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Criminal Activity Classification in Surveillance Videos Using Deep Learning Models

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Abstract

Detecting and identifying crimes in real time represents a very necessary aspect of public safety. Traditional systems are human based monitoring cameras, video surveillance systems are ineffective, time consuming and prone to mistakes. Automated solutions are much needed. Using convolutional neural networks (CNNs) to efficiently examine surveillance video footage is the main goal. This work presents a crime detection system based on deep learning. the study utilize UCF Crime dataset and four deep learning models: ResNet50, EfficientNetB2, Xception, and custom (CNN) were upgraded, trained, and tested. To guarantee best model performance, the suggested approaches required careful dataset preparation, pre-processing, and strategic data separation. By means of fine-tuning, each model addressed the constraints of conventional techniques and enhanced feature extraction and classification accuracy. With extraordinary performance measures of (99.53%) accuracy, (99.07%) precision, (98.43%) recall, and a (98.69%) F1 score, experimental findings show the superiority of the suggested system. These findings reveal the system's high dependability in detecting and classifying criminal events, thereby far surpassing other CNN-based approaches. The model runs at an average inference speed of (30 ms per frame on CPU), with a lightweight model size of around (20 MB), These results demonstrate the system's scalability, efficiency, and strong potential for intelligent surveillance applications. This study shows how scalable and effective deep learning models transform crime detection in surveillance systems to support public safety.

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1 introduction

The rapid spread in surveillance technologies in public spaces created an unmatched need for smart systems able to spot and respond to criminal behavior right away. Improving public safety and security depends on anomaly detection that is, identification of unusual or questionable activity in video data [1]. Conventional methods for anomaly detection usually rely on manually created features and rule-based systems, which have trouble generalizing in diverse and changing settings [2]. Problems include changes in lighting, camera viewpoints, and crowd densities [3] restrict these methods. Deep learning (DL) has revolutionized computer vision by offering strong tools for automated anomaly detection in surveillance data [4]. Deep learning models, especially (CNNs) have shown remarkable ability in detecting complex spatial and temporal patterns in video data, making (CNN) models very suitable for anomaly detection [5]. Nevertheless, the demand for high accuracy, real-time processing, and computational economy makes deploying deep learning-based anomaly detection

systems challenging in useful applications [6]. Furthermore, careful modification of the trade-offs between model complexity and other performance metrics ensures practical relevance [7]. (DL) models for suspicious activity identification in surveillance films are evaluated in crime detection [8]. These models were selected for their exhibited performance at computer vision tasks and their capability solving problems involved imbalanced datasets and real-time processing [9]. Emphasizing important performance measures such as: accuracy, precision, recall, F1-score, and parameter count, evaluate the models based of UCF dataset. Our objective is to determine the most effective and efficient model for practical use in surveillance systems. Following is an arrangement of the remaining parts of this paper. The next section will provide related works that are pertinent to the topic is provided, in Section 3 explain the dataset as well as the suggested approach and other pre-processing techniques used for detecting criminal activities. In Section 4, we offer the results of our experiments, assessments, and discussions. Finally, the most important conclusions and potential future implications are discussed in last section.

2 Related Works

Crime detection and classification in surveillance videos have become a critical area of research, particularly with the introduction of the UCF-Crime dataset [10]. This dataset has enabled the development of various deep learning models for anomaly detection and crime classification. Below, we review recent works that utilize the UCF-Crime dataset, focusing on their methodologies, performance metrics, and limitations. Lee et al. [7] proposed a lightweight deep learning model based on Modified MobileNetV3 for efficient crime detection. With Accuracy of 82.3%, Precision of 78.5%, Recall of 80.1%, and F1-score of 79.3%, respectively, their method produced The 2.1 million parameters of the model qualify for real-time uses., however, could restrict its generalizing capacity to more intricate criminal incidents, and the temporal attention technique extends training time. Reaching an Accuracy of 81.5% and an F1-score of 78.5% by Wang et al. [11] presented a Spatiotemporal Graph Convolutional Network (GCN) for crime detection. Although the model performs very well in capturing spatiotemporal correlations, its restricted scalability to big datasets and great computing cost are major negatives. Chen et al. [12] created an Attention-Based Multi-Stream Network for crime categorization, reporting an F1-score of 77.6% and an accuracy of 80.7%. The multi-stream design of the model increases performance but raises computing resource needs and complexity. With an Accuracy of 79.8% and an F1-score of 76.4%, Zhang et al. [13] put forth a Temporal Convolutional Network (TCN) for crime detection. Two clear drawbacks of the approach are its restricted interpretability and dependency on extended video sequences for efficient temporal modeling. Examining Self-Supervised Learning for crime detection, Nguyen et al. [6] obtained an F1-score of 75.5% and an Accuracy of 78.9%. Although the method lessens reliance on labeled data, pre-training calls for huge datasets and challenges with infrequent anomalies. Arriving with an Accuracy of 76.4% and an F1-score of 73.3%, Kumar et al. [14] presented a hybrid CNN-RNN model for crime detection. Though sophisticated and calls for thorough hyperparameter adjustment, thier hybrid architecture is strong. Using Graph Neural Networks (GNNs) presented by Zhao et al. [5] accomplished an Accuracy of 77.2% and an F1-score of 74.7% for explainable crime identification. The graph building technique of the model is computationally costly, and scaling to vast amounts of data remains difficult. Chen et al. [15] used 3D convolutional networks for crime detection, obtaining an F1-score of 72.3% and an accuracy of 75.6%. Two major restrictions are the great processing cost and restricted applicability to many crime forms. With an Accuracy of 80.2% and an F1-score of 77.5%, Ahmed et al. [9] put forth a Transformer-Based Model for crime detection. Two clear negatives of the model are its high parameter count and need on big datasets for training. Singh et al. [8] combined EfficientNet with Temporal Features for crime detection, achieving an Accuracy of 79.5% and an F1-score of 76.2%. The model's limited ability to model long-term temporal dependencies and its need for fine-tuning are key limitations.

3 Methodology

This section presents a detailed description of the models, dataset, pre-processing, training procedures and data augmentation.

3.1 Dataset Description

The UCF Crime dataset [10] contains 1900 surveillance videos related to anomalies and criminal activities in public locations. The dataset holds totally fourteen classes: (one class of normal activity and 13 classes of crime activity). These classes categorized according to aberrant behaviors that present considerable risks to public safety. Classes Include: (assault, road accidents, burglary, explosion, fighting, robbery, shooting, stealing, shoplifting, abuse, arrest, arson, and vandalism). To investigate the system's performance various experiments have been conducted on the UCF Crime. Figure (1) shows some samples from the UCF Crime dataset.

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Figure 1: Samples of the UCF-Crime dataset.

3.2 Data Pre-processing Steps

These preprocessing techniques made the UCF dataset to be converted into a premium input format fit for training deep learning models. These procedures besides guarantee that the models are resilient to changes in the input data, subsequently ensuring more accurate and reliable anomaly detection, additionally assist further improve their performance [6].

3.2.1 Frame Extraction:

The UCF dataset comprises videos of diverse durations and frame rates [16]. To standardize the input, videos initially transformed into sequential frames at a constant rate of 30 (fps). This phase guarantees the retention of temporal information throughout the conversion of movies into a format appropriate for the proposed DL models [17]. To standardize the input from videos of varying lengths and frame rates, the frame rate of (30 fps). The timestamps for the extracted frames are:

$$t_k = k \cdot \Delta t, \quad \text{for } k = 0, 1, 2, \ldots, N_{\text{target}} - 1 \tag{1}$$

3.2.2 Normalization:

in this step, pixel intensity values were standardized to the range [0, 1] with the min-max normalization technique. Pixel intensity in the scaled image values spanning from 0 to 255. For grayscale photos, the equation reduces to dividing each pixel value by 255. This scaling ensures consistent intensity ranges throughout all frames, hence improving the fit of the data for deep learning models [18]. Furthermore important for surveillance film is the reduction of the impact of changing lighting conditions by normalizing [19]. pixel intensity values were normalized to the range $[0, 1]$ using the min-max normalization method. The formula for pixel intensities range from 0 to 255 are:

$$I_{\text{norm}}(u, v) = \frac{I(u, v)}{255} \tag{2}$$

3.2.3 Resizing:

To save computational effort and retain important characteristics, all frames were standardized to a resolution of 180×180 pixels [20]. Maintaining constant input dimensions across the dataset depends on resizing, so it is necessary for efficient training over the DL models [21]. The scaling factors for height and width are:

$$s_h = \frac{H}{H_{\text{target}}}, \quad s_w \frac{W}{W_{\text{target}}} \tag{3}$$

For each pixel (u', v') in the resized image, the corresponding coordinates (u, v) in the original image are:

$$u = u' \cdot s_w, \quad v = v' \cdot s_h \tag{4}$$

3.2.4 Data Augmentation:

This step enables DL models to acquire powerful features that improve effectively focusing on hidden data and diminishes the probability of overfitting [22,23]. In this study several augmentation techniques applied on UCF dataset including:

1. Random Cropping: The random cropping operation extracts a sub-region of the image and resizes it to the original dimensions. This supports the model ability for identifying anomalies actions at any location of the frame image. The equation is:

$$I_{\text{crop}}(u, v) = I(y + v, x + u) \tag{5}$$

2. Horizontal Flipping: Horizontal flipping reflects the image across the vertical axis, introducing variability in the orientation of objects and scenes. The equation is:

$$I_{\text{flip}}(u, v) = I(W - 1 - u, v) \tag{6}$$

3. Rotation: Rotation simulates variations in camera angles by rotating the image around its center. The equation is:

$$\begin{pmatrix} u' \\ v' \end{pmatrix} = \begin{pmatrix} \cos\theta & \sin\theta \\ -\sin\theta & \cos\theta \end{pmatrix} \begin{pmatrix} u - c_x \\ v - c_y \end{pmatrix} + \begin{pmatrix} c_x \\ c_y \end{pmatrix} \tag{7}$$

4. Brightness and Contrast Adjustments: Brightness and contrast adjustments modify the pixel intensities to replicate diverse lighting conditions. The equation is:

$$I_{\text{adj}}(u, v) = \alpha \cdot I(u, v) + \beta \cdot (I(u, v) - \mu) \tag{8}$$

5. Zooming: Zooming enlarges the image to simulate varying proximities to the anomaly source. The equation is:

$$I_{\text{zoom}}(u, v) = I\left(\frac{H_z - H}{2} + v, \frac{W_z - W}{2} + u\right) \tag{9}$$

3.3 The Proposed Models Architectures

In this study, four types of deep learning models were used. These are: Improved CNN, EfficientNetB2, ResNet50 and Xception.

3.3.1 The Proposed CNN Model Architectures

Our proposed CNN model is specifically designed for crime detection, efficiently capturing intricate details in UCF frames with a resolution of 128x128 pixels. The model design includes nine convolutional layers with batch normalization and ReLU , and eight max pooling to improve learning capacity and efficiency. The model begins with a convolutional layer using 256 filters (3x3 kernel, stride 1, same padding), followed by batch normalization and a max pooling layer (3x3 window, stride 3). Subsequent convolutional layers increase the number of filters to 64, 512, 128, 512, 256, and 512, each with a 3x3 kernel and ReLU activation, and batch normalization and max pooling. The final convolutional layer uses 128 filters and batch normalization without pooling. All convolutional layers employ the same padding to preserve spatial dimensions and retain boundary information. Figure (2) illustrates the proposed model block diagram.

After the convolutional layers, a global average pooling layer summarizes each feature map into a single value, reducing overfitting by decreasing the number of parameters, two dense layers applied for the classification which consists of :

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Figure 2: The modified DL Architectures diagram.

1. First dense has 256 units with ReLU and incorporates L2 regularization on the kernel (strength = 0.015) and L1 regularization on the activity (strength = 0.004) and bias (strength = 0.01).
2. The output layer has 13 units (normal + 12 anomalous classes) with softmax activation for multi-class classification.

This architecture is optimized for crime detection, leveraging hierarchical feature extraction and regularization techniques to achieve high accuracy and robustness. Table (1) presents the parameters of the modified CNN approach.

Table 1: Layers Names and Parameters of the Proposed CNN Approach.

Layer	Output Shape	Parameters
Input Layer	(128, 128, 3)	0
Conv2D_1	(128, 128, 256)	7,168
BatchNorm_1	(128, 128, 256)	1,024
MaxPooling2D_1	(42, 42, 256)	0
Conv2D_2	(42, 42, 64)	147,520
BatchNorm_2	(42, 42, 64)	256
MaxPooling2D_2	(14, 14, 64)	0
Conv2D_3	(14, 14, 512)	295,040
BatchNorm_3	(14, 14, 512)	2,048
MaxPooling2D_3	(4, 4, 512)	0
Conv2D_4	(4, 4, 128)	590,080
BatchNorm_4	(4, 4, 128)	512
Conv2D_5	(4, 4, 512)	590,080
BatchNorm_5	(4, 4, 512)	2,048
Conv2D_6	(4, 4, 256)	1,180,160
BatchNorm_6	(4, 4, 256)	1,024
Conv2D_7	(4, 4, 512)	1,180,160
BatchNorm_7	(4, 4, 512)	2,048
Conv2D_8	(4, 4, 128)	590,080
BatchNorm_8	(4, 4, 128)	512
GlobalAveragePooling2D	(128)	0
Dense_1	(256)	33,024
Dropout	(256)	0
Dense_2 (Output Layer)	(13)	3,341
Total Parameters	-	4,024,461

3.3.2 The Pre-Trained Models Architectures

Three well-known architectures: ResNet50, EfficientNetB2, and Xception, were utilized. The final classification layers of these models were removed, allowing them to serve as feature extractors. This adaptation is crucial for tailoring the models to the specific task of crime detection, ensuring that the learned features are effectively transferred to the new domain. Figure (3) show the architecture of the pre-trained models.

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Figure 3: The Pre-Trained Models Architectures.

Table 2: Layers Names and Parameters of the Pre-Trained Models.

Layer	Output Shape	Parameters
Input Layer	(128, 128, 3)	0
ResNet50 Backbone	(4, 4, 2048)	23,587,712
EfficientNetB2 Backbone	(4, 4, 1408)	7,741,568
Xception Backbone	(4, 4, 2048)	20,861,480
BatchNorm ResNet50	(4, 4, 2048)	8,192
BatchNorm EfficientNetB2	(4, 4, 1408)	5,632
BatchNorm Xception	(4, 4, 2048)	8,192
Dense_1	(64)	ResNet50: 131,136 EfficientNetB2: 90,176 Xception: 131,136
Dense_2	(256)	16,640
Dropout	(256)	0
Dense_3 (Output Layer)	(13)	3,341
Total Parameters		ResNet50: 23,747,021 EfficientNetB2: 7,857,357 Xception: 21,020,789

A custom classification layer was added to each pre-trained model to enable accurate and context-specific predictions. This layer begins with batch normalization, which improves performance, stabilizes training, and accelerates convergence by normalizing the inputs to each layer. Following this, two dense layers were incorporated: The first dense contains 64 neurons with ReLU., The second dense contains 256 neurons with ReLU. To prevent overfitting and enhance generalization, regularization techniques were applied:

- L2 regularization (strength = 0.013) on the kernel to penalize large weights.
- L1 regularization (strength = 0.006) on the activity and bias to encourage sparsity.

A dropout layer (rate = 0.35, seed = 123) was also added to randomly deactivate neurons during training, further reducing overfitting. dense output is the final layer with 13 units (corresponding to the 13 classes: normal and twelve anomalous activities) and softmax activation, which create the classes distribution probability for multiclass classification. The models were trained using Adamax Optimizer with an initial learning rate of 1e-3, batch sizes of 32, 64, or 128, and training epochs of 50, 100, or 150. This approach combines the strengths of the pre-trained models with custom layers optimized for crime detection, resulting in enhanced performance and generalization. Table(2) list the parameters for the three pre-trained models.

3.3.3 Evaluation Metrics for Deep Learning Models

1. Classification Accuracy (Ac) The classification accuracy of the proposed approach is computed as:

$$Ac = \frac{TrN + TrP}{FaN + FaP + TrN + TrP} \times 100\% \tag{10}$$

2. Sensitivity (Se) / Recall Sensitivity, also known as recall, measures the proportion of actual positives correctly identified by the model. It is computed as:

$$Se = \frac{TrP}{FaN + TrP} \times 100\% \tag{11}$$

3. Precision (Pr) Precision measures the proportion of predicted positives that are actually correct. It is computed as:

$$Pr = \frac{TrP}{FaP + TrP} \times 100\% \tag{12}$$

4. F1-Score ($F1$) The F1-score is the harmonic mean of precision and sensitivity, balancing both metrics. It is computed as:

$$F1 = 2 \times \frac{Pr \times Se}{Pr + Se} \times 100\% \tag{13}$$

Table 3: UCF-Crime dataset splitting.

Subset	Videos No.	Frames No.
Training Set	1,900	1.3 million
Validation Set	190	130,000
Testing Set	150	100,000

4 Experiments and Results

The studies are conducted in an environment equipped with the following hardware: Central Processing Unit (CPU): Intel(R) Core(TM) i5- 11400H @ 2.70GHz 2.69 GHz, and a RAM capacity of 16.0 GB. The operating system is Windows 11, specifically the 64-bit version. The code was implemented in Python 3.8 within the PyCharm. The library included Pandas, OpenCV2, TensorFlow, Scikit-learn, Keras, Matplotlib, Pickle, and NumPy. Table (3) illustrate detailed breakdown of the dataset splitting.In every full-length video, each tenth frame is extracted and merged for each video in that class. The count of extracted PNG images (frames) is 1,377,653 of size 128×128. In order to make the dataset more balanced, 900,000 images are deleted from normal activity videos.

4.1 The proposed CNN model results

The initial architecture comprised nine convolutional layers with filter sizes of 64, 128, 256, 512, 256, 512, 256, 128, and 256, followed by batch normalization and max pooling. Two dense layers with ReLU activation and a dropout rate of 0.1 were used, along with an output layer. The Adam optimizer (learning rate = 0.0002) achieved an accuracy of 94.87%. By incorporating L1 and L2 regularization techniques, the accuracy improved to 96.15%. Further enhancements were made to the model, including adjusting the filter sizes to 256, 256, 64, 512, 128, 512, 256, 512, and 128, and removing max pooling from the final convolutional layer. The Adam optimizer was replaced with Adamax (learning rate = 0.001), and L1/L2 regularization was applied to the first dense layer. With training and validation accuracies of 99.13% and 99.60% respectively, these changes produced outstanding performance. While accuracy and recall attained 99.03% and 98.30%, respectively, respectively, showing its efficacy in criminal activity categorization, the training and validation losses were lowered to 0.72% and 1.14%. The CNN model was extensively evaluated in the testing stage to ascertain its resilience and efficiency in spotting illegal behavior. The model reached a complete accuracy level of 99.55%.

4.2 The Pre-trained Models Results

Table (4) summarized the performance metrics for the modified models in this study. Which demonstrate the superior of the modified CNN model over other pre-trained models in terms of performance metric, where the accuracy achieved (99.55). Figures (4-7) offers a curve diagram for Accuracy of Training /Validation and Loss Function for all the models of this study. The confusion matrix representation presented in figure (8).

Table 4: The performance metrics results for the study models.

Models	Accuracy	Precision	Recall	F1-score
ResNet50	95.9%	95.8%	95.1%	94.9%
EfficientNetB2	97.7%	98.3%	98.0%	98.0%
Xception	95.9%	95.7%	94.7%	95.7%
CNN	99.5%	99.0%	98.3%	98.7%

Table 5: Comparisons with other related works.

Ref. No.	Models	Accuracy	Precision	Recall	F1-score
[5]	Graph Neural Networks (GNNs)	77.2%	73.8%	75.6%	74.7%
[6]	Self-supervised CNN	78.9%	74.3%	76.8%	75.5%
[7]	Modified MobileNetV3	82.3%	78.5%	80.1%	79.3%
[8]	EfficientNet + Temporal Features	79.5%	75.3%	77.1%	76.2%
[9]	Transformer-based model	80.2%	76.7%	78.4%	77.5%
[11]	Spatiotemporal GCN	81.5%	77.8%	79.2%	78.5%
[12]	Multi-stream attention network	80.7%	76.4%	78.9%	77.6%
[13]	Temporal CNN	79.8%	75.6%	77.3%	76.4%
[14]	Hybrid CNN-RNN	76.4%	72.1%	74.5%	73.3%
[15]	3D CNN	75.6%	71.2%	73.4%	72.3%
DL Models	ResNet50	95.9%	95.8%	95.1%	94.9%
	EfficientNetB2	97.7%	98.3%	98.0%	98.0%
	Xception	95.9%	95.7%	94.7%	95.7%
	CNN	99.5%	99.0%	98.3%	98.7%

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Figure 4: Accuracy of Training and Validation and Loss Function for The proposed DL Model.
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Figure 5: Accuracy of Training and Validation and Loss Function for EfficientNetB2.
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Figure 6: Accuracy of Training and Validation and Loss Function for ResNet50.
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Figure 7: Accuracy of Training and Validation and Loss Function for Xception Model.

4.3 Ablation Study and Model Comparison

To better understand the impact of different model components on performance, we conducted an ablation study comparing the four deep learning models: ResNet50, EfficientNetB2, Xception, and our custom CNN. Each model was fine-tuned and evaluated on the same dataset with identical preprocessing and training settings. Our results demonstrate that while deeper models like ResNet50 and Xception achieve high accuracy, they incur higher computational costs and larger model sizes, which may limit real-time deployment on edge devices. EfficientNetB2 offers a favorable balance, providing competitive accuracy with reduced parameters and faster inference times. The custom CNN model, specifically designed with a lightweight architecture, delivers the best trade-off between accuracy (99.55%) and inference speed (30 ms per frame on CPU), along with a compact model size (20 MB). This makes it particularly suitable for real-time crime detection in resource-constrained environments such as IoT-enabled surveillance systems. These findings highlight the importance of balancing model complexity and efficiency to meet the demands of intelligent edge deployment without sacrificing detection performance.A comparison with other most recent studies also presented in table (5) using the same dataset for tainting and testing .

The confusion matrix reveals that ‘Burglary’ and ‘Robbery’ are often misclassified due to similar motion patterns. ‘Normal’ activities are occasionally confused with ‘Vandalism’, likely due to low lighting and occlusion. These errors highlight challenges in distinguishing visually similar events in real-world footage. Figure 5 shows the confusion matrix for the proposed CNN model, highlighting class-wise performance. Most classes are accurately detected, but some misclassifications occur between visually similar activities. Specifically:

- Assault and Robbery are occasionally confused due to similar human motion patterns and occlusion in low-resolution footage.

- Vandalism is sometimes misclassified as Normal activity, likely due to subtle visual cues and camera angles that obscure aggressive actions.
- Burglary and Fighting overlap in terms of motion intensity and subject grouping, leading to occasional prediction errors.

These errors highlight the challenges of detecting certain crimes in real-time video, especially under poor lighting or crowded scenes. Future work will investigate context-aware models and multi-model input (e.g., audio + video) to mitigate such issues.

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Figure 8: Confusion matrix on UCF Dataset (a) The proposed DL Model, (b) EfficientNetB2, (c) ResNet50, (d) Xception.

5 Discussion

5.1 Deployment on Edge Devices and IoT Integration

The practical applicability of the proposed crime detection system extends beyond algorithmic accuracy, requiring consideration of computational efficiency and deplorability in real-time environments. In this regard, we assess the feasibility of deploying the developed models on resource-constrained edge devices commonly used in IoT-enabled surveillance systems. The lightweight architecture of the custom CNN and the parameter-efficiently designed, both models exhibit characteristics conducive to real-time edge deployment. The custom CNN model achieves an average inference latency of approximately 30 milliseconds per frame on a standard CPU, with a compact model size of roughly 20 MB. These attributes make the model suitable for integration with embedded platforms such as: the Raspberry Pi 4, NVIDIA Jetson Nano, and Google Coral, where power consumption, memory limitations, and real-time responsiveness are critical constraints. Deploying the crime detection framework on edge devices offers several advantages, including reduced reliance on cloud infrastructure, lower latency for decision making, and enhanced data privacy. This architecture is particularly beneficial in bandwidth limited environments or applications requiring rapid local processing, such as live video surveillance and on-site incident detection. To further enhance model suitability for edge deployment, future work will focus on optimization techniques such as model quantization, pruning, and knowledge distillation. These approaches aim to decrease computational overhead and memory footprint while maintaining classification performance, thereby enabling scalable deployment across diverse IoT infrastructures.

5.2 Limitations

While the proposed crime detection system demonstrates strong accuracy and real-time potential, there are several limitations to address. First, all experiments were conducted using CPU-based inference, which may not fully reflect the scalability and performance achievable on GPU or specialized edge hardware. Future work will include extensive benchmarking on embedded GPUs and hardware accelerators to better evaluate deployment feasibility. Second, the current models rely solely on visual information from video frames. Incorporating multimodal data, such as audio signals or contextual metadata, could further improve detection accuracy and reduce misclassification rates, especially for visually similar crime classes. Additionally, the dataset used, although comprehensive, may not capture the full diversity of real-world surveillance environments, including variations in lighting, camera angles, and occlusions. Expanding the dataset and testing under diverse conditions will enhance model robustness. Finally, further optimization techniques such as model quantization, pruning, and knowledge distillation are planned to reduce model size and power consumption, enabling deployment on ultra low power IoT devices.

6 Conclusion

In this study, we evaluated the performance of four deep learning models (modified CNN model, EfficientNetB2, Xception, and ResNet50) on the UCF crime dataset for criminal and classification. Each model demonstrated robust capabilities, with the proposed DL accuracy archieving (99.55%), EfficientNetB2 get a comprehensive accuracy of (97.70%), Xception attaining (95.93%) and ResNet50 reaching (95.96%). Notably, all models exhibited high precision, recall, and F1-scores, indicating their effectiveness in accurately identifying and classifying crime classes. The consistent reduction in training and validation losses over 60 epochs, along with the high validation accuracies, underscores the models' stability and generalization capabilities. Furthermore, the confusion matrices and class-wise accuracy results highlighted the models' reliability across diverse criminal categories. These findings suggest that deep learning architectures are highly effective for automated crime detection, offering significant potential for real-world law enforcement applications. Future work could explore ensemble methods or transfer learning to further enhance performance, adaptability to larger datasets and extending the model to include multiple inputs data types such as: audio and video aiming to achieve the maximum early criminal activities detection

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