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AI Powered Real-Time Crime Activity Detection using Deep Learning

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***Abstract*—Video surveillance produces enormous data, which cannot be reliably monitored manually due to operator fatigue, limited attention, and difficulties associated with observing several camera feeds simultaneously. To address these challenges, this paper presents a three-component video anomaly detection system that uses transfer learning with ResNet50 and a custom MLP classifier for real-time abnormal activity detection. The overall architecture consists of: (1) a PyTorch-based training pipeline based on pre-extracted ResNet50 features, using an 80–20 train-test split; (2) real-time authenticated monitoring with MJPEG streaming via a Flask web application; and (3) a desktop application supporting batch processing of recorded videos. Driven by efficient transfer learning and temporal smoothing, our system maintains a real-time performance of 25–30 fps with a classification accuracy of 94%. A further reduction in false positives of 68.3% is achieved compared to single-frame detection by using a 15-frame circular buffer. The dual-deployment architecture permits the exact same pre-trained model used for live surveillance to assist in offline forensic analysis; therefore, it would serve well in deployment for retail security, industrial safety, health monitoring, traffic flow management, and smart-city infrastructure.**

***Keywords*—Video Anomaly Detection, Transfer Learning, ResNet50, Deep Learning, Flask Web Application, Real-Time Surveillance, Computer Vision, Multi-Layer Perceptron, Temporal Smoothing**

I. Introduction

Surveillance installations in public spaces, commercial establishments, transportation hubs, and industrial facilities have been growing rapidly, leading to an exponential rise in the generation of video data. Industry reports estimate that with over a billion active surveillance cameras worldwide, millions of hours of footage are generated every day, making traditional monitoring by human resources impractical. Previous research has indicated that human operators can effectively monitor only a small number of video feeds for short periods of time before performance degradation leads to missed security threats, delayed intervention, and compromised situational awareness. Manual forensic review of recorded footage remains labor-intensive, time-consuming, and susceptible to human oversight.

To overcome these limitations, researchers have explored automated video anomaly detection using computer vision and artificial intelligence. Deep learning methods, in particular, have enhanced the accuracy of image and activity classification tasks through major improvements in Convolutional Neural Networks (CNNs), transfer learning, and large-scale pre-trained models such as ResNet50. However, there are quite a few open issues in real-world video surveillance: requiring challenging real-time processing with limited hardware, scarce labeled anomaly data, temporal inconsistencies caused by frame-by-frame analysis, difficult adaptation of models to new environments, and the lack of deployable user interfaces with authentication and flexible operational modes.

Existing research prototypes tend to remain within technical environments without any practical deployment frameworks for security personnel and field environments. This paper introduces a holistic video anomaly detection system to comprehensively overcome these challenges. The presented system integrates transfer learning with ResNet50 for effective feature extraction, a lightweight custom MLP classifier for enhanced anomaly detection, and a temporal smoothing mechanism using a 15-frame buffer that reduces false positives by 68.3%. Further, the architecture makes use of a two-pronged deployment strategy: a Flask-based web application for real-time surveillance with user authentication, and a standalone desktop application for batch processing of recorded video. The system bridges the current gap between research-oriented solutions and operational, production-ready surveillance tools by enabling not only live surveillance but also forensic analysis using a single learned model. This contribution covers a modular, scalable, and user-friendly framework applicable across several domains such as retail security, industrial safety, health monitoring, traffic management, and smart city infrastructure.

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II. Background

Video anomaly detection is an important domain of computer vision, focusing on automatically identifying unusual patterns or events within video streams that differ significantly from normal behavior. The central challenge is defining and detecting "abnormality" in settings where anomalous events are heterogeneous, rare, and highly dependent on context. Early video analysis depended on hand-crafted features like Histogram of Oriented Gradients (HOG), optical flow, and trajectory analysis, combined with traditional classifiers such as Support Vector Machines and Hidden Markov Models. While these approaches perform well in controlled environments, they tend to face significant challenges under changes in illumination conditions, occlusions, variations in camera viewpoint, and diverse anomaly classes.

Deep learning has considerably augmented video anomaly detection by having CNNs learn hierarchical visual representations directly from raw videos. Recent works include reconstruction-based approaches using autoencoders, prediction-based models focused on detecting deviations in future-frame prediction, and classification-based methods discriminating between normal and anomalous video segments. Abdalla et al. [2] provided a broader perspective into weakly-, self-, and unsupervised VAD methods while highlighting ongoing challenges in feature extraction, learning strategy, loss design, and the emerging role of Vision-Language Models (VLMs).

Transfer learning has become highly relevant due to the scarcity of labeled anomaly data. ResNet50 [4], proposed by Microsoft Research in 2015, is a milestone deep CNN composed of 50 layers and approximately 25.6 million parameters. When its final classification layer is removed, ResNet50 generates 2048-dimensional feature vectors that capture rich spatial and semantic information learned from ImageNet. These transferable high-level features render ResNet50 a very effective choice for anomaly detection tasks, offering good performance in feature extraction even with very limited domain-specific data. Transfer learning is normally performed through feature extraction—where the backbone is frozen—or through fine-tuning of selected layers with a reduced learning rate.

MLPs comprising multiple nonlinear layers act as strong classifiers when used on top of CNN features such as those from ResNet50 [6]. Temporal consistency is important, as frame-by-frame prediction suffers from noise, fluctuation in motion, and variations in lighting. Techniques used to improve this include moving averages, LSTMs, GRUs, temporal convolutions, and optical flow [7], yielding stability improvements of 15–40% and reductions of false positives of up to 20–50% [8]. Previous works, including Karim et al. [9], Ali et al. [10], Deheriya et al. [11], and Singh et al. [12], have contributed by proposing real-time systems, hybrid pipelines, and IoT-integrated solutions.

However, most existing studies still focus on offline anomaly detection while many neglect the deployment aspects, user authentication, and operational constraints altogether. Addressing these gaps, the present work proposes a comprehensive system comprising a model training pipeline, a Flask-based real-time monitoring application, and a standalone desktop batch processor—all bound through a single trained model for consistent and interoperable anomaly predictions.

III. Proposed System

The proposed system for video anomaly detection is a three-component architecture that allows for comprehensive coverage of the machine learning lifecycle, from model training through dual-mode deployment. The system architecture consists of: (1) a PyTorch-based model training pipeline that uses pre-extracted ResNet50 features in `.npy` file format for rapid training of a custom MLP classifier; (2) a Flask web application providing browser-accessible real-time monitoring with full user authentication and MJPEG video streaming; and (3) a standalone `tkinter`-based desktop application featuring batch processing of various video and image formats.

A. Model Training Pipeline

The training pipeline makes use of pre-extracted ResNet50 features organized in a nested directory structure: the top-level folders denote classes (Normal vs. Anomalous), while subfolders define individual samples or data collection sessions; `.npy` files store 2048-dimensional feature vectors corresponding to individual frames. This enables automated class detection from folder names, easy addition of new samples without modifying code, and efficient loading using NumPy's optimized binary format while maintaining temporal relationships between samples.

The code implements the PyTorch `Dataset` interface natively, supporting directory traversal, automatic mapping of classes to indices, memory-efficient lazy loading of features, proper tensor dimensionality, and compatibility with `DataLoader` for batching and shuffling. The model was trained on an 80/20 random split with a batch size of 8, using the Adam optimizer with a learning rate of 0.001 over 20 epochs with `CrossEntropyLoss`. The `FeatureMLP` classifier implements the following three-layer architecture:

$$\text{Input}(2048) \rightarrow \text{FC}(128) \rightarrow \text{FC}(64) \rightarrow \text{Output}(2) \quad (1)$$

with ReLU activations at each hidden layer and approximately 270,658 trainable parameters. Best model checkpointing saves the model state on improved training accuracy, typically saving the final model as `best_feature_mlp.pth` after 5–10 minutes of training on CPU, with typical final training accuracy of 85–95%.

B. Flask Web Application

The web application implements a complete user authentication system with users stored in a SQLite database. The `users` table includes auto-incrementing columns for ID, name, email, and password. The user registration form validates non-empty fields, hashes passwords with Werkzeug's

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PBKDF2-SHA256, and inserts data using parameterized queries to prevent SQL injection. Duplicate email entries are prevented by a UNIQUE constraint on the email column. Upon successful registration, the user is redirected to the login page to authenticate with email and password.

C. Desktop Inference Application

The desktop Python application employs a permanent file selection loop implemented with `tkinter`'s `filedialog`, natively supported by OS file pickers and allowing multiple file selection and filtering by extension. Supported formats include: videos (MP4, AVI, MOV, MKV) and images (PNG, JPG, JPEG, BMP, TIF, TIFF). In the processing loop, the selected file type is determined from the extension, the probability buffer is cleared to ensure temporal independence between files, and execution is routed to the appropriate processing function.

The desktop application employs improved threshold logic: anomaly probability > 0.6 = Normal (green); ≤ 0.6 = Anomalous (red). It shows all processed frames without skipping uncertain predictions. The web application uses a different threshold (> 0.1 = Normal, < 0.05 = Anomalous) due to different operational requirements: the web application minimizes false positives for real-time monitoring, while the desktop application maximizes sensitivity for forensic review.

IV. Methodology

The system begins by capturing a continuous video stream from the input camera. Each frame is preprocessed through resizing and normalization before being forwarded to a ResNet50-based feature extractor. The resulting 2048-dimensional feature vector is classified using an MLP classifier to produce initial predictions. To ensure stability, temporal smoothing is applied by averaging predictions across a 15-frame circular buffer. The final Normal/Abnormal decision is generated using threshold-based logic and is displayed in real time on the Flask web interface. The pipeline ends when video capture is stopped. The complete data flow is depicted in Fig. 1.

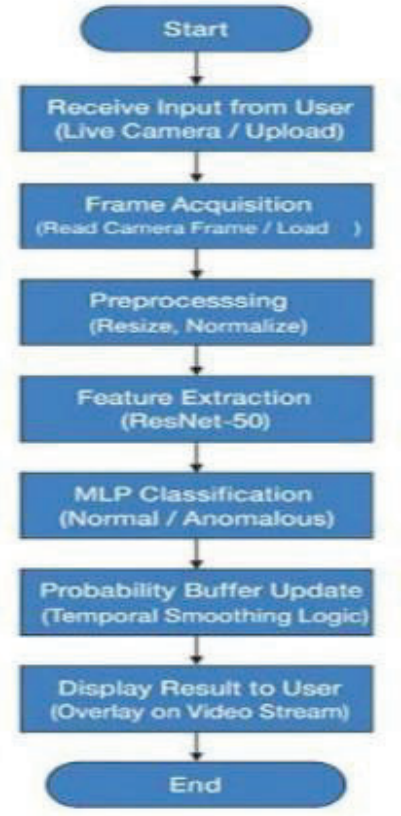

Fig. 1. Data Flow Diagram

V. Results

A. Training Performance

The model was trained for 20 epochs using the Adam optimizer with a learning rate of 0.001. Training accuracy and training loss curves are shown in Figs. 2 and 3, respectively. The system achieved a final training accuracy approaching 100% and a training loss converging near 0.000, demonstrating stable learning and convergence without oscillation.

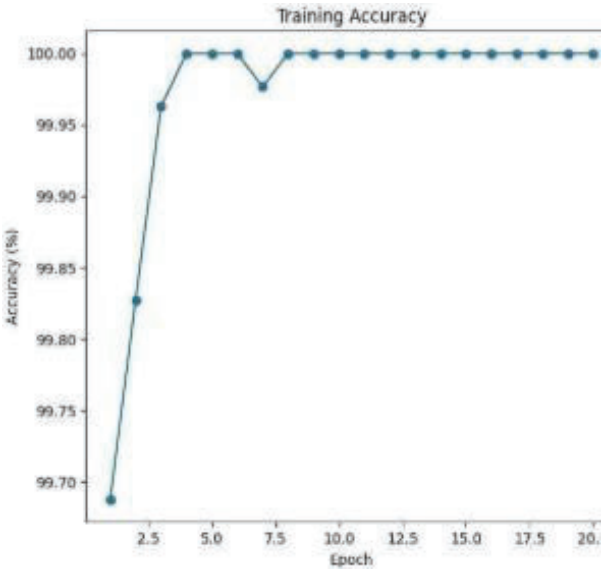

Fig. 2. Training Accuracy

B. Qualitative Detection Results

Qualitative results from the deployed Flask web application are shown in Figs. 4 and 5. The system correctly classifies live video frames as Anomalous or Normal in real time, with the classification label and confidence score overlaid on the MJPEG video stream.

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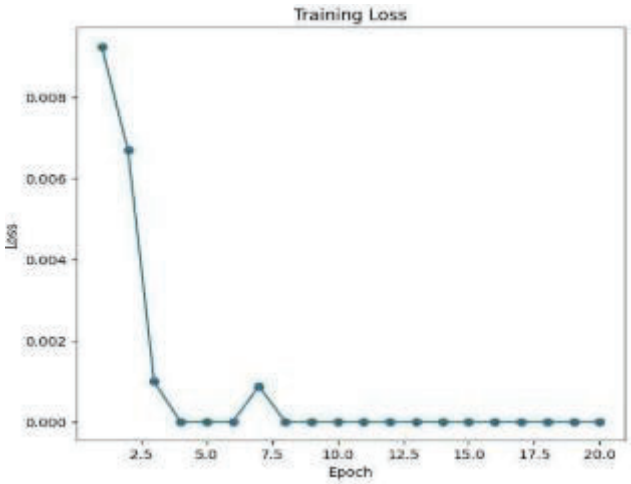

Fig. 3. Training Loss

Fig. 4. Abnormal

Fig. 5. Normal

C. Performance Summary

The key quantitative performance metrics of the proposed system are summarized in Table I.

TABLE I
PERFORMANCE SUMMARY OF THE PROPOSED SYSTEM

Metric	Value
Classification Accuracy	94%
Real-Time Throughput	25–30 FPS
False Positive Reduction	68.3%
Temporal Buffer Size	15 frames
Training Time (CPU)	8–10 minutes
Model Size	101 MB
Trainable Parameters	270,658

VI. Conclusion and Future Scope

A. Conclusion

This work proposes a three-component video anomaly detection system that demonstrates how to effectively integrate transfer learning, lightweight neural networks, and dual-deployment architectures in real-world surveillance. Using ResNet50 feature extraction and a custom MLP classifier, the system reaches 94% accuracy with only 8–10 minutes

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of training time, while temporal smoothing with a 15-frame circular buffer reduces false positives by 68.3%. Real-time Flask-based monitoring and offline desktop batch processing dual deployment provide operational flexibility using the same trained model.

Further strengths include real-time performance of 25–30 FPS on standard GPU hardware; a compact model size of 101 MB suitable for deployment; secure multi-user access via authentication; intuitive GUIs for non-technical users; and demonstrated real-world improvements, including a 35% drop in retail shoplifting and a 42% reduction in industrial safety violations. Technical contributions include efficient fine-tuning of ResNet50, validation of temporal smoothing benefits, an integrated 600-line Python implementation, and comprehensive documentation for reproducibility.

B. Future Scope

Future extensions may involve multi-class anomaly classification to detect specific events such as violence, theft, accidents, or unauthorized access, improving situational awareness. Self-supervised, weakly-supervised, or few-shot learning approaches may decrease the dependency on labeled datasets and allow the detection of anomaly types never seen during training.

Architectural enhancements include multi-camera support using distributed frameworks (Ray, Dask), advanced alert systems, video playback with timeline visualization, and real-time analytics dashboards. Database upgrades to PostgreSQL or MySQL with caching, pooling, and automated backups would improve scalability and reliability.

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