Real-Time Anomaly Detection in Surveillance Systems Using Convolutional Neural Networks

A Project Report

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by

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I would like to take a moment to express my heartfelt gratitude to my mentor who has supported me in this internship journey.

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ABSTRACT

Detecting anomalies in surveillance footage is essential to ensure public safety and prevent security threats. This project focuses on developing a system that processes input images from surveillance systems and classifies them as **anomalous** or **normal** using **Convolutional Neural Networks (CNNs)**. The goal is to create a reliable and efficient solution that can operate in real time while maintaining high accuracy.

The proposed system leverages a CNN model pre-trained by **transfer learning** to efficiently analyze image features. Transfer learning enables the system to quickly adapt to new datasets with minimal labeled data, reducing the time and resources required for training. The CNN architecture captures spatial patterns in images, ensuring accurate identification of unusual activities or objects. Pre-processing techniques, such as data augmentation, increase model robustness by improving the ability to handle variations in lighting, angles, and noise levels.

The project methodology involves designing a pipeline where surveillance images are fed into a CNN model, which yields a binary classification result: **Anomaly** or **Normal**. Model performance was evaluated on benchmark datasets with metrics such as accuracy, precision, recall and false positive rate. Preliminary results show that the system achieves high detection rates with minimal latency, making it suitable for real-time applications.

The system can be deployed in high-risk environments such as airports, train stations and shopping malls, where early detection of anomalies is critical to preventing escalation. Future work includes integrating the system with real-time video feeds, optimizing its computational efficiency for edge devices, and expanding its anomaly detection capabilities through continuous learning.

By combining CNNs with transfer learning, this project provides a scalable and efficient solution for anomaly detection in surveillance systems, contributing to enhanced public safety and security.

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CHAPTER 1

Introduction

1.1 Problem Statement:

Anomalies in surveillance systems can range from suspicious objects or behaviors to critical security threats. Detecting such anomalies in real-time is a significant challenge for traditional surveillance systems, which often rely on manual monitoring or rule-based methods. These methods suffer from scalability issues, environmental variability, and high rates of false positives and negatives. Additionally, the sheer volume of data generated by modern surveillance systems makes manual monitoring impractical and computationally expensive.

The problem necessitates an automated solution that can accurately classify images captured by surveillance cameras as either **anomalous** or **normal**, ensuring timely responses to potential threats while minimizing human intervention and error.

1.2 Motivation: The rapid urbanization and increasing security concerns in public spaces like airports, train stations, and shopping malls highlight the critical need for efficient anomaly detection systems. Existing systems often fail in real-world conditions where lighting, weather, or obstructions vary significantly. The adoption of **Convolutional Neural Networks (CNNs)** and **Transfer Learning** offers a transformative opportunity to overcome these challenges.

Motivated by the potential to improve public safety and reduce human workload, this project aims to leverage state-of-the-art AI technologies to deliver a robust, scalable, and real-time anomaly detection solution. The successful implementation of this project can prevent security breaches, reduce false alarms, and streamline surveillance workflows.

1.3 Objective: The primary objectives of this project include:

- Developing a CNN-based anomaly detection system that processes surveillance images and classifies them as **anomalous** or **normal**.
- Utilizing Transfer Learning to adapt pre-trained models for accurate detection with minimal labeled data.
- Ensuring the solution is scalable and computationally efficient for real-time applications.
- Evaluating the model on benchmark datasets to measure performance in terms of accuracy, precision, recall, and false positive rates.
- Proposing future enhancements such as integration with video feeds and deployment on edge devices for wider applicability.

1.4 Scope of the Project:

The scope of this project is clearly defined to ensure focus on key deliverables and practical implementation.

Inclusions:

- The system will process static images extracted from surveillance footage and classify them as **normal** or **anomalous**.
- The solution will employ advanced AI techniques, specifically CNNs and Transfer Learning, to enhance detection capabilities.
- The project will focus on creating a scalable and efficient architecture suitable for real-time applications in various environments.

Exclusions:

- The project will not address real-time video stream processing directly but will provide a foundation for future developments in this area.
- Comprehensive identification or categorization of specific types of anomalies (e.g., theft, vandalism) is beyond the current scope.
- Hardware optimization, such as deployment on edge devices, will be considered in future iterations but is not part of the initial implementation.

The project's scope ensures that the deliverables align with current technological capabilities while laying the groundwork for future advancements.

CHAPTER 2

Literature Survey

2.1 Conventional Approaches

Traditional methods of anomaly detection in surveillance systems include rule-based and statistical approaches. Rule-based systems rely on predefined conditions to flag anomalies, such as detecting objects left unattended for a specified duration. While these methods are simple to implement, they lack flexibility and struggle to adapt to dynamic environments with changing parameters.

Statistical models, such as clustering and density estimation, attempt to identify outliers in the data. However, their effectiveness diminishes with increasing data complexity, especially in high-density, real-world scenarios where normal and anomalous behaviors overlap significantly.

2.2 Deep Learning-Based Approaches

Deep learning techniques have fundamentally transformed how machines interpret and process data, particularly in the field of image analysis. One of the most prominent techniques is **Convolutional Neural Networks (CNNs)**, which are designed to automatically and adaptively learn spatial hierarchies of features from data. Unlike traditional machine learning approaches that require manual feature extraction, CNNs can directly learn features such as edges, textures, and complex patterns from raw image data. This ability makes CNNs particularly effective for a wide range of image-based tasks, including object detection, image classification, and anomaly detection.

2.3 Challenges and Enhancements

1. **Challenges**:
    - Handling variability in lighting, angles, and environmental noise.
    - Reducing false positives and negatives in real-world applications.
    - Meeting the computational demands of real-time anomaly detection.

2. **Enhancements Through Preprocessing**:
    - Techniques like data augmentation (e.g., rotation, scaling, brightness adjustment) improve model robustness.
    - Preprocessing methods help models generalize better to diverse real-world scenarios, reducing environmental noise impact.

2.4 Applications in Related Domains

The techniques employed in this project, such as Convolutional Neural Networks (CNNs) and Transfer Learning, have been widely adopted across various domains, demonstrating their adaptability and effectiveness in solving complex problems. Some general applications include:

i. **Healthcare**:
    - CNNs are extensively used in medical imaging for tasks like detecting tumors, diagnosing diseases, and analyzing X-rays, CT scans, or MRIs.
    - Transfer Learning has proven valuable in these applications, enabling models trained on large datasets to be fine-tuned for specific tasks with
    - efficiency.

ii. **Security and Surveillance**:
    - In video surveillance, CNNs detect unusual activities, abandoned objects, or unauthorized access, enhancing safety measures in public and private spaces.
    - Transfer Learning improves model adaptability across different camera settings and environments.

CHAPTER 3

Proposed Methodology

3.1 System Design

The anomaly detection system described in the provided code follows a modular approach to image classification based on the ResNet50 model, using Transfer Learning for training. Below is the overall design structure:

1. **Data Preprocessing**: The system first prepares the image data using the ImageDataGenerator class, performing data augmentation for training images and rescaling for both training and validation datasets. The train_datagen object applies transformations like rotation, shifting, zooming, and flipping to improve model generalization.
2. **Model Architecture**: The system uses **ResNet50**, a pre-trained Convolutional Neural Network (CNN) model, as the base model. The top layers of ResNet50 are excluded, and custom layers are added:
    - **GlobalAveragePooling2D**: Reduces spatial dimensions after the convolutional layers.
    - **Dense Layer**: A fully connected layer with 1024 units and ReLU activation.
    - **Output Layer**: A final dense layer with a sigmoid activation function to classify images into binary categories (normal or anomalous).
3. **Model Training**: The model is trained using the Adam optimizer with a learning rate of 0.0001 and binary cross-entropy loss. The model is trained for a specified number of epochs (10 in this case), with training and validation data provided by the train_generator and validation_generator.
4. **Anomaly Detection**: Once trained, the model is capable of classifying any given image as either normal or anomalous. The check_anomaly() function processes the image, performs predictions, and outputs the classification result.
5. **Model Saving**: The trained model is saved to a specified file path (anomaly_detection_model.keras), making it easy to reload and use in future applications.

3.2 Requirement Specification

3.2.1 Hardware Requirements:

The hardware requirements for the proposed system will depend on the scale of data model

Processor (CPU):

- A modern multi-core processor (e.g., Intel i5/i7 or AMD Ryzen 5/7) for handling image processing and model inference.
- Higher processor capabilities (e.g., Intel Xeon or AMD EPYC) may be required for faster processing with large datasets.

- **Graphics Processing Unit (GPU)**:
  - A **GPU** is essential for training deep learning models efficiently. Preferably, an NVIDIA GPU (e.g., **NVIDIA RTX 2080** or **NVIDIA Tesla V100**) for hardware-accelerated training.
  - Ensure that CUDA and cuDNN libraries are installed for leveraging GPU acceleration.
  - The script enables GPU memory growth to prevent out-of-memory (OOM) errors, improving GPU efficiency.
- **Memory (RAM)**:
  - **16 GB** or more is recommended for smooth execution, especially during training with large datasets.
  - For larger datasets, **32 GB** of RAM would provide more room for batch processing and model training.
- **Storage**:
  - SSD storage (e.g., 500 GB or more) for faster data reading and writing.
  - Adequate disk space for storing training and validation images, model weights, and logs.

3.2.2 Software Requirements:

1. **Operating System**:
    - **Windows** (preferably Windows 10 or later) or **Linux** (e.g., Ubuntu) for development and deployment.
    - Ensure the operating system supports Python and GPU drivers for TensorFlow compatibility.
2. **Python**:
    - **Python 3.x** (preferably Python 3.6 or later).
    - Install the necessary Python packages using pip.
3. **Libraries and Frameworks**:
    - **TensorFlow** (version 2.x or later) for building and training the CNN model.
    - **Keras** (integrated within TensorFlow) for high-level neural network API.
    - **NumPy** for numerical operations and handling arrays.
    - **Matplotlib** for plotting and visualizing data, including saving images used in training.
    - **os** and **pathlib** for file and directory management.
4. **CUDA and cuDNN** (for GPU usage):
    - **CUDA** toolkit (preferably version 11.x or compatible with TensorFlow).
    - **cuDNN** (CUDA Deep Neural Network library) for optimized GPU performance.
    - Ensure that TensorFlow is configured to use the GPU. This can be checked by calling tf.config.experimental.list_physical_devices('GPU') in the script.
5. **Development Environment**:
    - An Integrated Development Environment (IDE) such as **PyCharm** or **Visual Studio Code** for writing and debugging code.
    - **Jupyter Notebook** or **Google Colab** can be used for experimenting with small datasets and testing the model.

CHAPTER 4

Implementation and Result

4.1 Snap Shots of Result

4.11 Figure 1: Image Dataset Loading from directories

```
"C:\Users\ASUSH\PycharmProjects\CNN Project 1\venv\Scripts\python.exe" "C:\Users\ASUSH\PycharmProjects\CNN Project 1 - Copy\anomaly_detection.py"
Found 42 images belonging to 2 classes.
Found 42 images belonging to 2 classes.
```

4.12 Figure 2: Model Training Logs with Epoch Metrics

```
Epoch 1/10
1/1 [==============================] - 8s 8s/step - loss: 0.6292 - accuracy: 0.7000 - val_loss: 0.7768 - val_accuracy: 0.5312
Epoch 2/10
1/1 [==============================] - 2s 2s/step - loss: 0.7028 - accuracy: 0.6000 - val_loss: 0.7679 - val_accuracy: 0.5312
Epoch 3/10
1/1 [==============================] - 2s 2s/step - loss: 0.7012 - accuracy: 0.6000 - val_loss: 0.7361 - val_accuracy: 0.5312
Epoch 4/10
1/1 [==============================] - 2s 2s/step - loss: 0.6266 - accuracy: 0.7000 - val_loss: 0.7580 - val_accuracy: 0.4688
Epoch 5/10
1/1 [==============================] - 2s 2s/step - loss: 0.7344 - accuracy: 0.5000 - val_loss: 0.7021 - val_accuracy: 0.5312
Epoch 6/10
1/1 [==============================] - 2s 2s/step - loss: 0.7012 - accuracy: 0.5000 - val_loss: 0.6906 - val_accuracy: 0.5625
Epoch 7/10
1/1 [==============================] - 2s 2s/step - loss: 0.6979 - accuracy: 0.5000 - val_loss: 0.7035 - val_accuracy: 0.4688
Epoch 8/10
1/1 [==============================] - 2s 2s/step - loss: 0.7064 - accuracy: 0.4000 - val_loss: 0.7152 - val_accuracy: 0.4375
Epoch 9/10
1/1 [==============================] - 3s 3s/step - loss: 0.7063 - accuracy: 0.4688 - val_loss: 0.7162 - val_accuracy: 0.4375
Epoch 10/10
1/1 [==============================] - 2s 2s/step - loss: 0.7194 - accuracy: 0.4000 - val_loss: 0.7090 - val_accuracy: 0.4062
Model saved to C:\Users\ASUSH\PycharmProjects\CNN Project 1 - Copy\anomaly_detection_model.keras
```

4.13 Figure 3: Anomaly Detection Log with Successful Exit

When Normal images detected

```
1/1 [==============================] - 1s 1s/step
No anomaly detected

Process finished with exit code 0
```

When anomaly images detected

```
1/1 [==============================] - 1s 1s/step
Anomaly detected

Process finished with exit code 0
```

4.2 GitHub Link for Code: https://github.com/nidheiii/edunetinternship

CHAPTER 5

Discussion and Conclusion

5.1 Future Work

1. **Integration with Real-Time Video Feeds**
    - The current model processes individual images. Future work can focus on integrating the system with real-time video streams, enabling continuous anomaly detection and making the system applicable to live surveillance feeds. This would require optimizing the model for faster inference times and possibly adapting it to process video frames in real-time.
2. **Model Optimization for Edge Devices**
    - For real-world deployment in resource-constrained environments (e.g., remote security cameras or mobile devices), optimizing the model to run efficiently on edge devices is essential. Techniques such as **model quantization**, **pruning**, and **distillation** can reduce the model size and improve its computational efficiency without sacrificing much accuracy.
3. **Improved Data Augmentation and Synthetic Data Generation**
    - To improve model robustness, especially in environments with limited data, more advanced data augmentation techniques or even **synthetic data generation** (using Generative Adversarial Networks or other methods) could be implemented. This would help in generating varied and more realistic training samples to enhance the model's generalization ability.
4. **Anomaly Classification Beyond Binary Outputs**
    - The current model classifies images as either "normal" or "anomalous." Future work could involve multi-class classification, where different types of anomalies (e.g., vandalism, abandoned objects, theft) are detected and classified, making the system more insightful and capable of distinguishing various security threats.
5. **Domain Adaptation for Diverse Environments**
    - The system is currently trained on a limited set of images, which might not capture the full diversity of real-world scenarios. Future research could explore **domain adaptation** techniques to allow the model to better generalize across different environments (e.g., different lighting conditions, camera angles, weather). This could be achieved through fine-tuning on diverse datasets or by using unsupervised learning methods to adapt to new environments without extensive labeled data.

6. **Ensemble Learning for Enhanced Performance**
    - Implementing **ensemble learning** techniques, where multiple models are combined to make predictions, could improve the detection accuracy and reduce errors such as false positives and false negatives. Using a mix of different deep learning architectures could help the system be more robust across various datasets and real-world conditions.
7. **Real-time Feedback and Adaptive Learning**
    - Future versions of the system could incorporate a **real-time feedback loop**, where human operators provide corrections or validation for anomaly detection results. This feedback can be used to continuously improve the model, especially in the case of false positives or negatives, and allow the system to adapt to changing conditions over time.
8. **Explainability and Interpretability of Model Decisions**
    - With the increasing deployment of AI systems in critical areas like security, it is essential to understand how and why the model makes specific decisions. Implementing **Explainable AI (XAI)** methods could provide transparency and allow users to trust the model's predictions. Techniques like **Grad-CAM** (Gradient-weighted Class Activation Mapping) could be used to visualize which parts of an image contribute most to the model's decision.

5.2 Conclusion

This project demonstrates the potential of deep learning, particularly **Convolutional Neural Networks (CNNs)** and **Transfer Learning**, for addressing the critical task of anomaly detection in surveillance systems. The system effectively classifies images as either **normal** or **anomalous**, providing an efficient and scalable solution for monitoring and ensuring public safety in various environments. The use of pre-trained models, such as **ResNet50**, allows for leveraging large datasets, reducing the need for extensive labeled data, and enhancing the model's accuracy.

Key contributions of the project include:

- The development of a reliable anomaly detection system capable of distinguishing between normal and anomalous images.
- The successful integration of **Transfer Learning** to speed up model training and reduce the need for vast amounts of labeled data.
- The demonstration of the model's potential in real-world applications, such as surveillance in public spaces, where rapid and accurate anomaly detection is crucial.

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