Literature Review (Secondary Research) Template

Student Name	**Aarya Gouthula**
Project Topic Title	**Abnormal Event Detection on Pathway using deep learning**

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 variables. ● 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 the	● 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 medical care than those with low incomes. Medical care is an intervening

		association between X and Y variables.	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://www.sciencedirect.com/science/article/pii/S0925231223006847	Yuxing Yang Zeyu Fu Syed Mohsen Naqvi	Enhanced fusion framework, Classification, Prediction streams, Normality scores, Abnormal events.
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?**
Enhanced Fusion Framework with Classification and Prediction Streams	The system is designed to recognize anomalous items or unusual behavior in footage clips. The main objective is to enhance the detection of various abnormal events by using subject.	Author used Framework for object detection and abnormal event detection in classification of the actions in the video surveillance. It also aims to better detect and classify different types of abnormal events.
The Process (Mechanism) of this Work; Means How the Problem has Solved & Advantage & Disadvantage of Each Step in This Process		

The proposed framework for abnormal event detection (AED) consists of two concurrent streams: the action-based classification stream and the motion-based prediction stream.

	Process Steps	Advantage	Disadvantage (Limitation)
1	Object Detection and Pose Estimation	It also has the benefit of capturing the classes, confidence evaluations; and localization information of the targets, all of which are necessary for additional processing.	The drawback is that it might not identify small things like skateboards with enough clarity.
2	Action-Based Classification	The advantage of using the ST-GCN model is that it captures spatial and temporal features of body joints, allowing for more accurate classification.	The disadvantage is that it may not perform well in detecting abnormal events involving hidden drivers.
3	Motion-Based Prediction	This step predicts subsequent frames based on historical trajectories, which can help identify abnormal events.	This relies on optical flow calculations, which may not be accurate in all scenarios.

Major Impact Factors in this Work

<Find all main factors and variables that are related to each solutions. 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 Event Detection Performance	Two-Stream Fusion Method	Lighting Conditions or Camera Quality	Feature Representation Quality or Temporal-Spatial Information Integration

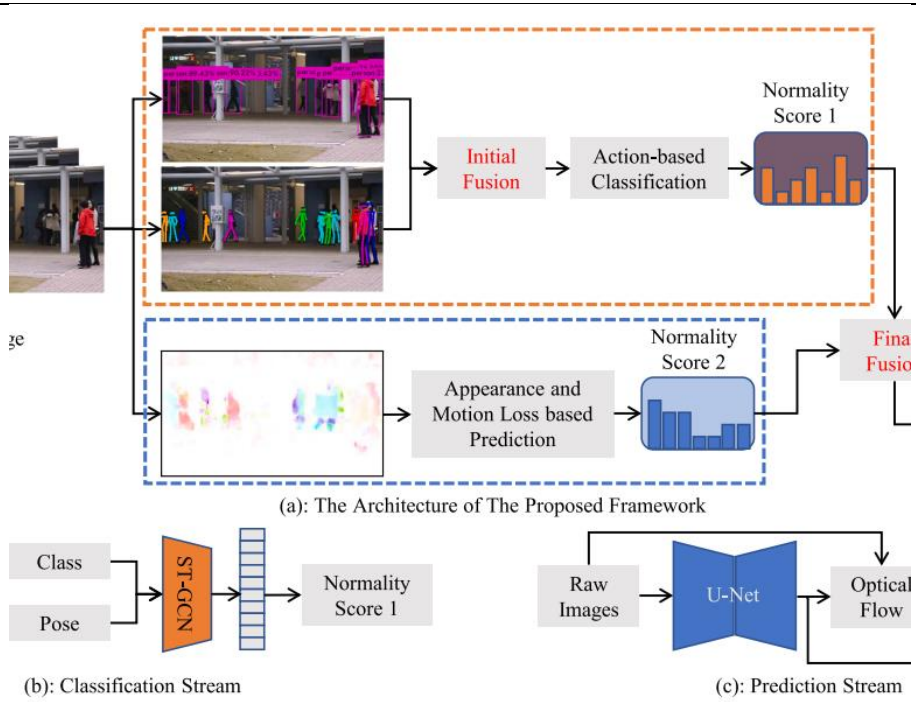
Relationship Among The Above 4 Variables in This article
This framework provides a foundation for understanding and studying the factors involved in the abnormal event detection process with a focus on the enhanced two-stream fusion method in video surveillance. However, it's important to tailor these variables based on the specific details and goals of your research or study.

Input and Output	**Feature of This Solution**	**Contribution & The Value of This Work**
Input / **Output** Photographs / Final normality score	This solution proposes a unified Abnormal Event Detection (AED) framework that combines multiple features to detect different types of video-based abnormal events..	The framework is suitable for detecting abnormal events containing abnormal behaviors and objects.

Positive Impact of this Solution in This Project Domain	**Negative Impact of this Solution in This Project Domain**
The proposed fusion framework offers improved detection accuracy, , flexibility in model selection,and potential for real-world applications.	**Limited consideration of non-human-related abnormal events and Data imbalance challenges.**

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

<table>
<tr>
<td>This work presents a joint fusion approach for abnormal event detection (AED) in surveillance videos. It combines pose, class, and motion information to improve the accuracy of anomaly detection.</td>
<td></td>
<td>Abstract
I. Introduction
II. Related Work
III. Proposed Framework
IV. Experiments
V. Conclusion</td>
</tr>
<tr>
<td colspan="3">Diagram/Flowchart</td>
</tr>
</table>



(a): The Architecture of The Proposed Framework

(b): Classification Stream

(c): Prediction Stream

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2		
Reference in APA format		
URL of the Reference	**Authors Names and Emails**	**Keywords in this Reference**
https://arxiv.org/pdf/2304.01226.pdf	Bo Yan Cheng Yang Chuan Shi Jiawei Liu Xiaochen Wang	Embedding learning,Heterogeneous information networks,Abnormal event detection,Contrastive learning,Graph neural networks .
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?**
AEHCL (Abnormal Event Hypergraph Contrastive Learning)	The solution aims to capture complex abnormal set-wise patterns in AHIN and develop a framework for detecting abnormal events.	Event Modeling, Intra-event Contrastive Module, Inter-event Contrastive Module and Abnormal Event Score Function are the components of AEHCL

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

All of these components work together in AEHCL in order to record abnormal event patterns in an unsupervised way, increasing AHIN's abnormal event detection capabilities.

	Process Steps	Advantage	Disadvantage (Limitation)
1	Intra-event Contrastive Module	It aims to capture abnormal patterns within an event by considering both pair-wise and multivariate interaction patterns	This may not fully capture the complexity of abnormal patterns

2	Inter-event Contrastive Module	it aims to capture abnormal patterns within an event by considering both pair-wise and multivariate interaction patterns.	This may weaken the true abnormal degrees when directly fusing all pair-wise matching degrees within an event to obtain an event abnormal score
3	Abnormal Event Score Function	This allows for more accurate detection of abnormal events and better understanding of abnormal event patterns.	This may be less discriminative in certain scenarios

Major Impact Factors in this Work

The main impacting factors in this work are the abnormal event score functions, hyper-parameters, pair-wise contrastive module, multivariate contrastive module, and inter-event contrastive module. These factors support the proposed AEHCL model's effects in AHIN abnormal event detection.

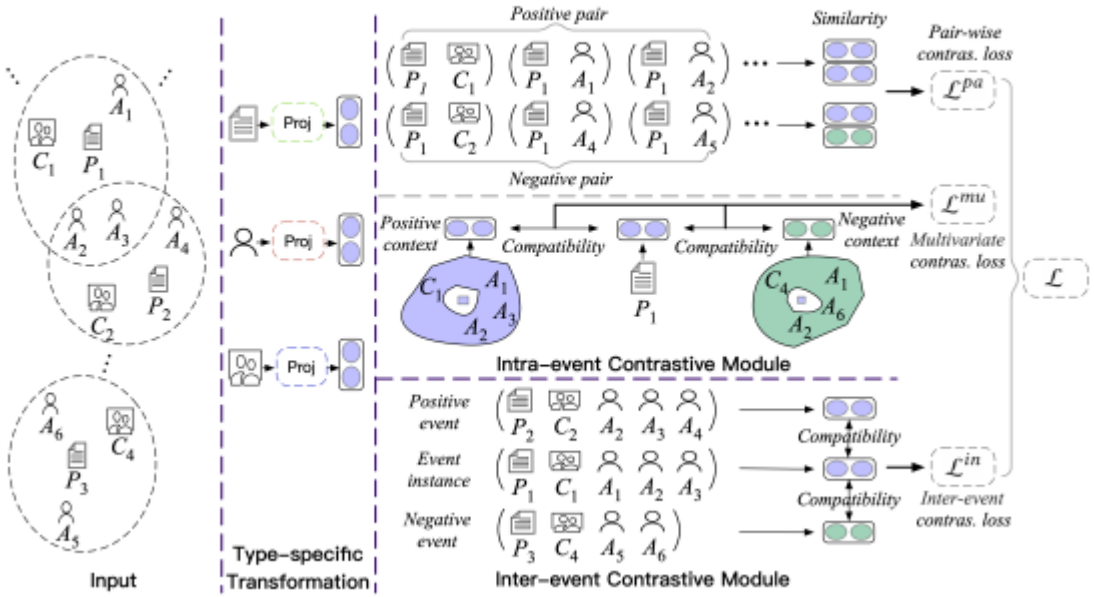
Dependent Variable	Independent Variable	Moderating variable	Mediating (Intervening) variable
Abnormal Event Detection Performance or Anomaly Score	Hypergraph Contrastive Learning Method	-	-

Relationship Among The Above 4 Variables in This article

This framework provides a foundation for understanding and studying the factors involved in abnormal event detection using hypergraph contrastive learning. However, it's crucial to adapt these variables based on the specific details and goals of your research or study.

Input and Output	Feature of This Solution	Contribution in This Work

<table>
<tr>
<td>
<table>
<tr><th>Input</th><th>Output</th></tr>
<tr><td>Images</td><td>Abnormal event score</td></tr>
</table>
</td>
<td>This is simply an integration of two classifiers features to design a hybrid one. We can still integrate other classifiers which gives us even more better results.</td>
<td>The contribution of this work is the development of a hypergraph contrastive learning method called AEHCL for abnormal event detection in Attributed Heterogeneous Information Networks (AHIN).</td>
</tr>
<tr><th colspan="2">Positive Impact of this Solution in This Project Domain</th><th>Negative Impact of this Solution in This Project Domain</th></tr>
<tr><td colspan="2">AEHCL model provides a comprehensive and effective solution for abnormal event detection in AHIN, leading to improved performance and the ability to capture complex interactions and rare event patterns.</td><td>Type-specific node transformation is that it may reduce the performance of downstream tasks when using the original features directly</td></tr>
<tr><th>Analyse This Work By Critical Thinking</th><th>The Tools That Assessed this Work</th><th>What is the Structure of this Paper</th></tr>
<tr><td>The framework aims to capture complex abnormal set-wise patterns in AHIN and proposes contrastive learning methods at the intra-event and inter-event levels.</td><td>.</td><td>Abstract
Introduction
Related Work
Proposed Method
Experiment Results
Conclusion
References
Acknowledgment</td></tr>
<tr><th colspan="3">Diagram/Flowchart</th></tr>
</table>



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3		
Reference in APA format		
URL of the Reference	**Authors Names and Emails**	**Keywords in this Reference**
https://www.researchgate.net/publication/329353016_Fast_Abnormal_Event_Detection	Cewu Lu Wei-Ming Wang Jiaya Jia	Abnormal Event Detection, Sparse Combination Learning, Framework Large Scale Dataset and Subspace Clustering
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?**
Current Solution: Maximum Commonness Representation Strategy (MCRS)	The goal is to reduce the number of combinations and represent as many training samples as possible.	Learning Combinations on Training Data Generating New Combinations
The Process (Mechanism) of this Work; Means How the Problem has Solved & Advantage & Disadvantage of Each Step in This Process		

	Process Steps	Advantage	Disadvantage (Limitation)
1	Sparse Combination Learning Framework:	Dividing the training data into passes allows for the creation of combinations that represent the remaining data, reducing the number of combinations needed.	The process of dividing the training data into passes may result in some training samples being left out if they cannot be well represented by the current combinations.

Major Impact Factors in this Work

the sparse combination learning framework, online extension, fast testing scheme, and benchmark datasets are the major impact factors in this work, contributing to the advancement of abnormal event detection in surveillance videos.

Dependent Variable	Independent Variable	Moderating variable	Mediating (Intervening) variable
Speed of Abnormal Event Detection or Latency	Detection Algorithm or Methodology	-	-

Relationship Among The Above 4 Variables in This article

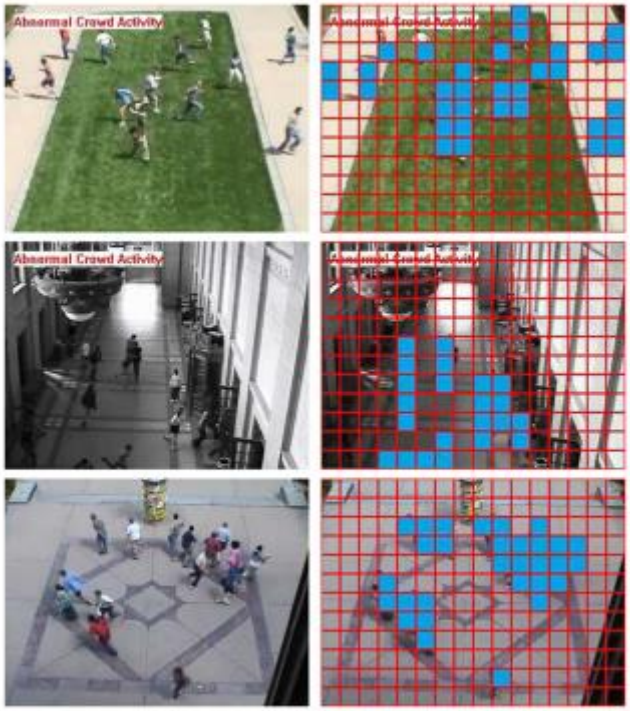
It's essential to adapt these variables based on the specific details and goals of your research or study. Additionally, consider other relevant factors that may impact the speed and efficiency of abnormal event detection in your particular context.

Input and Output	Feature of This Solution	Contribution & The Value of This Work
Input: Video Output: active scores	The approach is effective in distinguishing between normal and abnormal patterns and achieves high detection accuracy.	The work contributes to the understanding of crowd dynamics and provides insights into the factors that influence crowd behavior. This knowledge can be used to improve crowd management strategies and enhance public safety measures

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

The iterative update of combinations and weights allows for the refinement of the model, reaching a global optimum for anomaly detection.	No negative impact of this solution in the project domain

Analyse This Work By Critical Thinking	The Tools That Assessed this Work	What is the Structure of this Paper
The work also mentions the evaluation of the proposed method on benchmark datasets and compares the results with other approaches.		Abstract I. Introduction II. Related Work III. Sparse Combinations Training IV. Birth-and-Death Combination Online Learning V. Testing VI. Experiment VII. References
Diagram/Flowchart		



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4		
Reference in APA format		
URL of the Reference	**Authors Names and Emails**	**Keywords in this Reference**
https://ieeexplore.ieee.org/document/8824981	Hoang Duy Trinh Lorenza Giupponi Paolo Dini	LTE network data, Anomaly detection with LSTM neural networks
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?**
Long Short-Term Memory (LSTM) neural networks.	The problem that needs to be solved is the detection of urban anomalies, such as unexpected crowd gatherings, using mobile network data.	Data Collection, Data Preprocessing, LSTM Architecture, Anomaly Detection Algorithms,Performance Evaluation are the components
The Process (Mechanism) of this Work; Means How the Problem has Solved & Advantage & Disadvantage of Each Step in This Process		

	Process Steps	**Advantage**	**Disadvantage (Limitation)**

1	Data Collection	Using the LTE control channel data is that it provides fine-grained scheduling information for all connected users.	It requires the use of an over-the-air sniffer and specific hardware for decoding the DCI messages.
2	Data Preprocessing	It resampling and normalizing the data is that it helps in identifying anomalies quickly, even through visual inspection.	It filters the input sequence and may remove some important information.
3	Anomaly Detection with LSTM Neural Networks:	LSTM neural networks is that they can learn long-term dependencies and solve the vanishing-gradient problem	It requires tuning of training parameters and may have higher computational requirements compared to other algorithms.

Major Impact Factors in this Work

Dependent Variable	Independent Variable	Moderating variable	Mediating (Intervening) variable
Accuracy in Detecting Anomalies	LSTM Neural Network Model	Traffic Density	Sequential Pattern Recognition

Relationship Among The Above 4 Variables in This article

Important to adapt these variables based on the specific details and goals of your research or study. Additionally, consider other relevant factors that may impact the performance of anomaly detection in urban environments.

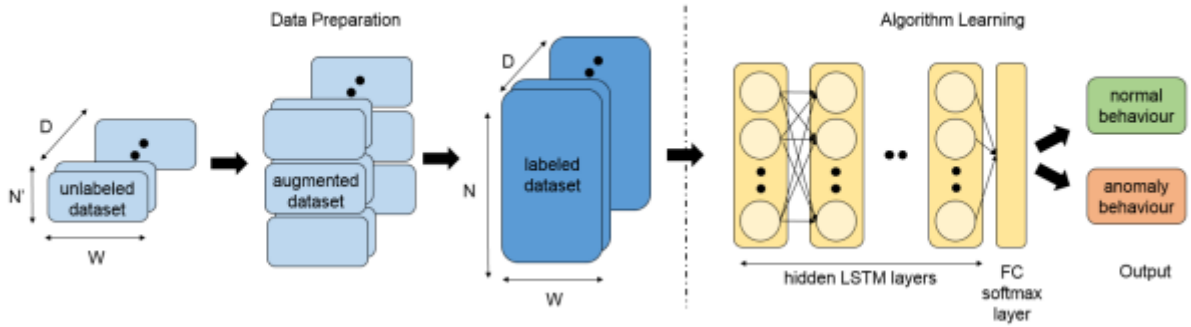
Input and Output	Feature of This Solution	Contribution & The Value of This Work
<table><tr><th>Input</th><th>Output</th></tr><tr><td>messages</td><td>values</td></tr></table>	The proposed solution leverages the pervasiveness of the mobile network as a sensing platform for anomaly detection in urban areas.	This work provides valuable insights into the potential of utilizing mobile network data for anomaly detection and emphasizes the advantages of a supervised learning approach when a labeled dataset is available.

Positive Impact of this Solution in This Project Domain	Negative Impact of this Solution in This Project Domain
This solution offers a cost-effective, privacy-preserving, and real-time approach to urban anomaly detection, contributing to sustainable development and utilizing the existing mobile network infrastructure.	Potential negative impacts related to coverage limitations, privacy concerns, reliance on mobile network operators

Analyse This Work By Critical Thinking	The Tools That Assessed this Work	What is the Structure of this Paper
The paper discusses the importance of detecting urban anomalies for public order management and proposes the use of the mobile network as a supplementary sensing platform. It introduces a Multi-access Edge Computing (MEC) architecture		Abstract I. INTRODUCTION II. SCENARIO III. DATASET IV. ANOMALY DETECTION FRAMEWORK V. PERFORMANCE EVALUATION VI. CONCLUSIONS

		VII. ACKNOWLEDGMENT VIII. REFERENCES

Diagram/Flowchart



--End of Paper 4—

5	

Reference in APA format		
URL of the Reference	**Authors Names and Emails**	**Keywords in this Reference**
https://www.ncbi.nlm.nih.gov/pmc/articles/PMC7506808/#sec1-sensors-20-04943title	Dimitriou N Lalas A Dasygenis M	Abnormal passenger behavior End-to-end detection Computer vision and deep learning
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?**
Stacked Bidirectional LSTM Classifier	The problem that needs to be solved is the detection and prevention of petty crimes in the context of autonomous shuttles	The components of the system include camera sensors, video analytics component, deep learning model, surveillance software, security alert system, data datasets, and performance/power analysis.

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

The proposed solution provides an end-to-end detection system for petty crimes using deep learning techniques

	Process Steps	**Advantage**	**Disadvantage (Limitation)**

1	Stacked Bidirectional LSTM Classifier	It achieves high accuracy and supports multiple camera types	It requires a lot of data and may have events of occlusion, leading to low accuracy.
2	Spatiotemporal Autoencoder	It offers robustness and high accuracy	It requires depth and acceleration data, which may not always be available
3	Hybrid LSTM Classifier	His approach combines the strengths of the previous methods and offers flexibility, high accuracy,	It also requires a significant amount of data and fine-tuning.

Major Impact Factors in this Work

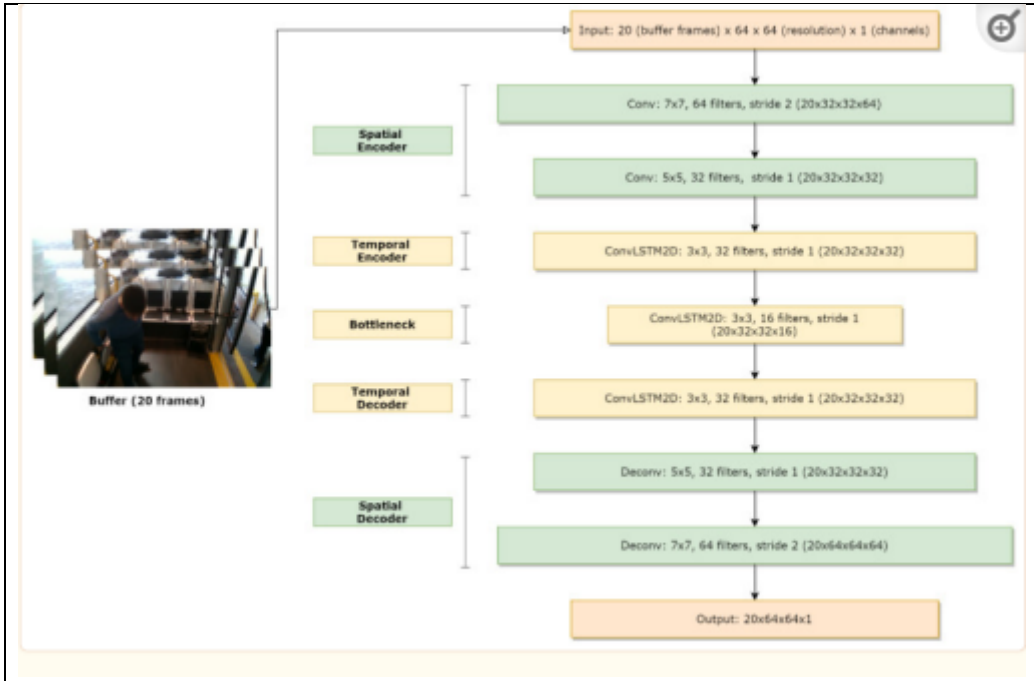
Dependent Variable	Independent Variable	Moderating variable	Mediating (Intervening) variable
Effectiveness of Abnormal Event Detection	Detection System Parameters or Sensor Inputs	Environmental Conditions or Traffic Density	Response Time of Emergency Systems or Communication Latency

Relationship Among The Above 4 Variables in This article

This is a generalized framework, and the actual variables might vary based on the specific details and objectives of your research or study. It's essential to tailor these variables to fit the unique characteristics of the autonomous shuttles mobility infrastructure and the goals of your investigation.

Input and Output	Feature of This Solution	Contribution & The Value of This Work
		This work contributes to the field of abnormal event detection by providing a comprehensive and

<table>
<tr><td><table><tr><th>Input</th><th>Output</th></tr><tr><td>video data</td><td>F1-Score metrics</td></tr></table></td><td>The proposed solution combines modern technologies and deep learning techniques to provide a robust and automatic detection system for petty crimes and the re-identification of offenders.</td><td>efficient solution that can improve passenger security and assist in the re-identification of offenders.</td></tr>
<tr><th colspan="2">Positive Impact of this Solution in This Project Domain</th><th>Negative Impact of this Solution in This Project Domain</th></tr>
<tr><td colspan="2">It enhances passenger security by detecting and addressing various petty crimes such as aggression, bag-snatching, and vandalism. This ensures the safety and well-being of passengers during their journey.</td><td>One potential negative impact is the reliance on camera sensors for surveillance, which may raise privacy concerns among passengers.</td></tr>
<tr><th>Analyse This Work By Critical Thinking</th><th>The Tools That Assessed this Work</th><th>What is the Structure of this Paper</th></tr>
<tr><td>The goal is to develop a solution that can address the complexities of detecting abnormal events using modern technologies and deep learning techniques.</td><td></td><td>Abstract
Introduction
Related Work
Dataset
Methodology
Experimental Results
Conclusions</td></tr>
<tr><th colspan="3">Diagram/Flowchart</th></tr>
</table>


Input: 20 (buffer frames) x 64 x 64 (resolution) x 1 (channels)
Spatial Encoder
Conv: 7x7, 64 filters, stride 2 (20x32x32x64)
Conv: 5x5, 32 filters, stride 1 (20x32x32x32)
Temporal Encoder
ConvLSTM2D: 3x3, 32 filters, stride 1 (20x32x32x32)
Bottleneck
ConvLSTM2D: 3x3, 16 filters, stride 1 (20x32x32x16)
Temporal Decoder
ConvLSTM2D: 3x3, 32 filters, stride 1 (20x32x32x32)
Spatial Decoder
Deconv: 5x5, 32 filters, stride 1 (20x32x32x32)
Deconv: 7x7, 64 filters, stride 2 (20x64x64x64)
Output: 20x64x64x1
Buffer (20 frames)

Work Evaluation Table

<Use the same factors you have used in "Work Evaluation Table" to build your own "Proposed and Previous comparison table ">

	Work Goal	System's Components	System's Mechanism	Features /Characteristics	Cost	Speed	Security	Performance	Advantages	Limitations /Disadvantages	Platform	Results
Yuxing Yang Zeyu Fu Syed Mohsen Naqvi	Abnormal event detection for video surveillance using an enhanced two-stream fusion method	Two-stream fusion method: Sensors, feature extraction, fusion algorithm for precise abnormal event detection in video surveillance.	Sensors capture video data, feature extraction refines, fusion method enhances precision—detecting abnormal events in surveillance.	Two-stream fusion method: heightened accuracy, improved precision, robust abnormal event detection for video surveillance excellence.	-	-	-	Enhanced two-stream fusion excels in video surveillance: heightened accuracy, rapid abnormal event detection, superior performance.	Enhanced two-stream fusion yields heightened accuracy, real-time detection, and improved adaptability for video surveillance advantages.	Challenges include potential high computational load, complexity, and sensitivity to diverse environmental conditions in surveillance.	Utilizes enhanced two-stream fusion method on a video surveillance platform for accurate abnormal event detection.	Enhanced two-stream fusion boosts video surveillance accuracy, detecting abnormal events with heightened precision and efficiency.

Bo Yan Cheng Yang Chuan Shi Jiawei Liu Xiaochen Wang	Abnormal Event Detection via Hypergraph Contrastive Learning	Hypergraph representation, contrastive learning algorithm, feature extraction modules—constituting a comprehensive system for abnormal event detection via hypergraph contrastive learning.	Hypergraph contrastive learning: intricate process involving hypergraph representation, feature extraction, and advanced algorithms for abnormal event detection.	Hypergraph-based representation, contrastive learning, robust feature extraction —culminating in precise abnormal event detection via hypergraph contrastive learning.	_	-	-	Hypergraph contrastive learning exhibits superior performance: enhanced accuracy, robust anomaly detection, and heightened efficiency in abnormal event detection research.	Benefits include precise anomaly detection, adaptability to complex scenarios, and improved accuracy—highlighting advantages of hypergraph contrastive learning in research. .	Challenges encompass potential complexity, computational load, and sensitivity to certain conditions—highlighting limitations of hypergraph contrastive learning in research.	Implemented on a robust platform, abnormal event detection via hypergraph contrastive learning ensures precision and adaptability in surveillance systems.	Research unveils superior results: heightened accuracy, efficiency, and adaptability in abnormal event detection through hypergraph contrastive learning methodologies..
Cewu Lu Wei-Ming Wang	Developing a swift	Components include real-time	Real-time sensors capture data, swift processing	Swift response, real-time				Swift response and real-time accuracy showcase the	Enhanced security and efficient	Potential limitations include the risk	The platform involves	The result of the fast

Jiaya Jia	abnormal event detection system to enhance security and responsiveness in real-time scenarios for efficient surveillance.	sensors, rapid data processing units, and efficient anomaly detection algorithms—forming a responsive system for fast abnormal event detection.	employs efficient algorithms—constituting a mechanism for fast abnormal event detection in responsive surveillance systems.	processing, and high precision characterize the fast abnormal event detection system, enhancing efficiency and security.				performance of the fast abnormal event detection system, ensuring efficient and effective surveillance.	surveillance highlight the advantages of the fast abnormal event detection system, ensuring improved responsiveness and heightened precision.	of a high computational load, which may impact the system's efficiency in fast abnormal event detection.	robust and adaptable systems for implementing the fast abnormal event detection method, ensuring efficiency and responsivenes	abnormal event detection research, showcasing the system's effectiveness in real-world surveillance scenarios.
Hoang Duy Trinh Lorenza Giupponi Paolo Dini	Developing urban anomaly detection via LSTM networks for enhance	Data Preprocessing Mechanis,Mobile Traffic Traces, Feature Extraction Modules,	Mobile traffic traces processed through LSTM networks for real-time anomaly detection, enhancing urban	Temporal pattern recognition, real-time anomaly detection, adaptability to urban dynamics—				High-performance: real-time anomaly detection, precision in traffic pattern recognition, ensuring urban security with LSTM neural networks.	Enhanced security, real-time anomaly detection, adaptability to dynamic urban environment	Potential drawbacks: High computational demand, sensitivity to diverse urban conditions—addressing challenges in	Implemented on a robust platform, seamlessly integrating LSTM	Improved urban safety: Enhanced anomaly detection, real-time

	d security in processing mobile traffic traces.		security and safety.	enhancing security in mobile traffic surveillance.					s—advancing safety with LSTM neural networks. .	mobile traffic anomaly detection.	neural networks for precise urban anomaly detection and surveillance	response, and adaptable surveillance in mobile traffic scenarios with LSTM networks.
Dimitriou N Lalas A Dasygenis M												