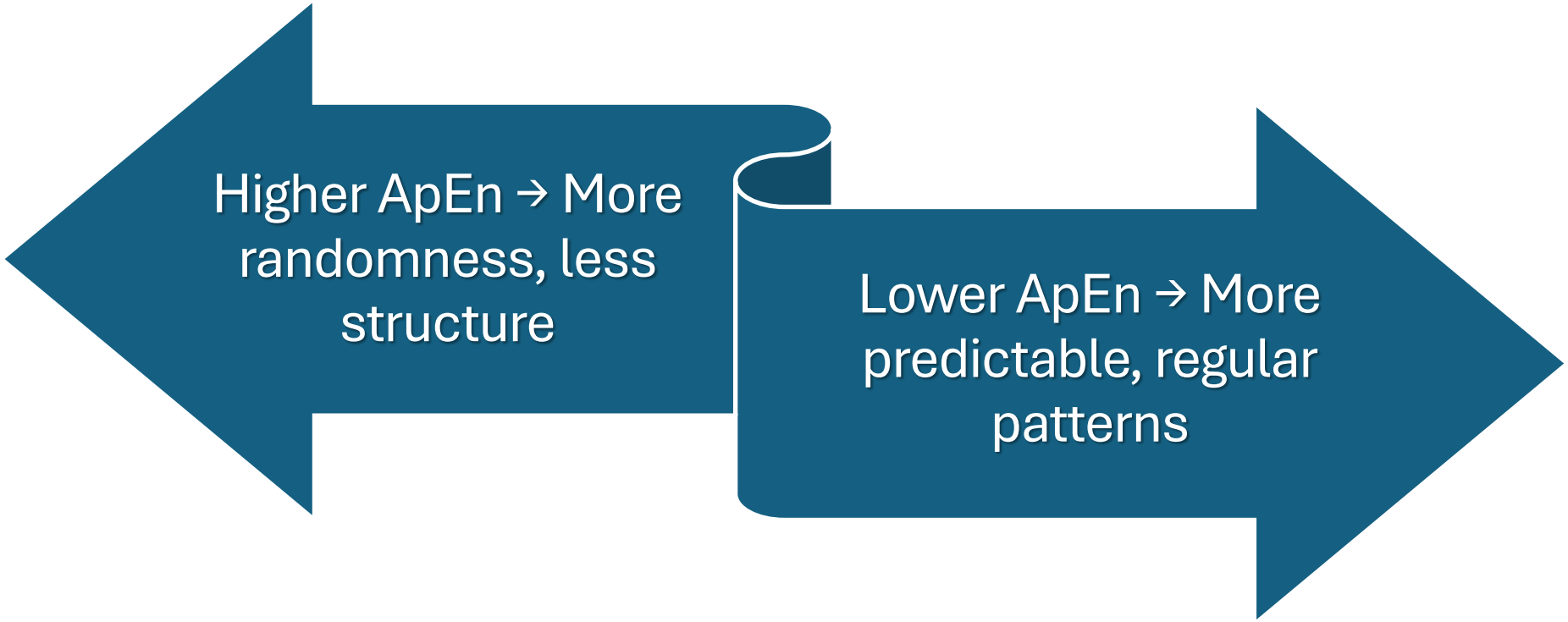
LE quantifies divergence in movement patterns over time

Calculated using the **Rosenstein algorithm**

Methodology

Understanding the Approximate Entropy (ApEn)

Measures the unpredictability of a time series by analyzing its pattern complexity



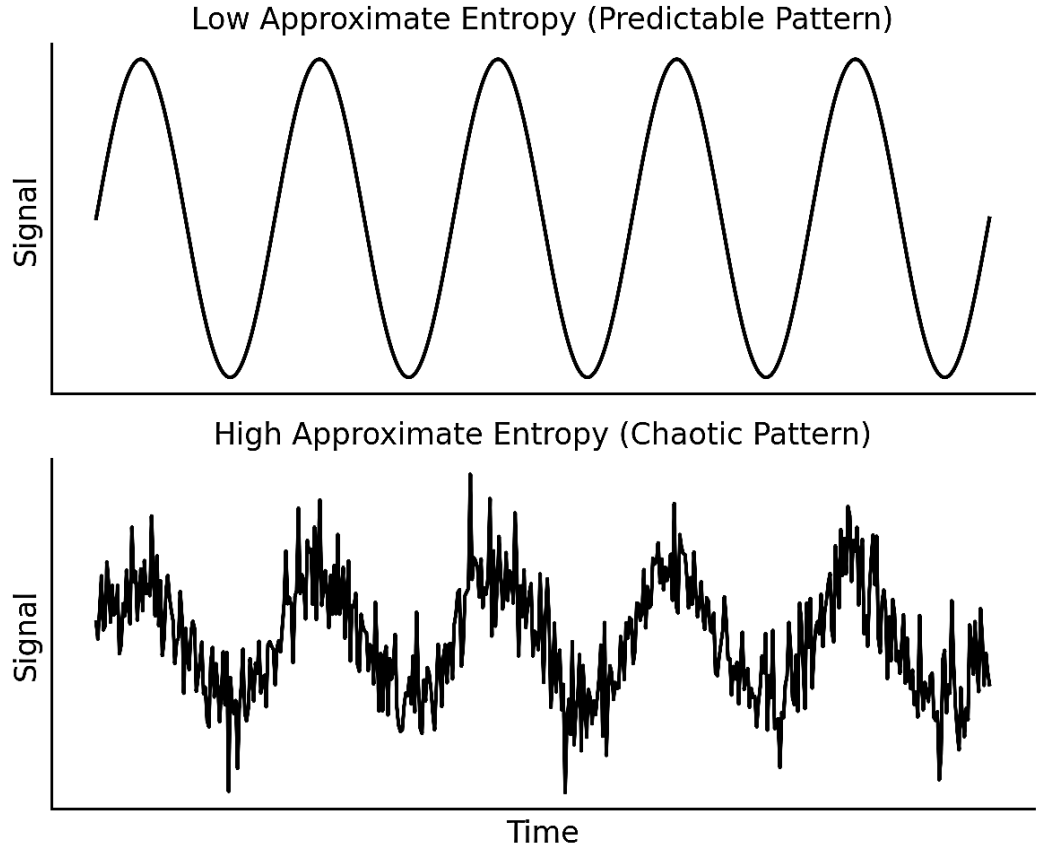
Methodology

Mathematical Representation of Approximate Entropy (ApEn)

$$ApEn(m, r, N) = \Phi^{m}(r) - \Phi^{m+1}(r)$$

Here,

- m is the embedding dimension
- r is the tolerance
- N is the total number of data points
- $\Phi^{m}(r)$ is a measure of the probability that two sequences of length m remain similar when extended to m+1



Methodology

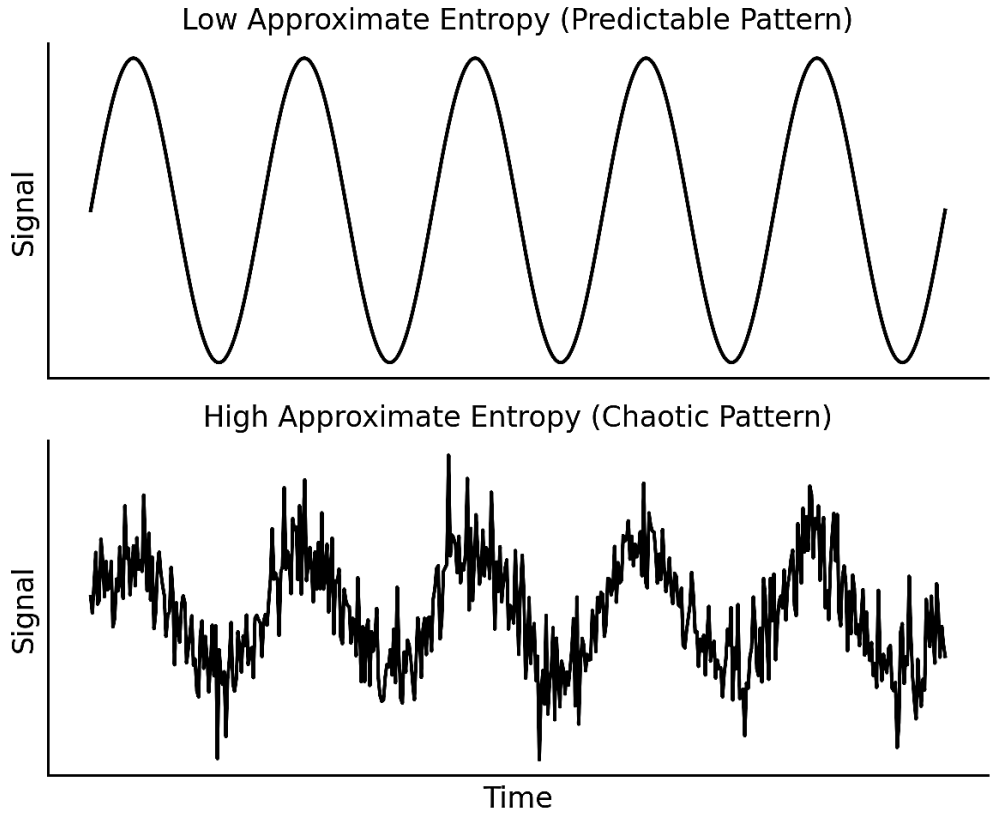
Mathematical Representation of Approximate Entropy (ApEn)

$\boldsymbol{\Phi^m(r)}$ is defined as

$$\boldsymbol{\Phi^m(r) = \frac{1}{N-m+1} \sum_{i=1}^{N-m+1} ln\, C_i^m(r)}$$

Here,

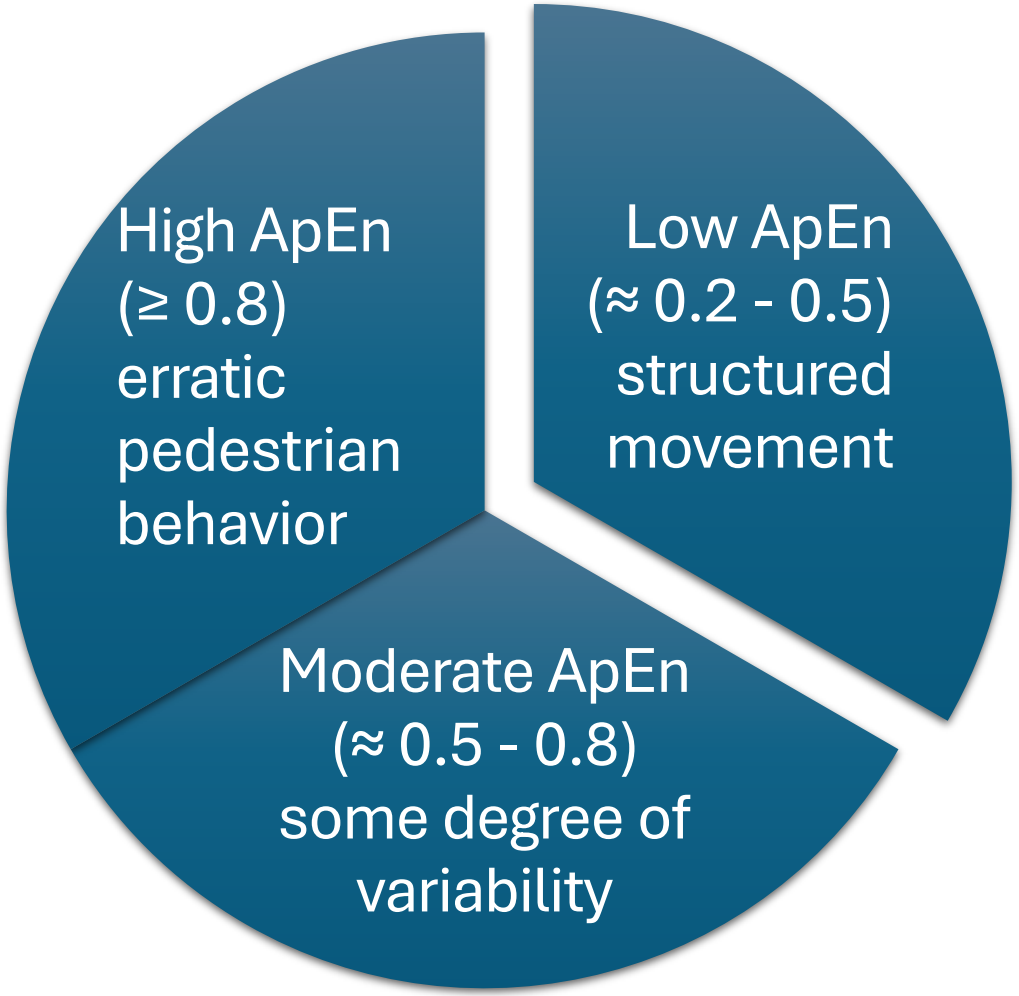
- $C_i^m(r)$ is the relative frequency of template vectors being similar (within tolerance r) to vector *X(i)*
- *X(i)* represents a sequence of m consecutive data points from the original time series.



Methodology

Applying Approximate Entropy to Pedestrian Movement

- ApEn quantifies movement randomness
- Analyzed velocity and direction change to capture speed variations and abrupt shifts



Data Collection

Selected Site

Shanarpar Foot Over Bridge, Narayanganj, Dhaka

Data Collection

Site Selection

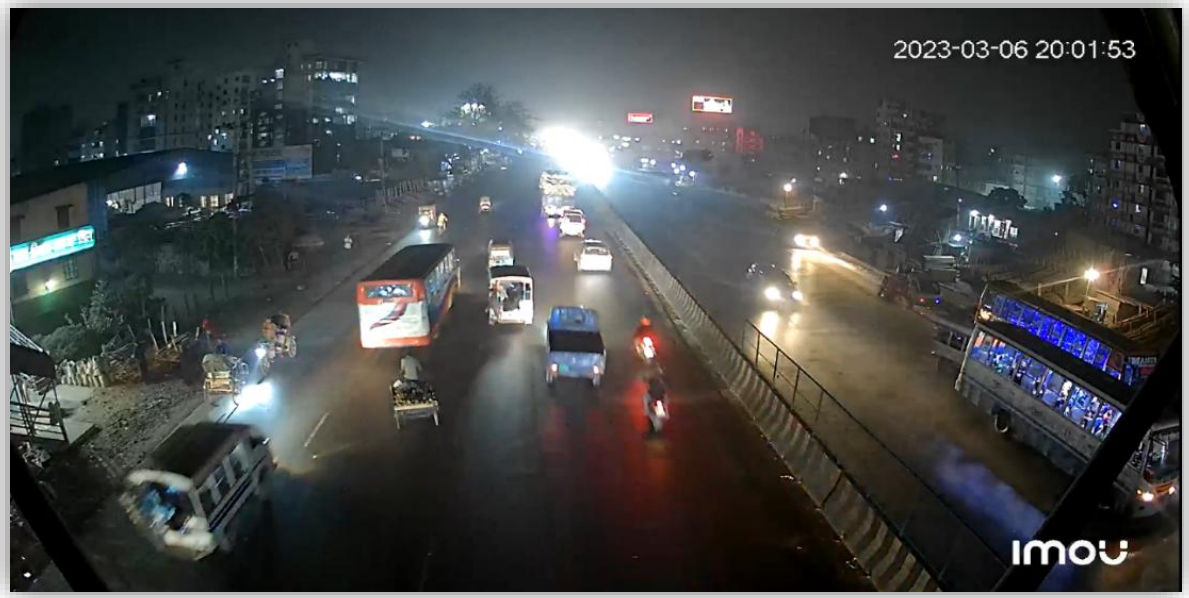
- Diverse Vehicle Types
- Pedestrian Activity
- Influence of the Bus Stand
- Proximity to Dhaka-Chittagong Highway

Recording Conditions

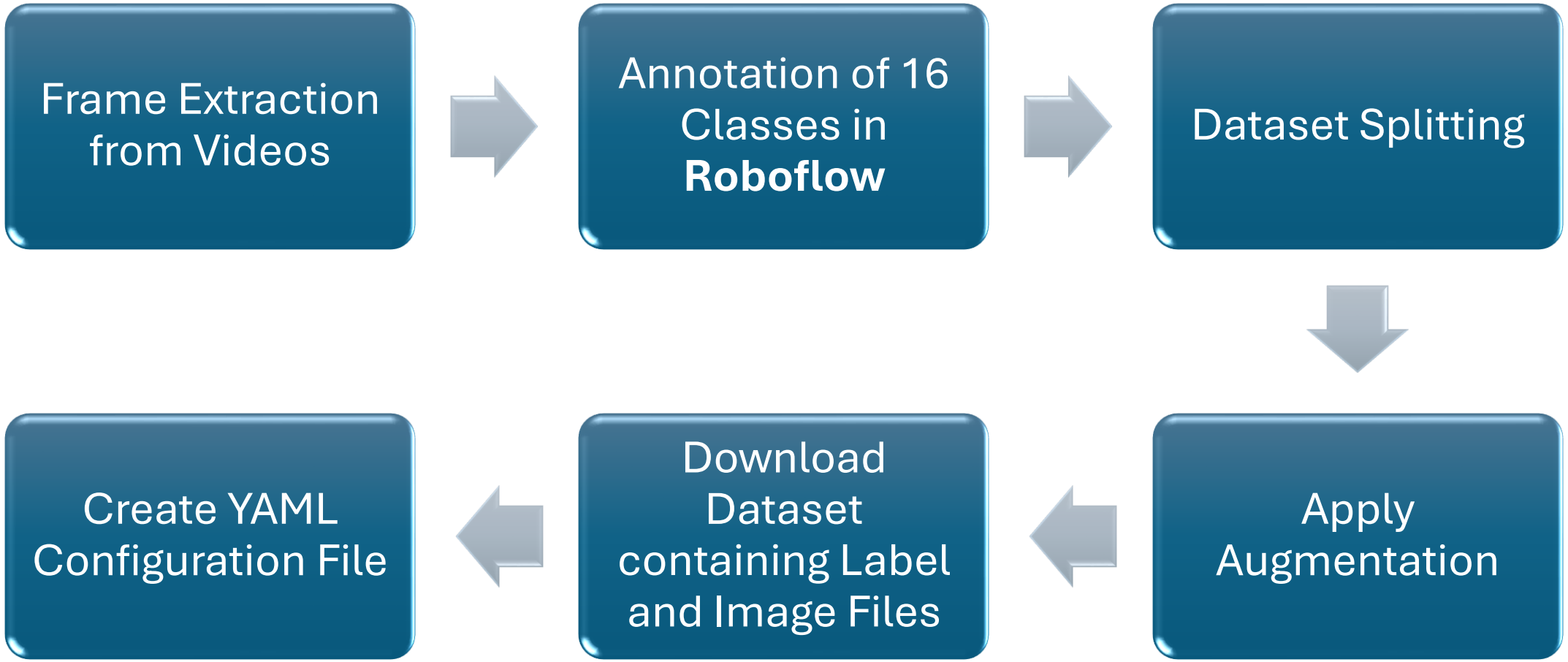
- Data Collected from **5 PM to 10 PM**
- Placed on the Foot Over Bridge
- Capturing the gradual shift from daylight to nighttime
- Separate Cameras for capturing movement in both directions

Data Collection

Sample Frames



Data Preprocessing



Data Preprocessing

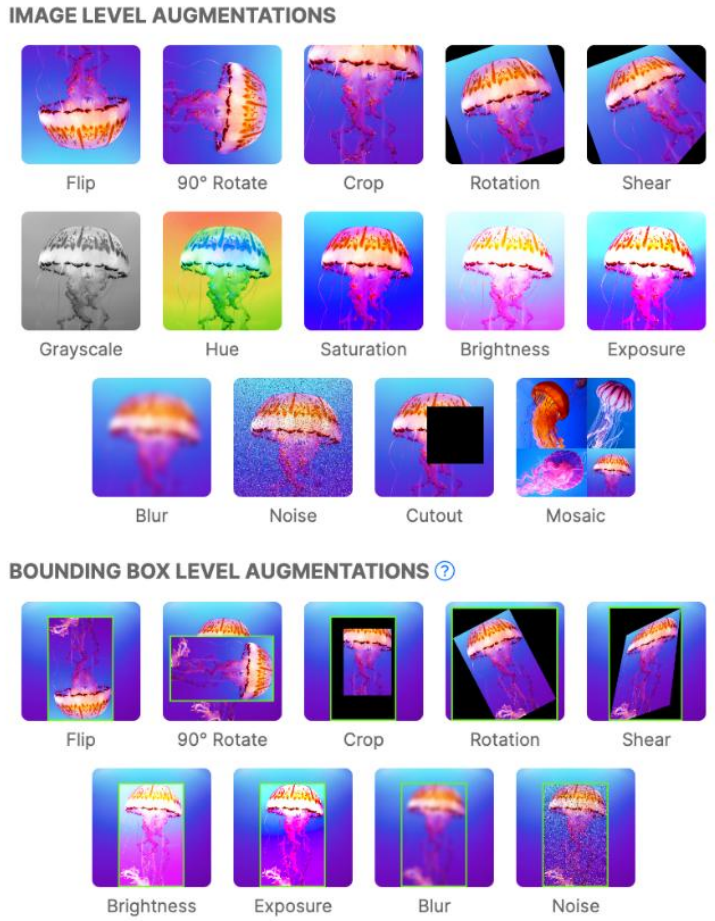
16 Classes are

- Ambulance
- Auto-Rickshaw
- Bicycle
- Bus
- C.N.G.
- Covered-Van
- Cycle-Rickshaw
- Human-Hauler
- Microbus
- Motor-Cycle
- Pedestrian
- Pick-Up
- Private-Passenger-Car
- Non-Motorized-Van
- Special-Purpose-Vehicles
- Truck

Data Preprocessing

Applied Augmentation Methods

- **Crop**: Minimum 0% and Maximum 20%
- **Rotation**: -15° to +15°
- **Shear**: Horizontal and Vertical within ±10°
- **Grayscale**: 15% of the images converted to grayscale
- **Hue**: Adjustments between -15° and +15°
- **Saturation**: Adjustments between -25% and +25%
- **Brightness**: Adjustments between -15% and +15%
- **Exposure**: Adjustments between -10% and +10%
- **Noise**: Added to up to 0.1% of the pixels



Model Building and Validation

Hardware Specification

GPU: NVIDIA RTX 4070 Ti Super (16GB VRAM)

RAM: 32GB DDR4

Hyperparameter Settings

YOLOv8 Variant	: Large
Batch Size	: 8
Image Size	: 640 × 640
Optimizer	: AdamW (default)
Initial Learning Rate	: 0.01
Final Learning Rate Fraction	: 0.01 (meaning the final learning rate is 1% of the initial learning rate)

Model Building and Validation

- Training conducted under multiple conditions to identify the optimal pedestrian detection model.
- Target is to Maximize mean Average Precision (mAP), the key performance metric for object detection models.
- Minimum acceptable mAP threshold: 0.5, based on literature review.
- Models with **mAP < 0.5** are generally ineffective for real-world applications.
- Highly accurate models require **mAP ≈ 0.8** for reliability.

Model Building and Validation

Without Augmentation

Number of Epochs	mAP Value	Time Taken to train model in seconds
100	0.20	15000
500	0.25	75000
1000	0.31	150000
1200	**0.35 (Highest Achieved mAP)**	180000
8000	0.35	1.2 Million (Around 14 Days)

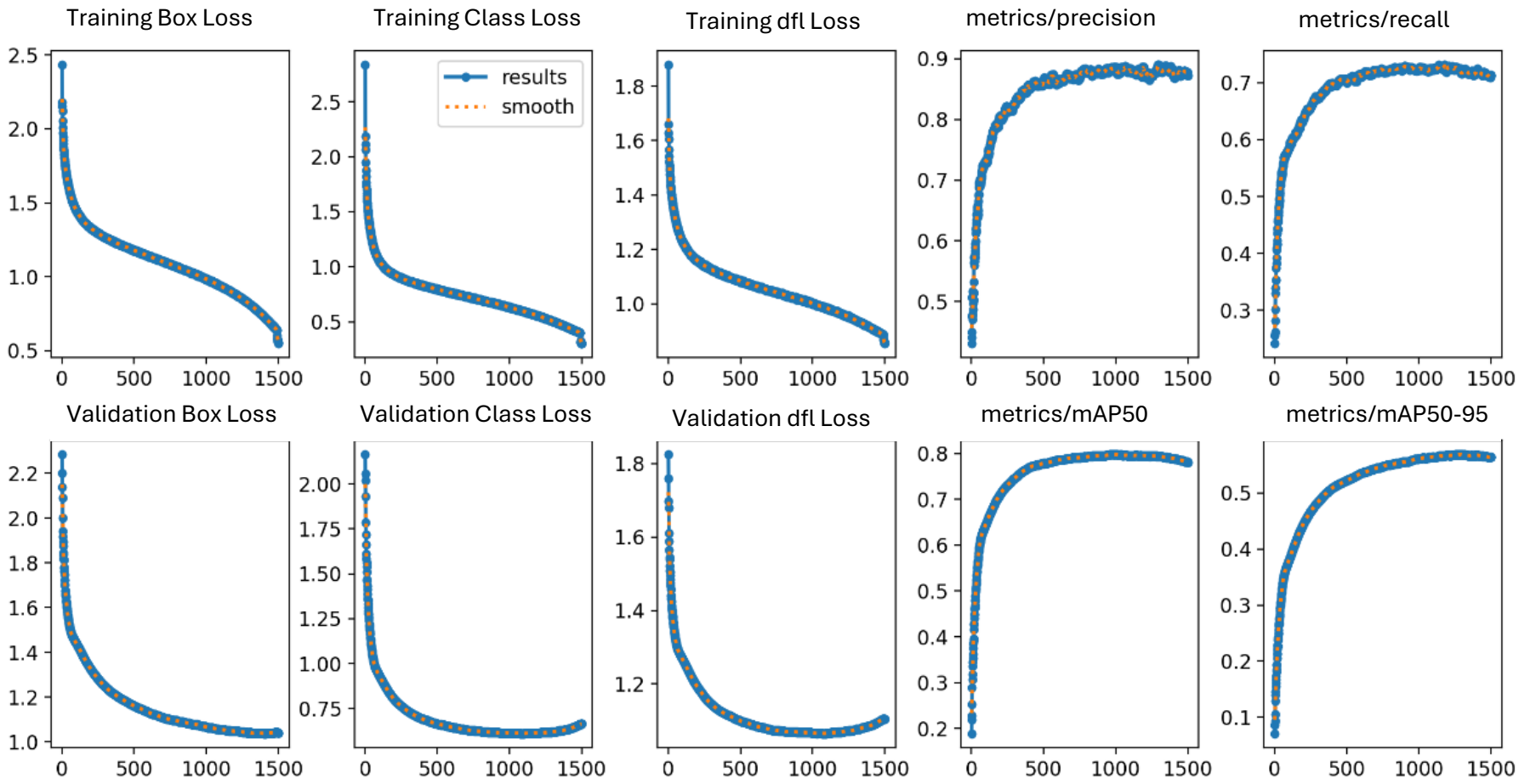
With Augmentation

Number of Epochs	mAP Value	Time Taken to train model in seconds
100	0.40	27000
500	0.64	135000
1000	0.785	270000
1500	**0.80 (Highest Achieved mAP)**	324000
8000	0.80	2.2 Million (Around 25 Days)

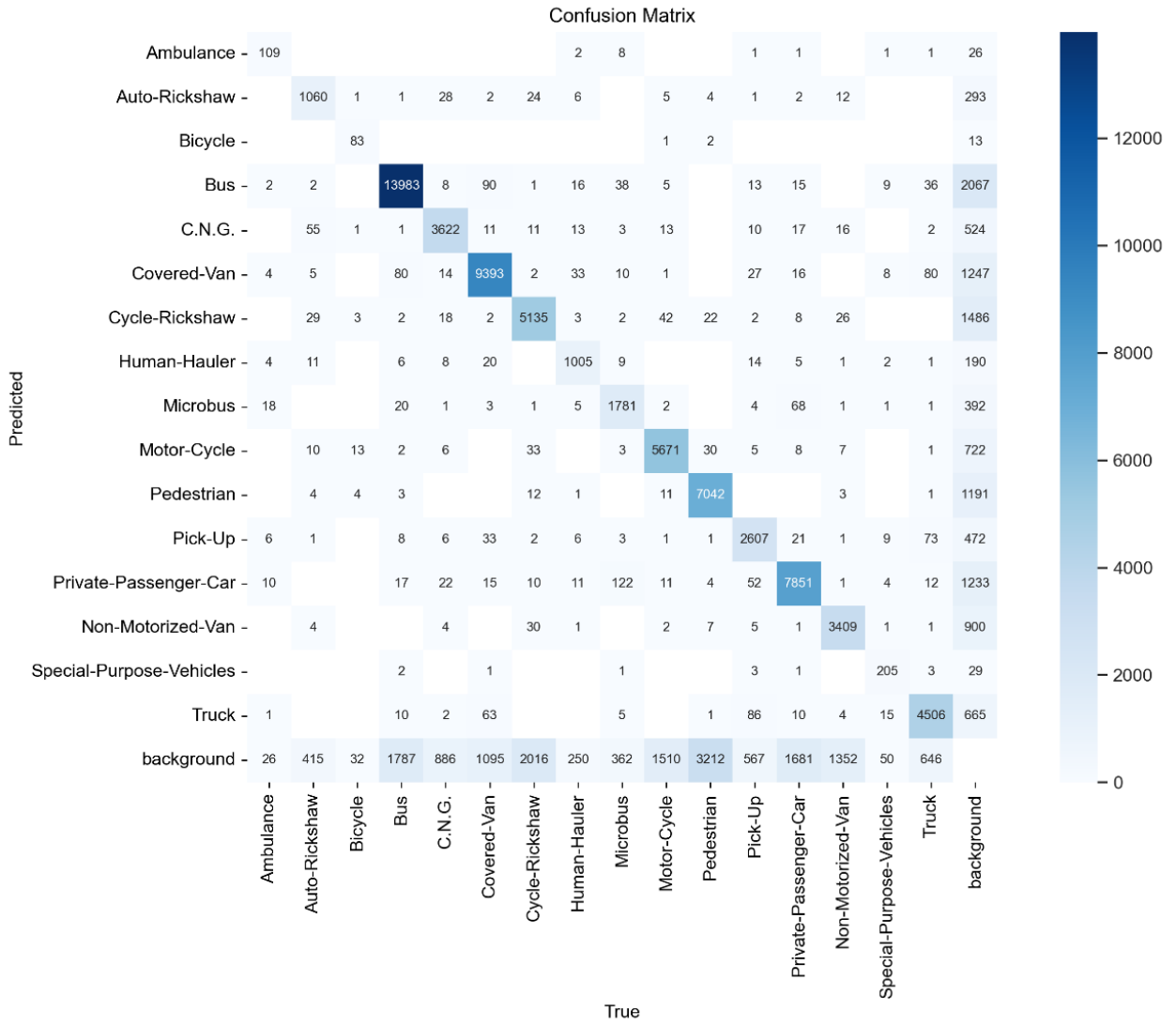
Model Building and Validation

Highest mAP without Augmentation: 0.35 with 1200 Epochs

Highest mAP with Augmentation: 0.80 with 1500 Epochs



Model Building and Validation



Model Building and Validation

Metric	Value
mAP@0.5	80%
mAP@0.5:0.95	56.86%
Best Performing Classes (Precision)	Bus (90.2%), Covered-Van (89.9%), Truck (88.1%)
Worst Performing Classes (Precision)	Bicycle (66.8%), Pedestrian (71.9%), Cycle-Rickshaw (74.7%)
Best Performing Classes (Recall)	Human-Hauler (74%), Microbus (76%), Motor-Cycle (78%)
Worst Performing Classes (Recall)	Pedestrian (68%), Non-Motorized Van (71%)
Best Performing Classes (F1-Score)	Bus (F1 = 0.902), Private-Passenger Car (F1 = 0.845), Truck (F1 = 0.881)
Worst Performing Classes (F1-Score)	Bicycle (F1 = 0.668), Pedestrian (F1 = 0.719), Cycle-Rickshaw (F1 = 0.747)
Mean Training Loss (Final Epoch)	Box Loss: ~0.5, Classification Loss: ~0.5, DFL Loss: ~0.5
Mean Validation Loss (Final Epoch)	Box Loss: ~1.0, Classification Loss: ~1.0, DFL Loss: ~1.2
Training Convergence (Epochs)	Stable after ~1200 epochs

Tracking and Chaos Analysis

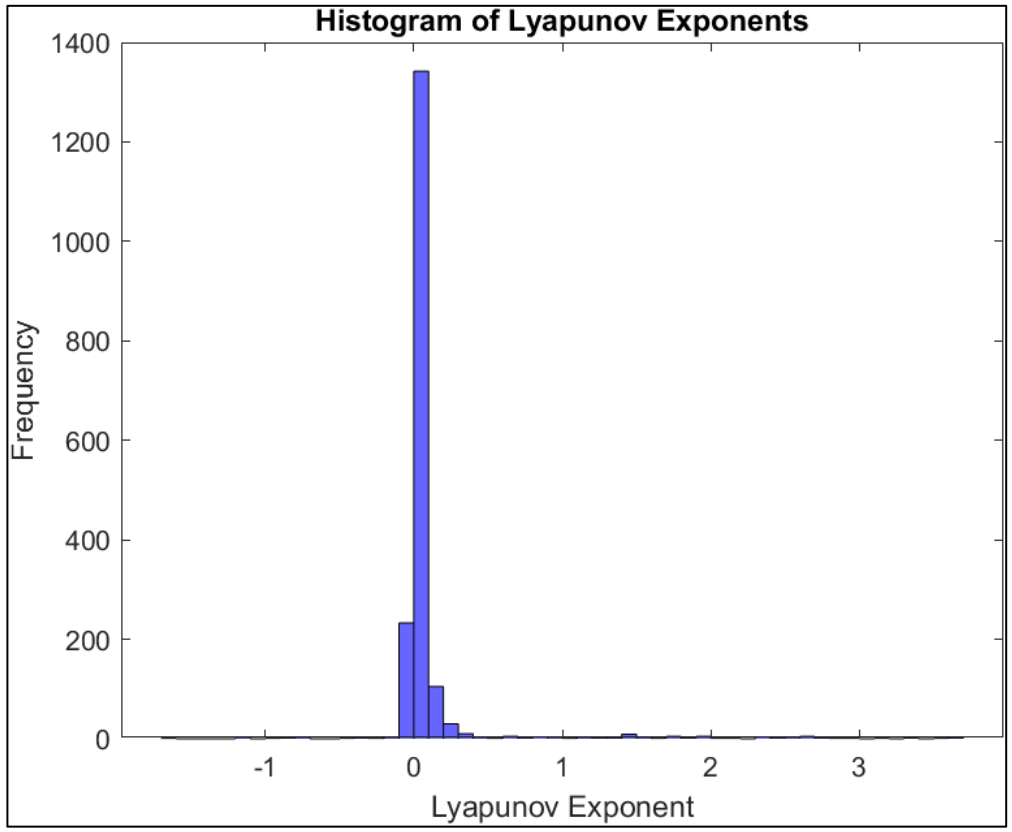
Tracked pedestrian trajectories using DeepSORT.

Applied Lyapunov Exponent (LE) to measure trajectory divergence (chaotic behavior).

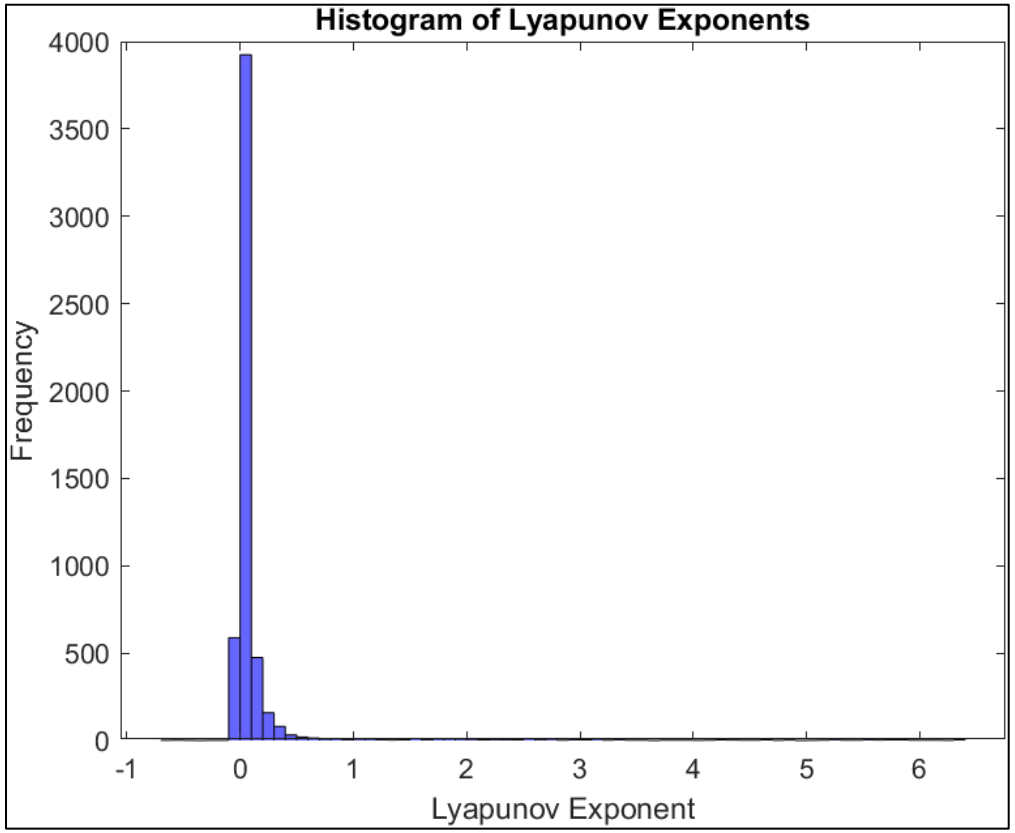
Used Approximate Entropy (ApEn) to quantify movement unpredictability.

Analysis & Result

Lyapunov Exponent Analysis Result

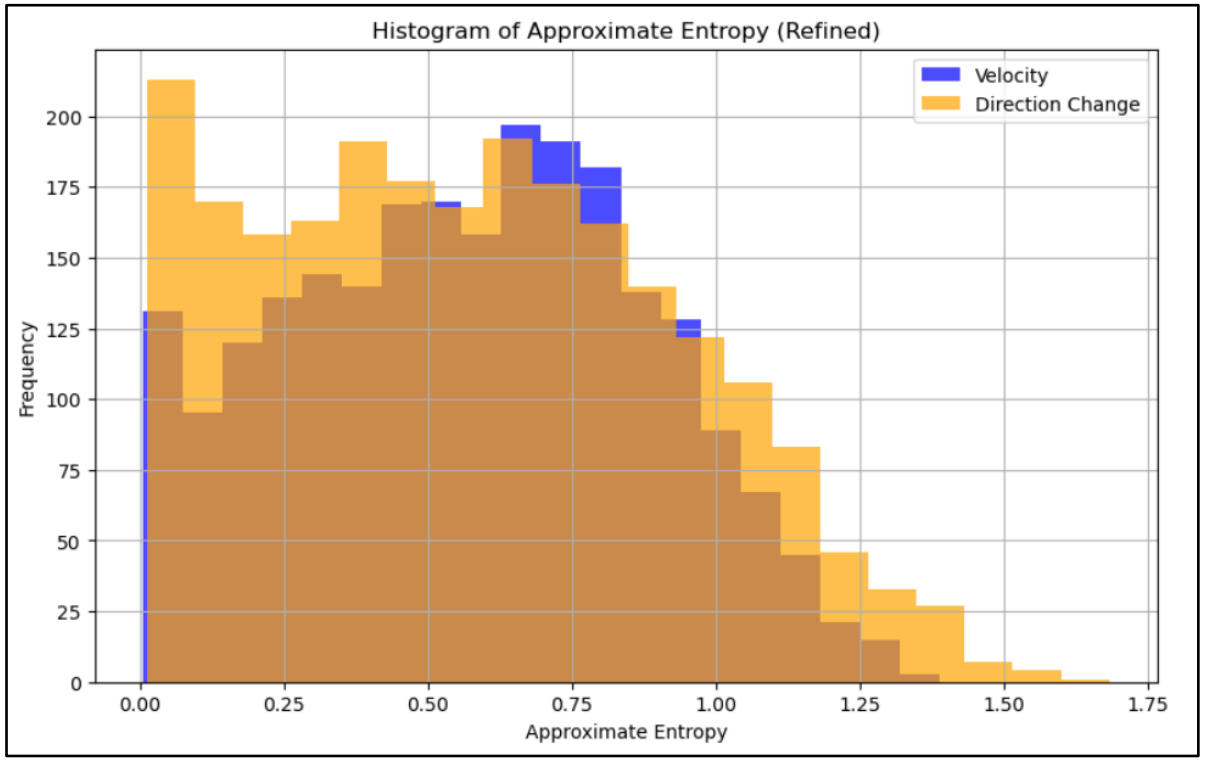


In Nighttime

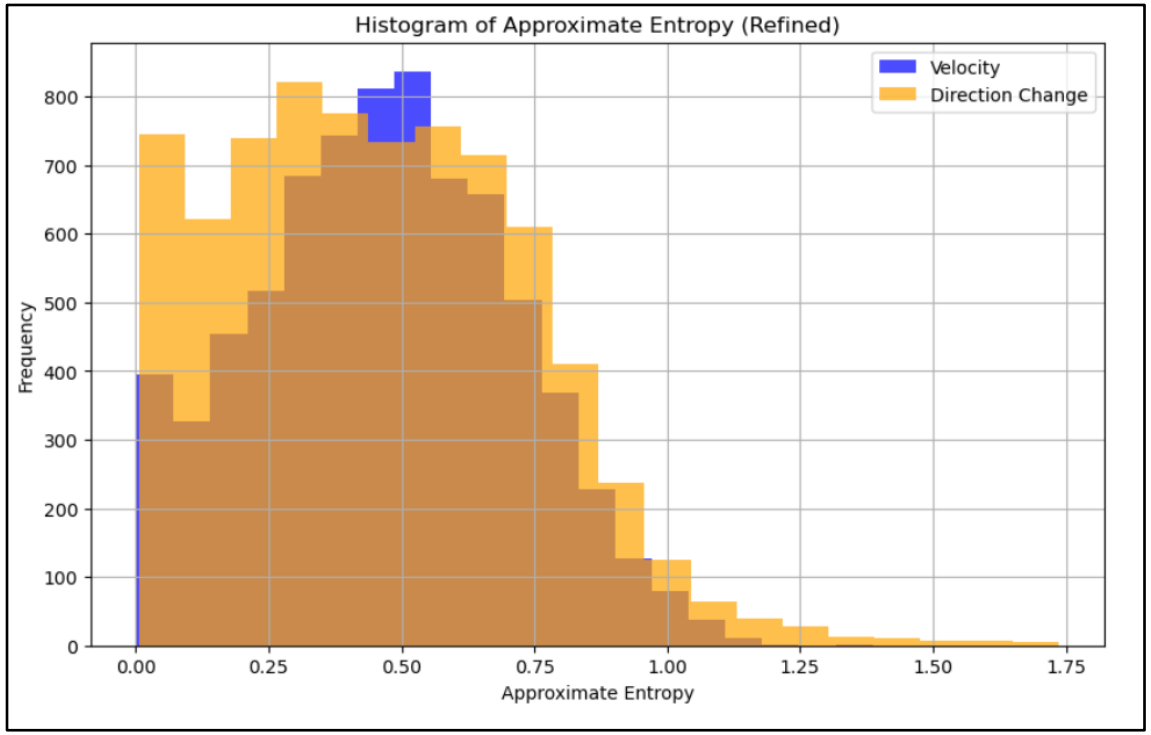


In Daytime

Approximate Entropy Analysis Result

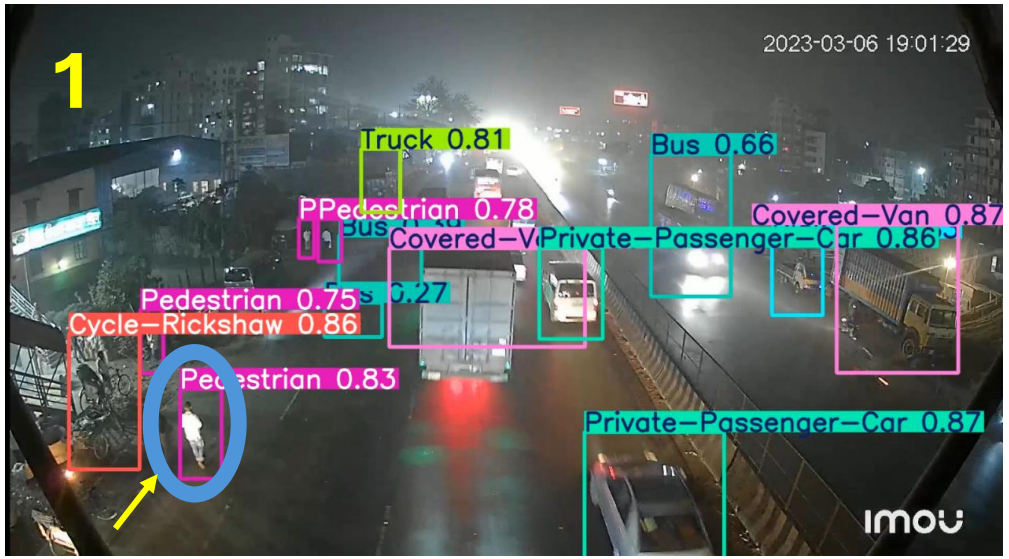


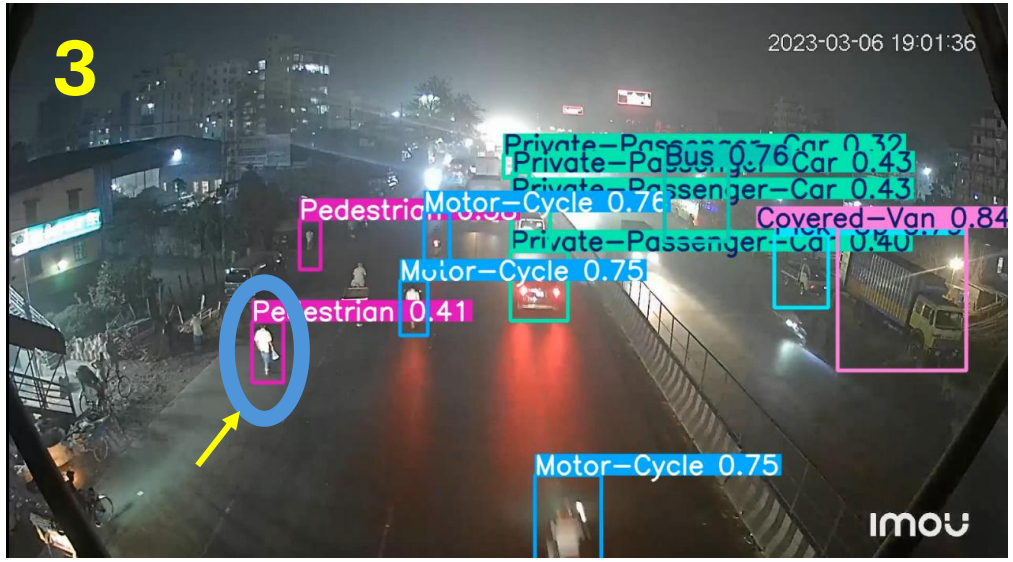
In Nighttime

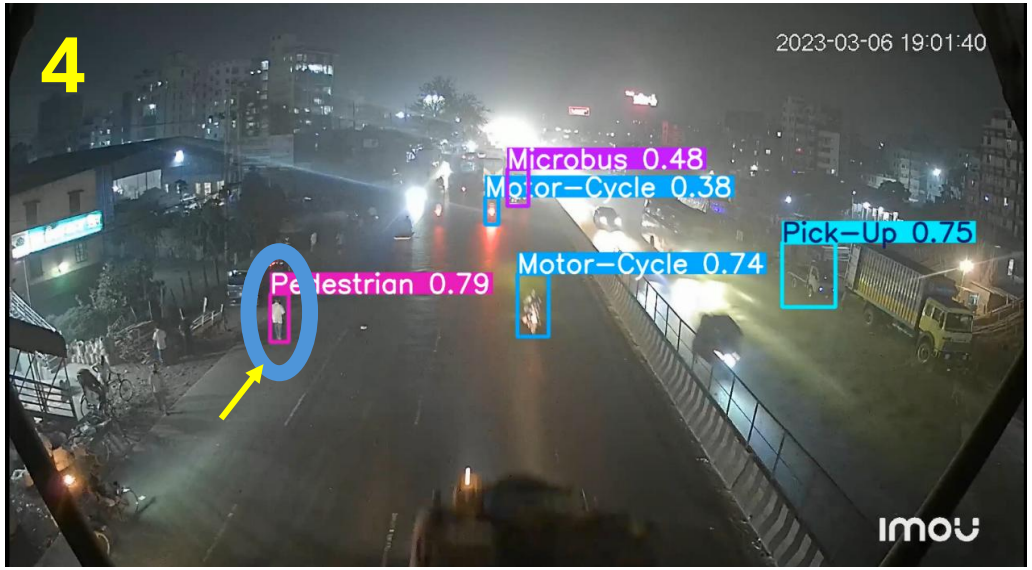


In Daytime

Visual Support: Tracked Chaotic Pedestrian Movement



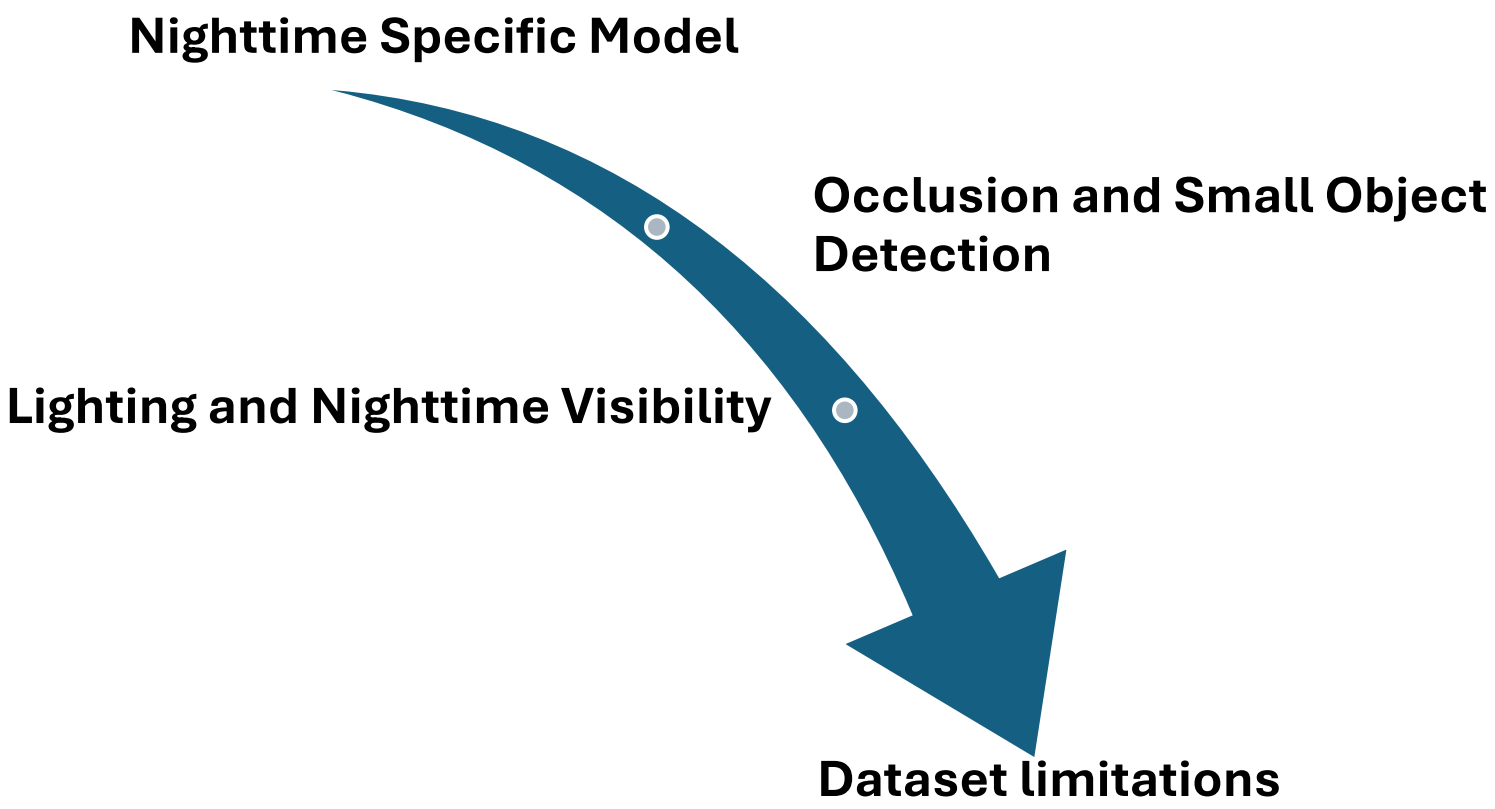




Major Findings

- Bus, Covered-Van, and Private-Passenger-Car classes performed well, with classification accuracy above 85%
- Auto-Rickshaw and Pedestrian classes had a moderate classification rate (~70-75%)
- Highest mAP achieved is 0.8 using Augmentation with 1500 Epochs
- Augmentation increases the accuracy of the model
- Pedestrian-vehicle interactions significantly influence trajectory deviations
- Nighttime pedestrian movement exhibits higher unpredictability
- Lyapunov Exponent for nighttime is 0.3 which is higher than daytime which is 0.1
- Approximate Entropy is higher for both direction change and velocity in nighttime than daytime

Study Limitations



Recommendations for Future Research

- Multi-Location Data Collection
- Integration of Weather and Environmental Factors
- Advancements in Deep Learning-Based Tracking
- Application of Additional Chaos Metrics


Thank
you