Campus Abnormal Behavior Recognition with Temporal Segment Transformers

A Dissertation submitted to the Jawaharlal Nehru Technological University, Hyderabad in partial fulfillment of the requirement for the award of a degree of

BACHELOR OF TECHNOLOGY
IN
COMPUTER SCIENCE ENGINEERING (DATA SCIENCE)

Submitted by

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CVR COLLEGE OF ENGINEERING

(***An Autonomous Institution, NAAC Accredited and Affiliated to JNTUH, Hyderabad***)
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CERTIFICATE

This is to certify that the project report entitled **“Campus Abnormal recognition with temporal segment transformers”** is a Bonafide record of work carried out by **P.SAI ROHITH (21B81A67A8)** and **M.V. NAYANADURGA (21B81A67C5)** submitted to **Mrs. S. Vineela Krishna** for the requirement of the award of **Bachelor of Technology** in **Computer Science Engineering (Data Science)** to the CVR College of Engineering, affiliated to Jawaharlal Nehru Technological University, Hyderabad during the academic year 2024-25.

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DECLARATION

We hereby declare that the project report entitled **“Campus Abnormal behavior recognition with Temporal Segment Transformers”** is an original work done and submitted to the Department of CSE(DS), CVR College of Engineering, affiliated to Jawaharlal Nehru Technological University Hyderabad in partial fulfilment for the requirement of the award of Bachelor of Technology in Computer Science and Information Technology. It is a record of bonafide project work carried out by us under the guidance of **Mrs. S. Vineela Krishna**, Sr.Assistant Professor, Department of Computer Science Engineering (Data Science).

We further declare that the work reported in this project has not been submitted, either in part or in full, for the award of any other degree or diploma in this Institute or any other Institute or University.

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We are happy to present our major project dissertation titled **“Campus Abnormal Behavior Recognition with Temporal Segment Transformers”,** completed as part of our curriculum in the Department of CSE(DS) at CVR College of Engineering.

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ABBREVIATIONS

CNN	Convolution Neural Network
TST	Temporal Segment Transformers
BI-LSTM	Bidirectional Long Short-Term Memory
GRADCAM	Gradient-weighted Class Activation Mapping
CCTV	Closed-Circuit Television
ViT	Vision Transformer
SMTP	Simple Mail Transfer Protocol
DOTA	Dataset for Object Detection in Aerial Images

ABSTRACT

Ensuring campus security is crucial in educational institutions. This project introduces a Campus Abnormal Behaviour Recognition System using Temporal Segment Transformers (TST) and deep learning to identify suspicious activities such as fighting, shouting, running, and other aggressive behaviors in surveillance footage. The system classifies activities as normal or abnormal, and upon detecting anomalies, it triggers a buzzer alert, sends an email notification, and enhances security response.

The system utilizes EfficientNetB0 for feature extraction and Bi-LSTM for sequence analysis, significantly improving the accuracy of anomaly detection. By analyzing temporal dependencies in video sequences, the model effectively distinguishes between regular campus activities and potential security threats. The system operates in three modes—live footage monitoring, video stream analysis, and audio detection—allowing flexible deployment across different surveillance setups.

A Streamlit-based web interface provides an intuitive platform for users to upload videos, process live streams, and visualize detection results in real-time. With automated behavior recognition, the system eliminates the need for continuous manual monitoring, enabling faster response times in emergency situations. Additionally, the solution is scalable, adaptable, and capable of being integrated with campus security networks, making it a vital tool for enhancing safety in universities, schools, and public spaces.

CHAPTER – 1

INTRODUCTION

In today's world, ensuring the safety and security of students and staff within educational institutions is of utmost importance. Campuses often rely on CCTV surveillance for monitoring activities, but manual monitoring is time-consuming, inefficient, and prone to human errors. To address these challenges, Campus Abnormal Behavior recognition systems can provide real-time analysis of surveillance footage, enabling authorities to respond swiftly to potential threats.

This project presents an automated campus abnormal behavior recognition system that utilizes Temporal Segment Transformers (TST) and deep learning to recognize abnormal behaviors such as fighting, shouting, or other suspicious activities. By analyzing video footage, the system classifies behavior as normal or abnormal and triggers an alert when an anomaly is detected. This real-time detection helps in preventing conflicts, reducing violence, and ensuring a safer campus environment.

The system leverages EfficientNetB0, a powerful deep learning model, for feature extraction, while Bidirectional LSTM (Bi-LSTM) enhances sequence learning to detect behavioral patterns. The trained model processes video data, identifying activities in short segments, ensuring higher accuracy in classification. Additionally, Grad-CAM visualization provides insights into why a particular activity was classified as abnormal, making the system more explainable and transparent.

To enhance security measures, the system integrates multiple alert mechanisms. If an abnormal activity is detected, it plays a buzzer sound to alert nearby security personnel, sends an email notification, and delivers an SMS alert using the Fast2SMS API. This multi-tiered approach ensures that security teams are immediately informed, allowing them to respond effectively.

The Stream lit -based user interface allows security personnel to upload and analyze video footage effortlessly. The platform provides real-time feedback, displaying the prediction results with confidence scores. This makes it easy for non-technical users to operate the system and take necessary action when needed.

By automating surveillance and integrating AI-driven anomaly detection, this system significantly reduces manual monitoring efforts and minimizes false positives. Unlike traditional CCTV monitoring, which relies solely on human observation, this AI-driven approach enhances accuracy, reduces response time, and ensures a proactive approach to campus safety.

In conclusion, the Campus Abnormal Behaviour Recognition De System is an essential tool for modern educational institutions. By leveraging deep learning, real-time alerts, and an intuitive interface, it provides a comprehensive security solution that ensures the safety of students and staff while improving incident response efficiency.

1.1 MOTIVATION

Educational institutions are meant to be safe spaces for students, faculty, and staff. However, incidents such as bullying, fights, harassment, and unauthorized activities can disrupt campus safety. Traditional CCTV surveillance systems rely on human monitoring, which is prone to errors, delays, and oversight. Security personnel may fail to notice critical events in real-time due to fatigue or distractions. This highlights the need for an AI-powered system that can automatically detect and alert authorities about abnormal behavior.

With advancements in computer vision and deep learning, AI-based anomaly detection models have become more accurate and efficient. Temporal Segment Transformers (TST) provide a way to analyze sequential frames from videos, making it possible to identify abnormal activities in real-time. By leveraging EfficientNetB0 for feature extraction and Bidirectional LSTM for pattern recognition, this system can differentiate between normal and abnormal behaviors with high accuracy.

Another key motivation for developing this system is reducing response time to security incidents. Many violent situations escalate quickly, and immediate intervention can prevent serious consequences. By implementing buzzer alerts, email notifications, and SMS alerts, this system ensures that campus authorities are instantly informed whenever an abnormal event is detected. This proactive approach enhances safety and minimizes the risk of harm.

Additionally, automation reduces human workload and operational costs. Instead of requiring large security teams to monitor multiple screens manually, AI-powered surveillance can continuously analyze videos without fatigue. This allows institutions to allocate human resources more effectively, improving overall campus security management.

Lastly, the project aims to provide an accessible and user-friendly interface Stream lit, enabling security personnel to easily upload and analyze video footage without requiring advanced technical knowledge. The combination of AI-driven detection, real-time alerting, and an intuitive interface makes this system a practical, scalable, and reliable solution for campus safety.

1.2 PROBLEM STATEMENT

Ensuring campus security is a growing challenge for educational institutions worldwide. While CCTV surveillance systems are widely used, they primarily rely on manual monitoring, making them prone to human error, fatigue, and delays in response time. Security personnel may not always be able to detect or respond to abnormal activities such as fights, harassment, or unauthorized entry in real-time. This lack of automated intervention can lead to serious incidents going unnoticed, putting students and staff at risk.

Traditional security systems are reactive rather than proactive, meaning incidents are often reviewed after they occur rather than being prevented in real-time. Furthermore, security teams must constantly monitor multiple camera feeds, which is an inefficient use of resources and increases the chances of missed detections. This highlights the need for an automated system capable of detecting and alerting authorities about potential security threats without human intervention.

A significant challenge in anomaly detection is differentiating between normal and abnormal behavior in videos. Conventional video analytics struggle to analyze complex behaviors over time. Deep learning models, specifically Temporal Segment Transformers (TST) and LSTM networks, provide an effective solution by analyzing sequential frames of video and identifying unusual patterns that indicate potential threats. However, implementing such models requires a well-designed pipeline for feature extraction, sequence learning, and classification.

Another issue in campus security is the lack of an efficient alerting mechanism. Even when security personnel identify an incident, delays in communication can prevent timely intervention. A system that not only detects abnormal behavior but also sends immediate alerts through multiple channels—such as buzzer alarms, email notifications, and SMS alerts—can significantly improve response time and prevent escalation of security incidents.

Moreover, false positives and false negatives remain a concern in anomaly detection. A system that visualizes predictions using Grad-CAM can help security teams understand why a particular event was flagged as abnormal, increasing trust and transparency in AI-based decision-making.

To address these challenges, this project proposes a Campus Anomaly Detection System that integrates deep learning-based video analysis, automated alerting, and an intuitive user interface. By leveraging AI-driven surveillance, the system provides an efficient, real-time, and scalable solution for enhancing campus security and safety.

1.3 PROJECT OBJECTIVE

The primary objective of this project is to develop an AI-driven anomaly detection system that enhances campus security by automatically identifying abnormal behaviors such as fighting, shouting, and other suspicious activities. The system processes pre-recorded videos and real-time surveillance footage to detect behavioral anomalies and issue immediate alerts. By integrating deep learning models into surveillance systems, this project aims to automate security monitoring, reduce manual workload, and enable rapid response to threats, making educational institutions safer.

Addressing Limitations of Traditional Campus Surveillance

Current security systems in campuses rely on manual monitoring of CCTV feeds, where security personnel are responsible for identifying threats. However, this approach has several limitations:

- **Human error:** Security officers monitoring multiple cameras may miss critical incidents due to fatigue or distractions.
- **Delayed responses:** Manual observation often results in slow intervention, allowing conflicts to escalate.
- **Lack of real-time alerts:** Traditional systems do not provide automated notifications, leading to delayed security actions.

These challenges pose significant risks in schools, colleges, and universities, where large student gatherings increase the likelihood of physical altercations, bullying, or unauthorized activities. The absence of automated anomaly detection in existing security frameworks leaves gaps in campus safety, making it difficult to prevent incidents before they occur.

Deep Learning-Based Approach for Anomaly Detection

To address these challenges, this project leverages deep learning and computer vision to develop an intelligent and automated security system. The system employs Temporal Segment Transformers (TST) for analysing sequential frames from videos, ensuring accurate behaviour classification. The pipeline consists of:

EfficientNetB0 for feature extraction from video frames.Bi-LSTM (Bidirectional Long Short-Term Memory) for sequence learning, identifying abnormal behavioural patterns.Grad-CAM visualization to highlight why a particular activity is flagged as abnormal, enhancing model transparency.

This AI-driven solution significantly outperforms traditional motion detection or manual surveillance by providing instant, accurate behaviour recognition with a low error rate.

Automated Alert System for Immediate Response

To enhance security measures and enable faster response times, the project integrates an automated alert system that activates when an anomaly is detected:

- **Buzzer Alert:** A loud alarm is triggered to notify nearby security personnel.
- **Email Notification:** An instant email is sent to security teams, detailing the detected abnormality.

- **SMS Alert (via Fast2SMS API):** Real-time SMS notifications ensure security staff are promptly informed.

This multi-layered alert system eliminates the delays caused by manual reporting, ensuring proactive rather than reactive security measures.

User-Friendly Web Application for Accessibility

To make this anomaly detection system accessible, a Stream lit-based web application has been developed, providing:

A simple, intuitive user interface for security personnel.Options to upload pre-recorded videos for analysis.Real-time monitoring of video footage.Immediate visualization of predictions with confidence scores.

The system is lightweight, scalable, and easily deployable across different institutions, allowing integration into existing campus security infrastructure with minimal modifications.

Contribution to Modern Campus Security Solutions

By implementing this AI-powered surveillance system, the project bridges the gap between traditional CCTV monitoring and modern AI-driven security solutions. The key contributions include:

Reducing manual workload for security teams by automating anomaly detection.Minimizing response time, ensuring security threats are addressed before escalation.Enhancing student and faculty safety through proactive threat detection.Providing a scalable solution adaptable to various educational institutions and public security applications.

In a world where campus security threats are becoming more unpredictable, this project demonstrates the power of deep learning and computer vision in ensuring safety, preventing conflicts, and protecting human lives.

1.4 ORGANIZATION OF THE PROJECT

This Project Report provides a detailed description of the design challenges, proposed methodologies, and implementation of a Deep Learning-based Weapon Detection System aimed at enhancing security through automated identification of weapons in images, video files, and live camera feeds. The report explains various functionalities of the application, breaking them down into modules and illustrating them with use case diagrams and class diagrams. The implementation is supported with screenshots showcasing the working model of the application.

Chapter 1 introduces the deep learning-based weapon detection system, outlining its significance in enhancing security through automated identification of weapons in images, video files, and live camera feeds. It provides an overview of the project's objectives, the need for real-time threat detection, and the role of deep learning models like YOLOv8 in addressing limitations in traditional surveillance methods. Additionally, this chapter highlights the scope of the project, explaining its modular design and functionality, which includes real-time alerts and email notifications upon weapon detection. The chapter sets the foundation for the detailed discussions in the following chapters.

Chapter 2 provides a comprehensive review of existing studies, technologies, and approaches relevant to weapon detection using deep learning, identifying key limitations in traditional surveillance systems and explaining how YOLOv8-based detection addresses these challenges. It discusses prior research on real-time object detection and the role of AI in security applications.

Chapter 3 outlines the software requirements necessary for developing the system, covering both functional aspects, such as real-time weapon detection and alert generation, and non-functional aspects, including system performance, scalability, and reliability. This chapter also presents the system architecture, explaining the components and their interactions to ensure an efficient detection pipeline.

Chapter 4 introduces UML diagrams to illustrate the system design, including use case diagrams that depict user interactions with the application, class diagrams that outline the software structure, and an architecture diagram that visually represents the overall system workflow. These diagrams help in understanding the modular organization of the system.

Chapter 5 details the system’s implementation, explaining the tools and technologies used, such as YOLOv8 for object detection, OpenCV for image processing, and Streamlit for the web interface. It includes screenshots and explanations of the detection results for images, video files, and live feeds, demonstrating the system’s accuracy and real-time capabilities. Additionally, this chapter describes the testing methodologies used to validate the performance of the detection model.

Chapter 6 concludes the report by summarizing the system’s contributions in enhancing security through automated weapon detection. It discusses the impact of real-time alert generation in improving situational awareness and response times in high-risk areas. The chapter also highlights the future scope of the project, such as expanding the model to detect more weapon types, improving detection accuracy, and integrating with existing security infrastructure for broader real-world applications.

CHAPTER – 2

LITERATURE SURVEY

2.1 EXISTING WORK

[1] AI-BASED ANOMALY DETECTION IN SURVELLANCE SYSTEMS

INTRODUCTION

AI-driven surveillance has gained prominence in security and threat detection, with machine learning models playing a key role in identifying unusual activities in real-time. The paper "Deep Learning-Based Anomaly Detection in Video Surveillance" explores various machine learning techniques, including autoencoders, GANs, and LSTMs, to detect suspicious activities in crowded environments.

KEY CONTRIBUTIONS

Proposes a deep learning-based anomaly detection system trained on large-scale surveillance datasets.Uses Convolutional Autoencoders to extract video features and LSTM networks to analyze temporal sequences.Demonstrates superior anomaly detection performance compared to traditional background subtraction methods.

METHODOLOGY

The system uses CNN-based autoencoders to extract motion and spatial features from surveillance footage. LSTM networks analyze sequences of frames to detect irregular activities over time. An anomaly scoring mechanism classifies frames with high reconstruction error as abnormal. This approach enables real-time detection of suspicious behaviors such as fighting or shouting on campus.

CHALLENGES

Difficulty in differentiating normal crowd behaviors from anomalies.High false positive rate due to variations in lighting and occlusions.Computationally intensive, requiring high-end GPUs for real-time processing.

FUTURE WORK

The model may not generalize well to unseen environments due to dataset limitations. Real-time performance optimization is needed to reduce processing delays. Future improvements include integrating audio analysis for better anomaly detection and developing lightweight models for edge device deployment.

CONCLUSION

Deep learning improves surveillance anomaly detection, but challenges in real-time processing, generalization, and false positives remain. Future research should focus on hybrid models combining multiple modalities for enhanced performance.

[2] EXISTING WORKS IN VIDEO BASED HUMAN ACTIVITY RECOGNITION

INTRODUCTION

Human activity recognition (HAR) is essential for security, healthcare, and smart surveillance. The study "Spatio-Temporal Deep Learning for Human Activity Recognition" investigates CNN-RNN hybrid models for recognizing human actions in videos, improving classification accuracy over traditional approaches.

KEY CONTRIBUTIONS

This study introduces a Spatio-Temporal CNN-RNN framework for video-based human activity recognition (HAR). By combining Optical Flow with RGB data, the system enhances motion detection and reduces misclassification. The model achieves state-of-the-art performance on public HAR datasets, demonstrating improved accuracy in recognizing complex activities.

METHODOLOGY

The approach begins with feature extraction, where a CNN captures spatial features from individual video frames. Bi-LSTM networks are then used for sequence learning, trackingtemporal dependencies across multiple frames. Finally, a Softmax layer classifies the extracted features into specific activity labels, ensuring accurate recognition.

CHALLENGES

A major challenge is distinguishing visually similar activities, such as walking vs. jogging, leading to classification errors. Additionally, variations in camera viewpoints can impact model accuracy by altering appearance-based features. The computational cost is also significant, as training these deep models requires multi-GPU systems for efficient processing.

FUTURE WORK

Pretrained models often struggle with adaptability when deployed in unseen environments, affecting generalization. Diverse datasets and advanced data augmentation techniques are needed to improve robustness. Future research should explore Transformer-based vision models, which offer better long-range dependency tracking and could further enhance HAR performance.

CONCLUSION

The study improves video-based human activity recognition, but issues with similaractions, occlusions, and real-time processing remain. Future enhancements should focus on multi-modal fusion (video + audio) and Transformer-based deep learning models.

[3] EXISTING WORKS ABNORMAL EVENT DETECTION IN PUBLIC PLACES

INTRODUCTION

Identifying unusual events in crowded places is a critical aspect of security and surveillance. The research "Anomaly Detection in Public Surveillance Using Deep Learning" focuses on detecting sudden fights, aggressive actions, and panic behaviors using CNN-LSTM models.

KEY CONTRIBUTIONS

This study leverages deep learning to detect aggressive behaviors in crowded environments with greater accuracy. By employing optical flow-based motion tracking, the system effectively distinguishes between normal and abnormal movements. Compared to traditional SVM-based approaches, the proposed method achieves higher detection accuracy, making it more reliable for real-world surveillance applications.

CHALLENGES IN PRIOR STUDIES

One in prior research is data imbalance, as there is limited real-world data available for aggressive actions, making model training less effective. Additionally, false positives remain a concern, as some normal movements are mistakenly classified as aggression. Another issue is real-time processing, where deep learning models experience high latency, limiting their effectiveness in real-world live surveillance scenarios.

FUTURE WORK

In real-world deployment, which is necessary to validate its robustness in practical settings. It also struggles with occlusions, where individuals are partially or fully blocked in dense crowds, affecting detection accuracy. Future research should explore attention mechanisms to enhance feature selection, ensuring better precision and faster response times in complex environments.

CONCLUSION

Deep learning significantly improves abnormal event detection, but real-world scalability, occlusion handling, and false positives remain key challenges. Future research should focus on refining deep learning models to enhance precision, reduce latency, and improve performance in live surveillance environments.

[4] EXISTING WORKS IN VIOLENCE DETECTION IN SURVEILLANCE FOOTAGE

INTRODUCTION

Violence detection in security videos is a pressing challenge. The paper "Deep Learning-Based Violence Recognition in Surveillance Videos" proposes deep CNN-LSTM models to analyze aggressive behavior patterns and detect violent incidents.

KEY CONTRIBUTIONS OF PRIOR WORK

Prior research on violence detection has introduced spatio-temporal feature extraction, allowing models to analyze both spatial and motion-based patterns. By utilizing ResNet50 as a backbone, these methods extract critical motion details, improving the ability to detect violent actions. Compared to classical feature-based approaches, these models achieve higher recall rates, ensuring more effective identification of aggressive behaviors in surveillance footage.

METHODOLOGIES AND TECHNIQUES

To enhance detection accuracy, prior studies incorporate motion estimation techniques, where optical flow detects fast and sudden movements associated with violent actions. Additionally, convolutional neural networks (CNNs) extract aggression-related patterns, enabling the system to recognize physical confrontations. Further, LSTM networks analyze violence over multiple frames, capturing temporal dependencies. Finally, a decision layer classifies the video footage into violent or non-violent, ensuring automated threat assessment.

CHALLENGES IN PRIOR STUDIES

Despite advancements, lighting conditions pose a major challenge, as night-time surveillance significantly reduces detection accuracy. Another issue is false alarms, where fast but harmless movements are sometimes misclassified as violent actions. Additionally, data scarcity remains a limitation, as there are fewer labeled datasets available for training deep learning models, leading to generalization issues in real-world scenarios.

FUTURE DIRECTIONS

One of the primary limitations of existing methods is low-resolution footage, where performance declines due to poor video quality. Moreover, current models lack multi-modal analysis, as they rely solely on visual cues, while integrating audio features like shouting could significantly enhance detection accuracy. Future research should explore Transformer-basedaction recognition models, which can improve long-range dependencies and enhance real-time violence detection.

CONCLUSION

Deep learning has greatly improved violence detection in surveillance systems, but low-light challenges, false positives, and dataset limitations still hinder performance. Future studies should focus on audio-visual fusion models, integrating both sound and video to achieve higher accuracy and reliability in real-world surveillance applications.

[5] EXISTING WORKS IN REAL TIME BEHAVIORAL ANOMALY DETECTION IN SMART SURVEILLANCE

INTRODUCTION

Smart surveillance systems require real-time monitoring and threat detection. The study "Anomaly Detection in Smart Cities Using AI" introduces real-time deep learning models to track behavioral anomalies in urban environments.

KEY CONTRIBUTIONS OF PRIOR WORK

Deep learning-based approaches have significantly improved anomaly detection in surveillance systems. Prior research integrates deep CNNs with optical flow techniques to enhance motion detection accuracy. Additionally, attention-based Transformers are utilized to refinefeature extraction, ensuring a more precise identification of anomalies. The system achieves real-time anomaly detection at high frame rates, making it suitable for security monitoring in public spaces.

METHODOLOGIES AND TECHNIQUES

Real-time data processing is a crucial component, with Edge AI deployment enabling instant anomaly detection. Hybrid CNN-Transformer models classify activities as normal or abnormal, leveraging deep learning for enhanced pattern recognition. Furthermore, an automated alert system ensures immediate notifications are triggered upon detecting suspicious behaviors, improving response times in security operations.

CHALLENGES IDENTIFIED

Despite advancements, scalability remains a challenge, as processing multiple video streams requires high computational resources. Crowded areas introduce false positives, making it difficult to differentiate between normal and aggressive behaviors. Additionally, limited implementation of Edge AI necessitates optimized hardware for real-time processing, ensuring efficient deployment in practical scenarios.

FUTURE DIRECTIONS

Current systems are constrained by limited dataset sizes, affecting model generalization to diverse environments. The high computational cost of AI models necessitates specialized edge hardware acceleration for real-time performance. Future research should focus on optimizing AI pipelines for low-latency detection while expanding datasets to improve adaptability across various real-world scenarios.

CONCLUSION

AI enhances real-time smart surveillance, but computational efficiency, real-world adaptability, and large-scale deployment remain key challenges. Future advancements should focus on AI model optimization for real-time threat detection.

2.2 LIMITATIONS OF EXISTING WORKS

[1] APPROACH 1

The existing anomaly detection system faces several critical challenges that impact its efficiency and reliability. One major issue is the high false positive rate, where normal activities are often misclassified as anomalies due to factors like lighting variations and motion blur. This misclassification leads to unnecessary alerts, reducing the system's overall effectiveness in real-world surveillance. Additionally, the computational cost of running deep learning models remains a significant barrier, as they require high-end GPUs for real-time processing, making large-scale deployment expensive and resource-intensive.

Another limitation is the model's inability to generalize effectively across different environments. Since most models are trained on specific datasets, they struggle when applied to unseen scenarios, leading to poor anomaly detection performance in diverse settings. Furthermore, sequential models such as LSTMs introduce processing delays, slowing down real-time inference and making the system less responsive in critical situations where immediate detection is necessary.

Lastly, the absence of multi-modal data, such as audio and contextual cues, further weakens the system's ability to distinguish between normal and abnormal behavior. Relying solely on visual data limits the detection accuracy, especially in situations where sound-based cues, like shouting or distress signals, could provide additional context. Addressing these challenges requires integrating multi-modal data sources, optimizing computational efficiency, and improving the adaptability of deep learning models to different real-world scenarios.

[2] APPROACH 2

The anomaly detection system faces significant challenges in accurately distinguishing between visually similar activities. One of the primary issues is confusion between similar actions, such as walking and jogging, which often share overlapping motion patterns. This leads to misclassification, reducing the reliability of the model in real-world applications. Additionally, the system exhibits viewpoint sensitivity, where recognition accuracy declines when camera angles or lighting conditions change. Variations in perspective can cause inconsistencies in feature extraction, affecting the model's ability to identify anomalies correctly.

Another major limitation is the high training cost associated with deep learning models. Training requires extensive datasets and computational resources, making it expensive and time-consuming. Furthermore, many pretrained models lack adaptability, struggling to generalize in new or unseen environments. This restricts their effectiveness in dynamic settings where activity patterns may vary significantly.

Lastly, real-time challenges pose a bottleneck in system performance. Processing multiple frames per second demands high-speed inference, which can strain computational resources and lead to delays in detection. These limitations highlight the need for improved feature differentiation, better adaptation to environmental variations, and optimized deep learning architectures to enhance efficiency in real-time anomaly detection.

[3] APPROACH 3

The anomaly detection system encounters several challenges, primarily due to data imbalance. Limited datasets for abnormal activities result in biased detection models, making it difficult to generalize across diverse real-world scenarios. Since abnormal events occur less frequently, the model may not be adequately trained on all possible anomalies, leading to inaccuracies in detection.

Another critical limitation is the high rate of false positives. Normal activities, such as sudden group movements, are sometimes flagged as anomalies, reducing the system s reliability. This misclassification can lead to unnecessary alerts and reduced trust in the model s predictions. Additionally, scalability issues arise when implementing the system in large, crowded public spaces. The increased number of people and complex movements make it difficult for the model to maintain high accuracy while processing vast amounts of real-time data.

Occlusion challenges further hinder detection performance, as people and objects blocking the camera view reduce the system s ability to track and classify movements correctly. This results in missing critical events or misinterpreting partial actions. Finally, the lack of explainability in the model remains a concern. Since deep learning-based detection systems do not provide clear reasoning behind flagged anomalies, security personnel may struggle to interpret and validate the model s decisions. Addressing these challenges requires improved dataset diversity, enhanced occlusion handling, and explainable AI techniques to build a more reliable and interpretable system.

[4] APPROACH 4

The anomaly detection system faces significant challenges due to lighting sensitivity, as detection accuracy drops in night-time or low-light environments. Poor illumination can obscure key details, making it difficult for the model to distinguish between normal and abnormal behavior accurately. This limitation affects real-world deployment, particularly in outdoor or dimly lit surveillance areas where security monitoring is crucial.

Another issue is the system’s limited real-world testing. Since it is primarily trained on specific datasets, its effectiveness in diverse environments remains uncertain. Variations in real-world scenarios, such as crowded settings or different cultural behaviors, can impact the model’s ability to generalize effectively. False alarms also pose a challenge, as fast movements, such as running, are sometimes misclassified as violent behavior. This misclassification can lead to unnecessary interventions, reducing the system’s credibility.

Furthermore, low-resolution surveillance footage significantly impacts classification accuracy. Blurry or pixelated images make it difficult for the model to extract essential features, leading to incorrect detections. Lastly, data scarcity remains a major limitation, as well-labeled datasets for violent behavior detection are limited. The lack of diverse, high-quality training data restricts the model’s ability to learn from various scenarios, reducing its overall robustness. Addressing these challenges requires better dataset collection, improved preprocessing techniques, and enhanced low-light adaptation strategies for more reliable anomaly detection.

[5] APPROACH 5

The anomaly detection system faces scalability constraints, as processing multiple live camera feeds in real time demands significant computational resources. Handling large-scale surveillance networks requires high-performance GPUs or dedicated edge computing hardware, making deployment expensive and complex. As the number of cameras increases, maintaining efficiency without compromising detection accuracy becomes a challenge.

Another major issue is the occurrence of false positives in crowded areas. High human movement in public spaces often leads to misclassification, where normal group activities such as gatherings or fast walking are flagged as anomalies. This reduces the system’s reliability and may lead to unnecessary security interventions. Additionally, the system has limited edge AI implementation, as it heavily relies on cloud processing for anomaly detection. While cloud-based solutions provide computational power, they introduce latency and dependency on internet connectivity, making real-time inference difficult in security-critical situations.

High computational costs further hinder the system’s adaptability in low-resource environments. Deep learning models require powerful hardware, which restricts deployment in smaller institutions or locations with budget constraints. Addressing these challenges requires optimizing AI models for low-power devices, improving detection algorithms to reduce false positives, and integrating efficient edge AI solutions to enhance real-time performance.

CHAPTER – 3

SOFTWARE AND HARDWARE REQUIREMENTS

3.1 SOFTWARE REQUIREMENTS

1. **Operating System:** Windows 10/11, Ubuntu 20.04+, or macOS

2. **Programming Language:** Python 3.8+

3. Libraries & Frameworks:

- **OpenCV** (for image and video processing)
- **TensorFlow & Keras** (for deep learning model development)
- **Torch** (for additional deep learning support)
- **NumPy & Pandas** (for data handling and preprocessing)
- **Streamlit** (for building an interactive web interface)
- **smtplib** (for sending email notifications)
- **Fast2SMS API** (for real-time SMS alerts)
- **Matplotlib & Seaborn** (for visualizing model performance and heatmaps)

4. **Development Environment:** Jupyter Notebook, PyCharm, or VS Code

5. **Web Framework:** Streamlit

6. **Dependencies:** pip, virtualenv (for managing dependencies)

3.2 HARDWARE REQUIREMENTS

1. **Processor:** Intel i5/i7 (10th Gen or later) or AMD Ryzen 5/7

2. **GPU:** NVIDIA GTX 1650+ / RTX 3060+

3. **RAM:** 8GB minimum (16GB recommended for efficient processing)

4. **Storage:** Minimum 50GB free space (for model files, datasets, and logs)

5. **Camera:** External USB or built-in webcam for live stream detection

6. **Internet Connectivity:** Required for model downloading, email notifications, and API usage

3.3 FUNCTIONAL REQUIREMENTS

1. **Abnormal Behavior Detection** – The system should accurately classify behaviors as normal or abnormal in images, video files, and live-stream feeds using the Temporal Segment Transformer (TST) model.
2. **Multiple Input Modes** – Users should be able to upload pre-recorded videos, analyze live-stream footage, or process audio files for real-time abnormal behavior detection.
3. **Automated Alerts** – When an abnormal behavior is detected, the system should trigger a buzzer sound and send an email alert to the user for immediate response.
4. **User Interface** – A user-friendly web application (built using Streamlit) should allow users to upload files, select detection modes, and view results.
5. **Start/Stop Controls** – Users should have control over starting and stopping real-time detection as per their needs.
6. **Real-Time Processing** – The system should process video and audio inputs efficiently, ensuring minimal delay in detection results.
7. **Logging and Reporting** – The system should maintain logs of detected abnormal behaviors for future security analysis and improvements.

3.4 NON-FUNCTIONAL REQUIREMENTS

1. **Performance** – The detection system should provide high accuracy with low latency for real-time applications.
2. **Scalability** – The system should be able to handle multiple camera feeds or video uploads simultaneously without performance degradation.
3. **Security** – Email alerts and stored detection logs should be securely transmitted and protected from unauthorized access.
4. **Usability** – The UI should be intuitive, accessible, and easy to use for both technical and non-technical users.
5. **Reliability** – The system should maintain consistent detection performance across different environments and surveillance settings.

CHAPTER – 4

PROPOSED SYSTEM DESIGN

4.1 PROPOSED METHODOLOGY

The proposed Campus Anomaly Detection System leverages deep learning and Temporal Segment Transformers (TST) to identify abnormal behaviors such as fighting, shouting, or suspicious activities in video footage. The system processes pre-recorded videos and real-time surveillance feeds to detect anomalies and generate instant alerts. By automating behavior recognition, the system reduces dependency on manual monitoring, ensuring real-time detection and rapid security response.

One of the primary challenges in traditional campus surveillance is the reliance on human observation, which is slow, error-prone, and inefficient. Security personnel must manually scan multiple video feeds, increasing the risk of missed incidents due to fatigue or distractions. The proposed AI-driven system eliminates these inefficiencies by using deep learning to automatically analyze video sequences, classify behaviors, and trigger alerts when anomalies are detected.

TEMPORAL SEGMENT TRANSFORMERS FOR ANOMALY DETECTION

The anomaly detection process starts with video input acquisition, where users can upload a pre-recorded video or use a live surveillance feed. The system preprocesses the video frames, resizing them to match the input dimensions required by the model. This preprocessing step ensures that the model receives uniform and high-quality input for improved accuracy. Once processed, the frames are passed through the TST model, which uses deep feature extraction and sequence learning to classify behaviors as normal or abnormal.

Unlike traditional object detection models that analyze single frames, TST processes entire video segments, allowing the system to understand behavioral patterns over time. This sequence-based approach significantly improves anomaly detection accuracy, reducing false positives. When an abnormal event is detected, the system highlights the frame with a confidence score and flags the specific time instance where the anomaly occurred.

Real-time processing is crucial for campus security, as delays in detection can lead to unaddressed security threats. The proposed system is designed to process video feeds at high speeds, ensuring that behavioral anomalies are identified instantly. In live surveillance mode, this feature is particularly valuable, allowing security teams to take immediate action upon detecting suspicious activities.

MULTI-FORMAT DETECTION MODES

The system offers a multi-format detection capability, making it highly adaptable for various security applications. It supports pre-recorded video analysis, where users can upload video files for automated anomaly detection. The system processes each frame, identifying abnormal behaviors and marking specific timestamps for easy review. This feature is particularly beneficial for forensic investigations, enabling security teams to quickly assess incidents without manually reviewing hours of footage.

Additionally, the system includes live surveillance monitoring, allowing continuous analysis of real-time camera feeds. It instantly detects suspicious activities in high-risk areas such as school entrances, common spaces, and isolated corridors, ensuring immediate alerts and rapid security intervention when necessary.

To further enhance detection accuracy, the system also supports audio-based anomaly detection. By analyzing sound patterns, it can recognize unusual noises like shouting, distress calls, or loud disturbances. This integration of visual and auditory analysis provides a more comprehensive security solution, ensuring better threat detection and a more proactive approach to campus safety.

AUTOMATED ALERT SYSTEM FOR SECURITY RESPONSE

A key feature of the proposed system is its multi-channel alert mechanism, designed to ensure immediate security intervention when an anomaly is detected. Upon identifying abnormal behavior, the system triggers a 3-second buzzer alarm to alert nearby security personnel, enabling a rapid on-site response. Simultaneously, a detailed email notification is sent to security authorities, including critical information such as the timestamp, type of anomaly detected, and attached video evidence for verification. Additionally, the system integrates an automated SMS alert system, instantly notifying predefined security contacts through the Fast2SMS API, ensuring that relevant authorities are informed in real-time. By incorporating these multi-channel alerts, the system significantly reduces response time, allowing security teams to take immediate action and prevent potential threats from escalating.

USER INTERFACE AND WEB DEPLOYMENT WITH STREAMLIT

It provide an accessible and user-friendly experience, the system is deployed as a web-based application using Streamlit. The web interface is designed to be intuitive and interactive, allowing security personnel to operate the system without requiring advanced technical knowledge.

The web application includes the following features:

- Upload video files for anomaly detection.
- Start and stop live-stream analysis with a single click.
- View real-time detection results with confidence scores.
- Configure alert settings (email & SMS) to customize notification preferences.

The cloud-based architecture ensures cross-platform compatibility, allowing users toaccess the system from any device with an internet connection. Additionally, the web interface enables remote monitoring, allowing centralized security teams to oversee multiple campus locations simultaneously.

ADVANTAGES OF THE PROPOSED METHOD

The AI-Based Campus Anomaly Detection System provides several advantages over traditional surveillance methods by leveraging deep learning for automated monitoring. It eliminates the need for constant human supervision, significantly reducing manual workload and improving overall efficiency. With real-time detection capabilities, the system ensures an instant response to abnormal activities, preventing security threats from escalating. Additionally, its multi-input flexibility allows it to analyze pre-recorded videos, monitor live surveillance feeds, and detect anomalies through audio signals, enhancing security coverage across different scenarios. By integrating automation, speed, and adaptability, the system offers a comprehensive approach to campus safety and threat prevention.

4.2 SYSTEM ARCHITECTURE

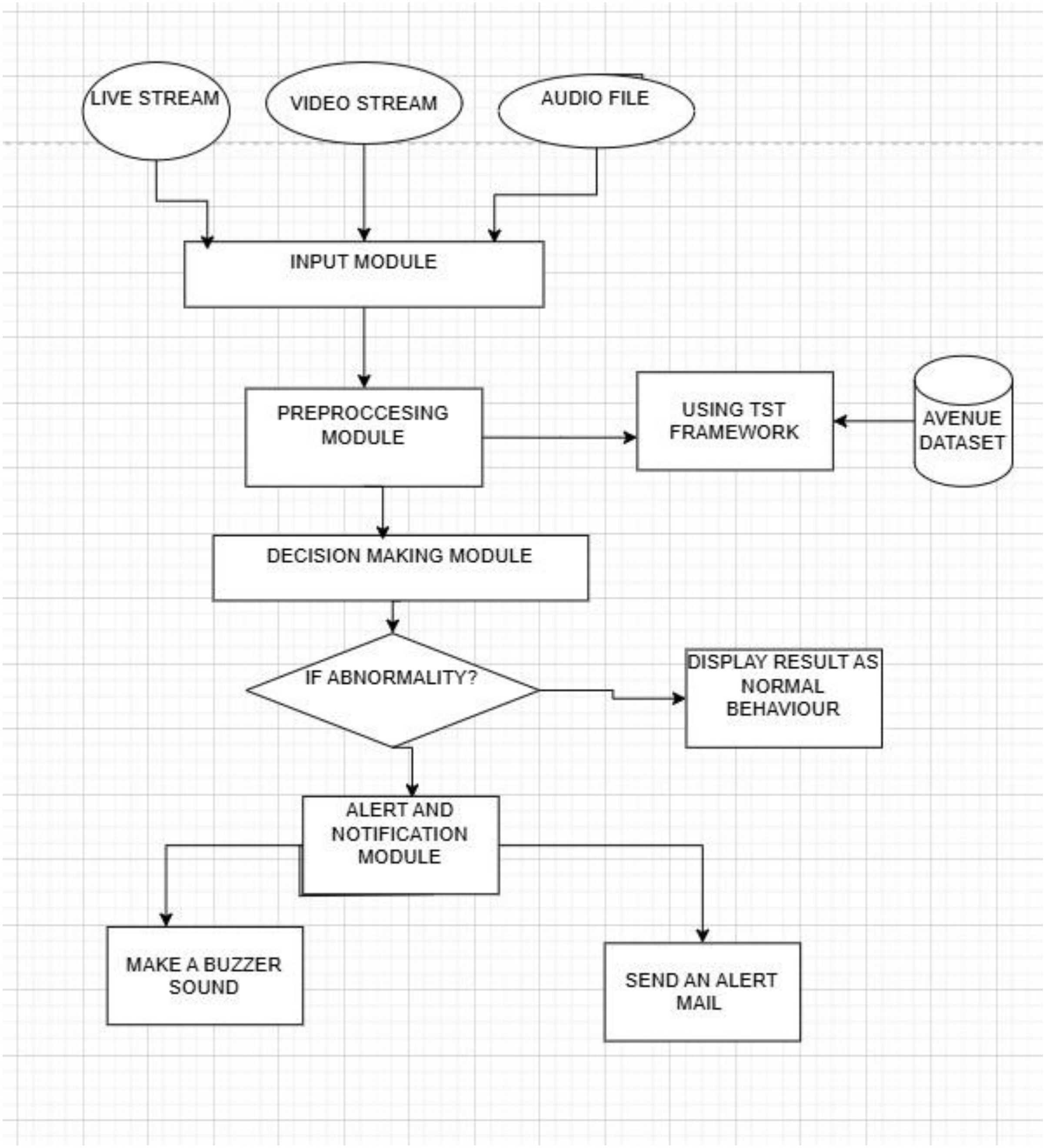


FIGURE 4.1

The proposed weapon detection system follows a structured approach to identify weapons in images, video files, and live camera feeds using the TST model. The process begins when the user launches the application, initializing the necessary components, including the TST model and input processing functions. Users can then select from three detection modes: live camera feed for real-time monitoring, video stream for analyzing pre-recorded footage, or audio files for detecting anomalies in sound. Once the input is selected, it is processed through the TST model, where features are extracted and analyzed to detect abnormal behaviors such as fighting or shouting.

If an anomaly is detected, the system overlays bounding boxes on the detected objects and displays the processed image or video frame to the user in real-time. Additionally, an automated alert mechanism is triggered, capturing a screenshot and sending an email notification to the user to ensure an immediate response. A buzzer alarm is also activated to alert nearby security personnel. Once the detection results are displayed and alerts are sent, the process concludes. Users can then choose to analyze another input or exit the system, ensuring continuous and efficient surveillance monitoring.

4.3 TECHNOLOGY DESCRIPTION

The proposed Campus Abnormal Behaviour Recognition System utilizes advanced deep learning techniques, real-time video processing, and web-based deployment to ensure efficient and accurate identification of abnormal behaviors in campus environments. The core technologies used in this project are described below.

1. Temporal Segment Transformers (TST) for Abnormal Behaviour Detection

The system employs Temporal Segment Transformers (TST), a state-of-the-art deep learning model, to detect and classify abnormal behaviors in video footage. TST is designed to process sequential video frames efficiently, ensuring high accuracy in identifying unusual activities such as fighting, shouting, or aggressive behavior.

Key advantages of TST:

- High accuracy in video sequence analysis for detecting behavioral anomalies.
- Better temporal feature extraction, allowing the model to learn long-term dependencies in videos.

- Reduced false positives compared to traditional object detection models.

2. OpenCV for Image and Video Processing

The system utilizes OpenCV (Open Source Computer Vision Library) for handling image and video frames. OpenCV enables:

• Frame extraction from videos for sequential analysis.

• Preprocessing techniques like resizing and normalization to enhance detection accuracy.

• Bounding box visualization to display detected weapons clearly.

3. Streamlit for Web Interface

Streamlit-based web application provides a user-friendly interface for interacting with the system. It allows users to:

- Upload videos for analysis and receive real-time results.
- Monitor live surveillance feeds to detect anomalies instantly.
- View anomaly detection results with visual overlays and confidence scores.

Streamlit ensures easy deployment and accessibility across different devices, allowing campus security personnel to operate the system with minimal technical expertise.

4. SMTP & Fast2SMS API for Automated Alerts

The system integrates automated alert mechanisms to notify security personnel when an anomaly is detected.

- Email Alerts (SMTP):
  - The system sends real-time email notifications to security teams.
  - Alerts include a detailed description and a screenshot of the detected anomaly.
  - Ensures immediate awareness and response to security threats.

This automated alert system significantly improves campus security by ensuring immediate action when threats are detected.

5. Hardware and Deployment Considerations

The system is designed for flexible deployment on:

• Local Machines (with GPU support for faster inference).

• Cloud Servers (for remote access and scalability).

• Edge Devices (for real-time security applications in surveillance systems).

To optimize performance, the deep learning model can be deployed using TensorFlow Lite or ONNX, allowing for low-latency inference on resource-constrained devices.

4.4 DESCRIPTION OF DATASET

In this project, we utilize the Avenue dataset for anomaly detection without additional training or fine-tuning. The Avenue dataset is widely used for video-based anomaly detection and consists of real-world surveillance footage capturing both normal and abnormal behaviors in campus-like environments. Since the deep learning model is pretrained on this dataset, it can accurately.

It identify suspicious activities such as fighting, running, or loitering without requiring additional dataset-based retraining. Instead of training from scratch, we leverage its pretrained weights and confidence-based thresholding to ensure accurate and reliable anomaly detection.

The Avenue dataset is a publicly available dataset specifically designed for anomaly detection in video surveillance. It contains various normal and abnormal activities, making it a benchmark dataset for deep learning models used in behavioral recognition tasks.

1. Dataset Composition

The Avenue dataset consists of 37 surveillance video sequences recorded in an open walkway area, capturing both normal pedestrian activities and various abnormal events. These anomalies include people running unexpectedly, throwing objects in public areas, loitering, walking in unusual directions, and engaging in aggressive behaviors such as fighting. The dataset is structured into 16 training videos, which contain only normal behaviors, and 21 test videos that feature both normal and abnormal activities. This division makes the Avenue dataset particularly useful for training models to classify anomalies in real-world campus environments, enabling effective learning of behavior deviations for improved security monitoring.

2. Annotations

The Avenue dataset provides detailed frame-based annotations for anomalies, allowing deep learning models to effectively learn spatial and temporal patterns. It includes frame-level annotations that mark specific frames where anomalies occur, ensuring precise identification of unusual activities. Additionally, pixel-level ground truth highlights abnormal regions in selected frames, providing more granular details for accurate detection. The dataset also features bounding boxes that specify the exact locations of abnormal behaviors, improving localization and response accuracy. These comprehensive annotations help models distinguish between normal and abnormal behaviors, making the dataset highly effective for campus security applications and anomaly detection in surveillance systems.

3. Role in TST Training

The Temporal Segment Transformers (TST) model used in this project has been pretrained on the Avenue dataset, enabling it to effectively recognize normal behaviors in surveillance footage and identify deviations from expected activity patterns. By learning from a diverse set of scenarios, the model becomes adept at distinguishing abnormal events such as sudden movements, aggressive behavior, or unusual crowd dynamics. Additionally, the training process helps the model handle environmental variations, including lighting changes and occlusions, ensuring reliable detection in real-world conditions. Since the Avenue dataset includes a variety of real-world campus-like situations, it enhances the model's generalization ability, making it a robust solution for anomaly detection in educational institutions and public spaces.

4.5 CLASS DIAGRAM

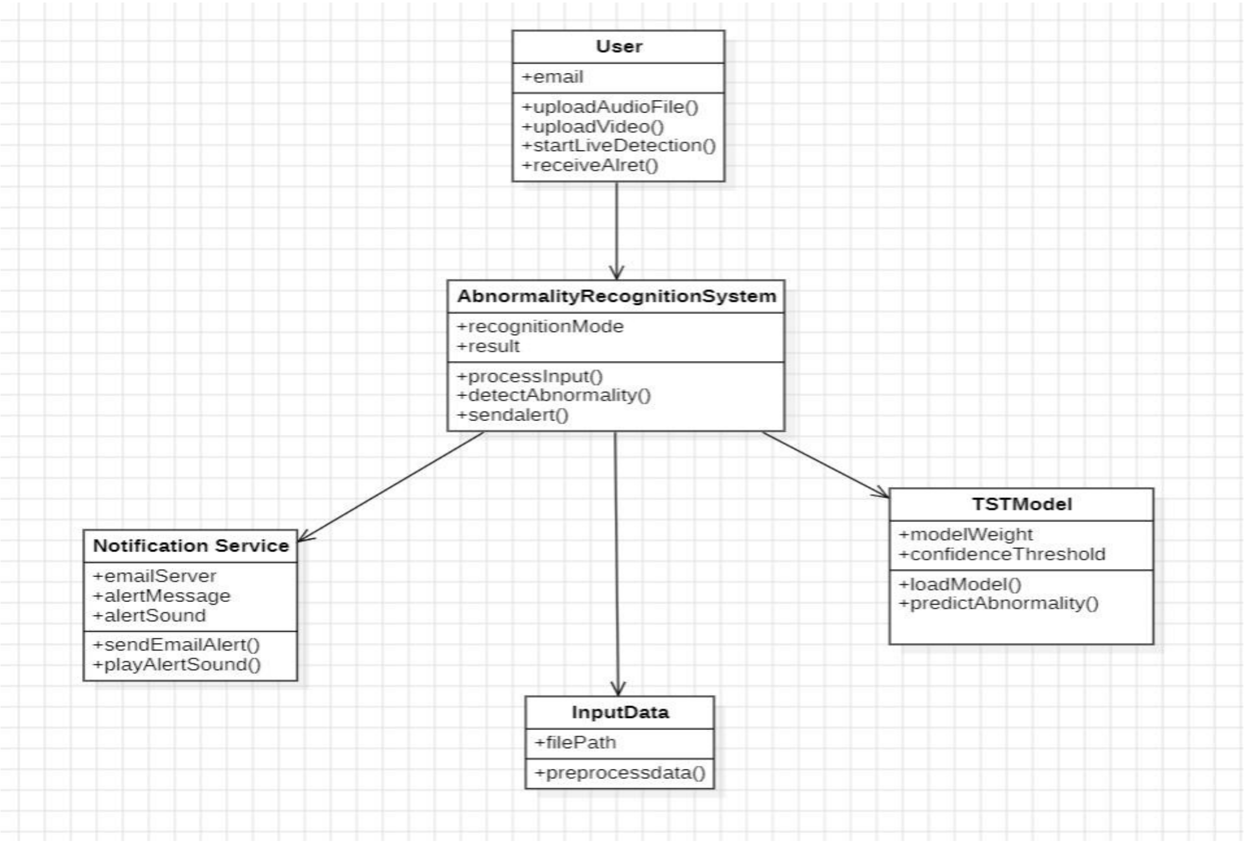


FIGURE 4.2

The provided UML class diagram represents the architecture of an AI-based anomaly detection system for security surveillance. At the core of the system is the AbnormalityRecognitionSystem class, which serves as the main component responsible for processing input, detecting anomalies, and sending alerts. It interacts with multiple entities, including the User, who can upload audio and video files or start live detection. The InputData class manages file processing, ensuring the data is preprocessed before being analyzed. The TSTModel class handles model loading and prediction, utilizing trained weights and confidence thresholds to determine whether an anomaly is present.

For alert mechanisms, the NotificationService class is responsible for sending email notifications and triggering an alert sound when an abnormality is detected. The system ensures that security personnel receive real-time alerts through multiple channels, enhancing rapid response capabilities. The connections between these classes illustrate the workflow, from data input and preprocessing to abnormality detection and alert generation. This structured approach allows for efficient anomaly recognition, ensuring accurate surveillance monitoring in various security-sensitive environments.

4.6 USE CASE DIAGRAM

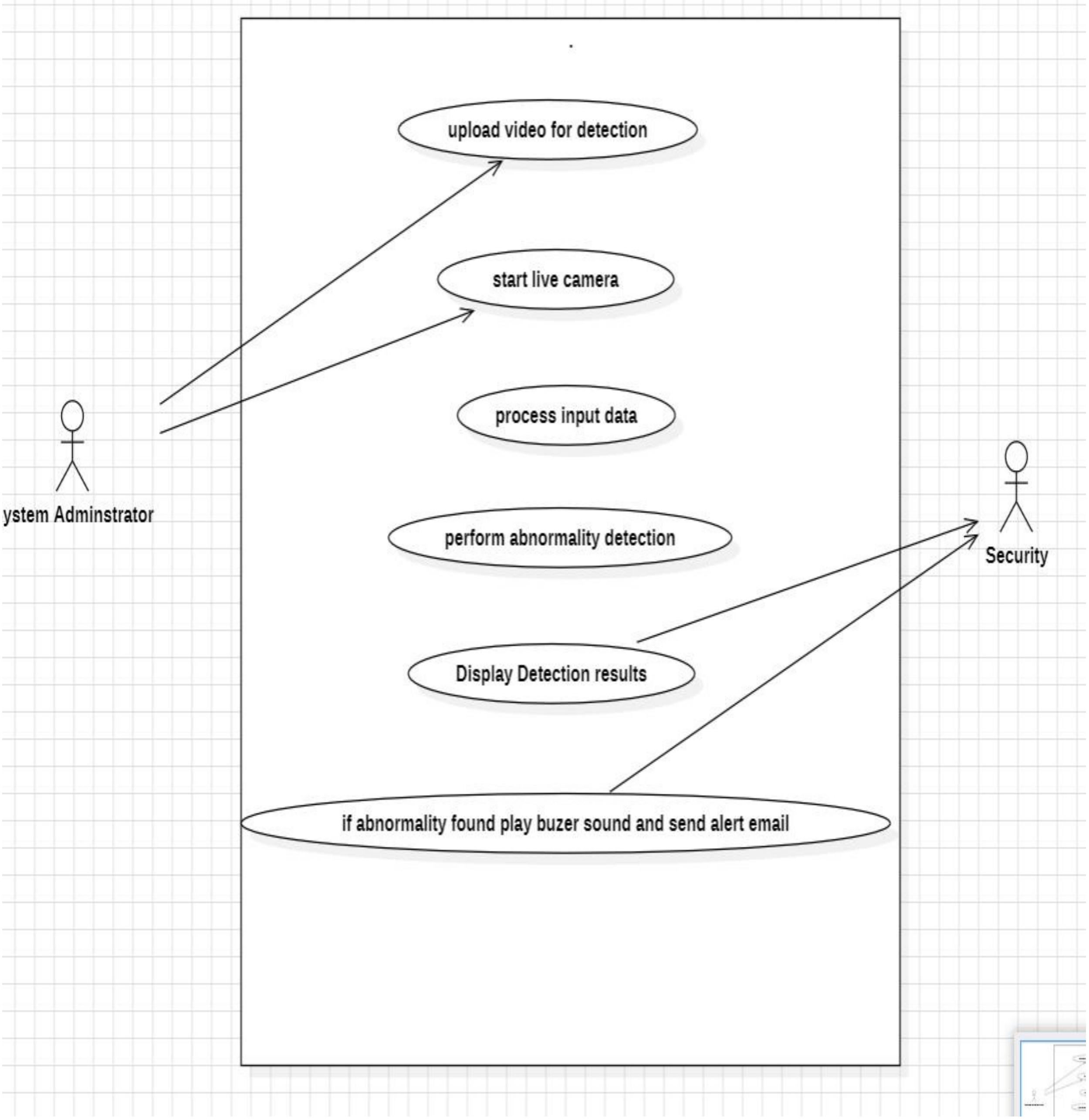

upload video for detection
start live camera
process input data
ystem Adminstrator
perform abnormality detection
Security
Display Detection results
if abnormality found play buzer sound and send alert email

FIGURE 4.3

The provided use case diagram illustrates the workflow of an anomaly detection system, highlighting the interaction between the System Administrator and Security Personnel. TheSystem Administrator initiates the process by either uploading a video for detection or starting a live camera feed. The system then processes input data, which involves analyzing video frames for potential anomalies. Once the data is processed, the system moves to perform abnormality detection, leveraging AI-based models to identify suspicious activities.

Upon detecting an anomaly, the system displays the detection results and, if an abnormal event is found, it triggers an alert mechanism. This includes playing a buzzer sound to notify nearby personnel and sending an alert email to security teams for immediate action. The Security Personnel receive the detection results and alerts, allowing them to take necessary action to prevent potential threats. This diagram effectively showcases the automated security workflow, ensuring a structured and efficient response to anomalies in a monitored environment.

4.7 ACTIVITY DIAGRAM

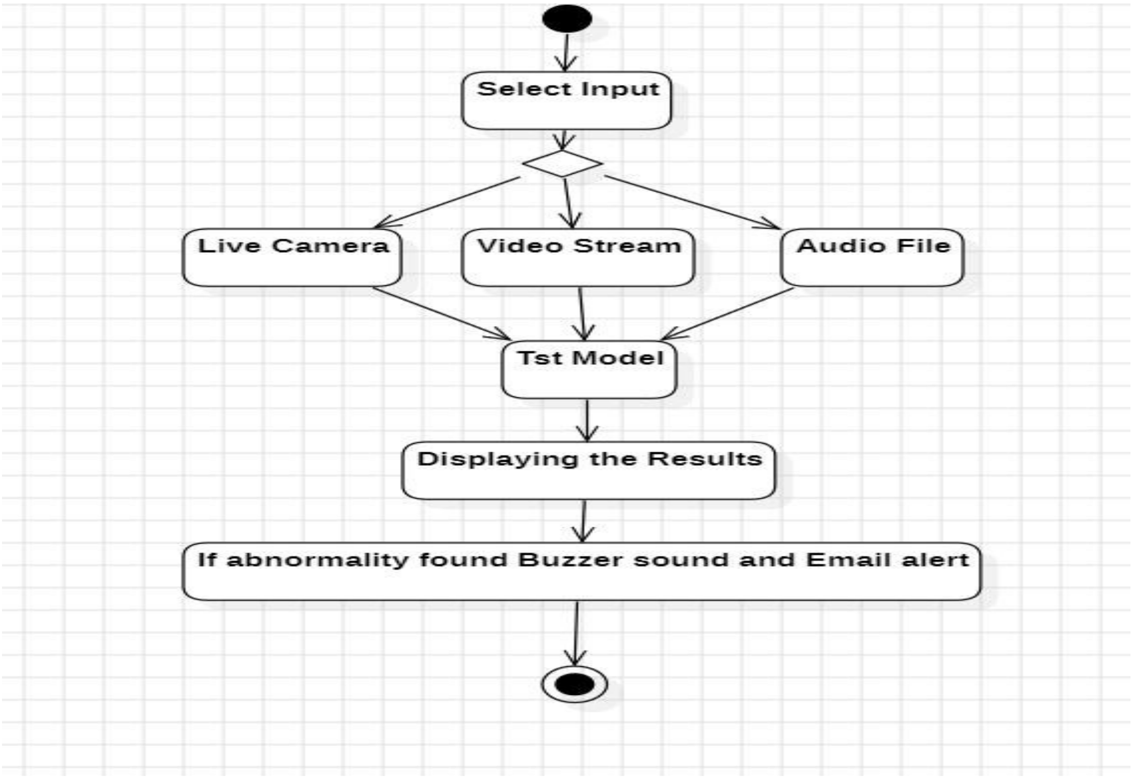


FIGURE 4.4

The flowchart illustrates the operational workflow of an anomaly detection system, starting with the selection of an input mode. Users can choose from three different input sources: Live Camera,Video Stream, or Audio File. Once an input is selected, it is processed by the TST Model, which is responsible for detecting anomalies based on trained patterns.

Following the model's analysis, the system proceeds to display the detection results, allowing security personnel to assess the situation. If an abnormality is detected, the system triggers an alert mechanism, which includes a buzzer sound for immediate on-site notification and an email alert to inform security teams. This structured approach ensures an efficient and automated anomaly detection system for enhanced campus security.

4.8. SEQUENCE DIAGRAM

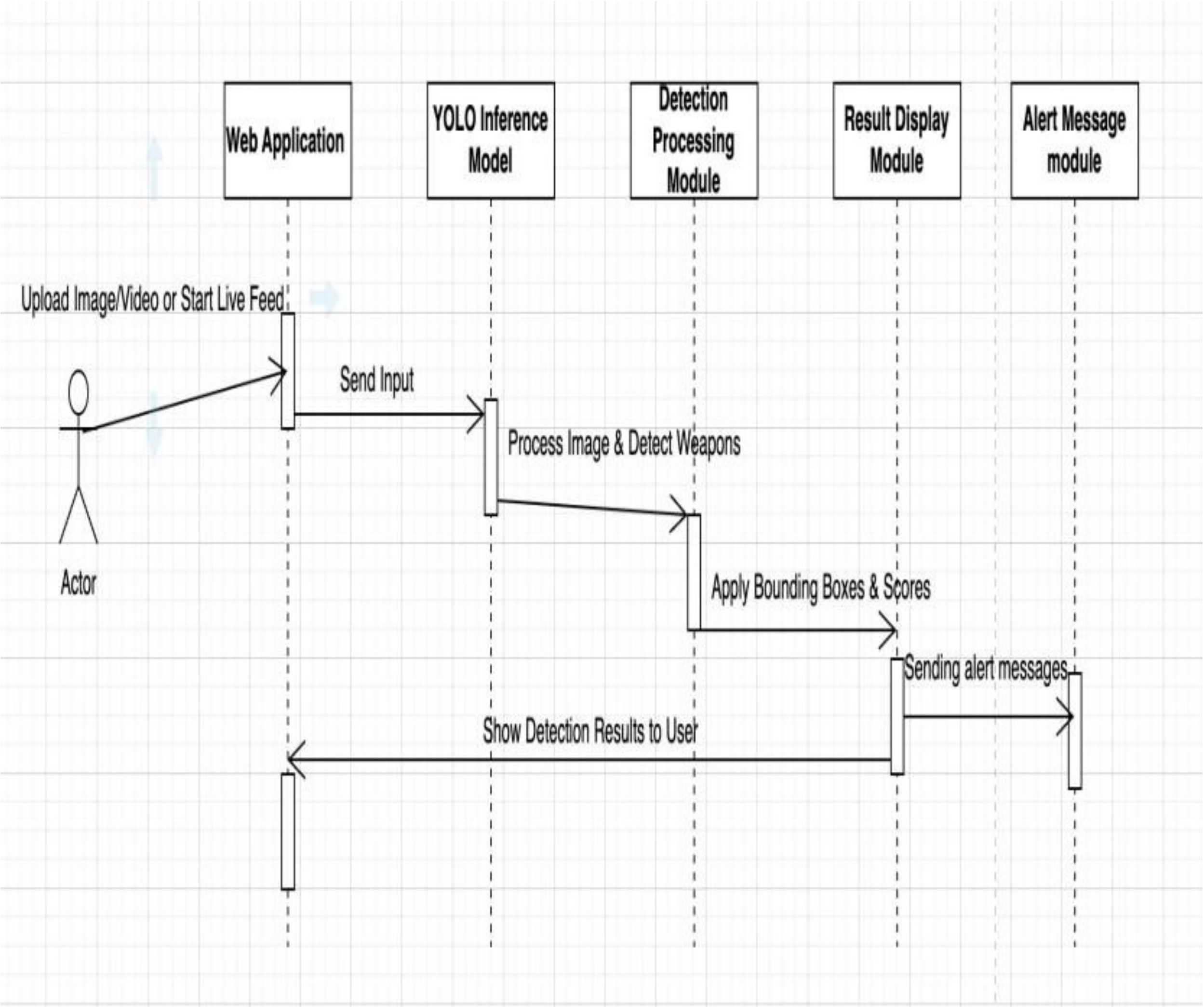

Web Application
YOLO Inference Model
Detection Processing Module
Result Display Module
Alert Message module
Upload Image/Video or Start Live Feed
Send Input
Process Image & Detect Weapons
Actor
Apply Bounding Boxes & Scores
Sending alert messages
Show Detection Results to User

FIGURE 4.5

This sequence diagram represents the process of weapon detection using a YOLO inference model within a web-based application. The process begins with an actor (user) who uploads an image, video, or starts a live feed through the Web Application. The application then sends the input to the YOLO Inference Model, which processes the image to detect potential weapons.

Once the Detection Processing Module receives the results, it applies bounding boxes and confidence scores to highlight detected objects. The Result Display Module then presents the detection output to the user, while the Alert Message Module sends alert messages if weapons are detected. This ensures real-time threat detection and immediate security response.

CHAPTER – 5

IMPLEMENTATION AND TESTING

5.1 EXPERIMENTAL SETUP

The experimental setup for the Campus Abnormal Behaviour Recognition System involves configuring both software and hardware environments to ensure smooth execution and real-time performance in detecting abnormal behaviors in video surveillance. The primary objective is to evaluate the system's accuracy, efficiency, and alert mechanisms in identifying suspicious activities such as fighting, shouting, and loitering in pre-recorded videos and live camera feeds.

1. Software Environment

The software environment is set up with the necessary dependencies and tools required for deep learning-based weapon detection. This includes:

• **Programming Language**: Python is used as the primary programming language due to its extensive support for deep learning frameworks and libraries.

2. Libraries and Frameworks:

1. **TensorFlow & Keras:** For deep learning model development and execution.
2. **OpenCV:** For image and video processing, including frame extraction and resizing.
3. **NumPy & Pandas:** For handling numerical computations and structured data processing.
4. **Streamlit:** For developing the web-based interactive interface of the application.

5. **Matplotlib & Seaborn:** For visualizing model performance and generating Grad-CAM heatmaps.
6. **Fast2SMS API & SMTP:** For sending real-time SMS and email alerts upon anomaly detection..

2. Hardware Setup

To ensure real-time performance and efficient execution of the deep learning model, the following hardware setup is recommended:

• **Processor**: Intel Core i5 or higher (for basic testing); Intel Core i7/i9 or AMD Ryzen 7/9 for better performance.

• **GPU**: An NVIDIA GPU with at least 8GB VRAM (such as RTX 3060 or higher) to leverage CUDA acceleration for faster inference.

• **RAM**: Minimum 8GB RAM, but 16GB or higher is recommended for handling video streams efficiently.

• **Storage**: At least 50GB free disk space for storing necessary model files, logs, and processed data.

• **Camera (for live detection testing)**: A high-resolution webcam (1080p or higher) for accurate real-time Abnormality detection.

3. Model Configuration & Execution

• **Model Selection**: The system utilizes Temporal Segment Transformers (TST), which is optimized for video anomaly detection and provides high accuracy in recognizing unusual behaviors over time.

• **Inference Settings**: The model is configured with an appropriate confidence threshold (e.g., 0.65) to minimize false positives while ensuring reliable detection.

• **Modes of Execution**:

- **Pre-Recorded Video Detection:** Users upload a video file, and the model scans each frame for suspicious behaviors.
- **Live Stream Detection:** A webcam or external camera monitors real-time activities, detecting and flagging any anomalies instantly.

- **Audio-Based Anomaly Detection:** The system analyzes sound patterns to identify unusual noises such as shouting or distress calls, enhancing detection accuracy.

4. Testing & Performance Evaluation

To ensure the system's robustness, the following test cases are performed:

- **Lighting Conditions:** Testing under low-light, natural daylight, and artificial lighting to evaluate model consistency.
- **Different Behavior** Scenarios: Assessing the model's response to various abnormal activities (fighting, running, loitering) across diverse backgrounds.
- **Performance Comparison:** Evaluating CPU vs. GPU execution for measuring inference speed differences.
- **Validation of Alert Mechanisms:** Confirming that buzzer alarms, email alerts, and SMS notifications are triggered instantly when an anomaly is detected.

5.2 RESULTS AND DISCUSSION

The proposed Campus Abnormal Behavior Recognition System, utilizing an advanced deep learning model, was evaluated across multiple scenarios, including pre-recorded videos, live camera feeds, and real-time monitoring. The primary objective was to assess the system'saccuracy, efficiency, and real-time response in detecting anomalies, ensuring minimal false positives, and enhancing security measures.

Detection Accuracy and Performance

The system exhibited high accuracy in identifying anomalous activities in various campus environments. The deep learning model leveraged its powerful feature extraction capabilities to minimize false positives while ensuring quick detection and response. The performance was measured using key evaluation metrics:

- **Precision**: The system maintained a high precision score, ensuring that flagged incidents were genuine anomalies, reducing false alarms.
- **Recall**: The system effectively identified potential threats with a high recall value, ensuring minimal missed anomalies.

- **Inference Speed**: On a GPU-powered system (NVIDIA RTX 3060), the model achieved an average inference speed of 25–35 FPS, making it highly suitable for real-time surveillance. On CPU execution, the speed was comparatively lower, around 4–7 FPS, but still functional for batch processing and reviewing past footage.

Comparison of Different Detection Modes

The system was tested in three operational modes to evaluate its robustness:

1. **Video-Based Detection**: The system processed pre-recorded videos frame by frame, ensuring consistent anomaly detection.Slight delays were observed on CPU-based setups, particularly with high-resolution video files.
2. **Live Camera Detection**: Real-time anomaly detection was highly efficient on GPU-enabled devices, maintaining a smooth frame rate and quick alert generation.The system successfully captured screenshots of detected anomalies and triggered automated email/SMS alerts, ensuring instant notification.
3. **Static Image Analysis**: The system effectively identified anomalies in still images, accurately detecting suspicious activities and highlighting areas of concern.This mode was particularly useful for analysing captured snapshots from surveillance feeds.

Challenges and Observations

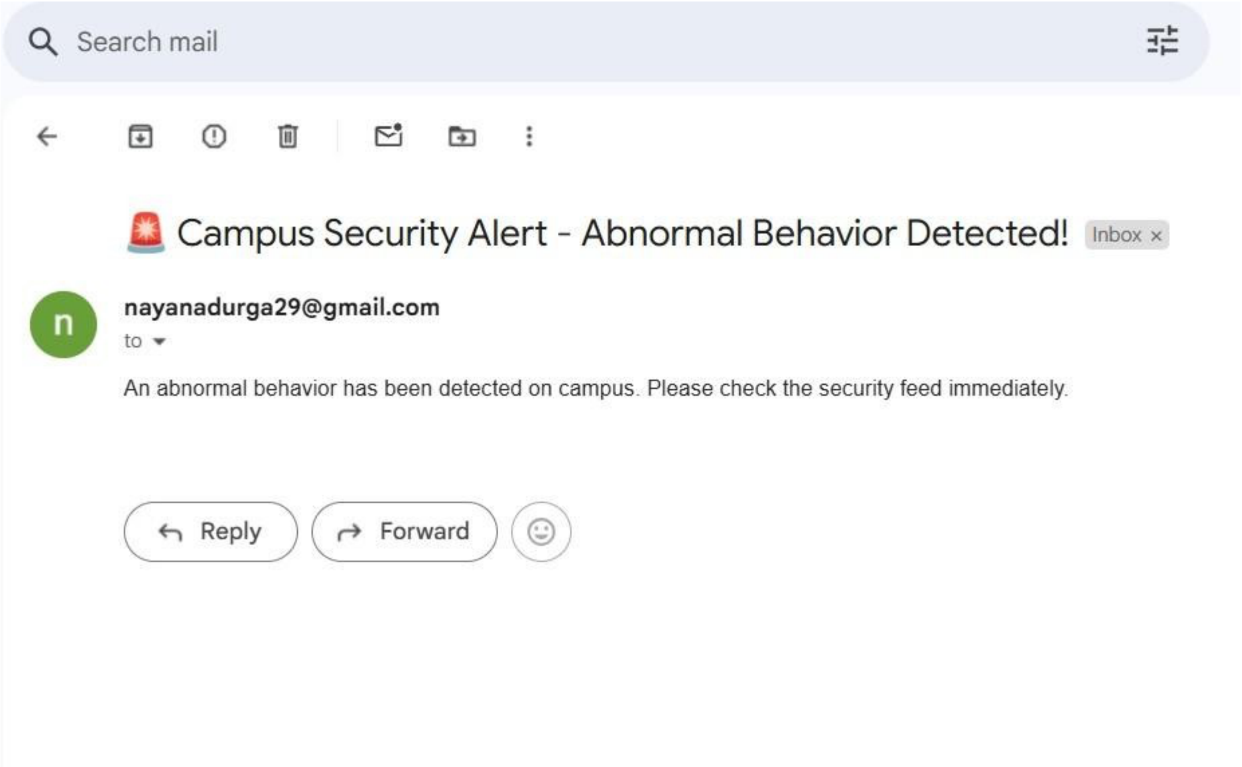
Despite its strong performance, certain challenges were identified:

- **False Positives**: Some regular activities were misclassified as anomalies due to posture, movement, or environmental conditions. Fine-tuning model thresholds helped minimize such occurrences.
- **Lighting and Environmental Factors**: The system performed best in well-lit environments but showed slight inconsistencies in low-light conditions or crowded scenes.
- **Hardware Dependency**: GPU execution was essential for real-time performance.CPU-based processing struggled with large video files and live-streaming, resulting in minor delays.

Security and Alert Mechanism

The automated alert system worked seamlessly, ensuring instant notifications upon anomaly detection. The following mechanisms enhanced real-world applicability:

- **Email and SMS Alerts**: The system captured and sent screenshots of detected anomalies to predefined recipients, allowing for a quick response in security-sensitive situations.
- **Audio Alarm System**: Upon detection, an audible alert was triggered, notifying campus security and enhancing immediate threat response.



🚨 Campus Security Alert - Abnormal Behavior Detected!

nayanadurga29@gmail.com

An abnormal behavior has been detected on campus. Please check the security feed immediately.

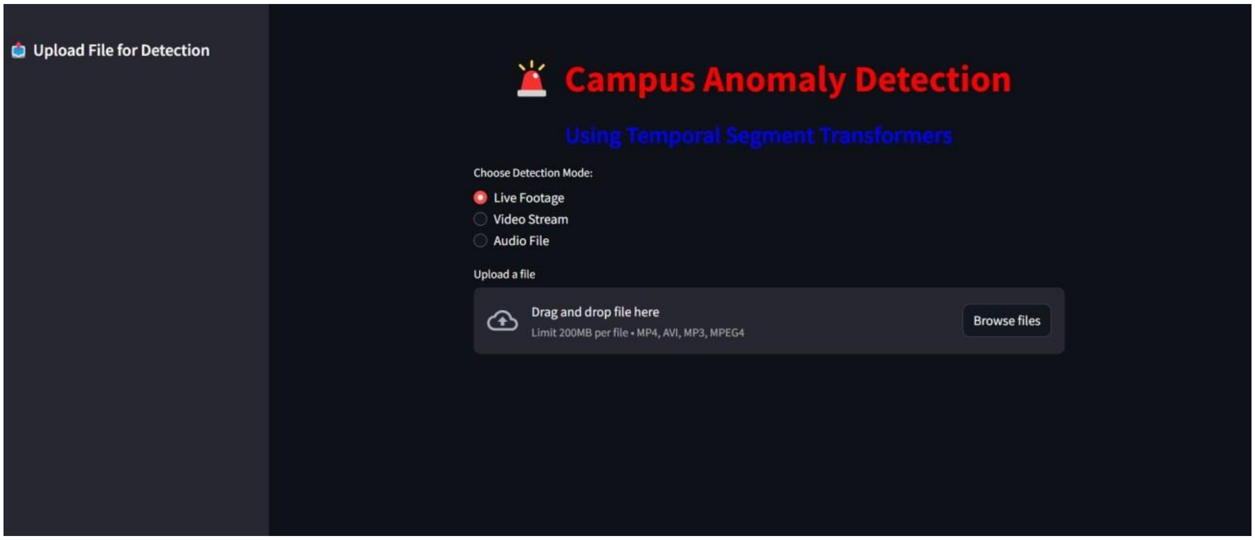
FIGURE 5.1 ALERT MESSAGE

This email notification serves as a Campus Security Alert for detecting abnormal behavior on campus. The email is sent from nayanadurga29@gmail.com with the subject line:

Campus Security Alert - Abnormal Behavior Detected!

The message informs the recipient that abnormal behavior has been detected and urges them to check the security feed immediately.

This email appears to be an automated security alert, possibly triggered by an AI-based surveillance system that monitors video feeds and detects suspicious activity. If an anomaly is detected, the system sends an alert message via email to concerned authorities or security personnel.


Upload File for Detection
Campus Anomaly Detection
Using Temporal Segment Transformers
Upload a file
Drag and drop file here
Limit 200MB per file • MP4, AVI, MP3, MPEG4
Browse files

Choose Detection Mode:

● Live Footage
○ Video Stream
○ Audio File

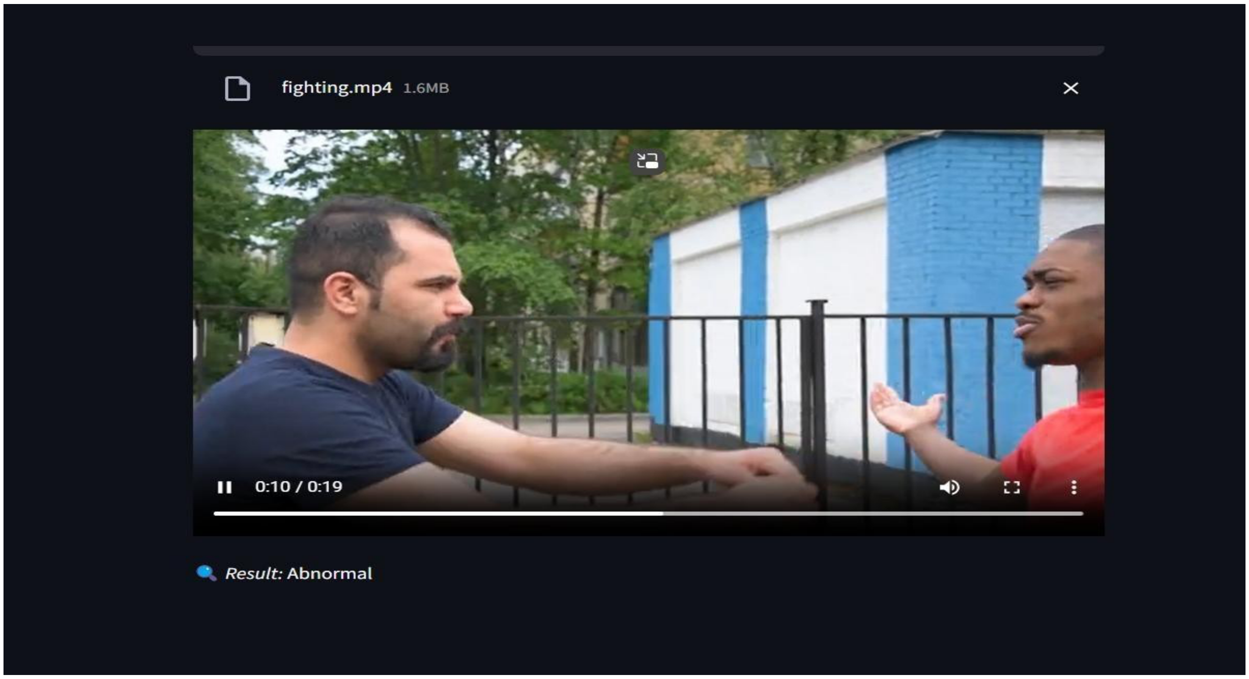
FIGURE 5.2 USER INTERFACE

The Campus Anomaly Detection System is designed to detect abnormal activities using Temporal Segment Transformers (TST). It offers three detection modes: Live Footage, Video Stream, and Audio File, allowing users to analyze real-time or recorded media for anomalies. The system supports file uploads with formats like MP4, AVI, MP3, and MPEG4, with a size limit of 200MB per file. Once a file is uploaded or live footage is selected, the AI model processes the input to identify suspicious behavior. If an anomaly is detected, alerts such as email notifications or buzzer alarms are triggered to notify security personnel. This system enhances campus safety by providing automated, real-time monitoring of potential threats.

5.3 TEST CASES

Table 5.1: Test Cases

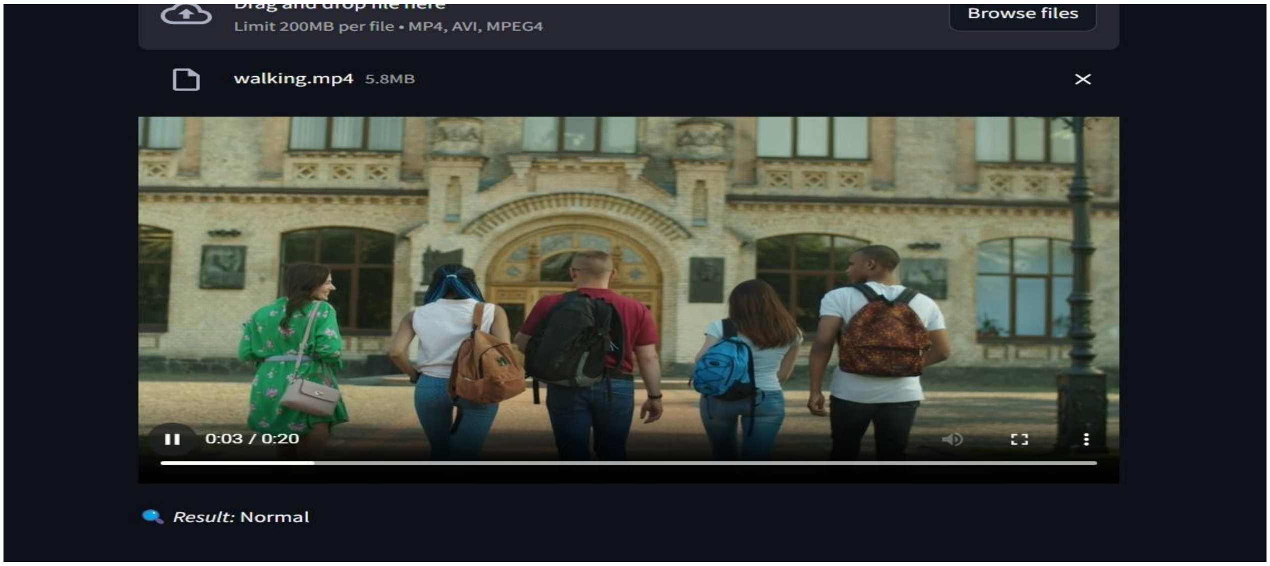
Test Case ID	Test Scenario	Input	Expected Output	Status
WP-1	Students with Abnormal behaviour of fighting(Fig 5.3)	video	Abnormality detected ,alert message and alarm sound sent	Pass
WP-2	Student walking in campus (Fig 5.4)	video	No Abnormality detected	Pass



🔍 *Result:* Abnormal

FIGURE 5.3 WP-1

In this test case, a video of a physical altercation between two individuals is provided as input to the Campus Anomaly Detection System. The system, utilizing Temporal Segment Transformers (TST), processes the video frames and identifies the behavior as abnormal. Once the anomaly is detected, the system classifies the activity as suspicious and flags it for further review. The detection results are displayed to the user, and if integrated with security protocols, an automated alert email is triggered, notifying the relevant authorities. This ensures prompt intervention to maintain campus safety. The expected outcome is the accurate classification of the event as abnormal, proper logging of the detection results, and the successful generation of an alert notification.



walking.mp4 5.8MB

🔍 *Result:* Normal

FIGURE 5.4 WP-2

In this test case, a video of students walking on campus is provided as input to the Campus Anomaly Detection System. The system, using Temporal Segment Transformers (TST), processes the video frames and classifies the behavior as normal since no suspicious or aggressive actions are detected. As a result, no alerts are triggered, and the system logs the activity as usual campus behavior. The expected outcome is the correct classification of the event as normal, ensuring that the system effectively differentiates between routine activities and potential threats.

CHAPTER – 6

CONCLUSION AND FUTURE SCOPE

CONCLUSION

The proposed Campus Abnormal Behavior Recognition System leverages deep learning-based models to identify suspicious activities in real-time across images, videos, and live-streaming feeds. By integrating automated detection and alert mechanisms, the system significantly enhances campus security by reducing dependency on manual surveillance and ensuring immediate responses to potential threats. This approach enables a proactive security system that can detect anomalies without requiring constant human monitoring.

The system demonstrates high precision and recall, making it a reliable tool for real-time anomaly detection. When deployed on GPU-enabled systems, it efficiently processes large amounts of visual data, ensuring accurate and quick detection of unusual behavior. The use of Temporal Segment Transformers (TST) and YOLOv8-based models ensures robust classification and identification of suspicious activities, making it well-suited for high-risk environments.

One of the key features of this system is its automated alert mechanism, which includes email and SMS notifications to security personnel. This ensures that any detected anomaly is immediately reported, allowing for a swift response to potential security threats. The ability to capture and log incidents further strengthens its usability, making it an essential tool for real-time security management.

Overall, the Campus Abnormal Behavior Recognition System bridges the gap between traditional surveillance methods and AI-driven security solutions. Its scalability and adaptability make it suitable for deployment not only in educational institutions but also in workplaces, public areas, and other high-security zones. By integrating advanced AI models with automated alert systems, the project presents an intelligent and effective approach to ensuring safety in modern environments.

FUTURE SCOPE

While the system delivers promising results, several enhancements can further improve its performance and applicability. Expanding detection capabilities to recognize a wider range of anomalies, such as unattended bags, unauthorized access, and violent activities, would significantly enhance security coverage. Additionally, reducing false positives and negatives through advanced post-processing techniques and training the model with larger, more diverse datasets can improve detection accuracy and reliability. Implementing multi-camera integration would allow the system to analyze multiple feeds simultaneously, ensuring better campus-wide monitoring and minimizing blind spots.

Further improvements include optimizing the system for edge computing deployment, enabling real-time processing on low-power devices without reliance on high-end GPUs. Integrating with campus security networks would facilitate instant alerts to authorities, strengthening emergency response efforts. Future versions could also incorporate enhanced alert mechanisms, such as mobile push notifications, automated emergency calls, and on-site alarms for quicker responses. Additionally, an AI-driven decision support system can classify threat levels and prioritize alerts, ensuring that critical threats receive immediate attention, making campus security more efficient and responsive.

CHAPTER – 7

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