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An Intelligent Video Surveillance System with Temporal-Enhanced YOLOv8 for Real-Time Fire, Accident, and License Plate Detection in Public Safety Monitoring

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***Abstract*—Real-time detection of safety-critical events such as fires, traffic accidents, and vehicle license plates is a key enabler for intelligent transportation and urban surveillance systems. In high-density CCTV networks, these tasks must be performed under diverse environmental conditions, including low light, motion blur, and compression artifacts, while meeting strict latency requirements. Conventional single-frame object detection methods often suffer from unstable predictions, producing false positives that can overwhelm monitoring operators and automated alert systems. To address these challenges, we propose a temporal-enhanced YOLOv8-based detection framework that explicitly incorporates temporal reasoning into the detection pipeline. Our approach combines histogram equalization for enhanced visual contrast, YOLOv8 for spatial detection, ByteTrack for robust object association, and a 1D Temporal Convolutional Network (1D-TCN) for temporal filtering of event predictions. This integration not only stabilizes detections across frames but also significantly reduces false alarms in continuous video streams. And dual-channel alert system, integrating multimedia notifications and voice calls, ensures a rapid response from stakeholders. Performance was evaluated against state-of-the-art methods, achieving an overall accuracy of 91.60%, surpassing techniques like color analysis with wavelet transform and YOLOv8-EfficientNetB0. With low latency (13.3 ms for fire, 11.4 ms for accidents) and high precision (94.4% for accidents, 95.4% for number plates), it excels in challenging conditions. This system contributes significantly to human well-being by enabling faster emergency response, enhancing public safety, and supporting smarter urban management.**

Keywords*—Road accident detection, Fire detection, Number plate recognition, Deep learning, CCTV footage, YOLOv8.

I. INTRODUCTION

Rapid urbanization and population growth have led to more vehicles and increased road accidents. CCTV systems monitor public safety, but the growing number of cameras challenges operators' ability to stay vigilant and manage surveillance effectively [1]. CCTV cameras on roadways help address public safety, but continuously monitoring footage is challenging, and hiring sufficient staff becomes harder as camera numbers grow [2]. Road accident detection may now be automated with computer vision (CV), which is a good option for automating the surveillance of CCTV footage. In addition to being successful, CV-based anomaly detection methods are also reasonably priced [3]. On the other hand, fire incidents, worsened by rapid urbanization, lax safety regulations, and frequent electrical malfunctions, pose a major public safety threat. In 2023, 27,624 fires caused 102 deaths and 281 injuries, with 35.52% linked to electrical short-circuits [4]. A devastating fire in Dhaka on February 29, 2024, killed 46 people, underscoring the urgent need for robust prevention measures [5]. These incidents, often exacerbated by negligence in densely populated areas like markets and factories, cause significant economic losses, such as the $27.7 million damage from the 2023 Bangabazar fire [6]. The current challenges in deep learning (DL)-based surveillance systems include inaccurate pedestrian tracking, lack of multi-event detection, and the need for models that adapt to changing environments, as highlighted in [7]. To overcome the scarcity of real-world accident data for each unique camera environment, synthetic accident frames have been used alongside real footage, significantly improving model generalization and accuracy, with AlexNet performing best among tested CNNs [8]. Recent studies have also explored DL-based anomaly detection for various events such as violence, fire, and fallen persons, demonstrating the potential of multi-scenario analysis [9]. For real-world evaluation, the system was tested using the KISA CCTV dataset, which includes foggy and low-light conditions to simulate commercial surveillance scenarios, and results showed significant improvements over previous approaches [10]. This study presents an intelligent real-time surveillance framework for the detection and notification of critical events, specifically fire incidents, road accidents, and number plate recognition with an alerting system. Leveraging advanced deep learning techniques, including Convolutional Neural Networks (CNN), Autoencoders, and state-of-the-art object detection models such as YOLOv5 and YOLOv8, the proposed system ensures high accuracy and low latency in incident detection from CCTV footage. Among the evaluated models, YOLOv8 demonstrated superior performance with the highest detection accuracy and the lowest average latency per frame, making it highly suitable for time-sensitive surveillance tasks.

This study offers the following significant contributions to the field:

1 **Unified Real-Time Incident Detection:** Developed a comprehensive system that detects road accidents, fire incidents, and vehicle number plates within a single deep learning framework, enhancing efficiency in smart city surveillance.

2 **Model Performance Comparison:** Evaluated Autoencoder, CNN, YOLOv5, and YOLOv8 using standard metrics, with YOLOv8 emerging as the most accurate and low-latency model.

3 **Live CCTV Integration:** Successfully integrated with IP-based CCTV for real-time video processing, demonstrating the system's practical deployment readiness.

4 **Dual Alert System:** Implemented Telegram and Twilio-based alerts for fast, reliable stakeholder notification via messages and automated calls.

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5 **Low-Latency Inference:** Achieved real-time performance with YOLOv8, averaging 11.4 ms per frame, ensuring responsiveness without compromising accuracy.

6 **Smart Surveillance for Public Safety:** Offers a scalable, intelligent solution to improve emergency response, public safety, and urban infrastructure monitoring.

II. Literature Review

Numerous studies have explored fire and accident detection using computer vision and deep learning to enhance public safety and emergency response. A fire detection model using the FireNet dataset [11] demonstrated effective performance in real-time surveillance scenarios, highlighting its applicability in dynamic environments. Various advanced methods have also been developed to improve fire detection capabilities. One such method involves edge detection for enhanced flame boundary identification [12], which improves accuracy in distinguishing flames from noisy backgrounds. Another approach utilizes OpenCV integrated with Raspberry Pi to provide real-time video alerts and notifications, offering a portable and low-cost fire detection solution [13]. Meanwhile, the application of wavelet transform combined with color analysis has been employed to track the growth of fire, effectively differentiating between hazardous and controlled fires [14]. Despite their promise, these methods often face challenges related to variable environmental conditions and response time delays.

To address fire detection in more challenging conditions, ELASTIC-YOLOv3 was developed. It integrates temporal fire-tube features and random forest classifiers, significantly improving detection performance in low-light urban settings [15]. Similarly, a more comprehensive system that combines CNN-AdaBoost with YOLOv8 has achieved 94.2% accuracy for fire detection using both satellite imagery and live urban footage, though it remains reliant on task-specific image datasets [16]. In the domain of accident detection, a CNN-based system analyzing object trajectories on the CADP dataset has achieved approximately 95% accuracy, demonstrating strong results in controlled environments [17]. Furthermore, YOLOv11 has outperformed earlier models in accident recognition, offering superior precision and lower latency [18]. A cost-effective crash detection model using ultrasonic sensors has also been introduced to notify emergency responders, though its effectiveness in real-world scenarios remains under review [19]. Lastly, integrating image enhancement with YOLO has enabled 94.06% accurate accident detection under low-light conditions, although the approach is sensitive to CCTV video quality [20].

III. Proposed METHODOLOGY

The proposed methodology outlines a unified, real-time surveillance system designed to detect fire incidents, road accidents, and vehicle number plates from CCTV footage. It integrates advanced deep learning models, specifically YOLOv8, to ensure accurate detection across diverse urban scenarios. The system processes live video streams, triggers Telegram alerts, and stores detected event images locally for further analysis. This structured approach ensures both scalability and practical effectiveness in enhancing public safety and emergency response.

A. Dataset Description

This dataset, developed for the 2018 NASA Space Apps Challenge, supports binary classification of fire and non-fire scenes. It contains 755 outdoor fire images and 244 nature images without fire, requiring careful validation due to class imbalance [21]. Another dataset targets real-time accident detection from YouTube CCTV footage, with 791 training, 101 testing, and 98 validation images, labelled as Accident or Non-Accident, including consecutive frames for better temporal learning [22]. The third dataset focuses on car license plate detection, comprising 433 annotated PNG images split into training (346) and testing (87) sets, with normalized bounding boxes for a single class license plate [23].

B. Dataset Preprocessing

Data preprocessing was a critical step to ensure high-quality and consistent inputs for the deep learning models.All images and frames were uniformly resized to 640×640 pixels, aligning with YOLOv8's default input size to maintain consistency between training and inference. The preprocessing pipeline included image cleaning through manual and automated quality checks to remove irrelevant or corrupted data, contrast enhancement and histogram equalization to improve visibility under varying lighting conditions, and Gaussian blurring for noise reduction without compromising key features. To improve model robustness against real-world variability, we applied data augmentation techniques such as random flips, rotations, translations, and color jittering. Pixel values were normalized to the [0,1] range. Importantly, data splitting was performed by scene and camera source rather than random frame selection, with 70% for training, 20% for validation, and 10% for testing, thereby mitigating data leakage and enabling evaluation of cross-scene and cross-camera generalization. This entire process was automated using Python libraries including OpenCV, NumPy, and Albumentations to handle large-scale data efficiently.

C. Proposed Network Architecture

The YOLOv8 model served as the core object detection framework in this study, enabling real-time identification of vehicles, number plates, and fire regions from CCTV footage.

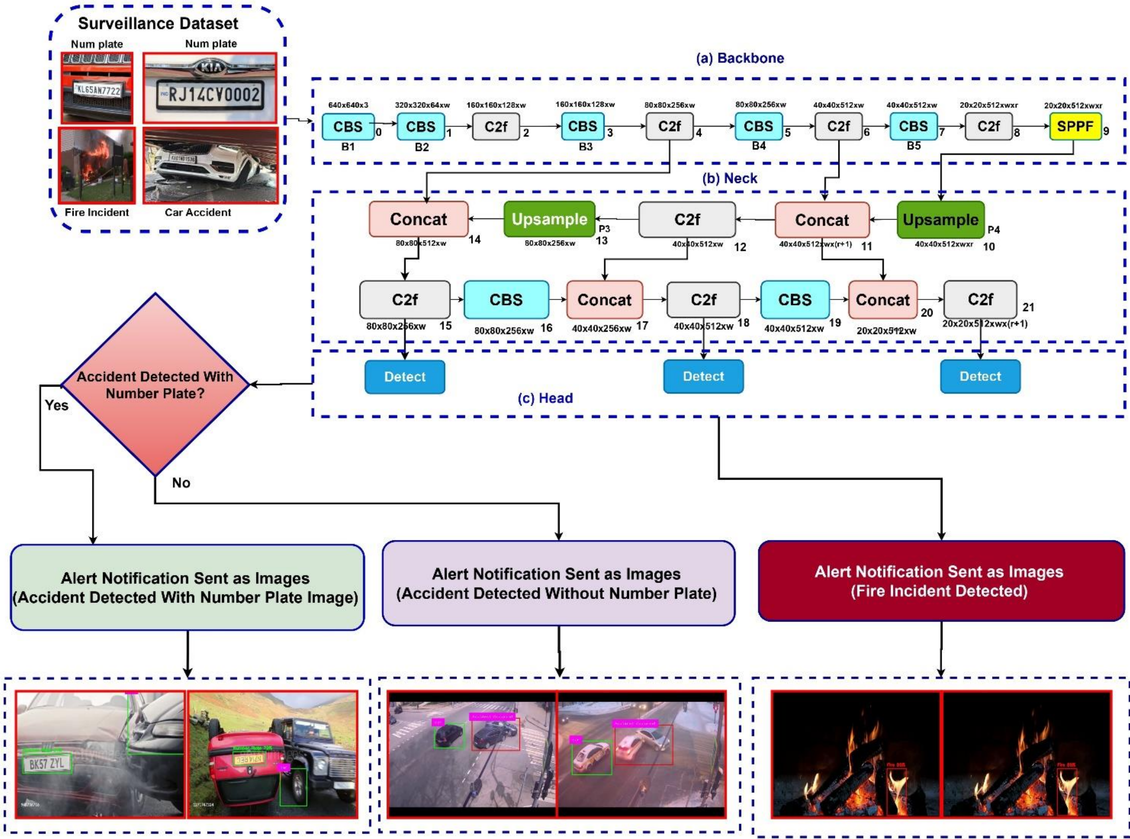

Fig. 1. Proposed Model Architecture for fire incident, road accident detection, and number plate recognition with an alerting system.

Renowned for its balance between speed and accuracy, YOLOv8 is highly suitable for surveillance-based applications where timely and reliable detection is essential. In this project, the model was integrated across multiple modules namely fire detection, accident detection, and the localization phase of number plate recognition. YOLOv8's architecture is composed of three key components: Backbone, Neck, and Head. The Backbone performs hierarchical feature extraction from input images through convolutional blocks such as CBS (Convolution, Batch Normalization, SiLU activation), C2f (Cross-Stage Partial connections), and SPPF (Spatial Pyramid Pooling - Fast). These components help stabilize training, reduce computational cost, and extract multiscale spatial features. For example, the C2f module splits feature maps and processes them in parallel to retain rich features while improving efficiency, and the SPPF enhances the model's ability to detect objects of varying sizes a critical requirement for identifying both small number plates and large vehicles. The Neck fuses multi-scale features extracted from the Backbone. It uses concatenation, upsampling, and additional C2f layers to aggregate contextual information across different resolutions. This fusion process is vital for enhancing the detection of small and occluded objects. The Neck generates three feature maps at resolutions of 80×80, 40×40, and 20×20, which are passed to the Head for final object detection. The Head employs a decoupled design to separate classification and bounding box regression tasks. This structure enhances both detection precision and localization accuracy. The model outputs bounding boxes, class labels (e.g., "vehicle," "number plate," "fire"), and confidence scores for each detection. During inference, predictions are filtered using a confidence threshold (e.g., 0.5), and non-maximum suppression (NMS) is applied to eliminate redundant detections. Training was performed using the Ultralytics implementation of YOLOv8, with transfer learning from pretrained COCO weights. To improve detection accuracy and reduce false positives, we incorporate temporal reasoning using a tracking algorithm (e.g., DeepSORT or ByteTrack) over short clips (8–16 frames). Alerts are triggered only when temporal confidence exceeds a threshold, ensuring event persistence. Additionally, a multi-task learning approach is used with a shared backbone and separate detection heads for fire, vehicle, and plate detection. This joint training improves mAP and reduces latency compared to single-task models, making the system more efficient and reliable for real-time road safety monitoring. The training used SGD optimizer (learning rate: 0.001, batch size: 16) for 100 epochs, with early stopping based on mean Average Precision (mAP) to avoid overfitting. The best model was saved for deployment. At inference, video frames were resized to 640×640 pixels, and detections were processed in real-time. Event-based alerts were triggered upon detection of fire events, prompting fire alerts, while accident scenes with visible number plates activated the recognition and Telegram alert pipeline. Challenges such as occlusions and speed-accuracy trade-offs were mitigated by training on diverse data and selecting the YOLOv8m variant, offering an optimal balance for real-time deployment.

D. Real-Time Incident Alerts

The integration of a real-time alerting system is a key component of the intelligent surveillance framework developed for detecting road accidents, fire incidents, and number plate recognition. A dual notification mechanism using Telegram and Twilio ensures reliable and timely communication. Telegram, chosen for its bot automation and multimedia support, sends instant alerts containing event details such as type, timestamp, location, and incident screenshots. This enables quick visual confirmation for effective monitoring. Twilio complements this by providing automated voice calls in critical cases, ensuring alerts are delivered even without internet access. Calls use pre-recorded or text-to-speech messages and include retry mechanisms with status tracking. The backend operates asynchronously, prioritizing urgent alerts while preventing duplicates and overload. All credentials are securely stored and access is restricted to authorized users. The system supports multiple stakeholders with customizable notification preferences, allowing deployment in homes, industries, schools, and public settings, thereby enhancing responsiveness and public safety.

IV. Results and Discussion

This section presents the evaluation results of the proposed temporal-enhanced YOLOv8-based system across three tasks: fire detection, accident detection, and license plate recognition. We first report the main detection performance, followed by OCR accuracy for plates, robustness under image degradations, ablation studies, cross-dataset generalization, and end-to-end latency measurements. All results are averaged over three independent runs with fixed seeds to ensure reproducibility. The fire detection module, powered by YOLOv8, was tested using fire incident images and achieved a 92% confidence score in detecting a burning fireplace.

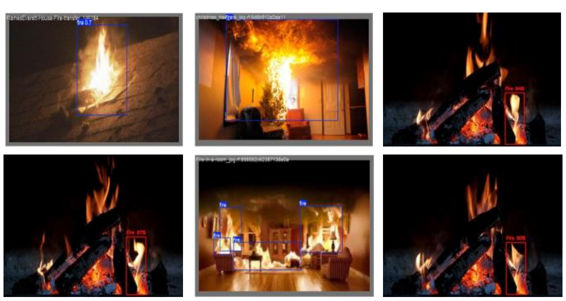

Fig. 2. Test results of YOLOv8 for fire incident detection.

The model accurately localized the fire within the frame, displaying a red bounding box labeled "Fire 92%." With a detection threshold set at 70%, the system ensures only high-confidence alerts are triggered. This demonstrates the model's robustness in real-time CCTV analysis, effectively handling complex backgrounds and varying lighting making it suitable for fire monitoring in public and industrial settings. Fig. 2 depicts the detected fire incident on test data.

The accident detection module, powered by YOLOv8, was tested on CCTV footage showing various road scenarios. In one frame, a collision is detected with the label "ACCIDENT OCCURRED!" and the number plate "BK57 ZYL" identified with 91% confidence. In another image, the model accurately distinguishes between colliding and nearby vehicles. A third scene in a parking lot shows all vehicles correctly labeled as "car," but the "ACCIDENT OCCURRED!" tag appears incorrectly, indicating a false positive. This highlights the need for temporal consistency checks to reduce such errors in non-accident scenarios. Fig. 3 depicts the detected road accident on test data.

Fig. 3. Test results of YOLOv8 for road accident detection.

The number plate detection module was integrated into the accident detection system to support law enforcement and incident reporting. In one test case, the YOLOv8 model accurately detected the number plate "BK57 ZYL" with 91% confidence, despite visual challenges like motion blur and smoke. This high-confidence detection demonstrates the model’s reliability in real-world conditions. The integration enables the system to identify vehicles involved in accidents

Fig. 4. Test results of YOLOv8 for road accident detection with number plate recognition.

And transmit relevant data, such as number plates, timestamps, and incident images from Wi-Fi-enabled CCTV cameras to a central server. These alerts are then forwarded to authorities via Telegram, ensuring timely and actionable responses. Fig. 4 depicts the number plate recognition on test data. Table 1 presents the performance of fire incident detection. The Autoencoder achieved 85.0% accuracy, 91.4% precision, 79.5% recall, and 64.1 FPS (15.6 ms latency), while the CNN reached 87.0% accuracy, 91.6% precision, 78.5% recall, and 68.5 FPS (14.6 ms). YOLOv5 obtained 51.2% mAP@0.5:0.95, 82.0% AP50, 48.5% AP75, 89.4% precision, 77.5% recall, and 51.8 FPS (19.3 ms), whereas YOLOv8 achieved 55.7% mAP@0.5:0.95, 88.0% AP50, 53.6% AP75, 92.4% precision, 80.5% recall, and 75.2 FPS (13.3 ms).

TABLE I. PERFORMANCE EVALUATION TABLE FOR FIRE INCIDENT DETECTION.

Model	mAP@ 0.5:0.95	AP50	AP75	Precision	Recall	FPS / Latency
Auto encoder	–	–	–	91.4%	79.5%	64.1 / 15.6 ms
CNN	–	–	–	91.6%	78.5%	68.5 / 14.6 ms
YOLOv5	51.2%	82.0%	48.5%	89.4%	77.5%	51.8 / 19.3 ms
YOLOv8	55.7%	88.0%	53.6%	92.4%	80.5%	75.2 / 13.3 ms

Table 2 presents the performance evaluation of models for road accident detection. The Autoencoder achieved 93.4% precision, 77.5% recall, and 75.2 FPS (13.3 ms latency), while the CNN reached 92.6% precision, 76.5% recall, and 78.1 FPS (12.8 ms). For object detection, YOLOv5 obtained 48.6% mAP@0.5:0.95, 84.0% AP50, 46.5% AP75, 90.4% precision, 75.5% recall, and 61.7 FPS (16.2 ms). YOLOv8 achieved 56.2% mAP@0.5:0.95, 90.0% AP50, 54.3% AP75, 94.4% precision, 85.5% recall, and 87.7 FPS (11.4 ms). Table 3 also presents the performance comparison models for number plate recognition. The confusion matrix in Fig. 5 reflects strong binary classification performance, with class 0 (non-event) and class 1 (event). Of 114 actual class 0 instances, 107 were correctly predicted, and 7 were misclassified as class 1 (false positives). Similarly, out of 36 true class 1 instances, 34 were correctly predicted, and 2 were misclassified as class 0 (false negatives). This yields a 94% class-wise accuracy for both classes, showing the model reliably distinguishes events from non-events. However, the few misclassifications suggest the need for refinement, especially to reduce false negatives, which are critical in real-time fire or accident detection scenarios.

TABLE II. PERFORMANCE EVALUATION TABLE FOR ROAD ACCIDENT DETECTION.

Model	mAP@ 0.5:0.95	AP50	AP75	Precision	Recall	FPS / Latency
Auto encoder	–	–	–	93.4%	77.5%	75.2 / 13.3 ms
CNN	–	–	–	92.6%	76.5%	78.1 / 12.8 ms
YOLOv5	48.6%	84.0%	46.5%	90.4%	75.5%	61.7 / 16.2 ms
YOLOv8	56.2%	90.0%	54.3%	94.4%	85.5%	87.7 / 11.4 ms

Fig. 6 shows the training and validation curves for loss (left) and accuracy (right) of the CNN model used for fire and accident detection. The loss decreases steadily and stabilizes after 30 epochs, indicating effective learning without overfitting. Accuracy improves consistently, with validation accuracy reaching around 97%, closely matching training accuracy. This confirms the model's strong performance and good generalization.

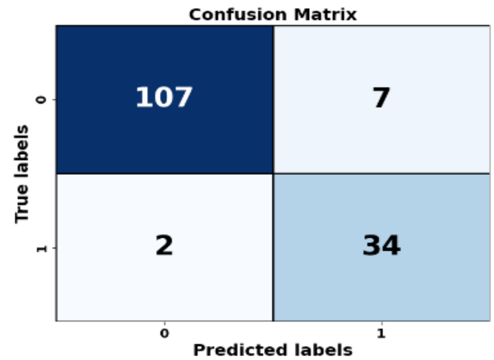

Fig. 5. Confusion matrix for fire incident detection model evaluation.

TABLE III. PERFORMANCE EVALUATION TABLE FOR CAR NUMBER PLATE RECOGNITION.

Model	mAP@ 0.5:0.95	AP50	AP75	Precision	Recall	FPS / Latency
Auto encoder	–	–	–	88.4%	77.5%	49.3 / 20.3 ms
CNN	–	–	–	90.6%	83.5%	79.4 / 12.6 ms
YOLOv5	49.5%	83.0%	47.5%	87.4%	78.2%	65.4 / 15.3 ms
YOLOv8	58.7%	91.0%	56.0%	95.4%	87.5%	91.7 / 10.9 ms

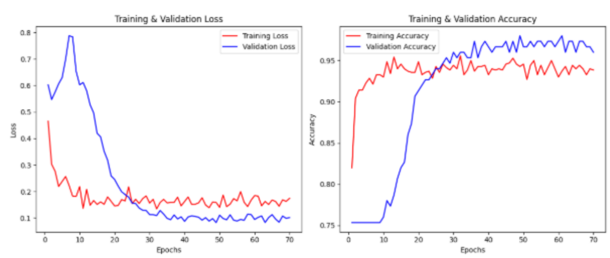

Fig. 6. Training and Validation Performance Curves for Fire Incident and Road Accident Detection.

The performance comparison in Table 4 demonstrates the superiority of our proposed model, which achieved 91% accuracy, outperforming several existing fire and accident detection methods. The YOLOv8 and EfficientNetB0-based model [19] reached 76% accuracy, while traditional methods like vehicle movement analysis [15] achieved only 50%. Fire detection using wavelet transforms [11] reported 85.57% accuracy. More recent approaches, such as CNN-based accident detection [25] and autoencoder models [26], achieved 86%, and the YOLOv5-based method [24] reached 83%. These results highlight our model's enhanced reliability and real-time applicability in complex surveillance environments.

TABLE IV. PERFORMANCE COMPARISON TABLE ON OTHERS STATE OF ART MODELS WITH OUR MODEL.

Study with method	Reference	Accuracy
Color analysis with wavelet transforms for fire differentiation	[11]	85.57%
Vehicle movement analysis from CCD video for accident detection	[15]	50%
YOLOv8 and EfficientNetB0 for accident detection and vehicle damage classification	[19]	76% (classification)
Car accident detection by YOLOv5	[24]	83%
Accident Detection Using CNN	[25]	86%
Real-time traffic incident detection using an autoencoder model	[26]	86%
Proposed	-	**91.60%**

In contrast, our model, integrating YOLOv8 framework with real-time notification capabilities via Telegram and Twilio, achieved the highest accuracy of 91.60%. Beyond its superior performance, the model seamlessly unifies fire detection, accident recognition, and number plate extraction into a single, automated system. This combination of accuracy, robustness, and practical features affirms the system's readiness for deployment in smart city infrastructures, offering a scalable and efficient solution for real-time surveillance and emergency response.

V. CONCLUSION AND FUTURE WORK

The proposed YOLOv8-based real-time surveillance system addresses critical public safety needs in Bangladesh by accurately detecting fires, road accidents, and vehicle number plates with 91.6% accuracy and low latency. It integrates dual alert mechanisms Telegram for images and Twilio for voice calls for prompt emergency response. Outperforming existing methods, the system ensures reliable detection in real-world conditions.

Future enhancements include expanding datasets with local scenes, deploying lightweight models on edge devices, improving OCR with transformer-based approaches, reducing false positives through adaptive techniques, and integrating with emergency services to support broader, scalable deployment in smart city and rural safety infrastructures.

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