Literature Review (Secondary Research) Template

Student Name	**B.Vamshi Yadav**
Project Topic Title	**Abnormal Event detection in pathway**

Type of Variables that You Need to Search for in Each Article (Each Current Solution)			
Dependent variable	**Independent variable**	**Moderating variable**	**Mediating (Intervening) variable**
● The presumed **effect** in an experimental study. ● The values of those variable depend upon another variable that are the independent variable. ● Strictly speaking, “dependent variable” should not be used when writing about non-experimental designs. ●	● The presumed **cause** in an experimental study. ● The variables that may impact on the dependent variable ● The values of those variable are under experimenter control. ● Strictly speaking, “independent variable” should not be used when writing about non-experimental designs.	● has a strong *contingent* effect on the independent variable-dependent variable **relationship** and thus produces an interaction effect.	● It comes between the independent and dependent variables and shows the **link or mechanism** between them.
● Examples: **1. performance**. **2. Test Score**. **3. stock market. 4. performance** of the students	● Examples: **1. run time** that will impact and cause high/low performance. **2. Time Spent Studying** that will cause the high/low score. **3. New product** that will impact on the stock market price. **4. quality of library facilities**	● Example: **4.** There is a strong relationship between the quality of library facilities (X) and the performance of the students (Y). Only those students who have the **interest and inclination** to use the library will show improved performance in their studies, which moderates the strength of	● Example: Parents transmit their social status to their children directly, but they also do so indirectly, through education: viz. Parent’s status ➛ child’s education ➛ child’s status ● Example: The statistical association between income and longevity needs to be explained because just having money does not make one live longer. Other variables intervene between money and long life. People with high incomes tend to have better

		the association between X and Y variables.	medical care than those with low incomes. Medical care is an intervening variable. It mediates the relation between income and longevity.

Relationship among Variables - Correlations (Univariate, Bivariate, Multivariate)
● Once the variables relevant to the topic of research have been identified, then the researcher is interested in the relationship among them. ● A statement containing the variable is called a **proposition**. It may contain one or more than one variable. ● The proposition having one variable in it may be called as **univariate** proposition, those with two variables as **bivariate** proposition, and then of course **multivariate** containing three or more variables. ● Prior to the formulation of a proposition the researcher has to develop strong logical arguments which could help in establishing the relationship. ● For example, age at marriage and education are the two variables that could lead to a proposition: the higher the education, the higher the age at marriage . What could be the logic to reach this conclusion? All relationships have to be explained with strong logical arguments. If the relationship refers to an observable reality, then the proposition can be put to test, and any testable proposition is hypothesis.

Research Model That The Author Followed to Propose His Solution			
1. Where we are now	**2. Where are we going**	**3. How do we get there**	**4. How do we know when we are finished**
● What the author has done in the area; The constructs that the literature examine ● **What the problem is available** in this paper that has solved by the author ● The purpose of that is to avoid pursing research which has already been undertaken	● What the author **objective** of the research is to gain a clearer understanding the relationships between variables ● What is the goal of the paper ● The purpose is to know what is the plan to do before he did the research	● How the author conducted the research; **How the problem has solved** ● How he analysed the data generated by the research; A quantitative research design	● What is the value of this solution ● A series of **recommendations** which flow from the data analysis have been made

Version 1.0 _ Week 1		
1		
Reference in APA format		
URL of the Reference	**Authors Names and Emails**	**Keywords in this Reference**
Https://doi.org/10.1051/itmconf/203203040	Riddhi Sonka, Sadhana Rathod, Renuka Jadhav , Deepali Patil.	Crowd analysis, pre-processing, object tracking, CCTV, Machine Learning, CNN, event behaviour recognition.
The Name of the Current Solution (Technique/ Method/ Scheme/ Algorithm/ Model/ Tool/ Framework/ ... etc)	**The Goal (Objective) of this Solution & What is the problem that need to be solved**	**What are the components of it?**
Crowd abnormal behaviour detection using deep learning	Aim is to develop a system for real-time detection of abnormal crowd behaviour using deep learning methods, like Convolutional Neural Networks and K-Means clustering, to enhance public security and mitigate potential threats.	The author utilized deep learning and surveillance technology, encompassing surveillance cameras for data collection, pre-processing modules for enhancing video data, deep learning-based object detection and tracking, behavior analysis modules for motion parameter computation, abnormality detection algorithms for identifying deviations from normal behavior, alert generation systems for timely notifications, user interfaces for monitoring, and integration with existing security infrastructure.

The Process (Mechanism) of this Work; Means How the Problem has Solved & Advantage & Disadvantage of Each Step in This Process

The proposed system combines surveillance cameras for data collection with pre-processing and deep learning algorithms for object tracking and behavior analysis. Abnormality detection triggers alerts for security personnel. Real-time monitoring and dynamic threshold adjustments enable continuous improvement. The author conducted comprehensive result comparisons using various machine learning techniques. The system integrates with security infrastructure, and regular maintenance and privacy measures contribute to public safety by detecting crowd abnormalities.

	Process Steps	**Advantage**	**Disadvantage (Limitation)**
1	Video data from surveillance cameras is collected to monitor and analyze crowd behavior. Cameras placed in public areas capture continuous footage, which is used for further analysis.	It provides a rich source of data for crowd behavior analysis. It allows for real-time monitoring and retrospective analysis of events.	Privacy concerns may arise as the process involves capturing video footage of people in public spaces. Additionally, labeled data is typically required for training machine learning models, which can be time-consuming and expensive.
2	Deep learning models, such as Convolutional Neural Networks (CNNs), are employed to identify and track objects within the captured video frames. These models can distinguish between different objects and their movements.	Accurate object detection and tracking are crucial for behavior analysis, as they provide the foundation for recognizing abnormal actions within a crowd	In crowded scenes, object tracking can be challenging due to occlusion (objects obstructing one another), overlap, and sudden changes in direction. These challenges can lead to tracking errors.
3	The system generates alerts or notifications when abnormal behavior is detected. These alerts can be sent to security personnel or relevant authorities for immediate action.	Alert generation facilitates a quick response to potential threats in crowded areas, contributing to public safety and security.	There is a risk of generating false alarms, which can lead to alert fatigue among security personnel if not properly managed. Fine-tuning the system to reduce false positives is an ongoing challenge.

Major Impact Factors in this Work

<Find all main factors and variables that are related to each solution. Then find the relationship between factors. (Independent variable) causes a change in (Dependent Variable) and it isn't possible that (Dependent Variable) could cause a change in (Independent Variable).

Dependent Variable	Independent Variable	Moderating variable	Mediating (Intervening) variable
Abnormal Detection Accuracy	Vibe, Crowd Characteristics	-	-

Relationship Among The Above 4 Variables in This article

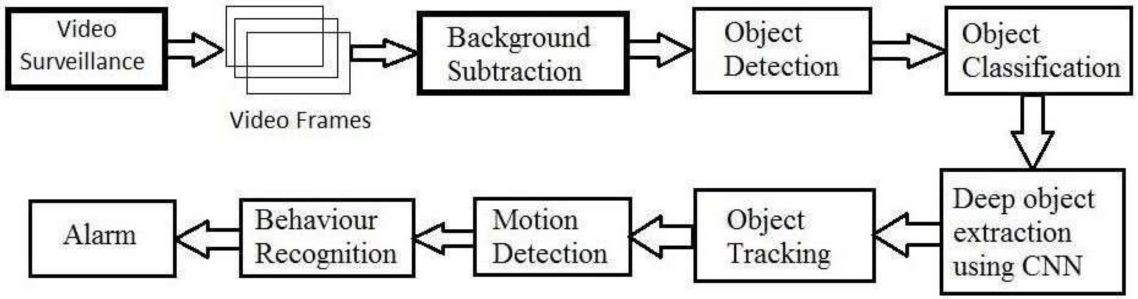
Input and Output	Feature of This Solution	Contribution & The Value of This Work
	This solution uses deep learning and real-time video analysis to quickly detect and handle abnormal crowd behavior, making public spaces safer. It's a forward-looking approach with ideas for ongoing security improvement.	Good to have this knowledge from this paper as we reviewing of ideologies for developing Crowd abnormal behaviour detection using deep learning .

Input	Output
video data of crowded areas.	The detection of abnormal behaviour.

Positive Impact of this Solution in This Project Domain	Negative Impact of this Solution in This Project Domain
Abnormal crowd behaviour detection enhances public safety by mitigating security threats and disturbances in crowded areas, contributing to a safer environment.	Real-time data processing for crowd behaviour analysis can be resource intensive, requiring significant computational power and storage capacity.

Analyse This Work By Critical Thinking	The Tools That Assessed this Work	What is the Structure of this Paper

The research on abnormal crowd behavior detection using machine learning is a valuable contribution to public safety. It leverages deep learning and video analysis, but lacks in-depth comparative analysis and should address privacy concerns associated with surveillance.	OpenCV, TensorFlow or PyTorch,Scikit-learn	Abstract I. Introduction II. Review of Literature III. Proposed Methodology IV. Algorithms V Results
Diagram/Flowchart		



---End of Paper 1---

Version 2.0 _ Week 2		
2		
Reference in APA format		
URL of the Reference	**Authors Names and Emails**	**Keywords in this Reference**
http://www.ijtrd.com/papers/IJTRD22751.pdf	Megha Chhirolya Dr. Nitesh Dubey .	Abnormal Behavior, Kinetic Energy, Image frames, Crowd Behavior, Optical Flow, Classifications.
The Name of the Current Solution (Technique/ Method/ Scheme/ Algorithm/ Model/ Tool/ Framework/ ... etc)	**The Goal (Objective) of this Solution & What is the problem that need to be solved**	**What are the components of it?**
Abnormal Human Behavior Detection and Classification In Crowd Using Image Processing	The aim is to develop a method for accurately detecting and classifying abnormal human behavior in crowded environments using image processing techniques. This addresses challenges such as diverse crowd behaviors, the need for socio-psychological considerations, and the limitations of conventional density-based analyses. The proposed solution, leveraging Optical Flow features, seeks to enhance situational awareness and response in scenarios like disaster management and crowd control.	The author used a comprehensive strategy, incorporating optical flow features and employing machine learning with Support Vector Machine, to tackle the detection of abnormal human behavior in crowded environments. This approach involves video capture, pre-processing, and feature extraction, enabling a detailed analysis of crowd dynamics. Performance metrics, particularly testing accuracy, validate the solution's efficacy in accurately identifying and classifying abnormal behaviors within crowded scenarios.

The Process (Mechanism) of this Work; Means How the Problem has Solved & Advantage & Disadvantage of Each Step in This Process

The proposed system Abnormal Crowd Behavior Detection using Image Processing uses processing video data through techniques such as image frame conversion, pre-processing for image enhancement, segmentation using edge detection, and feature extraction, which computes average kinetic energy, movement direction entropy, and population distance potential energy to reveal crowd behavior patterns. Object recognition is then applied for tracking individuals or groups based on these features, and a Support Vector Machine (SVM) classifies observed behavior as normal or abnormal.

	Process Steps	**Advantage**	**Disadvantage (Limitation)**
1	By converting the video data into individual image frames and enhancing the image quality. Pre-processing techniques may include noise reduction and brightness/contrast adjustments.	The input data is of higher quality, reducing noise and enhancing the accuracy of the subsequent analysis.	Converting video frames into images can increase the computational load, and it may require significant storage space
2	Image segmentation involves using edge detection algorithms to identify object boundaries within the images. It separates objects of interest from the background.	Segmentation isolates the objects in the crowd, making it easier to analyze individual or group behaviors.	Segmentation can be sensitive to variations in lighting conditions and may introduce noise, which can impact the accuracy of results.
3	Feature extraction is the process of computing various features from the segmented images. This step calculates features such as average kinetic energy, movement direction entropy, and population distance potential energy.	Feature extraction captures meaningful information about crowd behavior patterns, allowing for analysis and anomaly detection.	Selecting the most relevant features is crucial, as using irrelevant or redundant features can lead to inaccurate results.
4	Classification employs machine learning techniques, often using a Support Vector Machine (SVM), to classify observed behavior as normal or abnormal based on the features extracted.	The detection of abnormal crowd behavior, allowing for real-time monitoring and alerts.	Classification relies on labelled training data, and there may be false positives or false negatives in the classification process, impacting the system's accuracy.

Major Impact Factors in this Work

<Find all main factors and variables that are related to each solution. Then find the relationship between factors. (Independent variable) causes a change in (Dependent Variable) and it isn't possible that (Dependent Variable) could cause a change in (Independent Variable).

Dependent Variable	Independent Variable	Moderating variable	Mediating (Intervening) variable
Abnormal Behavior	Crowd Features		

Relationship Among The Above 4 Variables in This article

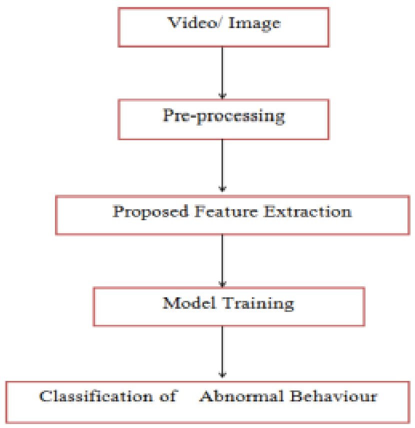
Input and Output	Feature of This Solution	Contribution & The Value of This Work
Input: video data of crowded areas. **Output:** The detection of abnormal behaviour.	Abnormal Crowd Behavior Detection using Image Processing incorporates key features such as optical flow analysis for crowd dynamics, machine learning with Support Vector Machine for accurate classification, and a robust algorithmic structure covering video capturing, pre-processing, and feature extraction. The solution aims to precisely	Good to have this knowledge from this paper as we reviewing of ideologies for Abnormal Human Behavior Detection and Classification In Crowd Using Image Processing.

	identify and classify abnormal behaviors in crowded environments, with a focus on enhancing security and market analysis. The effectiveness is measured through crucial performance metrics like testing accuracy.	

Positive Impact of this Solution in This Project Domain	**Negative Impact of this Solution in This Project Domain**
This solution positively impacts the project domain by advancing crowd behavior analysis, enabling precise detection of abnormal activities through optical flow features and machine learning, enhancing security, and finding applications in market analysis and public safety planning.	Potential negative impacts include challenges related to computational complexity, especially in dense crowd scenes. The reliance on optical flow and machine learning techniques for feature extraction and classification may introduce complexities in real-time processing, leading to increased computational demands.

Analyse This Work By Critical Thinking	**The Tools That Assessed this Work**	**What is the Structure of this Paper**
The approach employed in this study is a robust method for detecting abnormal crowd behavior through the integration of image processing and machine learning. Its include systematic methodology and the thoughtful selection of relevant features	OpenCV, MATLAB Image Processing Toolbox, Scikit-learn, TensorFlow.	Abstract I. Introduction II. Literature Survey III. Proposed method IV. Results V. Conclusion

Diagram/Flowchart



---End of Paper 2---

Version 3.0 _ Week 3		
3		
Reference in APA format		
URL of the Reference	**Authors Names and Emails**	**Keywords in this Reference**
https://ieeexplore.ieee.org/document/8296547	Mahdyar Ravanbakhsh Moin Nabi Enver Sangineto Lucio Marcenaro Carlo Regazzoni	Video analysis, abnormal event detection, crowd behaviour analysis, Generative Adversarial Network.
The Name of the Current Solution (Technique/ Method/ Scheme/ Algorithm/ Model/ Tool/ Framework/ ... etc)	**The Goal (Objective) of this Solution & What is the problem that need to be solved**	**What are the components of it?**
Abnormal event detection in videos using generative adversarial nets	The aim is to develop Abnormal event detection in videos using generative adversarial nets for detecting abnormal events in crowded video scenes. The problem is the challenge of distinguishing such events with limited data and subjective definitions of abnormality.	The author used training data with only normal scenes, and image-to-image translation using Generative Adversarial Networks which is a type of artificial neural network used in machine learning and deep learning, reconstruction of appearance and motion information, and fusion of differences to detect abnormal areas.

The Process (Mechanism) of this Work; Means How the Problem has Solved & Advantage & Disadvantage of Each Step in This Process

The proposed system "Abnormal event detection in videos using generative adversarial nets" is an innovative deep learning architecture that predicts abnormal events in crowded scenes. It uses Generative Adversarial Networks (GANs) to model normal crowd behavior and detect anomalies by comparing real data with GAN-generated representations. The author compared various results upon validating the test data and trained data using frame-level and pixel-level evaluation protocols, demonstrating the superiority of their approach over existing methods.

	Process Steps	**Advantage**	**Disadvantage (Limitation)**
1	The system starts by training two Generative Adversarial Networks (GANs) using a dataset of normal crowd behavior videos. The first GAN (N F→O) generates optical-flow images from video frames, while the second GAN (N O→F) generates video frames from optical-flow images.	Training GANs with normal data does not require labeled abnormal event data, making it feasible to create large training datasets. GANs learn to generate normal patterns effectively.	The GANs may not perform well in generating abnormal events since they have not been trained with such data
2	At testing time, the trained GANs (N F→O and N O→F) are used to generate appearance and motion information for input frames and optical-flow images.	The GANs generate representations that should match normal crowd behavior patterns in the input frames.	GANs may not accurately reproduce abnormal events in the input frames due to their training on normal data.
3	Differences are computed between the real data (frames and optical flow) and the generated representations. These differences highlight areas where the GANs fail to reproduce abnormal events.	Abnormal areas can be detected by measuring differences, allowing for the identification of potential anomalies.	Small or subtle anomalies might not be accurately detected, and false positives could occur.
4	The differences in optical-flow and appearance representations are fused to obtain an abnormality map that is used for abnormality detection and localization	Fusing differences can improve the accuracy of anomaly detection and localization by considering both motion and appearance.	The fusion process might introduce complexity, and the choice of fusion parameters (e.g., λ in the paper) can impact results

Major Impact Factors in this Work

<Find all main factors and variables that are related to each solution. Then find the relationship between factors. (Independent variable) causes a change in (Dependent Variable) and it isn't possible that (Dependent Variable) could cause a change in (Independent Variable).

Dependent Variable	Independent Variable	Moderating variable	Mediating (Intervening) variable
Abnormal Behavior	Manipulated Factor		

Relationship Among The Above 4 Variables in This article

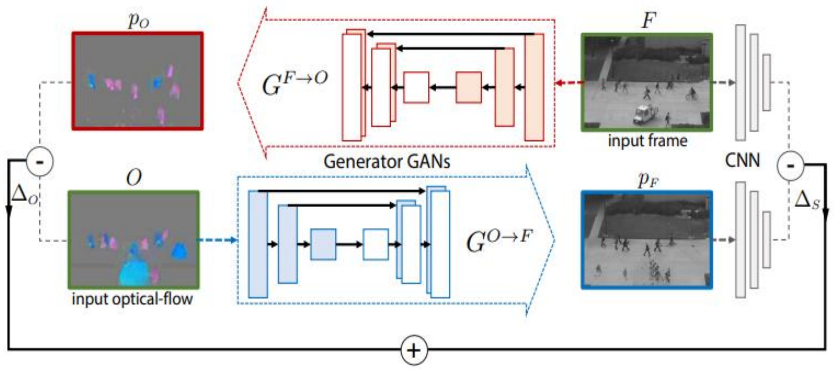
Input and Output	Feature of This Solution	Contribution & The Value of This Work
<table><tr><th>Input</th><th>Output</th></tr><tr><td>Video frames with normal and potentially abnormal events.</td><td>Abnormality detection heatmap.</td></tr></table>	Developing a solution for abnormal event detection in crowded video scenes, this approach utilizes Generative Adversarial Networks (GANs). Trained solely on normal data, it models normal behavior to detect abnormalities by comparing real and generated representations. It excels in frame-level and pixel-level detection, addressing	Good to have this knowledge from this paper as we reviewing of ideologies for developing Abnormal event detection in videos using generative adversarial nets

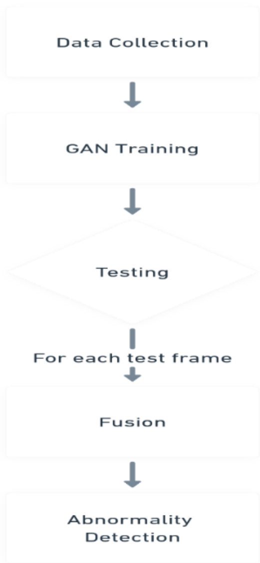
	challenges associated with limited ground truth samples for abnormal events. Its primary advantage lies in data efficiency, allowing training on large datasets with only normal samples.	

Positive Impact of this Solution in This Project Domain	Negative Impact of this Solution in This Project Domain
This solution greatly enhances abnormal event detection accuracy, improving public safety. It reduces the need for abnormal data during training, making it cost-effective	Implementing GANs can be computationally demanding, potentially requiring powerful hardware. Training GANs is complex and time-consuming, increasing development costs. There's a risk of false positives, leading to unnecessary alarms in surveillance.

Analyse This Work By Critical Thinking	The Tools That Assessed this Work	What is the Structure of this Paper
This work is good, as it utilizes GANs to address abnormal event detection in crowded scenes with limited abnormal data, providing data-efficient solutions but facing scalability and real-world deployment challenges.	TensorFlow,OpenCV,Scikit-learn,Matplotlib.	Abstract I. Introduction II. Local feature extraction III. Design of the abnormal event classifier IV. Experiment V. Conclusion

Diagram/Flowchart





---End of Paper 3--

Version 4.0 _ Week 4			
4			
Reference in APA format			
URL of the Reference	Authors Names and Emails	Keywords in this Reference	
https://ieeexplore.ieee.org/document/6099933	Lili Cui Kehuang Li Jiapin Chen Zhenbo Li	Optical flow; local features extraction; video surveillance; abnormal event detection	
The Name of the Current Solution (Technique/ Method/ Scheme/ Algorithm/ Model/ Tool/ Framework/ ... etc)	**The Goal (Objective) of this Solution & What is the problem that need to be solved**	**What are the components of it?**	
Abnormal Event Detection in Traffic Video Surveillance Based on Local Features	Aim is to develop an automated system for detecting and ranking abnormal events in traffic video surveillance, improving the efficiency and reliability of traffic monitoring and enabling early alarms for potential issues.	Author used Foreground Detection to identify moving objects, Object Classification to categorize them as pedestrians, vehicles, or noise regions, Active Driving Regions Identification to locate areas where vehicles should be, Local Feature Extraction to capture object characteristics, Local Velocity Distribution to estimate object velocities, and Cascade Classifiers to rank objects based on their abnormality	

The Process (Mechanism) of this Work; Means How the Problem has Solved & Advantage & Disadvantage of Each Step in This Process

The proposed system, "Abnormal Event Detection in Traffic Video Surveillance Based on Local Features," is a system that predicts abnormal events in traffic video surveillance. It uses local features extracted from video frames to make predictions. Even though the author compared various results upon validating the test data and trained data using machine learning with all supervised, unsupervised, and deep reinforcement learning algorithms.

	Process Steps	**Advantage**	**Disadvantage (Limitation)**
1	Foreground Detection is used detect objects (foreground) in video frames by distinguishing them from the background.	Identifies objects in motion, providing a starting point for analysis.	Foreground detection methods can be sensitive to variations in lighting and may produce false positives or miss objects in challenging conditions
2	Classify detected objects into categories such as pedestrians, vehicles, or noise regions based on features like size, shape, and more.	It helps categorize objects, making it easier to analyze their behaviour.	It may misclassify objects under certain conditions, such as noise regions being mistaken for pedestrians or vehicles.
3	Active Driving Regions Identification Identify regions within the video where vehicles are expected to be located.	These scores indicate the relevance of each frame.	This contextual information is crucial for understanding the scene and context of surveillance.
4	Local Feature Extraction is used for Extract local features such as region area, shape factors, and pixel moving velocity vectors to characterize object behavior.	These features provide valuable information about the objects' behavior, which can be used for further analysis.	The choice of local features and their extraction can be sensitive to noise and may not capture all aspects of object behavior.

5	Local Velocity Distribution is used to Estimate object velocities using optical flow and Gaussian models to determine normal velocity ranges.	Precise velocity estimation is essential for detecting abnormal movements.	Estimation may be challenging for objects with irregular shapes or in complex scenes. Cascade Classifiers
6	Cascade Classifiers Combine the results of previous steps to rank objects based on their abnormality, with a scale ranging from 0 (normal) to 10 (highly abnormal).	Provides a ranking system for identifying and prioritizing abnormal events.	The threshold values and ranking criteria may need fine-tuning, and it relies on the accuracy of earlier steps.

Major Impact Factors in this Work

<Find all main factors and variables that are related to each solution. Then find the relationship between factors. (Independent variable) causes a change in (Dependent Variable) and it isn't possible that (Dependent Variable) could cause a change in (Independent Variable).

Dependent Variable	Independent Variable	Moderating variable	Mediating (Intervening) variable
Abnormality Ranking	Local Features, Object Characteristics		

Relationship Among The Above 4 Variables in This article

<table>
<tr><th>Input and Output</th><th>Feature of This Solution</th><th>Contribution & The Value of This Work</th></tr>
<tr><td><table><tr><th>Input</th><th>Output</th></tr><tr><td>Video streams from surveillance cameras.</td><td>Detection and ranking of abnormal events.</td></tr></table></td><td>Developing a traffic video surveillance system that employs local feature analysis, object classification, active region identification, and precise velocity estimation to detect and rank abnormal events. It offers adaptability, low complexity, and a reduction in false alarms, making it valuable for real-time traffic surveillance systems and Intelligent Traffic Systems</td><td>Good to have this knowledge from this paper as we reviewing of ideologies for Abnormal Event Detection in Traffic Video Surveillance Based on Local Features</td></tr>
</table>

Positive Impact of this Solution in This Project Domain	Negative Impact of this Solution in This Project Domain
The positive impact of the project is that it enhances traffic video surveillance by enabling early detection of abnormal events, which improves safety and efficiency in surveillance systems	It requires human-aided training, relies primarily on visual data, is dependent on computational resources, faces scalability challenges in extensive surveillance networks, and its effectiveness is tied to the quality of extracted local features, which may limit its applicability in some scenarios.

Positive Impact of this Solution in This Project Domain **Negative Impact of this Solution in This Project Domain**

Analyse This Work By Critical Thinking	The Tools That Assessed this Work	What is the Structure of this Paper

Positive Impact of this Solution in This Project Domain	Negative Impact of this Solution in This Project Domain

The research on "Abnormal Event Detection in Traffic Video Surveillance Based on Local Features" introduces an innovative approach to early abnormal event detection in traffic surveillance using local features. While promising for accuracy, it relies on human training and visual data, potentially limiting scalability and adaptability to unforeseen situations.	Computer vision, MATLAB	Abstract I. Introduction related II. Local feature extraction III. Design of the abnormal event classifier IV. Experiment V. Conclusion
Diagram/Flowchart		

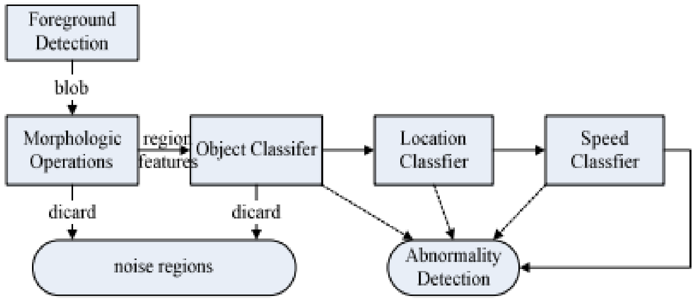


Figure 3. Diagram of abnormal event detection.

---End of Paper 4---

Version 5.0 _ Week 5		
5		
Reference in APA format		
URL of the Reference	**Authors' Names and Emails**	**Keywords in this Reference**
https://arxiv.org/pdf/1801.04264.pdf	Waqas Sultani, Chen Chen, Mubarak Sha	Video Anomaly Detection, Surveillance Videos, Real-world Anomalies, Deep Learning, Multiple Instance Ranking, Large-scale Dataset, Anomalous Activity Recognition, Baseline Methods, False Alarm Rate, Training Iterations
The Name of the Current Solution (Technique/ Method/ Scheme/ Algorithm/ Model/ Tool/ Framework/ ... etc)	**The Goal (Objective) of this Solution and what is the problem that needs to be solved**	**What are the components of it?**
The proposed solution is a deep multiple-instance ranking framework for real-world surveillance video anomaly detection.	Detect real-world anomalies in surveillance videos, addressing challenges of complexity, limited datasets, and realistic anomalies.	Deep Multiple Instance Ranking framework with weakly labeled data for anomaly detection in surveillance videos.

The Process (Mechanism) of this Work; Means How the Problem has been Solved & Advantages & Disadvantages of Each Step in This Process

The model learns anomaly detection using deep multiple instance ranking with weakly labeled data, leveraging both normal and anomalous videos. Advantage: Generalizable. Disadvantage: Limited temporal annotations.			
	Process Steps	**Advantage**	**Disadvantage (Limitation)**
1	Gathered 950 normal and abnormal surveillance videos covering 13 real-world anomalies from YouTube and LiveLeak.	An extensive, diverse dataset ensures robust model training for effective real-world anomaly detection in surveillance videos.	Limited control over video quality, authenticity; potential biases, ethical concerns, and legal issues in data collection.
2	Trained annotators for video-level labels; temporal annotations obtained by averaging annotators' markings.	Ensures diverse perspectives, reduces individual biases, enhances dataset reliability, and ensures accurate temporal annotations for training.	Annotation subjectivity potential inconsistencies among annotators, a resource-intensive, time-consuming, and costly process for large datasets.
3	Split the dataset into training (800 normal, 810 anomalous) and testing sets (150 normal, 140 anomalous).	Enables model training and evaluation, assesses generalization on diverse scenarios, and ensures effective anomaly detection performance.	Imbalanced training set; potential bias in model performance; limited diversity in abnormal events.
4	Used C3D network to extract visual features; applied l2 normalization, averaging, and input to a 3-layer FC neural network.	Leverages spatial-temporal features; captures complex patterns; enables end-to-end learning, accommodates diverse anomalies exhibits robust performance.	Limited explanation of feature extraction choices; lack of detailed analysis on the impact of network architecture variations.
5	Explored model training evolution, emphasizing the learned ability to predict anomaly locations,	Highlights the model's capability to learn anomaly locations autonomously; focuses on	Limited insight into network interpretability; does not address

	and evaluated false alarm rates on normal videos.	robustness with low false alarm rates on normal videos.	challenges related to scalability and real-time processing for large-scale surveillance.
	Used the dataset for activity recognition, demonstrating challenges for state-of-the-art action recognition methods due to long untrimmed surveillance videos.	Utilized dataset for activity recognition, revealing challenges for action recognition due to long, untrimmed surveillance videos.	Challenges for action recognition due to long untrimmed videos with low resolution, varied perspectives, and background noise.

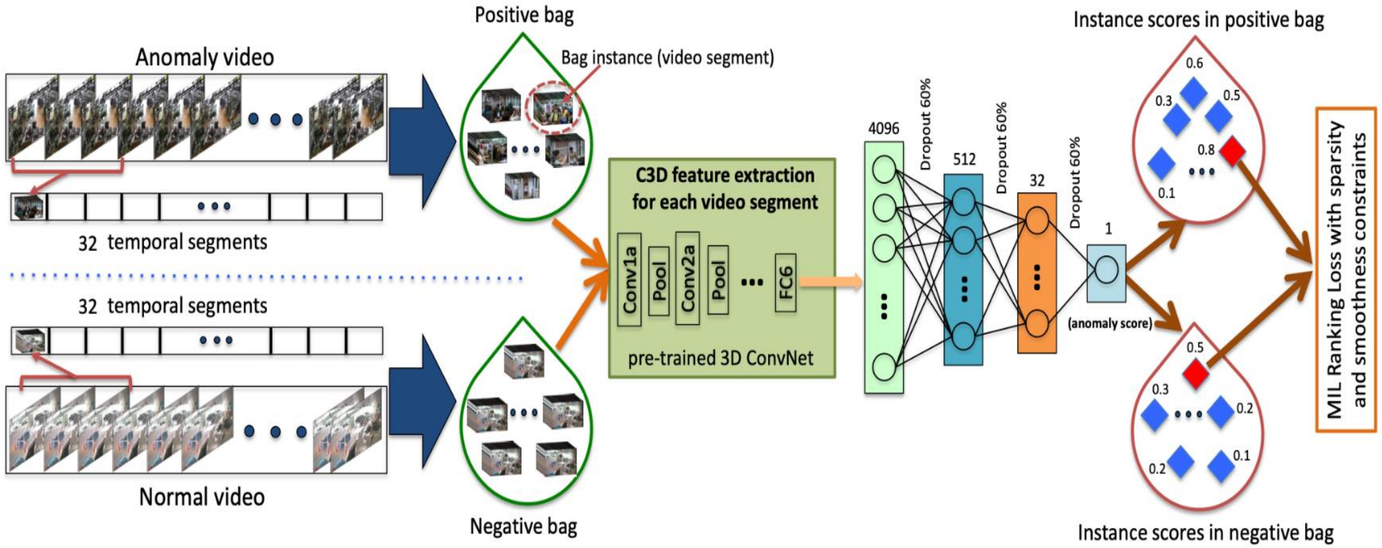
Major Impact Factors in this Work

<Find all main factors and variables that are related to each solution. Then find the relationship between factors. (Independent variable) causes a change in (Dependent Variable) and it isn't possible that (Dependent Variable) could cause a change in (Independent Variable).

Dependent Variable	Independent Variable	Moderating variable	Mediating (Intervening) variable
Anomaly Presence	C3D Features		

Relationship Among The Above 4 Variables in This article

<table>
<tr><td colspan="6"></td></tr>
<tr><th colspan="2">Input and Output</th><th colspan="2">Feature of This Solution</th><th colspan="2">Contribution & The Value of This Work</th></tr>
<tr><td colspan="2"><table><tr><th>Input</th><th>Output</th></tr><tr><td>video data of crowded areas.</td><td>Anomaly Detection.</td></tr></table></td><td colspan="2">Deep multiple instances ranking for anomaly detection, leveraging weakly labelled surveillance videos, achieving superior performance.</td><td colspan="2">The proposed method advances anomaly detection in surveillance, introducing a large-scale dataset, and enhancing real-world safety solutions.</td></tr>
<tr><th colspan="3">Positive Impact of this Solution in This Project Domain</th><th colspan="3">Negative Impact of this Solution in This Project Domain</th></tr>
<tr><td colspan="3">Enhances surveillance system efficacy, ensuring public safety through improved anomaly detection in real-world scenarios.</td><td colspan="3">Potential privacy concerns and ethical considerations arise due to increased surveillance, impacting personal freedoms in public spaces.</td></tr>
<tr><th colspan="2">Analyse This Work By Critical Thinking</th><th colspan="2">The Tools That Assessed this Work</th><th colspan="2">What is the Structure of this Paper</th></tr>
<tr><td colspan="2">Addresses real-world anomalies in surveillance, but ethical concerns and dataset biases should be scrutinized critically.</td><td colspan="2">TensorFlow, Scikit-learn, OpenCV,C3D Network</td><td colspan="2">Abstract
I. Introduction
II. Related work
III. Proposed Methodology
IV. Algorithms
V Results</td></tr>
<tr><th colspan="6">Diagram/Flowchart</th></tr>
</table>



---End of Paper 5---

Work Evaluation Table

	Work Goal	System's Components	System's Mechanism	Features /Characteristics	Cost	Speed	Security	Performance	Advantages	Limitations/Disadvantages	Platform	Results
Waqas Sultani, Chen Chen, Mubarak Sha 2019	The goal of the research was to develop a video anomaly detection algorithm using weakly labeled training videos, focusing on automatic anomaly detection in surveillance without detailed annotations.	The video anomaly detection system incorporates video segmentation, multiple instance learning, and a deep MIL ranking model trained with sparsity and smoothness constraints. It outperforms existing methods on a diverse real-world dataset, showcasing its robustness. The dataset also serves as a benchmark for	The system operates by segmenting surveillance videos, employing multiple instance learning (MIL), and training a deep MIL ranking model with sparsity and smoothness constraints for anomaly detection.	Video segmentation for bag formation. MIL to handle weakly labeled training data. Deep learning model for anomaly score prediction. Sparsity and smoothness constraints for enhanced performance.	-	The speed of anomaly detection is dependent on the efficiency of the deep MIL ranking model, which can be optimized for real-time applications.	-	The performance is driven by the accuracy of anomaly detection, with the deep MIL ranking model aiming to provide reliable results.	The system demonstrates a novel approach by effectively utilizing weakly labeled data for training, overcoming challenges prevalent in real-world surveillance scenarios. Through this innovative methodology, the system achieves remarkable accuracy in detecting anomalies, showcasing its potential to significantly	-	The system can be implemented on a computing platform with sufficient resources for deep learning model training.	The research in video anomaly detection introduced a method utilizing weakly labeled data and deep multiple instance learning. This approach outperformed existing methods, showcasing high accuracy in anomaly detection for real-world applications

		anomalous activity recognition, contributing to advancements in surveillance technology.							advance the field of video anomaly detection.			in surveillance and security.
Mahdyar Ravanbakhsh Moin Nabi Enver Sangineto Lucio Marcenaro Carlo Regazzoni 2017	The aim is to develop Abnormal event detection in videos using generative adversarial nets for detecting abnormal events in crowded video scenes. The problem is the challenge of distinguishing such events with limited data and subjective definitions of abnormality.	The author used training data with only normal scenes, and image-to-image translation using Generative Adversarial Networks which is a type of artificial neural network used in machine learning and deep learning, reconstruction of appearance and motion information, and fusion of differences to detect abnormal areas	The system utilizes Generative Adversarial Networks (GANs) trained on normal data to learn crowd behavior patterns. During testing, discrepancies between real and generated data highlight abnormal areas. This approach excels in crowded scene abnormality detection, surpassing state-of-the-art methods in experiments.	The system leverages Generative Adversarial Networks (GANs) to learn normal crowd behavior, focusing on appearance and motion patterns. It employs optical-flow images and frames during training, emphasizing unsupervised learning.	-	-		The system demonstrates superior performance in abnormality detection compared to state-of-the-art methods. It excels in both frame-level and pixel-level evaluation tasks, showcasing its effectiveness.	Advantages include the ability to learn normal patterns with minimal reliance on abnormal data during training. The GAN-based approach proves effective in detecting	Challenges include the subjective definition of abnormality and the limited availability of ground truth abnormality samples, particularly for deep learning methods. The paper also acknowledges a failure case in detecting small and normally	The system can be implemented on a computing platform with sufficient resources for deep learning model training.	Experimental results demonstrate the system's effectiveness, outperforming existing methods on challenging abnormality detection datasets such as UCSD. The approach shows promise for real-world applications in crowd behavior analysis and surveillance.

									abnormalities without explicit definition or ground truth for abnormality.	moving objects.		
Lili Cui Kehuang Li Jiapin ChenZhenbo Li 2011	Aim is to develop an automated system for detecting and ranking abnormal events in traffic video surveillance, improving the efficiency and reliability of traffic monitoring and enabling early alarms for potential issues.	Author used Foreground Detection to identify moving objects, Object Classification to categorize them as pedestrians, vehicles, or noise regions, Active Driving Regions Identification to locate areas where vehicles should be, Local Feature Extraction to capture object characteristics, Local Velocity Distribution to estimate object velocities, and Cascade Classifiers to	The proposed system relies on foreground detection, local feature extraction, and a cascade of classifiers. It starts with detecting moving foreground, extracting features like area and velocity, classifying objects, and determining abnormality through various classifiers.	Key features include local features extraction (area, shape factors), object classification (pedestrian, vehicle, noise), and the assessment of spatial and velocity characteristics. The system utilizes a comprehensive set of features to understand and classify objects in traffic video surveillance.		The system aims to provide early detection, which implies a focus on speed. The use of local features and a simplified classifier contributes to the system's efficiency in processing and analyzing video data.	-	The system's performance is highlighted through its ability to detect abnormal events based on local features efficiently. The use of multiple classifiers and the avoidance of complex trajectory analysis contribute to improved performance.	Advantages include low complexity, suitability for early alarm systems in intelligent traffic surveillance, and robust performance in detecting abnormal events using local features.	Limitations include the need for human-aid in the training stage and potential challenges in cases where objects do not conform to assumed shapes. The paper acknowledges the need for further testing and	The system is implemented and tested using MATLAB, indicating a platform choice for the development and experimentation stages.	The system's effectiveness is demonstrated through experiments on a traffic surveillance dataset. It successfully detects abnormal events, such as irregular vehicle movements and pedestrian behaviors, providing promising results for

		rank objects based on their abnormality								optimization.		its application in traffic surveillance.

Megha Chhirolya Dr. Nitesh Dubey . 2013	The aim is to develop a method for accurately detecting and classifying abnormal human behavior in crowded environments using image processing techniques. This addresses challenges such as diverse crowd behaviors, the need for socio-psychological considerations, and the limitations of conventional density-based analyses. The proposed solution, leveraging Optical Flow features, seeks to enhance situational awareness and response in	The author used a comprehensive strategy, incorporating optical flow features and employing machine learning with Support Vector Machine, to tackle the detection of abnormal human behavior in crowded environments. This approach involves video capture, pre-processing, and feature extraction, enabling a detailed analysis of crowd dynamics. Performance metrics, particularly testing accuracy, validate the solution's	The system likely employs image processing techniques, including optical flow and machine learning algorithms, to detect and classify abnormal behavior within crowded environments. It focuses on understanding collective motions and interactions to identify behaviors that deviate from the norm.	Key features include optical flow-derived characteristics such as average kinetic energy, movement direction entropy, and population distance potential energy. The system utilizes these features for the detection and classification of abnormal behavior in crowded scenes.	-	-	Although not explicitly discussed, the system's application in crowded environments suggests potential security benefits. The ability to detect abnormal behavior could contribute to enhanced security measures, especially in scenarios such as surveillance and crowd management.	The system's performance is evaluated based on testing accuracy, reaching 96.75% according to the presented results. This metric reflects the effectiveness of the proposed method in accurately classifying abnormal behavior in crowds.	Advantages include potential applications in security, disaster response, and crowd management. The utilization of optical flow features enhances the system's ability to analyze crowd behavior autonomously.	Challenges include difficulties in dense crowd scenes due to occlusions, where individuals or groups may obstruct each other. The paper also lacks detailed information on specific algorithmic approaches employed, which could impact transparency and reproducibility.	-	The testing accuracy results indicate the success of the proposed method, achieving an accuracy rate of 96.75%. These results suggest the potential effectiveness of the system in classifying abnormal behavior in crowded environments.

	scenarios like disaster management and crowd control.	efficacy in accurately identifying and classifying abnormal behaviors within crowded scenarios.										

Riddhi Sonka,Sadhana Rathod,Renuka Jadhav ,Deepali Patil. 2017	Aim is to develop a system for real-time detection of abnormal crowd behaviour using deep learning methods, like Convolutional Neural Networks and K-Means clustering, to enhance public security and mitigate potential threats.	The author utilized deep learning and surveillance technology, encompassing surveillance cameras for data collection, pre-processing modules for enhancing video data, deep learning-based object detection and tracking, behavior analysis modules for motion parameter computation, abnormality detection algorithms for identifying deviations from normal behavior, alert generation systems for timely notifications, user interfaces for monitoring,	The system employs a multi-step mechanism for crowd behavior analysis. It begins with pre-processing techniques, such as background subtraction using the ViBe algorithm. Object tracking and deep object extraction are conducted through Convolutional Neural Networks (CNN). K-Means clustering is then applied for motion detection. Abnormal behavior is identified based on the analysis of object motion	The system is characterized by its ability to handle real-time video surveillance, incorporating advanced deep learning techniques for object detection and tracking. It excels in crowd analysis by considering environmental factors like weather conditions and diverse crowd compositions. Notably, it provides a comprehensive approach to addressing security challenges in crowded urban environments.	-	-	the system enhances public safety by detecting abnormal crowd behavior, preventing potential threats. The integration of CNN allows for deep learning-based security analysis, ensuring the robustness of the surveillance system against security risks.	The system's performance is commendable, achieving an accuracy rate of 80.79% in abnormal behavior detection. The combination of ViBe, CNN, and K-Means proves effective in capturing and analyzing complex crowd dynamics.	1) Real-time crowd analysis 2) Effective abnormal behavior detection 3) Consideration of environmental factors 4) Low-cost implementation using open-source tools	1)Dependency on quality and availability of surveillance data 2)Challenges in handling diverse crowd characteristics 3)Potential computational resource requirements for CNN-based processing	The system is implemented using common programming languages such as Python, along with libraries like OpenCV, TensorFlow or PyTorch, and Scikit-learn. It is adaptable to various platforms supporting these technologies.	The system's results demonstrate a significant improvement compared to existing methods, achieving an accuracy rate of 80.79% in abnormal behavior detection. This underscores the effectiveness of the proposed combination of ViBe, CNN,

		and integration with existing security infrastructure.	parameters, such as speed, angle, and direction.									and K-Means clustering for crowd analysis in urban environments.