Project Review-3

Crime Classification Using Deep Learning

Team Members

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BackGround

Crime Statistics in IndiaAnnual Reported Crimes (NCRB 2022):

4.45 million cognizable crimes registered
1 violent crime every 2 minutes
12% increase in cybercrimes from previous year

Critical Detection Gaps:

58% of street crimes go unreported due to delayed identification
Average 47-minute lag between crime occurrence and police notification
Only 29% of CCTV footage gets reviewed due to manpower constraints

The Human Limitations in Crime Detection

- Surveillance Blind Spots
- Human Operator Challenges:
- Maximum 20-25 minutes of sustained attention span
- Miss 45% of critical events during night shifts
- Can monitor only 4-6 camera feeds effectively simultaneously

Background

Consequences of Delay

Justice Impact:

b22% higher recidivism when criminals aren't caught immediately

Economic Cost:

Estimated ₹1.2 lakh crore annual loss due to:

Unrecovered stolen property

Increased security expenditures

Judicial backlog expenses

Traditional Surveillance Flaws

Issue Impact Current Solution Limitations

Delayed Review 72% footage never analyzed Manual monitoring Human fatigue, high cost

False Alarms 98% motion alerts are false Basic motion detection Wastes police resources

No Proactive Detection Reactive not preventive Post-crime investigation Lets criminals escape

Judicial Process Bottlenecks

- Evidence Collection: Takes 3-7 days currently
- Suspect Identification: Average 11 hours manually
- Case Documentation: 42% of time spent on admin work

Introduction

Crime detection and prevention are crucial for maintaining public safety, especially in an era where surveillance cameras generate vast amounts of video footage. Traditional manual monitoring is inefficient, time-consuming, and prone to human error, making it difficult for law enforcement to respond effectively to criminal activities. With rising crime rates, there is an urgent need for smarter, faster, and more accurate tools for real-time crime detection and prevention.

To address this challenge, we propose an AI-powered crime detection system that analyzes surveillance footage in real time, identifying and classifying criminal activities such as burglary, robbery, and arson. By leveraging deep learning techniques, our system bridges the gap between traditional surveillance methods and intelligent automation, providing law enforcement with actionable insights to enhance security measures.

Why It Matters:

- Faster Response Times: Enables authorities to react swiftly, improving resource allocation.
- Enhanced Public Safety: Reduces crime through proactive detection and prevention.
- Minimized Human Error: Automates monitoring, reducing fatigue-related oversight.
- Scalable & Adaptable: Designed to handle evolving surveillance challenges across various environments.

Problem Statement

Problem Statement:

Despite the widespread deployment of CCTV infrastructure across India, the country's crime detection and prevention efforts remain critically hampered by human limitations, technological inefficiencies, and delayed responses. Law enforcement agencies face an overwhelming volume of surveillance data, of which only a fraction is ever analyzed due to limited manpower and attention spans.

This results in low conviction rates, increased recidivism, and a significant economic burden—estimated at ₹15,000 crore annually—due to unrecovered assets, judicial delays, and escalating security costs. Traditional surveillance systems are reactive, error-prone, and incapable of real-time intervention. There is an urgent need for an AI-powered solution that can bridge these detection gaps, provide accurate and real-time alerts, and support law enforcement with automated evidence analysis and crime classification to enable faster, more effective, and preventive policing across India.

Existing System Limitations:

Manual Surveillance

- Most systems rely heavily on human operators monitoring CCTV footage, which is prone to human error and fatigue

Time-Consuming Response

- Detection and reporting of criminal activity are often delayed, reducing the chances of timely intervention.

High Operational Costs

- Continuous human monitoring and traditional system maintenance increase financial and resource burdens.

Justice Delays

- Lack of real-time evidence collection hampers swift justice, leading to prolonged legal procedures and delayed outcomes

Literature Survey:

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Objectives

- Develop an AI-powered crime detection system that analyzes surveillance footage in real time to detect and classify criminal activities like burglary, robbery, and arson.
- Utilize MobileNetV2 with transfer learning and additional convolutional layers for high-accuracy crime recognition.
- Process video frames intelligently, extracting critical features to identify crimes while maintaining temporal context for accurate classification.
- Optimize real-time performance, ensuring the system can handle large-scale video streams with minimal latency for immediate response.
- Enhance public safety by providing law enforcement agencies with actionable insights to improve crime prevention and investigation.

Applications:

- Law Enforcement Support – Provides real-time crime alerts to police and security agencies.
- Smart Surveillance Systems – Enhances CCTV monitoring by automating crime detection.
- Public Safety – Identifies suspicious activities in public places, transportation hubs, and high-security zones.
- Retail & Business Security – Detects shoplifting and fraudulent activities, improving loss prevention.
- Traffic & Road Safety – Identifies hit-and-run incidents, reckless driving, and vehicle theft.
- Forensic Investigations – Assists law enforcement by analyzing past footage for evidence collection.
- Smart City Security – Integrates with urban surveillance systems for enhanced public safety.

Advantages

Automated Crime Detection – Eliminates manual monitoring inefficiencies, enabling real-time classification of criminal activities.

High Accuracy & Robustness – MobileNetV2 ensures low false positives and better generalization across different crime scenarios.

Fast Response Time – Helps law enforcement take immediate action by providing instant alerts.

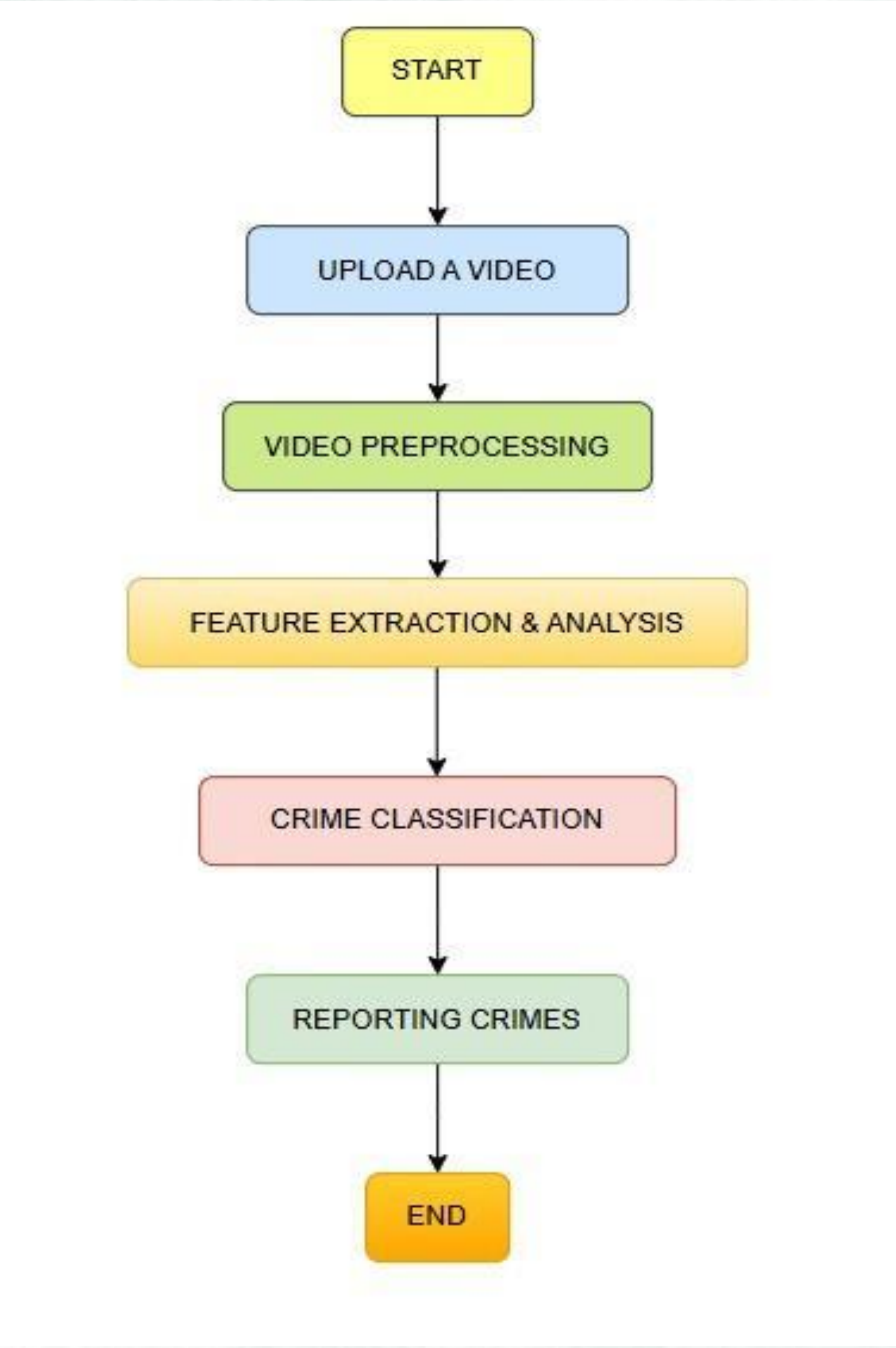
Scalability & Flexibility – Can be deployed on cloud servers or used offline for localized surveillance.

Seamless Integration – Works with existing CCTV systems, requiring no major hardware changes.

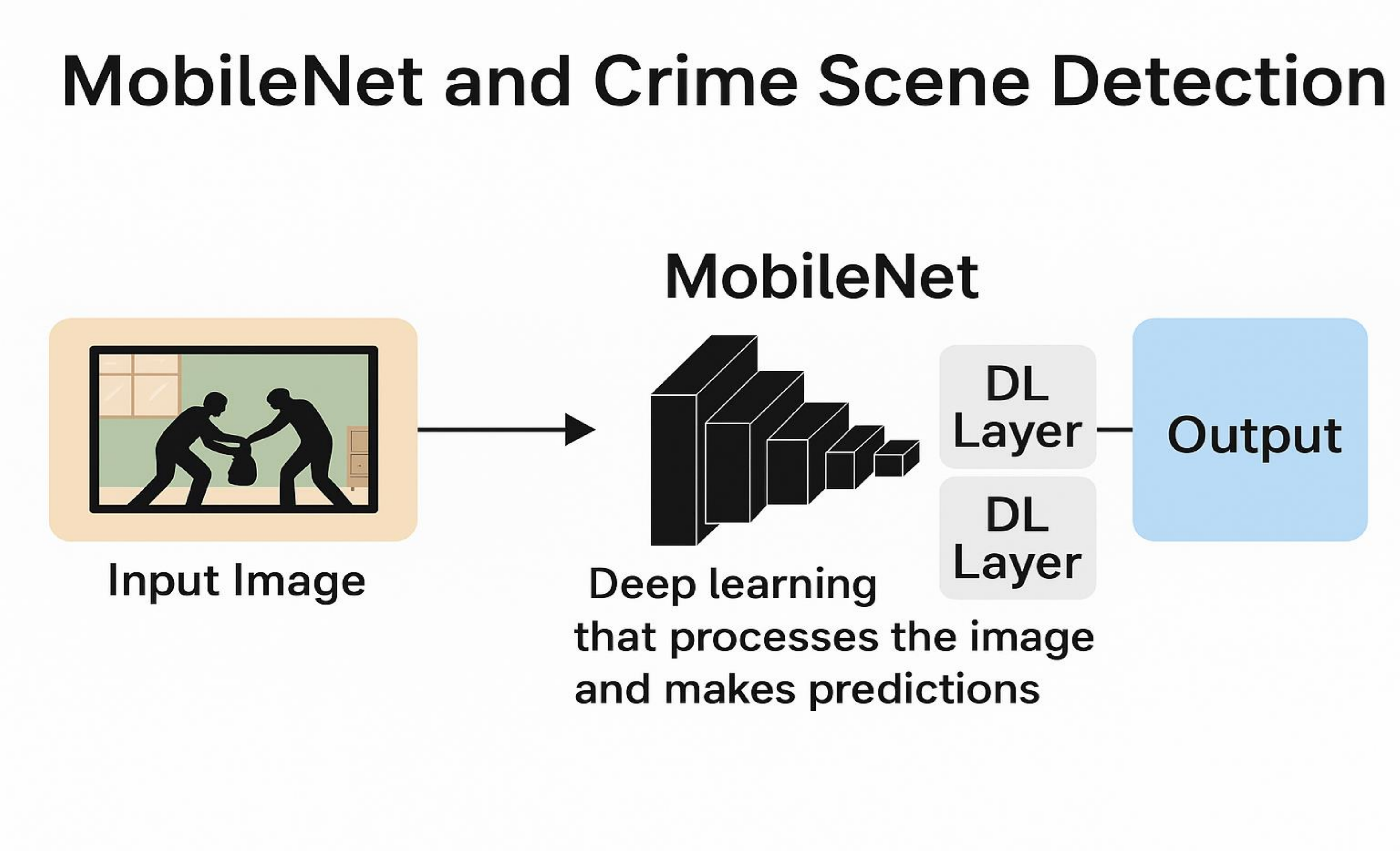
Handles Video Variability – Efficiently processes footage under varied lighting, weather, and camera angles.

Optimized Resource Allocation – Allows security teams to focus on high-risk areas, improving efficiency.

Methodology – Architecture



Methodology - Architecture



Methodology

1. Data Acquisition

- Collected crime-related video datasets from open sources.
- Categories included: theft, assault, vandalism, fighting, and burglary.
- Videos were labeled frame-by-frame for supervised learning.

2. Frame Extraction & Preprocessing

- Videos converted into frames at 1 frame per second (FPS).
- Frames resized to 224×224 pixels.
- Normalized pixel values to [0,1] for model compatibility.
- Optional background subtraction to reduce noise.

3. Model Design

- Chose MobileNetV2 as the base model for real-time performance.
- Pretrained on ImageNet and fine-tuned on the crime dataset.
- Added custom dense layers for classification into crime categories.

Methodology

4. Training & Validation

- Dataset split into training and validation sets (e.g., 80:20).
- Used categorical cross-entropy as the loss function.
- Early stopping and learning rate reduction applied to avoid overfitting.

5. Inference & Post-processing

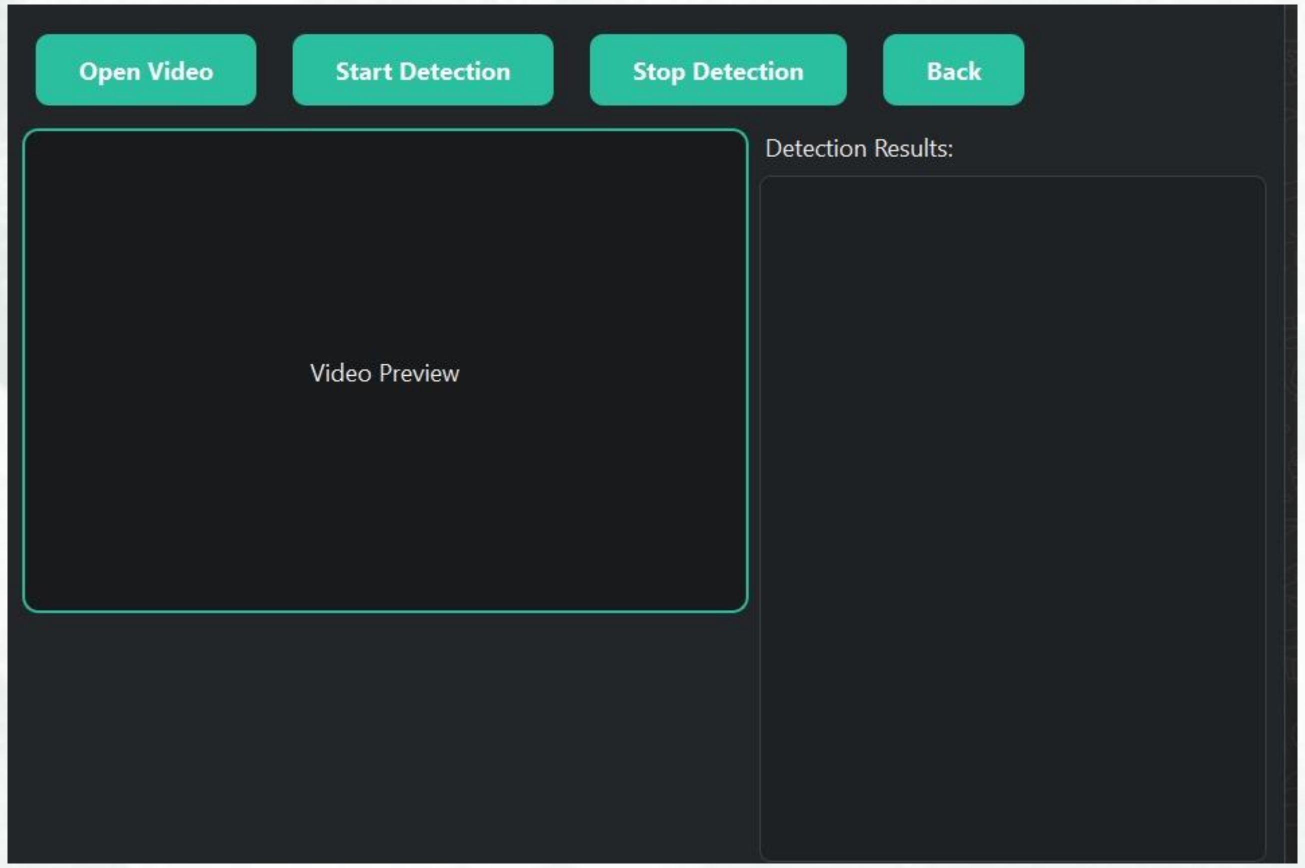
- Input video processed frame by frame.
- Each frame passed through MobileNetV2 for classification.
- Confidence threshold applied (e.g., >80%) to ensure reliability.
- Temporal logic applied to:
  - Detect start time
  - Estimate duration
  - Filter out false positives

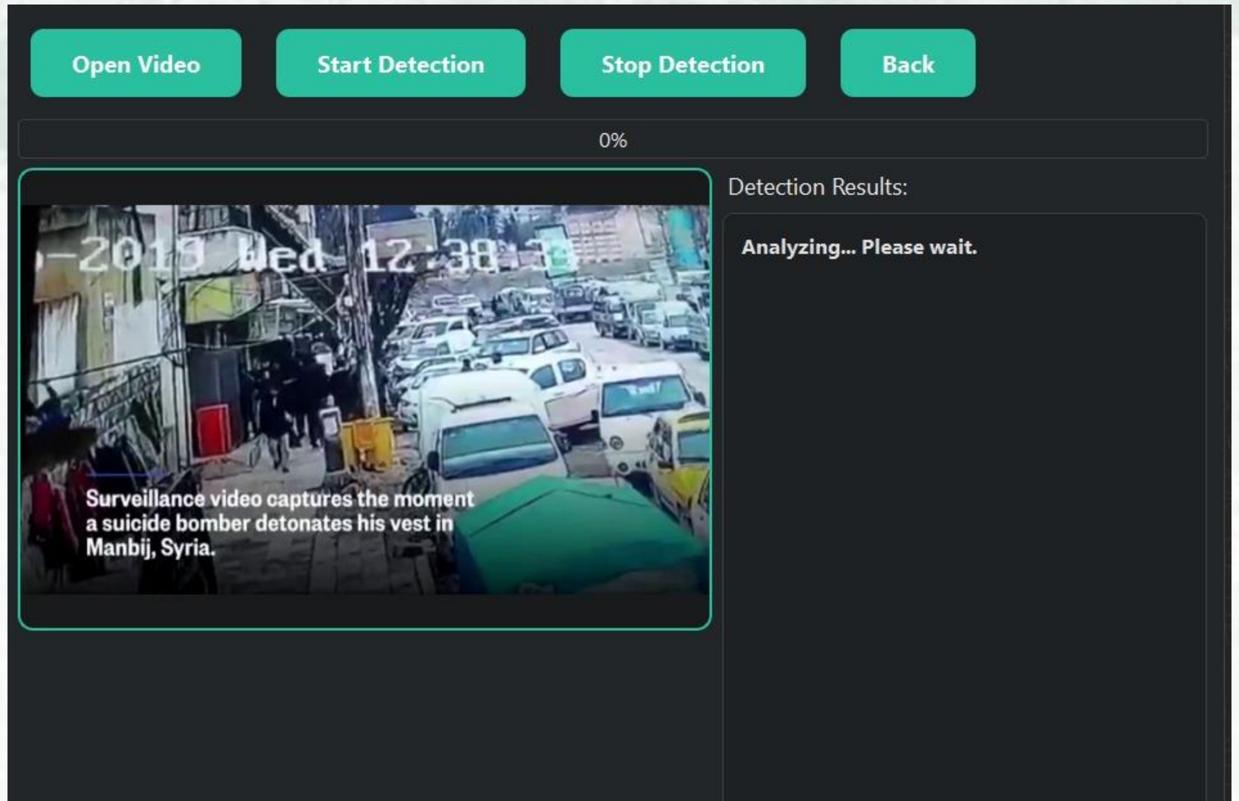
Model Performance - Table

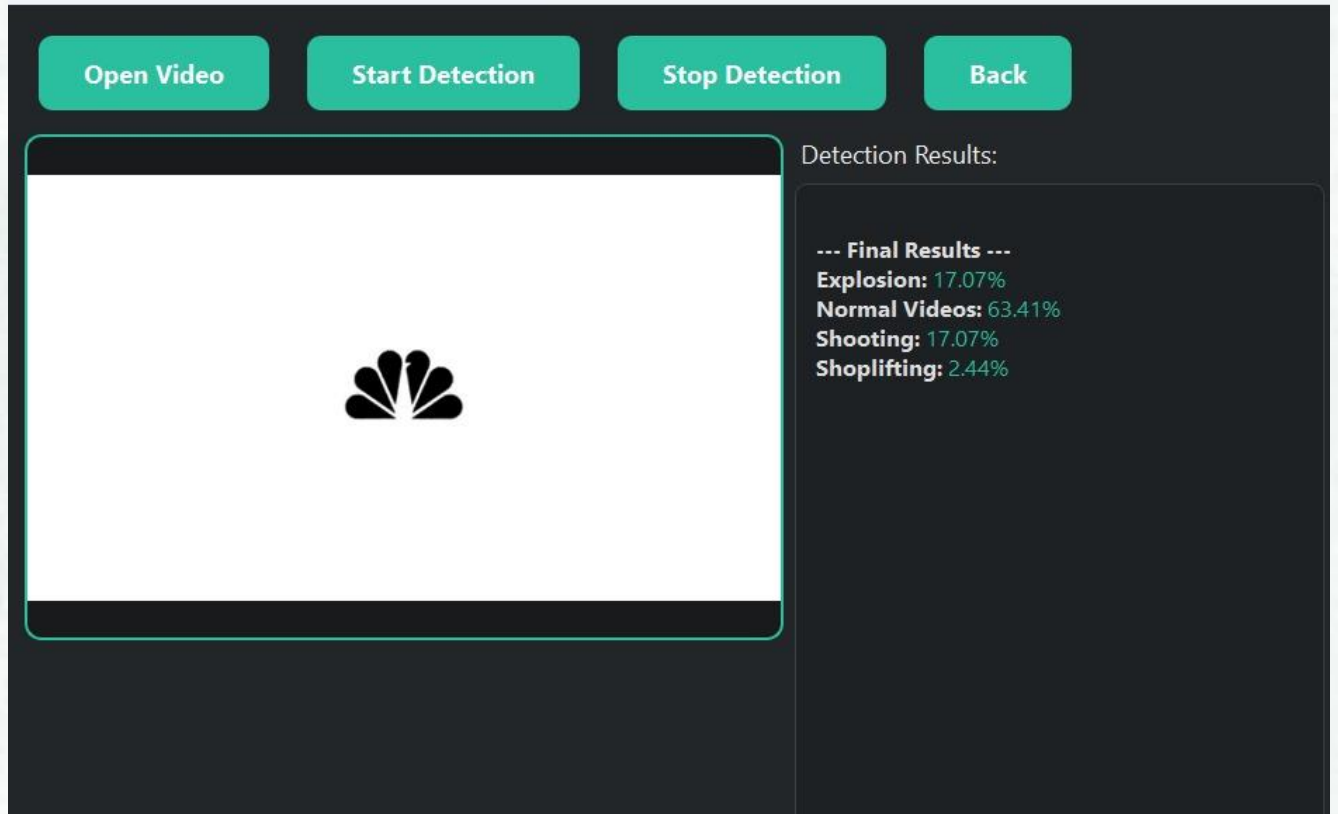
Classification Report:

	precision	recall	f1-score	support
Abuse	1.00	0.60	0.75	58
Arrest	0.97	0.99	0.98	694
Arson	0.97	0.94	0.96	542
Assault	1.00	0.98	0.99	555
Burglary	0.99	0.99	0.99	1535
Explosion	0.93	0.98	0.95	1280
Fighting	1.00	0.93	0.96	240
NormalVideos	0.98	1.00	0.99	13110
RoadAccidents	1.00	0.96	0.98	541
Robbery	0.95	1.00	0.97	154
Shooting	1.00	0.93	0.97	1477
Shoplifting	0.99	0.87	0.92	1496
Stealing	1.00	0.96	0.98	389
Vandalism	0.99	0.95	0.97	191
accuracy			0.98	22262
macro avg	0.98	0.93	0.95	22262
weighted avg	0.98	0.98	0.98	22262

Visual Output (Web Site))







Future Work

- Improve Accuracy in Challenging Environments – Enhance detection in low-light conditions, occlusions, and noisy backgrounds.
- Advanced Data Augmentation – Use synthetic crime scene generation to improve training data diversity.
- Hyperparameter Optimization – Further tune model parameters for better real-time performance.
- Multi-Crime Detection – Extend capabilities to identify multiple criminal activities simultaneously.
- Robustness Against Video Variations – Develop adaptive models to handle different frame rates and resolutions.
- Scalable Real-Time Processing – Further optimize inference speed for instant decision-making in live surveillance.
- Expanded Crime Categories – Train the model to detect a broader range of crimes, improving generalization.

Conclusion

- DeepVision automates real-time crime detection by analyzing surveillance footage, reducing the need for manual monitoring and improving response times. By implementing MobileNetV2 with transfer learning, the system achieves high accuracy and efficiency in crime classification.
- The model processes video frames using deep learning-based feature extraction, ensuring accurate and reliable crime recognition. While the system performs well, challenges such as low-light conditions and video variability highlight the need for future refinements through advanced data augmentation and optimized hyperparameters.
- We conclude that deep learning-driven crime classification is a scalable, efficient, and impactful solution for law enforcement. DeepVision bridges the gap between traditional surveillance and AI-powered security, contributing to a safer and more secure world.

Thank You

– By

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