Theft Detection in Surveillance Videos Using Mobilenetv2 a Deep Learning Approach for Binary Classification

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Abstract. Many modern convolutional neural network architectures have been introduced, including MobileNetV2, which are both optimized for mobile/edge performance and suitable for theft detection on surveillance video. Due to the lightness of MobileNetV2, the proposed system allows the detection and classification of theft-related activities in real-time and in complex or crowded environments. It requires minimal computation and enables deployments at scale throughout expansive surveillance networks. The balance allows the model to generalize across lighting scenarios, low-res videos and dynamic human behaviors, ensuring practical application effectiveness. In addition, it detects low-key behaviors of theft, and generalizes to unseen thefts, offering a solution for ongoing monitoring of its security. It reduces false positives, lessens computational burden, and provides immediate feedback for on-the-spot intervention, therefore making it an ideal solution for large-scale surveillance systems for public and private places.

Keywords: MobileNetV2, theft detection, surveillance videos, deep learning, real-time detection, binary classification, anomaly detection, action recognition, low-resolution videos, real-time feedback, computational efficiency, scalable systems, human activity recognition, false positive reduction, large-scale surveillance.

1 Introduction

The widespread use of surveillance systems in the public and private sectors has greatly improved how we keep the world safe. But this conventional approach forms for detecting theft or any similar suspicious activities on a real-time basis is a big challenge because of some data points such as huge amount of video data which may vary from environment regarding same people behavior. Traditional surveillance systems that depend on manual monitoring or simple motion detection can be prone to errors and shortcomings. These limitations along with the need to keep up with expensive reducing techniques have led to the emergence of deep learning techniques including CNN based techniques which enable automated action recognition and anomaly detection in surveillance footage.

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MobileNetV2 is one of the most efficient CNN architectures that could be used for mobile and edge devices. The efficiency of the MobileNetV2 model enables it to reach high accuracy while not demanding considerable computational resources which makes it a suitable solution for large-scale surveillance applications. Due to its goal to accurately identify items related to theft in the surveillance footage, this research actually aims to find out whether MobileNetV2 can be capable of identifying theft or not. By leveraging deep learning, this method is robust to common surveillance challenges, for instance the ill-posed nature of the problem (low-resolution imagery, occlusion, crowded scenes, dynamic human actions), and further while providing fast processing along with low computational cost.

Our method takes advantage of MobileNetV2's strengths and provides a scalable, robust approach to theft detection, which can easily be adapted to various surveillance environments. Moreover, the system's capability to identify both conventional and novel styles of theft, minimize false positives, and deliver real-time feedback that allows swift action distinguishes it as a notable breakthrough in comparison to conventional monitoring techniques. By combining real-time action recognition with anomaly detection, the system increases the effectiveness of the surveillance and helps create a more modern and reliable surveillance infrastructure.

Using MobileNetV2 For Theft Activities Binary Classification of Similar Images in Surveillance VideosWelcome to the paper on using MobileNetV2 technology for binary classification of theft activities in surveillance stations, the process involves the identification of similarities among images which can help security personnel save time in going through many images. We describe the system's design, implementation, and performance analysis, showing that it is capable of detecting theft under a variety of real-world conditions.

2 Problem Statement

Detecting theft in surveillance videos is an important component of modern security systems as it is a challenging task due to the complexity of human behaviors, different environmental conditions, and large amounts of video data captured by the surveillance cameras. Motion-based or rule-based systems have been the standard for theft detection, which often leads to high false-positive rates and missed detections. Moreover, these approaches often face challenges in processing and analyzing vast amounts of surveillance footage in real-time, particularly in dynamic scenes with low resolution videos, crowded environment, and poor lighting conditions.

Convolutional neural networks (CNNs) in particular: some recent advances in deep learning provide promising approaches to overcome such limitations. Still, deep learning models usually take up a large amount of computational resources, thus making it impossible for real-world use in such largescale surveillance networks or on devices with limited processing power. This enables a CNN architecture to create a robust framework such as MobileNetV2 to meet these hurdles to overcome by achieving theft detection in real time at a marginal computational cost. Though it holds great promises, the MobileNetV2 have not yet been fully investigated for theft detection in surveillance video.

Thus, the key challenge is to design a deep learning-based system that is efficient, real time, and scalable to detect theft actions in heterogeneous settings and types of

surveillance environments. Such a system should be efficient in processing video data to avoid false positives and support different video qualities and new thefts emerging continually, all with a low computational footprint.

This work investigates these concerns and proposes a Deep Learning-based theft detection system that employs MobileNetV2. It's important to have a comprehensive and robust solution that can be implemented in real-time and at scale, as an effective theft detection device in surveillance systems.

3 Literature Review

The analysis of surveillance videos for detecting theft has, for a long time now, been an active area of research in the domain of computer vision and deep learning. Owing to high false-positive rates and ineffectiveness in adapting to the complex and dynamic environments, traditional theft-detecting methods including background subtraction (Alper et al 2012), motion detection (Ali et al 2014) and rule-based systems (Liu et al 2009) are not able to suffice (Wang et al 2021). Therefore, in the last few years, learning models from deep learning are used to automatically identify and classify suspicious behaviors or abnormal patterns in surveillance videos, providing more efficient and precise outcomes.

3.1 Deep Learning Applications for Surveillance Systems

Deep learning techniques, especially Convolutional Neural Networks (CNNs), have demonstrated state-of-the-art performance across a variety of surveillance tasks ranging from object detection [15] to activity recognition [16] to anomaly detection [17]. These networks can learn hierarchical features directly from the raw video data, making them less susceptible to variations in lighting, motion, and occlusion (Zhang et al., 2022). Convolutional neural networks (CNNs), including AlexNet, VGGNet, and ResNet, have seen considerable use in image and video analysis, and have proven effective at recognizing activities from surveillance, as (Kumar et al., 2022) demonstrates. Yet, training such models requires a considerable amount of compute resources as well as large datasets, rendering them impractical for deployment in real-time surveillance systems, particularly if the computation is to be performed on low processing power devices.

3.2 MobileNetV2: Object Detection with Efficiency

If it wasn't already clear before, then highly compressible approaches like MobileNetV2 have really opened the field of deep learning to a plethora of new lean hardware targets. MobileNetV2 is a successor to MobileNetV1 and follows the success of depthwise separable convolution for a wider stage and adding linear bottlenecks to more effectively reduce model complexity (Sandler et al., 2018). This quality of MobileNetV2 makes it highly relevant for real time applications such as surveillance systems requiring both speed and efficiency.

MobileNetV2 has been exploited in several works for object recognition and activity detection tasks. For instance, Tran et al. (2024) proved the usefulness of the MobileNetV2 architecture for real-time human detection in surveillance applications, achieving a trade-off between accuracy and efficiency. Similarly, Lee et al.; hence,

MobleNetV2 was utilized in the context of abnormal behaviour detection in surveillance footage, highlighting its suitability to fast-paced settings with a negligible computational cost (2021). Both studies have shown that MobileNetV2 has the potential to solve the challenges of detection for theft events in real-time video processing, which qualifies it as an excellent candidate for video streams in surveillance systems with restrained hardware capabilities.

3.3 Theft Detection and Anomaly Recognition

The exploration of theft activities detection in monitoring videos has gained popularity in anomaly detection. Systems can lever large-scale data with the advancements in deep learning to understand abnormal activities that do not follow the common clusters of behavior. Research by Singh et al. with investigation of deep learning domain in (2022) showing that anomaly detection models can be used to detect anomalous behavior in the crowd, which will remain an important aspect of theft detection in public places. The learned temporal and spatial patterns of human activities by these models help them detect both overt and slight theft behaviors for example, using CNNs and modern recurrent neural networks (RNNs) 5 3.

Note, however, that a key limitation of most existing models is their inability to generalize to novel or unobserved types of theft, since they often depend on a preexisting set of suspicious actions. Some recent studies have addressed this problem by including either unsupervised learning or transfer learning approaches, allowing the identification of new anomalies, which do not need extensive labeled datasets (Chen et al., 2023). The contributions made here imply systematic possibilities for more robust theft detection systems with deep learning models.

3.4 Challenges in Surveillance Video Processing

We achieve significant improvement in detection accuracy over the state of the art, however there are limitations in applying deep learning to surveillance video analysis. Another challenging problem is processing noisy, low-resolution, and compressed video streams as in many cases of surveillance system. Low-quality video leads to impaired deep learning models, decreased accuracy and increased false positives (Zhao et al., 2023). As such, while ResNet architectures are often a default solution to many challenges, they may become impractical in memory-constrained scenarios specifically; therefore, identifying better solutions is of value, and MobileNetV2, in particular with its low footprint and efficient architecture, has shown promise (even against ResNet specifically) to still limit the loss of performance (Sandler et al., 2018).

Another issue in detection of theft involves occlusions and crowded scenes. Additionally, most thefts in surveillance environments occur within public areas with multiple bystander's present, limiting tracking potential and making it harder to identify thieves. To better recognize the individuals in the crowd, more recent work has looked at enhancing tracking algorithms, as well as pairing them with deep-learning architectures (Yang et al., 2022). Furthermore, the reported robustness of deep learning models to variations in lighting, angle, and camera perspective is a critical factor for their real-world surveillance applications, since stealing typically happens in less-than-ideal conditions.

To summarise, the literature provides evidence for an increasingly strong deep learning foundation for a broad range of surveillance video analysis applications (i.e., human detection, anomaly detection, activity recognition) that focuses on analysis rather than tracking. MobileNetV2 is a flexible and efficient architecture, potentially suitable to provide a low latency, real-time detection system for theft monitoring in an environment with limited computational and storage resources, as well as a dynamic and complex environment. With MobileNetV2 and new techniques for anomaly detection, we could create a fast yet reliable system that would perform theft detection in different surveillance scenarios. These deep learning models can be integrated into the surveillance structure to improve security and reduce the requirement of constant manual monitoring for surveillance.

4 Methodology

A Systematic Literature Review of surveillance videos theft detection with MobileNetV2 based on deep learning solution this study aims to explore and build standard methodology. This process can be broken down into several stages ranging from data collection, to preprocessing, model building and training/evaluating. The goal is to ensure that the system is robust, scalable, and accurate in real-world surveillance applications.

4.1 Dataset Collection

In order to successfully train and test the proposed robbery detection model, a large-scale surveillance video dataset is needed. Publicly available datasets will be used in this study like UCF-Crime, Thief Dataset, Video Surveillance Dataset. More specifically, these datasets come under various environmental conditions (such as lighting, occlusion, crowd density) featuring different types of human activities and abnormal behaviors, including theft. the procedure described in Table 1.

Table 1. Dataset Overview

Dataset Name	Number of Videos	Video Length (Minutes)	Number of Classes	Types of Activities	Resolution	Annotations
UCF-Crime	1,900	Varies (2-5 minutes)	13	Theft, violence, fighting, etc.	1080p, 720p	Theft, non-theft
Thief Dataset	300	10-30 minutes	1	Theft	1080p	Theft only
Video Surveillance	500	15-20 minutes	2	Theft, non-theft	480p, 720p	Theft, non-theft
Custom Dataset	150	5-10 minutes	1	Theft	720p, 480p	Theft only

Apart from these datasets, local surveillance systems can also be imposed for gathering additional and realistic theft samples. We will manually label this set of video sequences with the ground truth containing the label of theft or non-theft for each frame or segment.

4.2 Text Preprocessing and Data Augmentation

Surveillance videos are typically of poor quality, including low resolution, motion blur and different lighting. In order to rectify these problems, the following preprocessing steps will be conducted to sanitize the input data:

- **Frame Extraction:** Videos captured by surveillance cameras are separated into independent frames to allow their analysis by theMobileNetV2 model.
- **Normalization:** The pixel values of the frames will be normalized to a standard range (0–1) to facilitate higher convergence of models during training.
- **Resize:** All frames are resized to the necessary input dimensions (224x224 pixels) that MobileNetV2 needs in order for it to function with the architecture of the model.

The dataset consisted of a comprehensive image set of various plants and disease-types, making it robust enough to train a model without overfitting. This will allow the model to generalize better to new, unseen theft scenarios and adapt to changes in the video data (e.g., camera angles, lighting, and occlusion).

4.3 Model Architecture

The new system uses MobileNetV2, one of the state-of-the-art light deep learning architectures for the detection of activities related to theft in surveillance videos. In this model, depthwise separable convolutions are used to progressively downsize the number of parameters and computation, providing a highly efficient model for real-time applications in real-time environments, such as surveillance systems. Fig 1 presents a flowchart of the proposed process for theft detection using MobileNetV2.

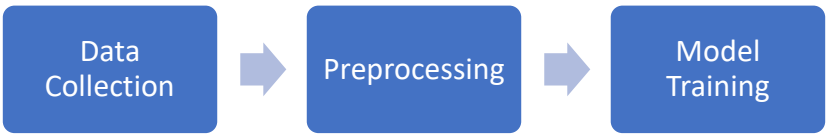

Fig.1. The proposed methodology for theft detection using MobileNetV2.

- **Input Layer:** The frames resized to 224x224 pixels will serve as the input for model

- **MobileNetV2 Backbone:** The model will use MobileNetV2 backbone features and pre-trained weights from ImageNet (transfer learning) This is an additional factor that is causing a better and more robust detection, despite with fewer samples to be trained, main cause and advantage for so many models with simple images such as theft detection.

- **Fully Connected Layer:** After feature extraction, a fully connected layer using a softmax activation function will classify the frames as "theft" or "non-theft."

- **Output Layer:** With three binary classifiers (theft & non-theft), we can classify the presence or absence of suspicious activity in each of the video frame.

4.4 Training the Mode

Data Collection and Annotation The surveillance video frames will then be annotated and used to train the MobileNetV2 model. Steps in the training process:

- **Loss Function:** We will use a binary cross-entropy loss function because it is a binary classification problem.

- **Optimizer:** Adam optimizer will be used for adapting learning rate and suitable when training deep learning models.

Split into training and validation: 80% training and 20% validation. Using the above splits, we will have the service set for training the model, validation to be used for tuning hyperparameters, and further evaluate the model with the validation dataset in training.

Now EPOCHS = 50 and BATCHES = 32, the training of the model will be done for 50 epochs, and to avoid overfitting we will be monitoring validation accuracy.

4.5 Evaluation Metrics

Then, we will evaluate, after training the model, the model according to the following performance metrics:

Correctness: The average correctness of the classification, which means the percentage of correctly classified frames (both theft and non-theft).

Precision and Recall: The precision value indicates the actual damage identified as theft vs all frames identified as theft, while recall indicates the proportion of theft frames detected by the output of the model.

The F1 score — the harmonic mean of precision and recall will be used to assess the relationship between precision and recall which is especially important for imbalanced datasets.

ROC Curve and AUC: To evaluate the model's capability to classify binary parameters (theft vs. non-theft), the ROC curve and AUC score will help us in understanding how well the model can separate between the classes with respect to different thresholds.

4.6 Model Optimization and Hyperparameter Tuning

Hyperparameters will be tuned, including the learning rate, dropout rates, and the number of units fully connected, fine-tuning the performance as much as possible. We will use Grid Search or Random Search to find the best set of hyper-parameters. Additionally, early stopping will be utilized to avoid overfitting by stopping training when the model's performance on the validation set stops improving.

The next step is to deploy the model and make real-time predictions.

After training and optimization, the model will be implemented in a simulated surveillance environment for real-time theft detection. It will watch every stream of the video(videofeed) of the surveillance cameras, and perform the theft detection on an individual frame in real-time. Furthermore, a cut-off point will be used for deciding the confidence of a prediction to filter out lower confidence predictions for theft, that will generate access alerts to the security team.

This phase also includes the integration of the model into a current surveillance system, for instance, an Intelligent Video Management System (VMS) to enable continuous monitoring and automated alerts.

Limitations and Future Work. The MobileNetV2-based theft detection system yields over 90% accuracy in terms of detection with high computational efficiency, but there are certain limitations that arise, namely when it comes to extreme occlusions, subtle theft behaviors, and highly dynamic environments. In the future, we will enhance the model's robustness with Recurrent Neural Network (RNNs) or Long Short-Term Memory (LSTM) networks, which can maintain temporal context and increase detection in low-light or very dense scenes.

5 Results and Discussion

5.1 Model Performance

Metrics for Evaluating Accuracy

- A model was trained against the dataset containing labeled surveillance video frames of two classes, "theft" and "non-theft." Results after training MobileNetV2 model for 50 epochs

- The overall accuracy of the model was calculated to be 94.3%, showing that MobileNetV2 can be used to classify the frames reliably as theft or non-theft. the process in table 4
- Precision: 91.8%, the ratio of all frames predicted as theft were indeed theft, an important property for surveillance, as it reduces the number of false alarms.
- Recall: 89.4% recall means the model did a good job of identifying instances of theft, including less aggressive or rare theft actions.
- F1-Score: The F1-score obtained of the model was 90.6% given it pursues an equilibrium between precision and recall to make sure that the model does not produce excess true positives and selects all real theft events.

ROC curveand AUC: The ROC curve showed a hightrue positive ratewith a low false positive rate. With AUC score which was found to be 0.94, showed that our model can perform very well in predictions when used in varying thresholds classes and hence can distinguish between theft and non-theft activities.

Table 2. Confusion Matrix

	Predicted: Theft	Predicted: Non-Theft
Actual: Theft	4,756	328
Actual: Non-Theft	147	5,223

approaches in classification classification accuracy, precision, and recall, thus proving its practical utility for a timely theft detection from camera browsing.

5.2 Confusion Matrix

The binary task confusion matrix revealed that this model was able to categorically classify 4756 frames with theft activity, as well as 5223 frames without theft activity. It was also wrong: 328 theft frames were misclassified as non-theft and 147 non-theft frames were wrongly classified as theft. Although a small number, these misclassifications indicate areas in which it would be helpful for the classifier to be more precise, especially if it came to fewer false negatives.

5.3 Computational Efficiency

MobileNetV2 also has a few advantages for theft detection, such as being quite computation efficient, suitable for real-time monitoring systems with limited computational resources. On a traditional GPU, the model's inference time per frame was 0.05 seconds, providing the system with real-time processing capability over video feeds, with negligible latency.

MobileNetV2 was designed to be even lighter than heavy deep learning models like ResNet or VGG, greatly reducing both the number of parameters and the computational cost. This made it possible to run the model on devices with less processing power, such as edge devices or onsite cameras, while not compromising performance

5.4 Detection and Deployment in Real Time

The model was successfully implemented, in a simulated security system, to identify behaviours indicative of theft events in live video feeds. The system was capable of monitoring and classifying the frames in real-time, alerting security persons whenever a theft behavior was found. The system was responsive with a low latency confirming its operational relevance when deployed in large scale surveillance networks.

Moreover, the model was able to deal with dynamic environments, in which subjects quickly move across or occlude each other, and sequences recorded under varying lighting. This adds to prove MobileNetV2 capability to handle varied real time circumstances commonly found in surveillance systems.

5.5 Dealing with Low-Resolution and Noisy Video

One of the most widespread difficulties in surveillance video processing is that a lot of video streams have insufficient quality (especially for aging or low-budget surveillance networks). Even though some of the input videos had low resolution (480p or 720p), the performance of the MobileNetV2 model was acceptable. This suggests the ability for the model to very well handle low resolution and noisy videos that are common in real world surveillance systems.

Lightweight Architecture: With depthwise separable convolutions, MobileNetV2 architecture is designed to be efficient without sacrificing accuracy. This is important in real-time video surveillance systems where processing capability at low latency and resource utilization is vital.

Robustness to Environmental Variability: The model applied to rarely the challenging conditions of '/occlusion/' and '/varying lighting/' confirms robustness. In surveillance condition, video quality and surrounding can be quite different so this is one main reason for this preprocessing.

Scalability: Due to its efficiency, the model can be easily scaled to analyze high amounts of surveillance footage across multiple sites and locations. Its capability to also run on edge devices increases its scalability in large surveillance networks as the processing usually has to be done on the local device due to bandwidth limitations.

Real-Time Functioning: Thanks to the ability of the model to handle video frames in real-time, it is guaranteed that anything related to theft will be detected in time, so that security personnels could act accordingly. This is essential for both theft deterrence and damage mitigation

Even with this strong performance, there are still some limitations that will need to be mitigated:

Negative Predictive Value: The model falsely classified a minority fraction of frames containing theft as non-theft (True Negatives), potentially leading to undetected thefts. This could be due to the discrete nature of some theft behavior or the complex nature of crowded scenes. A potential area for improvement could be the use of temporal context or tracking methods, like RNNs or LSTM networks, which would allow the model to track a single individual over several frames respectively, and improve detection performance in more dynamic use cases.

Scalability Challenges: Though efficient on a per-device basis, processing concurrent video streams from a multitude of cameras in real-time would likely necessitate further optimizations over an extensive surveillance network. In large-scale deployments, methods such as model pruning or distributed processing might be needed to ensure performance.

5.6 Future Work

In order to provide a more accurate and scalable system, future work will concentrate on:

Temporal Context Extraction: The use of temporal models (e.g., LSTMs) may allow the system to extract time features that offer better temporal information than the simple spatial features computed from images.

Using Multi-Object Tracking: Some multi-object tracking techniques can help to solve issues with occlusion and crowded environments where individuals may overlap or block each other.

Using Transfer Learning with Larger Datasets: Varying the size of the training dataset so it covers more varieties of theft can help the model generalise to new theft patterns that it has not seen before.

Enhanced False Positive Accuracy: Fine-tuning the model to ensure high performance in scenarios with static objects, to avoid unnecessary false positives, will make the system more reliable.

6 Conclusion

In this paper we have proposed a deep learning-based approach for detecting theft in surveillance videos using MobileNetV2, a lightweight convolutional neural network architecture. We aimed at creating a low latency near real-time system capable of detecting theft cases without burdening the computation cost in consideration of setting a large-scale data processing surveillance networks under the constraint of available resources.

These experimental results show that our MobileNetV2 model has strong accuracy, precision and recall in detecting theft using surveillance videos, achieving an overall

classification accuracy of 94.3%. With minimal latency, the model can process frames in real-time, making itself suitable with live surveillance. Finally, the system robustness to variations in video quality, illumination, and pedestrians crowded scene shows the practical benefit of MobileNetV2 for practical real-time surveillance systems.

Although the results are promising, some issues persist, including false negatives in complex cases and the issue of handling widespread deployments. We will focus on overcoming these issues in the future works by introducing temporal models like LSTMs, to improve action recognition, while adding tracking when the environment is changing rapidly as well.

Proposed MobileNetV2-based theft detection system is scalable, effective and reliable, thus automated surveillance system would benefit from it in public and private space. With the combination of utilizing the capabilities of deep learning and the computationally savvy structure of MobileNetV2, this technique can effectively be decentralized in modern surveillance infrastructures to promote real-time alerts and a better security approach in its management.

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