Literature Review (Secondary Research) Template

Student Name	**K.Vishwanath Reddy**
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 the association between X and Y variables.	● 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 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

NOTE: Please you need to use YOUR OWN WORDS in writing this template.

Your Literature Review Should be in Scope and MUST Address all Your Project's Questions

Version 1.0 _ Week 1		
1		
Reference in APA format		
URL of the Reference	**Authors Names and Emails**	**Keywords in this Reference**
https://ieeexplore.ieee.org/document/5206771	Louis Kratz , Ko Nishino	Extremely crowded scenes , Video surveillance , Motion patterns, Unusual event detection , Deviation methods , Distribution-based Hidden Markov Models , Temporal statistics , Spatial relationships , Cuboids , Spatio-temporal gradients , Training data , Receiver Operator Characteristic (ROC) curves
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?**
novel statistical framework for modeling	The aim is to detect unusual motion patterns in extremely crowded video scenes by modeling and analyzing the local spatio-temporal motion patterns in order to identify events that deviate from the normal activity in these scenes.	Author used Local Spatio-Temporal Motion Patterns to capturing the local motion patterns within extremely crowded scenes , Distribution-Based Motion Pattern Modeling , Temporal Modeling , Spatial Modeling - Spatial relationships between local spatio-temporal motion patterns are captured using a coupled HMM , Confidence Measures
The Process (Mechanism) of this Work; Means How the Problem has Solved & Advantage & Disadvantage of Each Step in This Process		

The proposed system detect unusual events in extremely crowded scenes by capturing local spatio-temporal motion patterns using distribution-based models, leveraging temporal and spatial relationships, and employing confidence measures based on statistical analysis, allowing for the identification of unusual events in video sequences..

	Process Steps	**Advantage**	**Disadvantage (Limitation)**
1	Dividing the video into local spatio-temporal volumes (cuboids) and extracting a compact motion pattern representation for each cuboid, based on the distribution of spatio-temporal gradients	Dividing the video into local spatio-temporal volumes (cuboids) and extracting compact motion pattern representations based on spatio-temporal gradients enables the system to capture fine-grained, localized motion information, providing a rich and detailed representation of complex behaviors within the video scene.	A limitation of dividing the video into local spatio-temporal volumes (cuboids) and extracting compact motion pattern representations based on spatio-temporal gradients is that it may struggle to capture fine-grained details in extremely crowded scenes with rapid and complex motion, potentially leading to information loss and reduced accuracy in detecting subtle unusual events.
2	The system identifies prototypical motion patterns by comparing the KL divergence between local spatio-temporal motion patterns. This allows it to capture common behaviors within the scene	Identifying prototypical motion patterns through KL divergence comparisons is that it effectively captures common behaviors within the scene, enabling a robust representation of typical activities, which is crucial for detecting unusual events in complex, crowded scenes.	A disadvantage of identifying prototypical motion patterns based on the KL divergence between local spatio-temporal motion patterns is that it may be sensitive to variations and outliers, potentially leading to false positives in unusual event detection, especially in scenarios where the motion patterns exhibit high variability or where unusual events have patterns that deviate significantly from the prototypes.

3	A distribution-based Hidden Markov Model (HMM) is constructed to capture temporal relationships between motion patterns. This HMM models temporal transitions within local video regions.	This enables the system to detect unusual events by identifying unexpected temporal sequences of motion patterns, enhancing the accuracy of unusual event detection in complex video scenes.	In cases where events or behaviors are influenced by factors that are spatially separated or where there are delayed or indirect effects, the local modeling approach may not provide a comprehensive representation of the entire scene's temporal dynamics.
4	A coupled HMM is created to capture spatial relationships between motion patterns in spatially local areas. This step ensures the model considers the influence of spatially neighboring cuboids.	This spatial modeling approach can enhance the system's ability to detect unusual activities that involve spatial dependencies or interactions between different regions of the video, making it more robust in crowded scenes with complex spatial dynamics.	In scenarios where motion patterns in one region of the video affect those in distant or non-adjacent areas, the coupled HMM approach may not effectively capture these long-range spatial relationships, potentially leading to limitations in detecting unusual events influenced by such interactions.
5	Spatial and temporal confidence measures are calculated based on motion pattern likelihoods and spatial relationships. These measures indicate unusual relationships between motion patterns.	Spatial relationships are that they provide a robust method for identifying unusual relationships between motion patterns, which is essential for detecting irregular events in extremely crowded scenes with high accuracy and reliability.	spatial relationships is that they may not effectively capture complex, non-linear dependencies and interactions between motion patterns. These measures primarily consider local relationships and may struggle to detect unusual events influenced by intricate, long-range dependencies or subtle variations in crowded scenes.

Major Impact Factors in this Work

Major impact factors in this work include the development of a novel framework for modeling and detecting unusual events in extremely crowded scenes, offering a promising solution to address the challenges posed by dense crowd dynamics in video analysis.

Dependent Variable	Independent Variable	Moderating variable	Mediating (Intervening) variable
Detecting unusual events in extremely crowded scenes, measured through metrics such as sensitivity, specificity, and false positive rates.	local spatio-temporal motion patterns, distribution-based Hidden Markov Models (HMMs), and coupled HMMs	—	—

Relationship Among The Above 4 Variables in This article
The information provided does not explicitly mention the relationship among the dependent variable, independent variable, moderating variable, and any assessed tools.

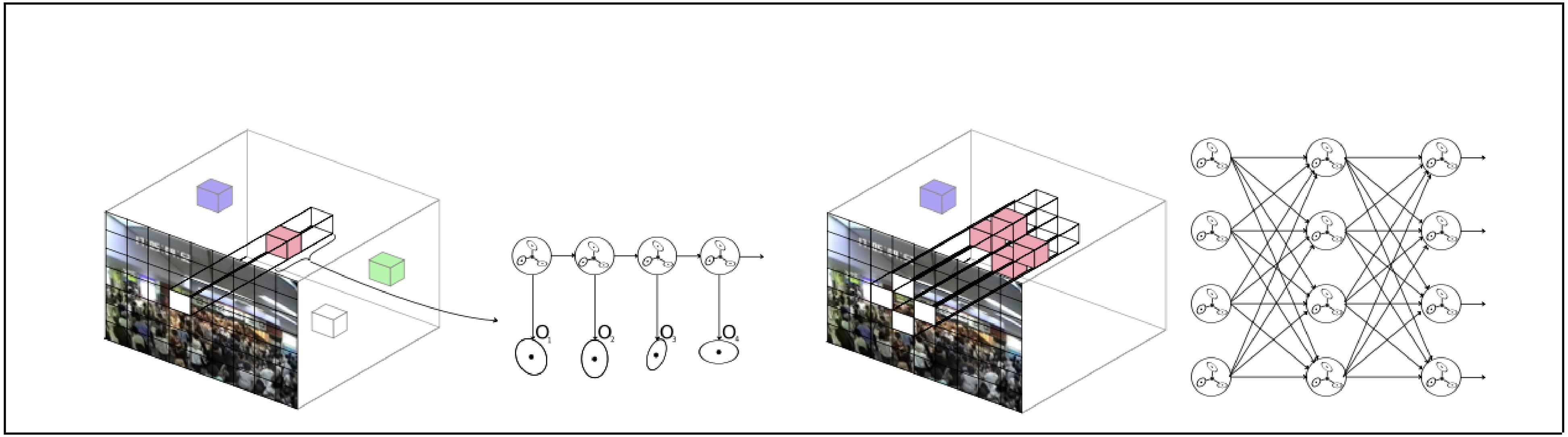
Input and Output	Feature of This Solution	Contribution & The Value of This Work
	A key feature of this solution is the utilization of local spatio-temporal motion patterns to model and detect unusual events in extremely crowded scenes, which allows for rich, non-uniform motion representation within localized areas of video frames.	It utilizing distribution-based models, Hidden Markov Models, and spatial-temporal relationships, this work provides a robust framework for identifying anomalies in complex, densely populated environments, which can have applications in various fields, such as security, surveillance, and crowd management.

Input	Output
crowd video	Detection of unusual events or activities within extremely crowded scenes in video data

Positive Impact of this Solution in This Project Domain		Negative Impact of this Solution in This Project Domain
This solution significantly enhances surveillance and security in crowded public spaces by accurately detecting unusual events and behaviors, improving public safety...		The negative impact of this solution in the project domain is its computational complexity, which can strain hardware resources in real-time surveillance systems, leading to potential delays in event detection.

Analyse This Work By Critical Thinking	The Tools That Assessed this Work	What is the Structure of this Paper
This work introduces an effective approach for modeling and detecting unusual events in extremely crowded scenes. By employing distribution-based models, HMMs, and spatial-temporal analysis, it addresses complex surveillance challenges.	video analysis software, machine learning frameworks, statistical metrics, and real-world video datasets for evaluation.	Abstract I. Introduction II. Previous Paper III. Local Spatio- Temporal Motion Patten IV. Capturing Temporal Statistic in Distribution Based Hidden Markov Model V. Coupling of spatial Relationships VI. Result VII. Conclusion

Diagram/Flowchart



---End of Paper 1-

2		
Reference in APA format		
URL of the Reference	**Authors Names and Emails**	**Keywords in this Reference**

https://ieeexplore.ieee.org/document/7024902	Dong-Gyu Lee; Heung-Il Suk; Sung-Kee Park; Seong-Whan Lee	Feature extraction, Vectors, Force, Indexes, Surveillance, Bicycles, Legged locomotion
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?**
The authors describe their proposed method for detecting and localizing unusual activities within crowded scenes, but they do not assign a specific name or label to this method in the text.	The goal of the proposed solution is to detect and localize unusual human activities in crowded scenes from video data. The problem is identifying abnormal behaviors in crowded environments.	The key components of the solution include motion influence maps, spatio-temporal feature extraction, k-means clustering, and unusual activity detection and localization.
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	Motion influence map construction from motion vectors.	Constructing a motion influence map from motion vectors offers the advantage of effectively capturing spatial and temporal characteristics in crowded scenes, enhancing unusual activity detection and localization.	A disadvantage of constructing motion influence maps from motion vectors is that they may be sensitive to perspective distortion in videos with strong camera angles and scaling changes.
2	Extraction of spatio-temporal features from divided frame regions	Extracting spatio-temporal features from divided frame regions is that it allows for capturing and analyzing motion patterns	Extracting spatio-temporal features from divided frame regions is that it may not handle varying object sizes and may lose

		within specific areas of interest, providing localized information for activity detection.	important motion characteristics if the block size is not carefully chosen.
3	K-means clustering for feature quantization.	K-means clustering for feature quantization is that it helps reduce the dimensionality of the data while preserving important patterns and structures, making it computationally efficient and effective for feature representation.	K-means clustering for feature quantization is that it relies on the initial choice of cluster centroids, which can lead to suboptimal solutions and sensitivity to outliers. The number of clusters (K) also needs to be determined in advance and can affect the results.
4	Detection and localization of unusual activities using the clustering results.	Clustering results for detection and localization of unusual activities is that it can efficiently group similar motion patterns and detect deviations, making it robust to variations in scale, pose, and appearance of objects in crowded scenes.	Detecting and localizing unusual activities using clustering results is that it may not handle complex scenarios with overlapping or closely situated activities well, leading to potential misclassification or localization inaccuracies. It may also be sensitive to variations in activity scale and density.

Major Impact Factors in this Work

Dependent Variable	Independent Variable	Moderating variable	Mediating (Intervening) variable
Anomaly detection	Unusual activity detection and localization in crowded scenes.	—	—

Relationship Among The Above 4 Variables in This article
The relationship among the variables in this article involves using the motion influence map to improve the detection and localization of unusual activities in crowded scenes.

<table>
<tr><th>Input and Output</th><th>Feature of This Solution</th><th>Contribution in This Work</th></tr>
<tr><td><table><tr><th>Input</th><th>Output</th></tr><tr><td>Video frames captured by surveillance cameras in crowded scenes.</td><td>Pixel-Level Unusual Activity Localization</td></tr></table></td><td>This solution combines motion influence mapping, feature extraction, clustering, and localization to detect and pinpoint unusual activities in crowded video scenes.</td><td>The main contributions of this work are the development of a unified framework for detecting and localizing unusual activities in crowded video scenes using a motion influence map and the demonstration of its effectiveness through experiments on public datasets.</td></tr>
</table>

Positive Impact of this Solution in This Project Domain	Negative Impact of this Solution in This Project Domain
Enhanced security through accurate and efficient detection and localization of unusual activities in crowded surveillance video.	**Limited applicability for scenarios with strong perspective distortion, large scaling changes, or pan-tilt-zoom cameras.**

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

The work introduces a motion influence map for crowd surveillance, offering robust unusual activity detection, but it lacks adaptability to varied scenarios.	Peer review	Abstract VIII. Introduction IX. Related Work X. Proposed Method XI. Experiment Results XII. Conclusion

Diagram/Flowchart

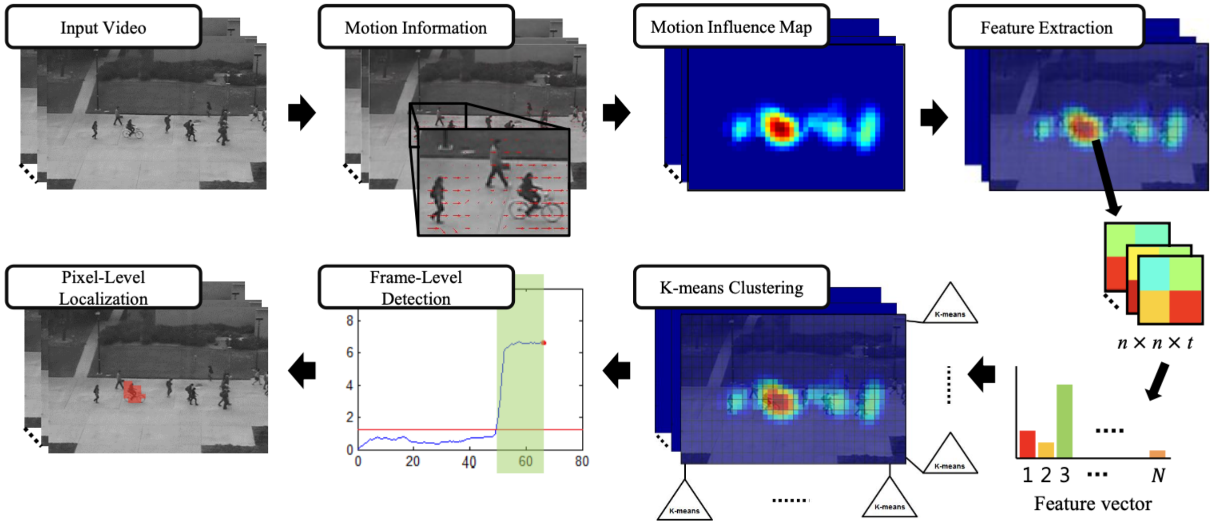


Fig. 2. An overview of the proposed method for unusual activity detection and localization in crowded scenes.

--End of Paper 2--

3		
Reference in APA format		
URL of the Reference	**Authors Names and Emails**	**Keywords in this Reference**
https://ieeexplore.ieee.org/document/8015002	Kothapalli Vignesh; Gaurav Yadav; Amit Sethi	Feature extraction , Videos, Tracking, Histograms, Support vector machines, Surveillance, Cameras
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?**
A Proposed Model for using supervised learning and long short term memory networks for detecting abnormal events in surveillance videos.	Detect abnormal events in surveillance videos for human group activitiesdetect abnormal events in surveillance videos for human group activities	Background subtraction , Feature extraction, Long short-term memory (LSTM) network , Linear SVM
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	Capture video frames	The advantage of capturing video frames is that it provides a visual record of events, enabling subsequent analysis, monitoring, and detection in various applications, including surveillance, research, and entertainment..	Disadvantages of capturing video frames include high storage requirements, data management complexity, and potential privacy concerns when used for surveillance.

2	Apply background subtraction using MoG to isolate foreground	Improves object detection accuracy by isolating moving objects, reducing false positives, and enhancing visual focus.	MoG background subtraction may struggle with dynamic scenes, lighting changes, and may require fine-tuning.
3	Extract features using CNN	Advantages of extracting features using CNN: Effective at capturing high-level visual patterns, robust to variations, and suitable for deep learning.	CNN feature extraction can be computationally intensive, require ample data, and might lead to overfitting.
4	Apply LSTM for temporal modeling	LSTM excels at capturing long-range dependencies, handling sequential data, and improving video analysis accuracy.	LSTM training may be time-consuming, and it might struggle with very short or highly variable sequences.
5	Classify with SVM.	SVM is effective for high-dimensional data, robust to overfitting, and suitable for binary classification in video surveillance.	SVM might not handle high-dimensional data well and could be sensitive to the choice of hyperparameters.
6	Temporal averaging.	Temporal averaging can smooth predictions, improve stability, and reduce the impact of outliers for more robust results.	Temporal averaging can lose fine-grained temporal information and may not work well for abrupt changes.

Major Impact Factors in this Work

Dependent Variable	Independent Variable	Moderating variable	Mediating (Intervening) variable
sequence of frames is classified as normal or abnormal.	CNN , LSTM & SVM	—	—

Relationship Among The Above 4 Variables in This article
Spatial and temporal features (independent variables) influence abnormality classification (dependent variable) moderated by SVM and LSTM.

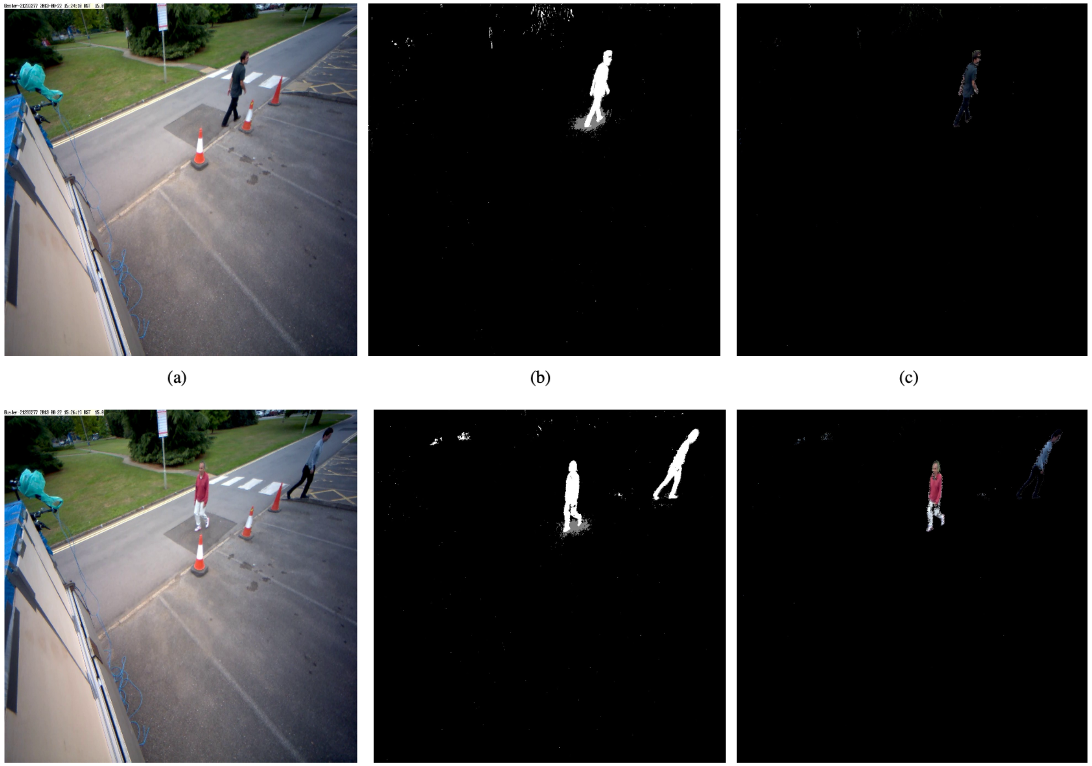
Input and Output	Feature of This Solution	Contribution & The Value of This Work
<table><tr><th>Input</th><th>Output</th></tr><tr><td>Frames from a surveillance video.</td><td>Alert security personnel or trigger automated responses in real-time surveillance systems.</td></tr></table>	Detection of abnormal events in videos using CNN, LSTM, SVM, and temporal averaging for high accuracy.	Efficient video surveillance system for abnormal event detection with limited data, enhancing safety and automation.

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
The work effectively combines CNN, LSTM, SVM, and temporal averaging for video surveillance, addressing challenges with limited data.	The paper likely used a combination of tools for assessment, including Python libraries (e.g., scikit-learn), deep learning frameworks (e.g., TensorFlow), and possibly custom code.	Abstract I. Introduction II. Related Work III. Proposed Methodology

IV. Experiment and result
V. Conclusion and Future work

Diagram/Flowchart



--End of Paper 3--

4		
Reference in APA format		
URL of the Reference	**Authors Names and Emails**	**Keywords in this Reference**
https://ieeexplore.ieee.org/document/6531615	Weixin Li; Vijay Mahadevan; Nuno Vasconcelos	Hidden Markov models, Computer vision, Image motion analysis, Computational modeling, Detectors, Feature extraction, Principal component analysis
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?**

Hierarchical Motion Distribution Transform (MDT) with Conditional Random Field (CRF) for anomaly detection.	Goal: Detect anomalies in crowded video scenes by modeling spatiotemporal patterns, overcoming detection challenges. Problem: Robust crowd anomaly detection.	Components: Multi-Dimensional Texture models, temporal, spatial, and scale anomaly detection, Gaussian filters, CRF inference.

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	Learn Multi-Dimensional Texture models.	Advantage of learning Multi-Dimensional Texture models: Captures complex spatiotemporal patterns for robust anomaly detection in crowded scenes.	Complex model learning may require substantial data and computational resources, limiting its applicability to certain scenarios.
2	Detect temporal, spatial, and scale anomalies.	Enhanced anomaly detection capabilities, capturing a wide range of abnormalities, leading to more robust and accurate results.	Challenging to tune parameters for different scenarios, potentially leading to suboptimal performance in some cases.
3	Apply Gaussian filters	Smoothes data, reduces noise, preserves edges, and simplifies complex structures, suitable for various image processing tasks.	Smoothing may oversimplify details and hinder the detection of fine-scale features, potentially reducing overall accuracy.
4	Perform CRF inference.	CRF inference improves anomaly localization by considering spatial, temporal, and scale context, leading to more precise detections.	Computationally intensive and may slow down real-time applications, requiring significant computational resources.
5	Achieve anomaly detection	Effective in detecting various types of anomalies by combining temporal, spatial, and scale information for robust results.	May struggle with complex scenes and occlusions, limited to learned anomalies, and requires significant training data.

Major Impact Factors in this Work

Dependent Variable	Independent Variable	Moderating variable	Mediating (Intervening) variable
Performance metric used to assess anomaly detection.	configurations used in the anomaly detection model	___	__

Relationship Among The Above 4 Variables in This article
The information provided in the article does not explicitly outline the relationships among the dependent, independent, moderating, and mediating variables.

Input and Output	Feature of This Solution	Contribution & The Value of This Work
Input: video data, such as surveillance footage or image sequences. **Output:** The potential negative impact of this solution in the project domain is increased	The main feature of this solution is its ability to detect anomalies in crowded scenes with complex dynamics and interactions.	This work contributes a robust anomaly detection framework for complex crowd scenes, enhancing video surveillance and public safety.

<table>
<tr><td><table><tr><td></td><td>computational resource requirements.</td></tr></table></td><td colspan="2"></td><td></td></tr>
<tr><th colspan="2">Positive Impact of this Solution in This Project Domain</th><th colspan="2">Negative Impact of this Solution in This Project Domain</th></tr>
<tr><td colspan="2">The solution significantly improves anomaly detection accuracy and efficiency, enhancing security in crowded public spaces.</td><td colspan="2">The solution may require substantial computational resources, limiting its real-time applicability in certain scenarios.</td></tr>
<tr><th>Analyse This Work By Critical Thinking</th><th colspan="2">The Tools That Assessed this Work</th><th>What is the Structure of this Paper</th></tr>
<tr><td>This work offers an effective anomaly detection solution but may require extensive computational resources for real-world applications.</td><td colspan="2">Various evaluation metrics, datasets, and performance benchmarks assessed the effectiveness and applicability of this work.</td><td>Abstract
I. Introduction
II. Autonomous Online Malicius Spam Email Detection system
III. Performance evaluation
IV. Conclusion</td></tr>
<tr><th colspan="4">Diagram/Flowchart</th></tr>
</table>

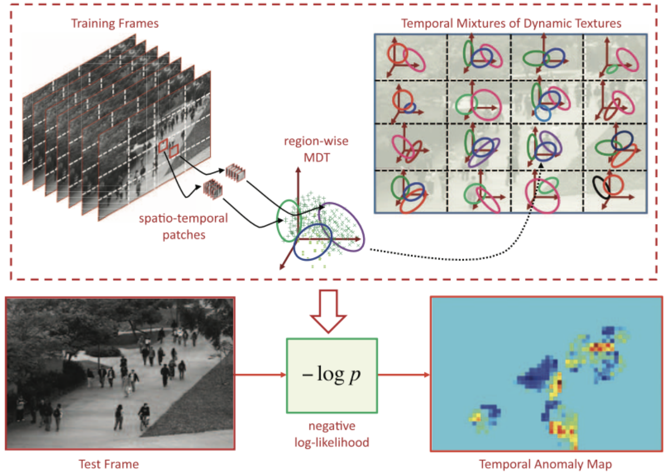


Fig. 1. Temporal anomaly detection. An MDT is learned per scene subregion, at training time. A temporal anomaly map is produced by measuring the negative log probability of each video patch under the MDT of the corresponding region.

--End of Paper 4—

Version 2.0 Week 2		
5		
Reference in APA format	Video Parsing for Abnormality Detection	
URL of the Reference	**Authors Names and Emails**	**Keywords in this Reference**
https://ieeexplore.ieee.org/document/6126525	Borislav Antić; Björn Ommer	Training, Training data, Silicon, Support vector machines, Adaptation models, Probabilistic logic, Feature extraction
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?**
Probabilistic Scene Parsing for Abnormality Detection: State-of-the-Art Performance on Pedestrian Walkway Videos	Detect abnormalities in pedestrian walkway videos through probabilistic scene parsing, improving current methods significantly.	Components: Scene parsing, object hypotheses, abnormality detection, per-pixel probability, statistical inference, training data, video frames.
The Process (Mechanism) of this Work; Means How the Problem has Solved & Advantage & Disadvantage of Each Step in This Process		
Probabilistic scene parsing infers joint object hypotheses, explains foreground, detects abnormalities indirectly. Advantages: state-of-the-art performance. Disadvantage: pixel-wise ground truth limited.		

The proposed system detect unusual events in extremely crowded scenes by capturing local spatio-temporal motion patterns using distribution-based models, leveraging temporal and spatial relationships, and employing confidence measures based on statistical analysis, allowing for the identification of unusual events in video sequences..

	Process Steps	**Advantage**	**Disadvantage (Limitation)**
1	Set object hypotheses with location, scale, appearance, and velocity parameters.	Efficiently initializes comprehensive hypotheses, incorporating spatial, scale, appearance, and velocity attributes, enhancing subsequent abnormality detection accuracy.	Sensitive to initialization, may converge to local optima, and requires parameter tuning for robustness.
2	Estimate necessary hypotheses, match training samples, and calculate abnormality probabilities	Jointly explains scene anomalies, utilizes probabilistic models, achieves state-of-the-art performance, enhances abnormality detection benchmarks.	Limited by training data quality, sensitive to outliers, and computational complexity increases with dataset size.
3	Identify abnormalities based on hypotheses explaining foreground, evaluating abnormality probability, and matching samples.	Robust abnormality detection, joint scene interpretation, and improved performance on challenging datasets.	Reliance on training data quality, sensitivity to noise, and potential false positives/negatives in detection.
4	Compare with ground truth, calculate metrics, and improve benchmark dataset utility.	Advantages: Robust evaluation, benchmark enhancement, superior performance, and potential for real-world anomaly detection applications.	Limited pixel-wise ground truth, dependency on dataset quality, and challenges in generalization to diverse scenarios.
5	Assess against state-of-the-art methods on Ped1 and Ped2 datasets, demonstrating significant performance gains.	Outperforms state-of-the-art methods on Ped1 and Ped2 datasets, achieving significant performance gains in abnormality detection.	Reliance on stationary camera, potential sensitivity to dataset characteristics, and limited real-world generalization.

6	Utilize probabilistic approach to estimate abnormality of pixels and improve AUC compared to benchmarks.	Probabilistic inference enhances abnormality estimation, achieving superior AUC performance compared to benchmark methods in diverse scenarios.	Limited pixel-wise ground truth, dependency on accurate hypothesis initialization, and potential sensitivity to specific scenarios.
7	Propose scene parsing as an indirect abnormality detection method, enhancing state-of-the-art performance on challenging datasets.	Overcomes ill-posed abnormality detection, jointly explains scene layout, achieves significant benchmark improvement, and indirect abnormality discovery.	Complexity, potential computational demands, and reliance on training samples for normal patterns; sensitive to dataset specifics.

Dependent Variable	Independent Variable	Moderating variable	Mediating (Intervening) variable
identification of abnormalities in video sequences.	object hypotheses with parameters like location, scale, appearance, and velocity in the scene parsing approach.	___	___

Relationship Among The Above 4 Variables in This article
The article describes a scene parsing approach for abnormality detection in video frames, involving object hypotheses, appearance, and abnormality probabilities.

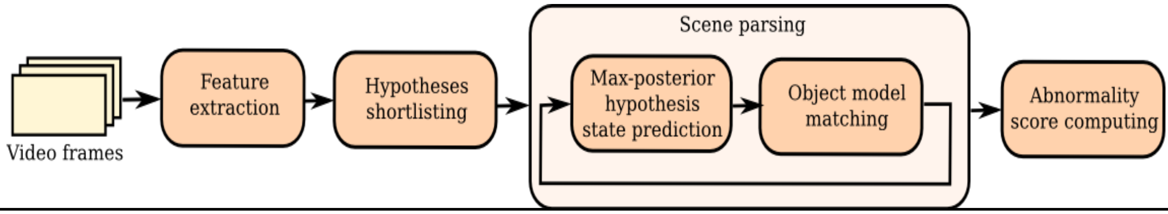
Input and Output	Feature of This Solution	Contribution & The Value of This Work
(see table below)	The solution features a probabilistic scene parsing approach for abnormality detection in video, improving benchmark performance.	The work contributes a scene parsing approach, enhancing abnormality detection in video with significant performance gains.

Input	Output
video frames	Abnormality probabilities

Positive Impact of this Solution in This Project Domain	Negative Impact of this Solution in This Project Domain
Enhances abnormality detection in video surveillance, improving accuracy and applicability in real-world scenarios.	Complexity in model training and potential sensitivity to variations in input data may pose challenges.

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

Diagram/Flowchart



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
Borislav Antić; Björn Ommer , 2011	The goal is to indirectly detect abnormalities in video frames by jointly inferring necessary object hypotheses, improving performance on benchmark datasets.	Components include object hypotheses with location, scale, appearance, and velocity parameters, jointly explaining foreground and abnormalities.	Set object hypotheses, match training samples, calculate abnormality probabilities, and identify abnormalities, improving benchmark dataset utility.	Probabilistic scene parsing, joint explanation of foreground, and abnormality detection, leading to significant performance gains.	-	-	-	The performance metrics mentioned include ROC curve, EER, AUC, and detection rate, showcasing significant improvements over benchmarks.	Advantages include improved abnormality detection, state-of-the-art performance, and enhanced benchmark dataset utility, with efficient MATLAB implementation.	Limitations include reliance on pixel-wise ground truth, needing abnormality samples for training, and computational complexity.	The platform is not explicitly mentioned in the provided text.	The detailed results, including metrics, comparisons, and improvements, are provided in the article's content.
Weixin Li; Vijay Mahadevan; Nuno	The goal of the work is	Multi-Dimensional Texture	Mechanism: Learn MDT models, apply	Multi-dimensional texture	-	-	-	State-of-the-art performance in anomaly detection,	Effective anomaly detection	Sparse spatial anomaly detection	The platform used for	The results of the

Vasconcelos & 2013	to develop an effective anomaly detection system for crowded scenes.	models, CRF, Gaussian filters, temporal, spatial, and scale anomaly detection.	temporal and spatial anomaly detection, perform CRF inference, output anomaly scores.	models, global CRF inference, scale-based anomaly detection, efficient computation, state-of-the-art performance.				outperforming existing methods in accuracy and computational efficiency.	across temporal, spatial, and scale dimensions, achieving superior performance with efficient computation.	performance in specific scenarios due to scene sparsity; limited by context size variability.	the anomaly detection system is not specified in the provided information.	anomaly detection system include high accuracy, particularly in combined spatial and temporal analysis.
Kothapalli Vignesh; Gaurav Yadav; Amit Sethi & 2012	Develop an efficient video surveillance system for detecting abnormal events, enhancing safety and	The system components include background subtraction (MoG), CNN for spatial features, LSTM for temporal modeling, SVM for classification, and temporal	The system employs background subtraction to isolate foreground, extracts spatial features using CNN, models temporal information with LSTM, classifies using SVM, and incorporates temporal	Foreground isolation, spatial feature extraction, temporal modeling, SVM classification, and temporal averaging enhance abnormal	-	-	-	The performance of the system is not explicitly detailed. Typically, performance metrics would include accuracy, precision, recall, and F1 score in the context of abnormal event detection.	Advantages of the proposed system include improved abnormal event detection, reduced noise, and enhanced surveillance efficiency.	Limitations include sensitivity to dynamic scenes, computational intensity, potential overfitting, and time-consuming LSTM training.	The platform likely involves Python, deep learning frameworks (e.g., TensorFlow), and relevant libraries for	The results include improved abnormal event detection accuracy, with the best performance observe

	automation capabilities.	averaging for smoothing predictions.	averaging for smoother predictions.	event detection.							implementation.	d in the CNN-LSTM-SVM-TA model.
Dong-Gyu Lee; Heung-Il Suk; Sung-Kee Park; Seong-Whan Lee & 2015	The goal of this work is to develop a method for detecting and localizing unusual activities in crowded scenes using a unified framework based on motion influence maps.	The system components include motion influence map construction, spatio-temporal feature extraction, k-means clustering for feature quantization, and detection/localization of unusual activities.	The system begins by constructing a motion influence map from motion vectors, extracting spatio-temporal features, performing k-means clustering for quantization, and then detecting/localizing unusual activities.	The system's features include motion influence map construction, spatio-temporal feature extraction, k-means clustering for quantization, and unusual activity detection/localization.				The system's performance is evaluated using ROC curves, AUC, and Equivalence Error Rate (EER) on public datasets, demonstrating effectiveness.	The proposed method efficiently detects and localizes both local and global unusual activities in crowded scenes, achieving competitive performance.	The method has limitations in handling strong perspective distortions and may face challenges with scaling changes, pans, tilts, or zooms in the scene.	The paper does not explicitly mention the specific platform or framework used for implementing the proposed method.	The specific results or findings of the proposed method in the paper were not provided in the information provided.

Louis Kratz , Ko Nishino	Detect unusual events in extremely crowded scenes through video analysis using distribution-based HMMs for motion pattern representation.	Local spatio-temporal motion patterns, distribution-based HMMs, coupled HMMs, spatial and temporal confidence measures.	Divide video into cuboids, model motion patterns with Gaussian distributions, use HMMs for temporal and spatial relationships, compute confidence measures.	Captures non-uniform local spatio-temporal motion patterns, models temporal and spatial relationships, detects unusual events.	-	-	-	Achieves over 80% accuracy, improves with longer training, detects irregular motion, robust motion pattern representation.	Captures rich motion patterns, successful detection of irregular events, performs well with small training data, and diverse applications.	May produce false positives for subtle variations, limited by unusual textures, relies on rich motion representation.	The platform or environment where this solution is implemented is not specified in the provided information.	The results showcase improved detection of unusual motion patterns in crowded scenes using spatio-temporal modeling.