Spectrum of Engineering Sciences
ISSN (e) 3007-3138 (p) 3007-312X Volume 3, Issue 2, 2026

TRAFFIC AND SECURITY MANAGEMENT SYSTEM: REAL-TIME VIDEO ANOMALY DETECTION USING AI MODELS

Ghazanfar Rehman[a,b], Muhammad Aqeel[c], Anis Maqbool[d], Muhammad Allah Razi[c], Hammad Shahab[c], Shahzad Hussain[e]

[a]*Central Protection Services Inc., Canada*
[b]*Central Technologies Inc., Canada*
[c] *Institute of Computer and Software Engineering, Khwaja Fareed University of Engineering and Information Technology, Rahim Yar Khan 64200, Pakistan*
[d] *Swedish College of Engineering and Technology, Rahim Yar Khan, 64200, Pakistan.*
[e]*Institute of Computer Science, Khwaja Fareed University of Engineering and Information Technology, Rahim Yar Khan, 64200, Pakistan.*

DOI: https://doi.org/10.5281/zenodo.20261344

Keywords
Video anomaly detection, abnormality detection, machine learning, deep learning.

Article History
Received on 02 January 2026
Accepted on 20 February 2026
Published on 27 February2026

Corresponding Author: *
shahzad.hussain@kfueit.edu.pk

Abstract

The traffic and security management systems need effective real-time monitoring to guarantee the safety of the people, especially in the high-risk and crowded areas. Manual monitoring of CCTV video streams is time-consuming, prone to errors, and ineffective, which necessitates intelligent automated solutions. This paper introduces a real-time video anomaly detection system to monitor traffic and security with the help of LSTM-based deep learning. The suggested method uses a hybrid spatio-temporal feature extraction system that involves Convolutional Neural Networks (CNN) and Long Short-Term Memory (LSTM) networks to extract spatial features and temporal motion patterns in video sequences. The LSTM model is effective in learning sequential dependencies and thus detecting abnormal events accurately with time. The extracted features are then categorized with the help of various machine learning models, such as Histogram-Based Gradient Boosting (HGB), Gradient Boosting (GB), Extreme Gradient Boosting (XGBoost), Light Gradient Boosting Machine (LGBM), Support Vector Machine (SVM), and K-Nearest Neighbor (KNN). The UCSD Anomaly Detection Dataset is tested on the framework with performance measures of accuracy, precision, recall, F1-score, Cohen Kappa, Matthews Correlation Coefficient (MCC), and loss. Experimental results show validation accuracies of 76% (SVM), 72% (KNN), 90% (HGB), 98% (XGBoost), 95% (GB), and 98% (LGBM). Among them, XGBoost has the highest performance with 98 percent accuracy, better classification rates, and low loss, which proves the efficiency and strength of the suggested system in the context of real-time traffic and security surveillance applications.

Keywords: Video anomaly detection, abnormality detection, machine learning, deep learning.

ISSN (e) 3007-3138 (p) 3007-312X Volume 3, Issue 2, 2026

INTRODUCTION

Globally, the high rate of urban traffic and security-related events has rendered real-time monitoring and anomaly detection a pressing issue in terms of maintaining the safety of people and effective city management [1]. Video streams or image abnormal events detection is a difficult and critical task in contemporary traffic and security management systems [2]. As urban infrastructure grows and expands at an alarming rate, and vehicular traffic moves more and more, video-based surveillance has become an essential part of intelligent traffic control and community safety systems. Closed-Circuit Television (CCTV) cameras have been extensively used in road networks, intersections, transportation centers, and strategic places in cities to monitor traffic and human activities at all times [3]. Nevertheless, the rapid increase in surveillance data has rendered manual surveillance very inefficient because human operators are prone to fatigue, observations, and inconsistent decision-making [4]. This has increased the urgency of automated, real-time anomaly detection systems that can improve traffic management and security operations. Anomaly detection in this context can be defined as the detection of abnormal patterns like traffic offenses, accidents, unforeseen congestion, illegal vehicle access, or abnormal human behavior in the areas under surveillance [5]. These anomalies are hard to identify because traffic scenes are dynamic, environmental conditions are different, there are occlusions, different camera angles, and there are no obvious differences between normal and abnormal events [6], [7].

An anomaly is defined as a data point or behavior that is not within the normal pattern in a dataset as shown in Fig.1. The left diagram of Fig.1 shows that clustered points indicate normal behavior and the isolated point indicates an outlier (anomaly). In the right diagram of Fig.1, an anomaly is identified when the signal is above a predefined threshold, and values below the threshold are regarded as normal [19].

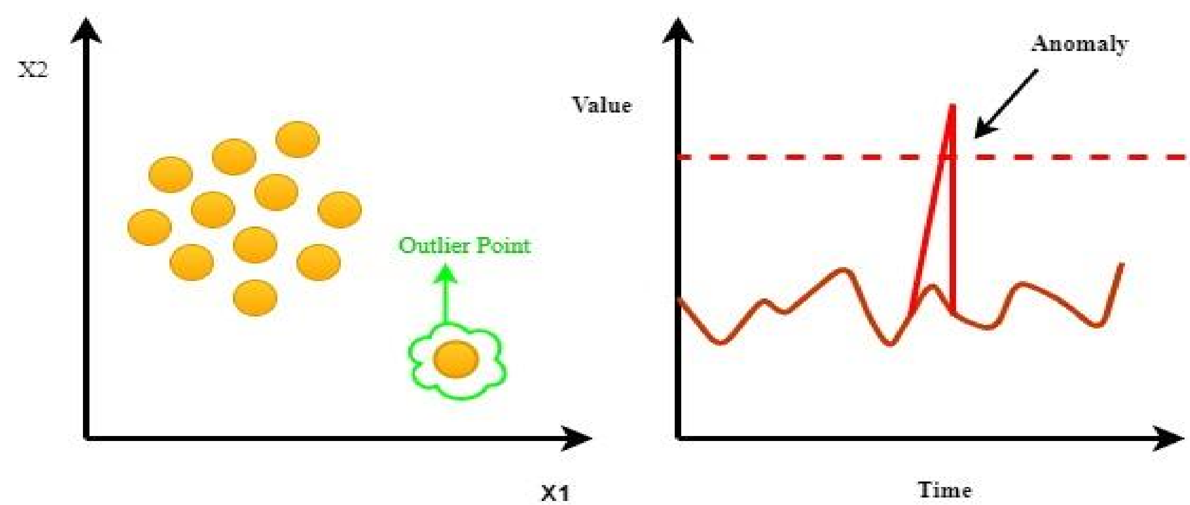


Fig1: An anomaly is marked when the threshold value is crossed.

Additionally, anomalies tend to be context-dependent and uncommon, and it is hard to explicitly model them in the traditional rulebased methods. Traditional computer vision methods of anomaly detection mainly used handcrafted features and statistical models, which are not always robust and generalizable in the real-world context. The introduction of deep learning has brought about major advancements in the form of automatic feature learning and hierarchical visual data representation [8]. Specifically, Convolutional Neural Networks (CNNs) have been shown to be highly effective in learning spatial features of image frames, whereas Recurrent Neural Networks (RNNs), and in particular Long Short-Term Memory (LSTM) networks, are effective at learning temporal dependencies in sequential data. CNN and LSTM architecture integration has become an effective method of learning spatio-temporal patterns in video sequences [20]. In spite of these developments, deep learning models alone might not necessarily provide the best classification results, particularly when it comes to various and complex anomaly patterns. To address this key limitation of the hybrid techniques that integrate deep feature extraction with unique machine learning classifiers have been of interest in the proposed work. Gradient Boosting and its variations are ensemble learning algorithms that employ a mixture of weak learners to improve the accuracy and strength of prediction. HGB, Extreme Gradient Boosting (XGBoost), and Light Gradient Boosting Machine (LightGBM) are particularly helpful when dealing with high-dimensional data and decision boundaries [21]. In addition, classical algorithms like Support Vector Machine (SVM) and K-Nearest Neighbor (KNN) have complementary benefits in classification. In this paper, a detailed real-time anomaly detection system is presented, which involves the combination of CNN-based spatial feature extraction and LSTM-based temporal modeling and then classifies it using various machine learning and ensemble models [22].

The proposed system of this research work is able to learn the normal behavioral patterns and detect deviations that are signs of anomalies. The framework is tested on the UCSD Anomaly Detection Dataset, which contains real-life situations of abnormal object movement and irregular pedestrian behavior. The key contributions of this work can be summarized as follows:

Introduced a hybrid deep learning architecture, which combines CNN and LSTM models to be effective in the extraction of spatio-temporal features in real-time video anomaly detection.

Created a multi-classifier assessment plan based on HGB, GB, XGBoost, LGBM, SVM, and KNN to improve detection accuracy and strength.

Obtained high performance, and XGBoost provided the highest performance (98% validation accuracy and zero loss), indicating good generalization.

Tested the suggested method on the UCSD dataset with detailed performance measures (accuracy, precision, recall, F1-score, Cohen Kappa, and MCC) and proved that it is effective in real-time surveillance applications.

1. Materials and Methods

This section describes the overall methodology adopted to real-time anomaly detection (see Fig.2) in video sequences. The framework proposed includes video data acquisition of the UCSD Anomaly Detection Dataset, preprocessing, and frame extraction. The hybrid deep learning architecture based on Convolutional Neural Networks (CNN) and Long Short-Term Memory (LSTM) models is then used to extract spatio-temporal features that capture both spatial and temporal dynamics. The obtained features are then classified using various machine learning and ensemble models, including Histogram-Based Gradient Boosting (HGB), Gradient Boosting

(GB), XGBoost, LightGBM, Support Vector Machine (SVM) and K-Nearest Neighbor (KNN). Lastly, the effectiveness of the proposed system is measured by standard measures like accuracy, sensitivity, specificity, Dice coefficient, and loss functions to determine how well the system can identify anomalous events [23].

1.1. Dataset

The UCSD Anomaly Detection Dataset is divided into two subsets Ped1 and Ped2 which differ in perspective (see Fig.3), structure of the scene, and the density of the crowd. Ped1 demonstrates a walkway with distortion of perspective, which complicates the recognition of objects, whereas Ped2 demonstrates a more homogeneous image with better visibility. The subsets are further divided into training sequences which include normal pedestrian activities only and testing sequences which include normal and anomalous events. The dataset contains real-world anomalies like bicycles, carts, wheelchairs, and skateboarders, and odd motion patterns, such as running or sudden movements that are not typical of pedestrians. The videos are in black and white, fairly low-resolution, and filmed with fixed cameras in outdoor pedestrian settings, which guarantees the same backgrounds but focuses on the change of motion [9]. This setup is particularly suitable to study spatio-temporal patterns, in which regular activities are characterized by predictable behavior and anomalies by specific deviations. The dataset also includes frame-level and pixel-level annotations, allowing to accurately assess the performance of detection. It is widely known as a benchmark dataset and is widely applied in video anomaly detection, deep learning, and spatio-temporal modeling studies [24]. The metrics used to evaluate performance are usually frame-level accuracy, pixel-level detection accuracy, and other important metrics, which allow making fair comparisons between various approaches. In testing, the anomalies are detected by reconstruction error: values that are above a predetermined threshold are considered to be abnormal [25].

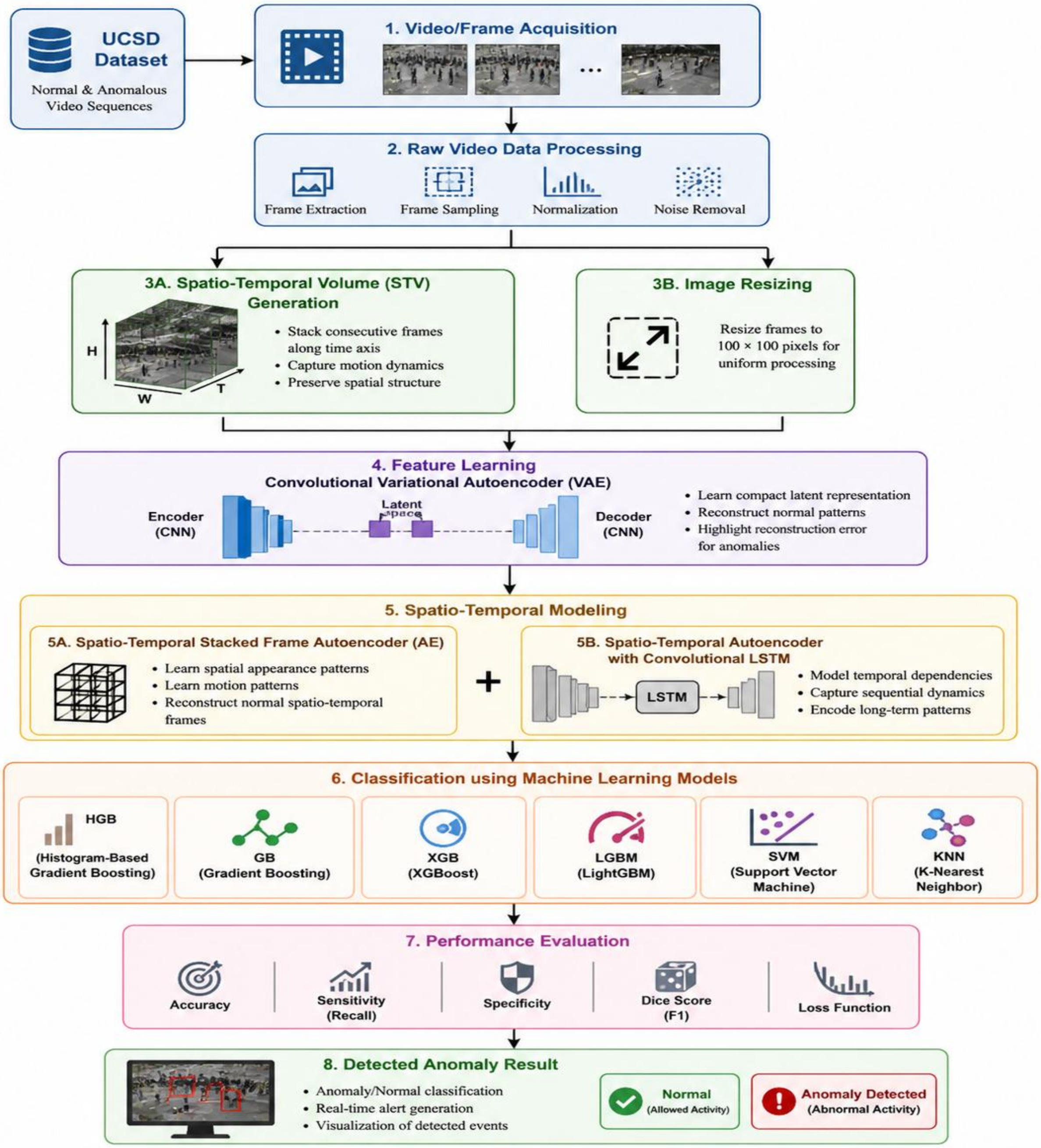


Fig.2: Proposed working mechanism for anomaly detection.

Overall, the dataset has significantly contributed to advancements in intelligent surveillance systems and remains a foundational resource for developing robust real-time anomaly detection models.

ISSN (e) 3007-3138 (p) 3007-312X Volume 3, Issue 2, 2026

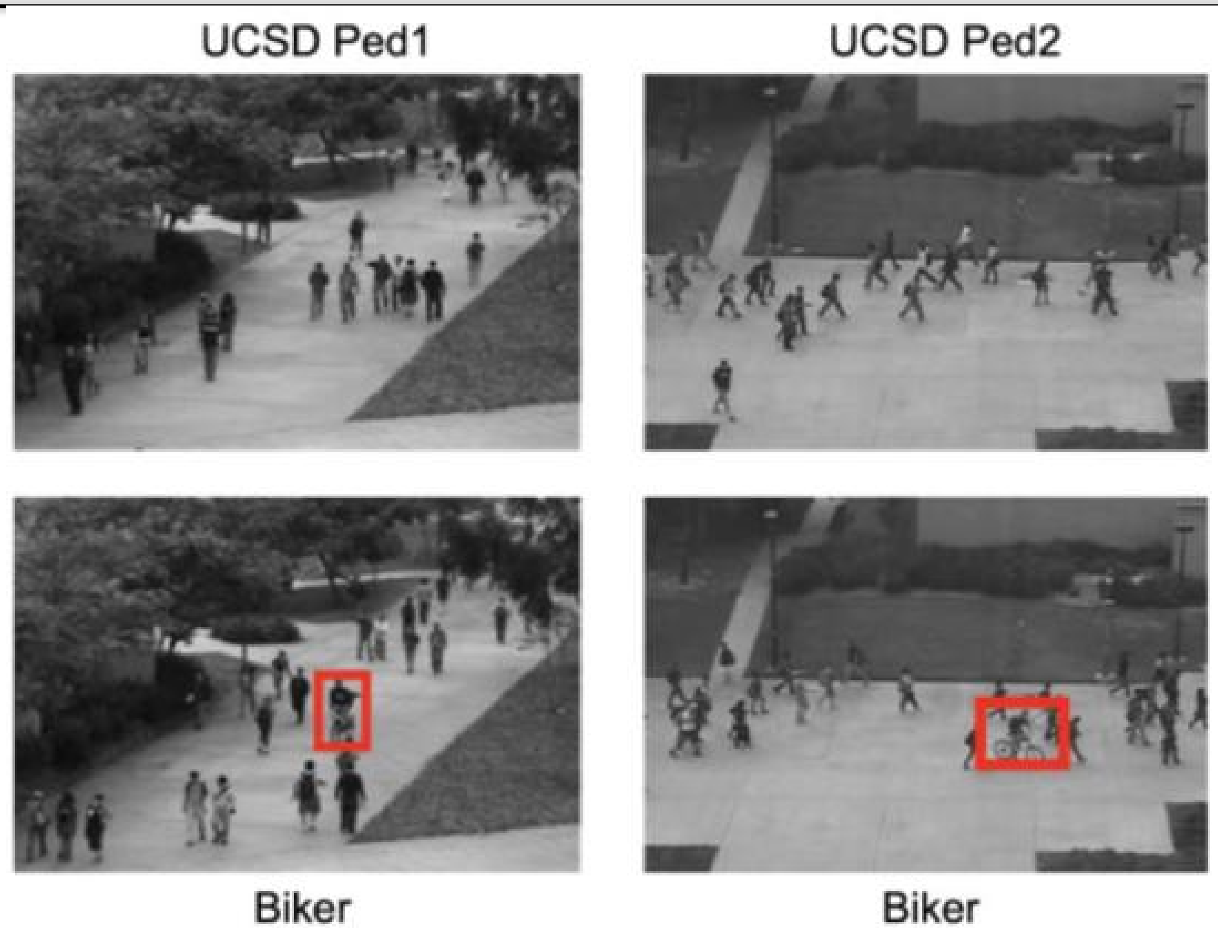


Fig 3: Present the normal and abnormal behavior of the used dataset.

1.2. Data Preprocessing

In the process of data preprocessing data has been prepared through a raw video data of the UCSD Anomaly Detection Dataset to effectively use in detecting anomalies by transforming videos into sequential frames and performing operations such as frame extraction, sampling, normalization and noise removal to enhance the quality and consistency of data. The processed frames of the video data are then stacked together to form spatio-temporal volumes (STVs) to enable the model to capture the spatial properties as well as the temporal motion dynamics. Also, each frame is resized to a fixed size (e.g., 100 × 100 pixels) to make them all the same size and to simplify the computation. This preprocessing step guarantees that the data of input is organized, standardized, and optimized to learn the spatio-temporal features and detect anomalies in real-time [26].

.3. Feature Extraction

In this stage, a Convolutional Variational Autoencoder (VAE) is used to learn compact and meaningful spatio-temporal features from the preprocessed video data. The encoder compresses input frames into a latent representation, while the decoder reconstructs them, enabling the model to learn normal patterns effectively. Trained only on normal data, the model produces low reconstruction error for regular events and higher error for anomalies, making these learned features highly effective for detecting abnormal activities [27].

.4. Spatio-Temporal Modeling

The spatio-temporal modeling stage further refines the learned features to effectively capture both spatial structures and temporal dynamics of video sequences. This stage consists of two complementary components: a Spatio-Temporal Stacked Frame Autoencoder (AE) and a Spatio-Temporal Autoencoder with Convolutional LSTM (ConvLSTM).

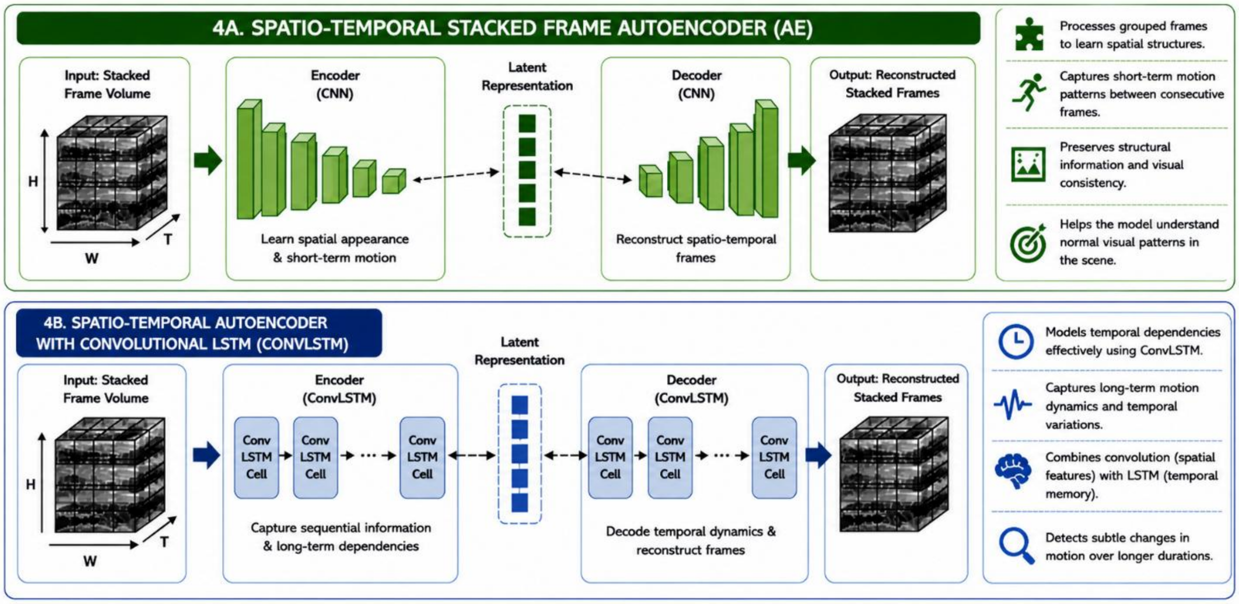


Fig.4: Present the working mechanism of important information extraction in video frames.

In Step 5A, the stacked frame autoencoder processes grouped frames to learn spatial appearance and short-term motion patterns. It reconstructs spatio-temporal frames by preserving structural information across consecutive frames, enabling the model to understand normal visual patterns in the scene. In Step 5B, the convolutional LSTM-based autoencoder is employed to model temporal dependencies more effectively. ConvLSTM model incorporates sequential information and long-term motion dynamics through the combination of convolution operations and memory-based learning. This enables the model to encode the time variations and capture the slight changes in movement with time. The combination of these two elements gives a complete picture of short and long term spatio-temporal trends, which increases the capability of the model to differentiate between normal and abnormal events in video sequences [28].

.5. Machine Learning Models for Classification

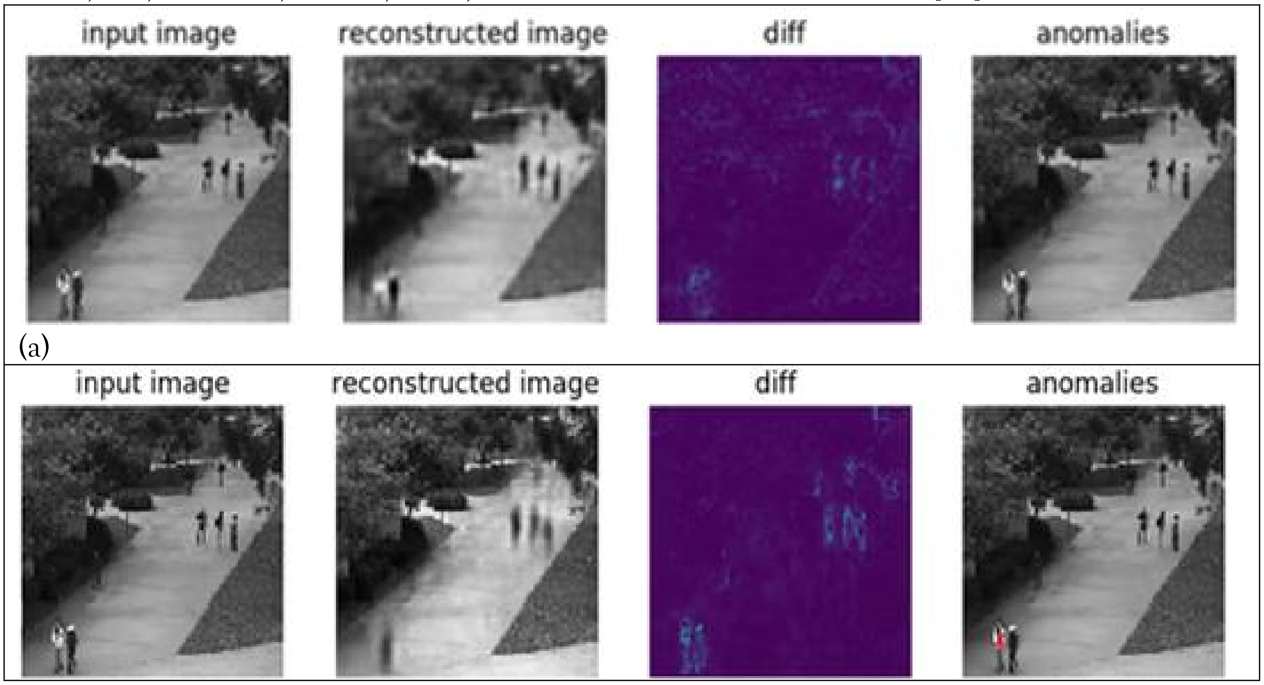
In this stage, the deep features obtained in the spatio-temporal modeling module are categorized with the help of various machine learning and ensemble learning algorithms in order to properly differentiate between normal and anomalous events. This stage aims at improving the performance of the detection by using a variety of classifiers with varying learning abilities. The suggested framework uses a mixture of the advanced models, such as Histogram-Based Gradient Boosting (HGB), Gradient Boosting (GB), Extreme Gradient Boosting (XGBoost), Light Gradient Boosting Machine (LGBM), Support Vector Machine (SVM), and K-Nearest Neighbor (KNN). These models are chosen to offer a trade-off between high accuracy, robustness, and computational efficiency. HGB, GB, XGBoost, and LGBM are ensemble-based techniques that are especially useful in dealing with high-dimensional feature spaces that are complex, and where multiple weak learners are combined to create a strong predictive model. These methods enhance generalization and minimize overfitting. Conversely, the conventional classifiers such as SVM and KNN have complementary advantages, with SVM being useful in identifying the best decision boundaries, and KNN offering instance-based learning to identify similarities in patterns. These classifiers are fed with the extracted features and each model is trained to distinguish between normal and abnormal patterns using the training data. The end classification results show whether a particular video segment is a normal activity or an anomaly. The system is more reliable and robust in real-time anomaly detection by combining several classifiers [29].

2. Results and Discussion

This part shows the performance analysis and evaluation of the proposed real-time anomaly detection framework. The UCSD Anomaly Detection Dataset is tested on the model with various machine learning classifiers, such as HGB, GB, XGBoost, LGBM, SVM, and KNN. The evaluation metrics are standard evaluation measures like accuracy, sensitivity, specificity, Dice score, and loss function to evaluate the results. Comparative analysis shows that deep spatio-temporal feature learning with ensemble classifiers can be used to enhance the performance of anomaly detection [30]. The suggested method is highly accurate and less false detections in differentiating normal and abnormal events. The discussion identifies the strengths, weaknesses, and practicality of the model in real-time intelligent surveillance systems [31].

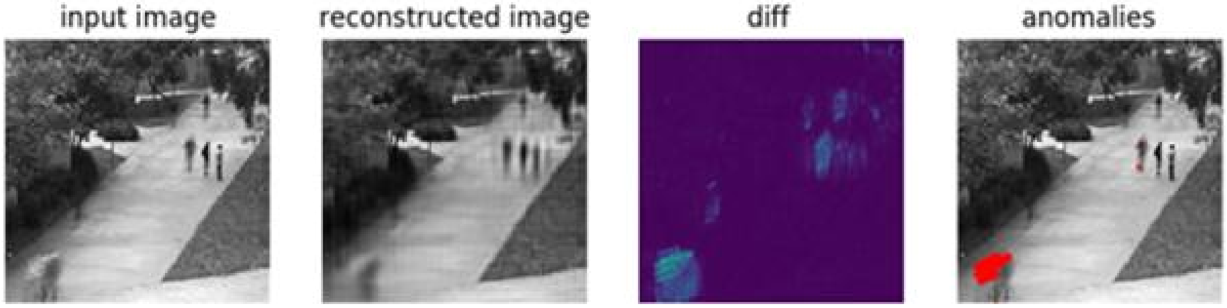
.1. Spatio-Temporal Anomaly Detection

The qualitative findings in Fig.5 indicate that the proposed reconstruction-based anomaly detection framework is effective with various auto encoders. The rows are associated with the various model variations and the columns with the input frame, reconstructed frame, difference map and the detected anomalies respectively. The idea behind the approach is that models that are trained on normal data can be used to reconstruct regular patterns, but not anomalous regions, leading to increased reconstruction error [32].

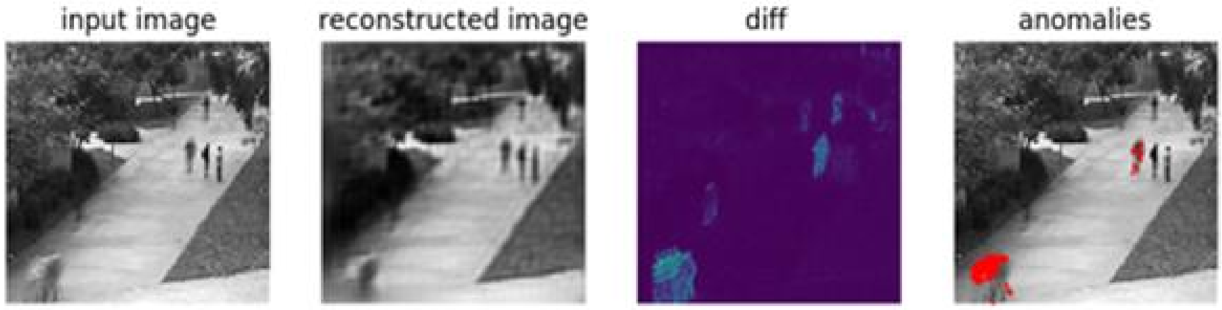


ISSN (e) 3007-3138 (p) 3007-312X Volume 3, Issue 2, 2026

(b)



(c)



(d)

Fig.5: Qualitative comparison of anomaly detection results using different autoencoder architectures: (a) autoencoder without bottleneck layer, (b) encoder–decoder autoencoder with bottleneck, (c) spatio-temporal stacked frame autoencoder, and (d) spatio-temporal autoencoder with convolutional LSTM. Each row shows the input image, reconstructed image, difference map, and detected anomalies, respectively.

Fig.5(a) indicates that the autoencoder with no bottleneck layer has high-quality reconstruction, but it does not identify anomalies effectively. The reason is that the lack of a constrained latent representation enables the model to directly transfer information, minimizing reconstruction error even in abnormal regions. Fig.5(b) encoder-decoder architecture with a bottleneck layer enhances the compression of features but still has a low level of anomaly detection. Despite the fact that there are certain differences in the error map, the model has a hard time localizing anomalies because of the lack of temporal context. Fig.5(c) shows that the Spatio-Temporal Stacked Frame Autoencoder is much more effective as it works with several consecutive frames. This allows the model to capture both spatial and short-term temporal variations, leading to more understandable difference maps and more precise localization of anomalies like irregular motion or foreign objects. The best performance is in Fig.(d) with the Spatio-Temporal Autoencoder using Convolutional LSTM (ConvLSTM). The model is able to capture long-term dependencies and motion dynamics by including temporal memory. This results in increased reconstruction errors and accurate localization of anomalies, even in complicated situations. The difference maps (third column) show pixel-wise reconstruction errors, with brighter areas showing greater deviation of normal patterns. The last anomaly detection outcomes (fourth column) indicate that the suggested ConvLSTM-based model is capable of detecting abnormal regions accurately, which proves its superiority over less complex auto encoder variants.

The results of sample anomaly detection are presented in Figure 6, with the abnormal objects and activities being marked in red. The model is able to detect several anomalies including biker, wheelchair, car, golf cart, and abnormal human behavior like abrupt turning or abnormal interaction. These findings indicate that the suggested approach is capable of identifying and localizing various forms of anomalies in complicated pedestrian scenes with high accuracy..

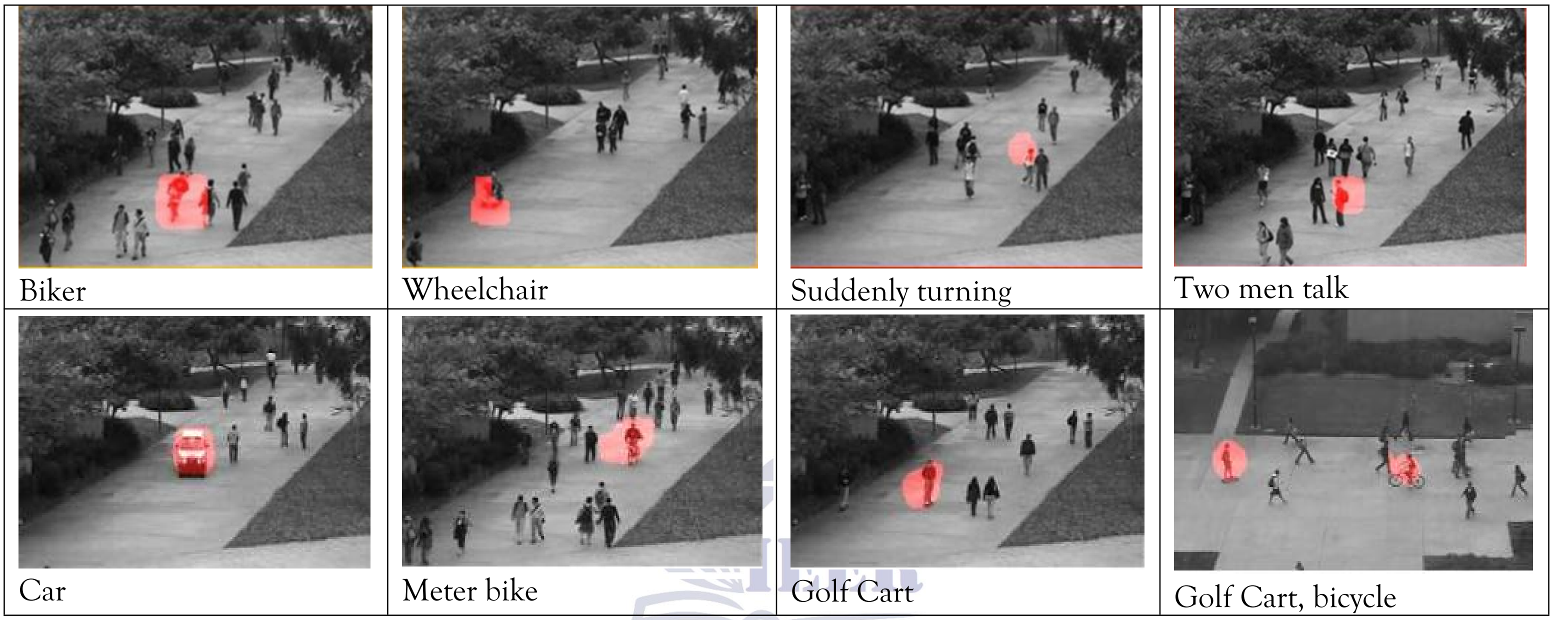


Figure 6: The highlighted regions indicate abnormal activities identified by the proposed model, including (a) biker, (b) wheelchair, (c) sudden directional change, (d) two persons interacting unusually, (e) car, (f) motorbike, (g) golf cart, and (h) multiple anomalies such as golf cart and bicycle within pedestrian walkways.

The quantitative data in the Fig.7 show the relative performance of various machine learning models, such as SVM, KNN, HGB, XGBoost, Gradient Boosting (GB), and LightGBM (LGBM), measured in terms of training, testing, and validation accuracy, precision, recall, F1-score, Cohen Kappa, MCC, and loss. XGBoost (XGBM) has the highest overall performance, with 98 percent training accuracy and 98 percent testing and validation accuracy, and a high precision, recall, F1-score, Cohen Kappa, and MCC (98 percent) and zero loss, which means that it generalizes well and has a low error rate. This underscores its better ability to deal with intricate spatio-temporal feature representations. The LGBM and Gradient Boosting (GB) models are also highly performing with accuracies of over 95 percent and low loss values, which are good in terms of robustness and generalization. The Histogram-Based Gradient Boosting (HGB) model has a stable performance of about 90 percent in all metrics, which means that it is reliable but with a relatively low accuracy compared to the sophisticated boosting techniques. Conversely, SVM and KNN have a comparatively lower performance with an accuracy of between 72 and 76 percent and greater loss rates indicating that they are not able to capture complex patterns in high-dimensional spatio-temporal data. In general, the findings validate that ensemble boosting

ISSN (e) 3007-3138 (p) 3007-312X Volume 3, Issue 2, 2026

algorithms, especially XGBoost, are much more effective than conventional classifiers, and thus they are very appropriate in detecting anomalies in video surveillance systems in real-time and with high accuracy and reliability.

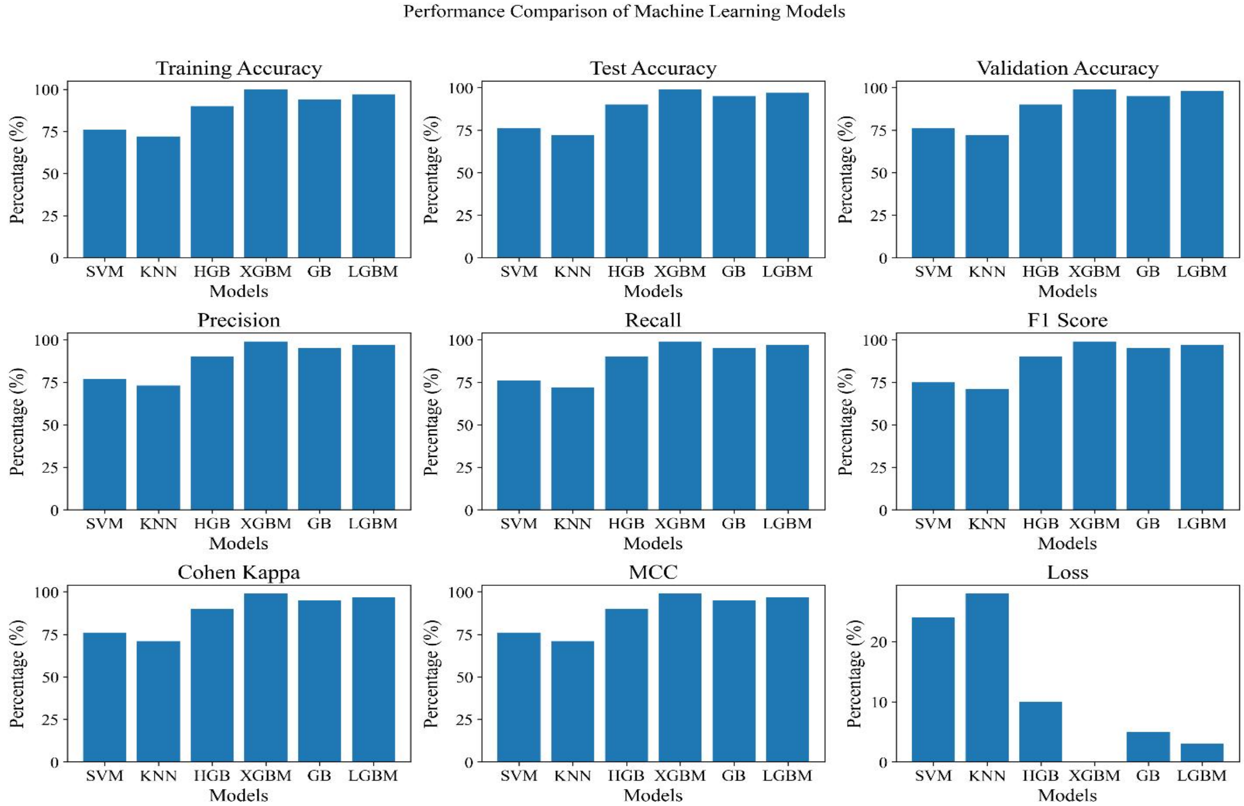


Fig.7: Overall Model performance evaluation for anomaly identification.

Table 1 provides a comparative study of the available anomaly detection methods in terms of methodology, type of anomaly, data, and evaluation parameters. Previous methods like HMM, EM, GMM, and MIL are mainly based on statistical modeling and handcrafted features, which demonstrate a weak ability to deal with complex spatio-temporal patterns. Approaches that rely on CNN, VAE, AE, and RNN enhance performance through learning deep representations, but most are limited to particular datasets or performance measures like ROC and AUC. Some of the studies employ feature engineering methods such as HOG, HOF, GLCM, and STV, which are based on motion and texture analysis, but are not always robust in dynamic and real-time settings. Also, the majority of the literature focuses on the few types of anomalies or on particular situations like trajectory analysis, crowd density estimation, or gesture recognition. Conversely, the suggested work builds on a hybrid deep learning and ensemble-based model with the UCSD dataset, which can identify various anomalies, such as bikers, wheelchairs, vehicles, and abnormal human behaviors. The approach has a high performance of 98% in validation, which is better than the traditional and recent methods. This proves its efficiency, ability to generalize, and applicability in real-time detection of anomalies in complicated surveillance settings.

Table 1: State-of-the-art comparison of the suggested mechanism.

Ref.	Technique	Anomaly	Dataset	Parameters
[10]	VAE, CNN	Safety in a public place	UMN, Avenue	ROC, AUC
[11]	CNN, AE, RNN	Irregular behavior in a crowd	UCSD, UMN	AUC
[12]	HOFO, KNN	Auto-detection, abnormality	UMN	ROC
[13]	UCSD	GMM and MDS	Temporal Regularity.	ROC
[14]	UCF	MIL	Anomalous Activity	EER, AUC, ROC
[15]	Avenue, UMN	STT Extraction and GLCM	Abnormal behavior.	Acc, ROC
[16]	UMN, PETS.	FSCB, Image Segmentation	Anomalous events.	ROC, AUC
[17]	UCSD, UMN	GMM, STV construction	Crowd Density Est.	AUC, ROC
[18]	CG Dataset	HOG and HOF	Gesture Recognition	RP
This Work	UCSD Dataset	Biker, wheelchair, car, golf cart, and unusual human behaviors	Abnormal behavior	Accuracy, Precision, Recall, F1 Score

1. **Conclusion**
2. This research work introduces an effective traffic and security management system that is grounded on real-time video anomaly detection through LSTM-based deep learning. The proposed framework is effective in capturing the intricate spatio-temporal patterns in traffic and surveillance video streams by combining CNN-based spatial feature extraction with LSTM-based temporal modeling. This allows proper detection of abnormal activities like traffic offences, suspicious vehicle activities and security threats. The use of several machine learning classifiers also enhances the ability of the system to differentiate between normal and abnormal activities. Experimental analysis of the UCSD Anomaly Detection Dataset shows high performance in terms of different metrics. XGBoost is the most successful model among the tested ones, as it has the highest validation accuracy (98) with the lowest loss, which means that it has good generalization and reliability. In general, the suggested system offers a scalable and efficient solution to real-time traffic and security monitoring, and it has a great potential to improve the safety of the population, traffic management, and intelligent surveillance systems.
3. **References:**

4. [1] J. González-Villa *et al.*, "Decision-support system for safety and security assessment and management in smart cities," *Multimed. Tools Appl.*, vol. 83, no. 22, pp. 61971–61994, Jun. 2024, doi: 10.1007/s11042-023-16020-6.
5. [2] S. Wan, X. Xu, T. Wang, and Z. Gu, "An Intelligent Video Analysis Method for Abnormal Event Detection in Intelligent Transportation Systems," *IEEE Trans. Intell. Transp. Syst.*, vol. 22, no. 7, pp. 4487–4495, Jul. 2021, doi: 10.1109/TITS.2020.3017505.
6. [3] S. Marakkar and S. K. Thakur, "Surveillance and security: integrating video, audio, and sensor data," in *Multimodal Learning Using Heterogeneous Data*, Elsevier, 2026, pp. 229–238. doi: 10.1016/b978-0-443-27528-9.00020-6.
7. [4] M. Kumari and V. S. Verma, "Deep Learning Techniques for Aircraft Corrosion Detection: a Comprehensive Review," *High Temp. Corros. Mater.*, vol. 103, no. 2, pp. 1–30, 2026, doi: 10.1007/s11085-026-10388-0.

8. [5] P. Wu *et al.*, "Deep Learning for Video Anomaly Detection: A Review," *IEEE Trans. Neural Networks Learn. Syst.*, pp. 1–21, 2026, doi: 10.1109/tnnls.2025.3647892.
9. [6] A. Jency and K. Ramar, "A Review of Abnormal Behaviour Detection in Crowd for Video Surveillance: Advances and Trends, Datasets, Opportunities and Prospects," *Expert Syst.*, vol. 42, no. 4, p. e70013, Apr. 2025, doi: 10.1111/exsy.70013.
10. [7] S. S. Reddy, G. Rahul, T. Nischitha, and K. N. Reddy, "Identifying Abnormal Behaviors in a Large Crowd using C3D and MobileNetV2," in *Proceedings of the 9th International Conference on Electronics, Communication and Aerospace Technology, ICECA 2025*, IEEE, 2025, pp. 1364–1368. doi: 10.1109/ICECA66444.2025.11382630.
11. [8] M. Aqeel, K. B. Khan, M. A. Azam, M. H. Ghouri, H. U. R. Khalid, and F. H. Jaskani, "Detection of Anomaly in Videos Using Convolutional Autoencoder and Generative Adversarial Network model," in *Proceedings - 2020 23rd IEEE International Multi-Topic Conference, INMIC 2020*, IEEE, Nov. 2020, pp. 1–6. doi: 10.1109/INMIC50486.2020.9318140.
12. [9] V. Mahadevan, W. Li, V. Bhalodia, and N. Vasconcelos, "Anomaly detection in crowded scenes," *Proc. IEEE Comput. Soc. Conf. Comput. Vis. Pattern Recognit.*, pp. 1975–1981, 2010, doi: 10.1109/CVPR.2010.5539872.
13. [10] T. Wang *et al.*, "Generative Neural Networks for Anomaly Detection in Crowded Scenes," *IEEE Trans. Inf. Forensics Secur.*, vol. 14, no. 5, pp. 1390–1399, 2019, doi: 10.1109/TIFS.2018.2878538.
14. [11] L. F. Borja-Borja, M. Saval-Calvo, and J. Azorin-Lopez, "A Short Review of Deep Learning Methods for Understanding Group and Crowd Activities," *Proc. Int. Jt. Conf. Neural Networks*, vol. 2018-July, pp. 1–8, 2018, doi: 10.1109/IJCNN.2018.8489692.
15. [12] J. Konečný and M. Hagara, "One-shot-learning gesture recognition using HOG-HOF features," *J. Mach. Learn. Res.*, vol. 15, pp. 2513–2532, 2014, doi: 10.1007/978-3-319-57021-1_12.
16. [13] M. Hasan, J. Choi, J. Neumann, A. K. Roy-Chowdhury, and L. S. Davis, "Learning temporal regularity in video sequences," *Proc. IEEE Comput. Soc. Conf. Comput. Vis. Pattern Recognit.*, vol. 2016-December, pp. 733–742, 2016, doi: 10.1109/CVPR.2016.86.
17. [14] W. Sultani, C. Chen, and M. Shah, "Real-World Anomaly Detection in Surveillance Videos," *Proc. IEEE Comput. Soc. Conf. Comput. Vis. Pattern Recognit.*, pp. 6479–6488, 2018, doi: 10.1109/CVPR.2018.00678.
18. [15] Y. Hao, Z. J. Xu, Y. Liu, J. Wang, and J. L. Fan, "Effective Crowd Anomaly Detection Through Spatio-temporal Texture Analysis," *Int. J. Autom. Comput.*, vol. 16, no. 1, pp. 27–39, 2019, doi: 10.1007/s11633-018-1141-z.
19. [16] A. Pennisi, D. D. Bloisi, and L. Iocchi, "Online real-time crowd behavior detection in video sequences," *Comput. Vis. Image Underst.*, vol. 144, pp. 166–176, 2016, doi: 10.1016/j.cviu.2015.09.010.
20. [17] X. Hu, Y. Huang, Q. Duan, W. Ci, J. Dai, and H. Yang, "Abnormal event detection in crowded scenes using histogram of oriented contextual gradient descriptor," *EURASIP J. Adv. Signal Process.*, vol. 2018, no. 1, 2018, doi: 10.1186/s13634-018-0574-4.
21. [18] Y. Ke, R. Sukthankar, and M.

Hebert, "Spatio-temporal shape and flow correlation for action recognition," *Proc. IEEE Comput. Soc. Conf. Comput. Vis. Pattern Recognit.*, 2007, doi: 10.1109/CVPR.2007.383512.

22. [19] Abbas, M. A. (2025). Advanced Synthesis and Multifunctional Characterization of Neodymium-Doped $Ba_2NiCoFe_{28-x}O_{46}$ X-Type Hexagonal Ferrites: A Comprehensive Study of Structural, Morphological, and Electromagnetic Properties. *Sch Acad J Biosci*, *8*, 1213-1227.
23. [20] Abbas, M. A., Junaid, M. J. M., Rasool, M. S., & Mahar, J. (2025). Structural and NLO Properties of Novel Organic 4-Bromo-4-Nitrostilbene Crystal: Experimental and DFT Study. *International Research Journal of Management and Social Sciences*, *6*(4), 1-20.
24. [21] Abbas, M. A., Junaid, M. J. M., Rasool, M. S., & Mahar, J. (2025). Structural and NLO Properties of Novel Organic 4-Bromo-4-Nitrostilbene Crystal: Experimental and DFT Study. *International Research Journal of Management and Social Sciences*, *6*(4), 1-20.
25. [22] Atif, H. M., Shahzad, A., Khan, M. Z., Abbas, M. A., & Mahar, J. (2025). Design of Novel drug as Potential Anti-Prostate Cancer Activity: Thiophene Derivatives against prostate cancer cell line as therapeutic agents using Pharmacokinetics molecular docking and DFT studies. *Indus Journal of Bioscience Research*, *3*(6), 548-559.
26. [23] Abbas, M. A., Khan, M. Z., Atif, H. M., Shahzad, A., & Mahar, J. (2025). Computer-Aided Analysis of Oxino-bis-Pyrazolederivative as a Potential Breast Cancer Drug Based on DFT, Molecular Docking, and Pharmacokinetic Studies: Compared with the Standard Drug Tamoxifen. *Indus Journal of Bioscience Research*, *3*(6), 535-537.
27. [24] Abbas, M. A., & Rasool, M. S. (2026). Eco-Friendly Synthesis of Ag–Co3O4 Nanoparticles for Visible-Light Photocatalysis and DFT-Based Nonlinear Optical Investigation. *Chemical Technology and Engineering Applications*, *1*(1), 23-34.
28. [25] Rasool, M. S., Abbas, M. A., Khan, M. J., Mahar, J., & Khan, M. Z. IDENTIFICATION OF NATURAL EGFR TYROSINE KINASE INHIBITORS FROM CHENOPODIUM QUINOA WILLD. VIA COMBINATORIAL IN SILICO AND PHARMACOLOGICAL SCREENING.
29. [26] Akram, S., Abbas, M. A., Mahar, J., Rasool, M. S., & Junaid, M. INTERFACIAL DEFECT PASSIVATION AND PHOTOPHYSICAL ENGINEERING OF $CSPBCL_3$ QUANTUM DOTS VIA BISBENZIMIDAZOLIUM LIGANDS FOR ADVANCED ELECTRONIC DEVICES.
30. [27] Junaid, M., Rasool, M. S., Abbas, M. A., & Mahar, J. (2024). Formulation Development and Evaluation of a Bilayered Tablet Containing Dapagliflozin and Metformin. *Global Research Journal of Natural Science and Technology*, *2*(3).
31. [28] Amin, M., Abbas, M. A., Mahar, J., Shahzad, M. S., & Rasool, M. S. (2026). Phyto-Mediated Green Synthesis and Physicochemical Characterization of Titanium Dioxide Nanoparticles for Environmental and Pharmacological Applications. Journal of Physical and Chemical Studies (JPCS), 1(4), 17–56. https://doi.org/10.5281/zenodo.19767807
32. [29] Abbas, M. A., Mahar, J., Ali, N., Junaid, M., & Rasool, M. S. (2026). Green Synthesis of SnO_2 Nanomaterials: Photocatalytic Degradation of Methylene

Blue and DFT-Based Investigation of Nonlinear Optical Properties. Journal of Physical and Chemical Studies (JPCS), 1(3), 1–29. https://doi.org/10.5281/zenodo.19693725

33. [30] Abbas, M. A., Mahar, J., Ali, N., Junaid, M., & Rasool, M. S. (2026). Photocatalytic Dynamics of Organic Dye Degradation on Graphitic Carbon Nitride: An Integrated Experimental and Theoretical Investigation. Journal of Physical and Chemical Studies (JPCS), 1(2), 1–23. https://doi.org/10.5281/zenodo.19693515
34. [31] Abbas, M. A., Mahar, J., Ali, N., Junaid, M., & Rasool, M. S. (2026). Interfacial Defect Passivation and Photophysical Modulation in Cesium Lead Chloride Perovskite Quantum Dots Using Bisbenzimidazolium Ligands for Advanced Optoelectronic Devices. Journal of Physical and Chemical Studies (JPCS), 1(1), 1–18. https://doi.org/10.5281/zenodo.19666800
35. [32] Akram, S., Abbas, M. A., Mahar, J., Rasool, M. S., & Junaid, M. (2026). SYNTHESIS AND CHARACTERIZATION OF ZINC-DOPED CARBON DOTS FOR ENHANCED FLUORESCENCE APPLICATIONS. *Policy Research Journal, 4*(2), 168–177. https://policyrj.com/1/article/view/1550