

PROFESSIONAL TRAINING REPORT - II

entitled

Smart Anomaly Detection Systems: Leveraging AI for Enhanced Performance

Submitted in partial fulfillment of the requirements for the award of
Bachelor of Engineering degree in Computer Science and Engineering
with specialization in AI and Robotics

by

Kevin Bryan Mathew [41612020]



**DEPARTMENT OF COMPUTER SCIENCE AND ENGINEERING
SCHOOL OF COMPUTING**

SATHYABAMA

**INSTITUTE OF SCIENCE AND TECHNOLOGY
(DEEMED TO BE UNIVERSITY)
CATEGORY -1 UNIVERSITY BY
UGC**

**Accredited with Grade "A++" by NAAC | 12B Status by UGC | Approved by
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BONAFIDE CERTIFICATE

This is to certify that this Professional Training Report is the bonafide work of **Mr. Kevin Bryan Mathew (41612020)** who carried out the project entitled "**Smart Anomaly Detection Systems: Leveraging AI for Enhanced Performance**" under my supervision from January 2024 to April 2024.

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DECLARATION

I, Kevin Bryan Mathew (41612020) , hereby declare that the Professional Training Report-II entitled "Smart Anomaly Detection Systems: Leveraging AI for Enhanced Performance" done by me under the guidance of Dr. Sonia Jenifer Rayen, M.Tech., Ph.D., is submitted in partial fulfillment of the requirements for the award of Bachelor of Engineering degree in Computer Science and Engineering with specialization in AI and Robotics.

DATE: 7th May, 2024

PLACE: Chennai



SIGNATURE OF THE CANDIDATE

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COURSE CERTIFICATE



ABSTRACT

In today's data-rich world, the emergence of smart anomaly detection systems powered by artificial intelligence (AI) presents a paradigm shift in enhancing performance across diverse domains. These systems harness the capabilities of advanced machine learning algorithms and deep neural networks to efficiently sift through massive datasets, identifying deviations from expected patterns and behaviors. By autonomously learning from historical data, AI-driven anomaly detection systems enable proactive intervention, minimizing potential risks and optimizing operational efficiency. This abstract delves into the foundational principles and methodologies underpinning smart anomaly detection systems, elucidating their adaptability and scalability in dynamically evolving environments. Through real-world examples and case studies, the abstract illustrates their indispensable role in various industries, including finance, healthcare, cybersecurity, and industrial automation. From detecting fraudulent transactions to identifying anomalies in medical data and safeguarding critical infrastructure, AI-driven anomaly detection systems offer unparalleled accuracy and reliability. Moreover, the abstract explores how these systems facilitate swift decision-making processes by providing timely insights into emerging anomalies, thereby empowering organizations to mitigate risks and capitalize on opportunities. By leveraging the transformative potential of AI, these systems not only bolster performance but also drive innovation, enabling organizations to stay ahead in an increasingly competitive landscape. In conclusion, this abstract underscores the transformative impact of AI-powered anomaly detection systems in optimizing operations, enhancing security, and fostering innovation across industries. As organizations continue to harness the power of AI-driven technologies, smart anomaly detection systems stand out as indispensable tools for navigating the complexities of modern data environments and achieving sustainable growth and success.

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CHAPTER 1

INTRODUCTION

1.1 OVERVIEW

In the rapidly evolving landscape of computer vision, where machines are endowed with the remarkable capability to interpret and understand visual data, the detection of anomalies emerges as a cornerstone for ensuring the reliability, accuracy, and safety of automated systems. From surveillance cameras surveilling public spaces to autonomous vehicles navigating bustling city streets, computer vision applications have become ubiquitous, offering unprecedented opportunities for innovation and efficiency. However, these applications are not impervious to anomalies, which can manifest as unexpected objects, events, or behaviors in visual data streams.

Traditional methods of anomaly detection in computer vision have predominantly relied on handcrafted features, predefined thresholds, or rule-based systems. However, as the volume and diversity of visual data continue to burgeon, these conventional approaches confront formidable challenges in coping with the complexity and variability of real-world visual environments. Consequently, there arises a pressing need for smarter, more adaptive anomaly detection systems capable of discerning anomalies amidst the complexity of dynamic scenes and diverse contexts.

Enter smart anomaly detection systems, propelled by the fusion of artificial intelligence (AI) and machine learning. These systems herald a paradigm shift in anomaly detection within the realm of computer vision, harnessing advanced algorithms and deep learning techniques to analyze visual data, learn intricate patterns, and identify anomalies with unparalleled accuracy and efficiency. By training on extensive datasets, these systems autonomously extract features, detect anomalies, and dynamically adapt to evolving conditions, rendering them robust and versatile across a spectrum of real-world scenarios.

At the core of smart anomaly detection systems for computer vision lie deep learning architectures, notably including convolutional neural networks (CNNs), recurrent neural networks (RNNs), and generative adversarial networks (GANs). These architectures have demonstrated remarkable prowess in tasks such as object detection, image classification, and semantic segmentation, thereby forming the bedrock of anomaly detection systems in computer vision. Leveraging the hierarchical representations distilled by these architectures, anomaly detection systems can discern anomalies predicated on deviations from learned patterns or distributions.

Beyond their technical intricacies, the efficacy of smart anomaly detection systems in computer vision is profoundly influenced by contextual factors encompassing the characteristics of the visual data, scene complexity, and application domain specificity.

For instance, anomaly detection in surveillance footage may necessitate distinct methodologies and thresholds relative to anomaly detection in medical imaging or industrial inspection. Likewise, the performance of anomaly detection systems may be contingent upon factors such as lighting conditions, occlusions, and camera perspectives.

However, amidst the promise of smart anomaly detection systems in computer vision, a spectrum of challenges and considerations looms large. Data quality imperfections, encompassing noise, artifacts, and occlusions, pose significant hurdles to anomaly detection algorithms, potentially engendering false positives or false negatives. The selection of appropriate algorithms assumes paramount importance, as disparate architectures and training strategies may exhibit varying efficacy contingent upon the idiosyncrasies of the visual data and the nature of the anomalies therein.

Furthermore, ethical and societal considerations pervade the development and deployment of AI-driven anomaly detection systems in computer vision. Privacy apprehensions arise vis-à-vis the collection and analysis of visual data, prompting queries surrounding consent, surveillance, and data privacy. Instances of bias, whether endemic to the data or algorithms, precipitate concerns regarding fairness and equity, potentially exacerbating extant inequalities. Moreover, the accountability and responsibility of organizations deploying these systems are paramount, as erroneous or deficient anomaly detection may wield profound repercussions for individuals, communities, and society writ large.

In this expansive exploration, we embark on an odyssey into the realm of smart anomaly detection systems in computer vision, unraveling their potential to revolutionize operations, fortify security, and propel innovation across sundry domains. Through a multidisciplinary lens encompassing computer vision, machine learning, ethics, and beyond, we interrogate the foundational principles, methodologies, and applications of these systems. Real-world case studies and examples serve as beacons, illuminating how organizations harness AI-driven anomaly detection to detect intruders, diagnose anomalies in medical images, monitor industrial processes, and more.

Moreover, we navigate the labyrinthine landscape of challenges and considerations associated with the deployment and adoption of smart anomaly detection systems in computer vision, proffering practical guidance and recommendations. From data preprocessing and algorithmic selection to interpretability and accountability, we navigate this intricate terrain, offering insights to empower decision-makers and practitioners seeking to harness the transformative potential of these technologies.

In the pursuit of advancing anomaly detection capabilities in computer vision, researchers and practitioners are continually exploring innovative approaches and cutting-edge technologies. One such avenue of exploration is the integration of

multimodal data sources, where visual information is complemented by other modalities such as textual data, sensor data, or audio signals. By fusing information from multiple sources, smart anomaly detection systems can enrich their understanding of complex scenes, enhancing their ability to discern anomalies and reducing false positives. Moreover, advancements in explainable AI (XAI) are opening new avenues for interpreting and understanding the decisions made by anomaly detection systems. By providing insights into the underlying reasoning behind anomaly detections, XAI techniques empower stakeholders to trust and validate the outputs of these systems, fostering greater transparency and accountability. Through ongoing research and development efforts, the frontier of anomaly detection in computer vision continues to evolve, promising ever more sophisticated solutions for addressing the challenges of anomaly detection in complex visual environments.

Therefore, the proliferation of edge computing and Internet of Things (IoT) devices has brought about new opportunities and challenges for anomaly detection in computer vision. With the ability to process data locally at the edge, smart cameras and IoT devices can perform real-time anomaly detection without relying on centralized processing or cloud connectivity. This distributed approach offers advantages such as reduced latency, improved privacy, and resilience to network outages. However, it also poses challenges in terms of resource constraints, scalability, and the need for efficient algorithms tailored to edge computing environments. As organizations increasingly deploy edge-based anomaly detection systems, there is a growing demand for lightweight, energy-efficient algorithms capable of running on resource-constrained devices while maintaining high detection accuracy.

In addition to technical considerations, the ethical and societal implications of AI-driven anomaly detection in computer vision demand careful attention. As these systems become more pervasive in public spaces, workplaces, and other domains, questions arise regarding privacy, surveillance, and individual rights. Striking a balance between the benefits of anomaly detection for enhancing security and efficiency and the protection of individual privacy and civil liberties is essential. Moreover, efforts to mitigate bias and ensure fairness in anomaly detection algorithms are imperative to prevent discriminatory outcomes and uphold principles of equity and justice. By fostering interdisciplinary collaboration and stakeholder engagement, the development and deployment of AI-driven anomaly detection systems can be guided by ethical principles and societal values, promoting responsible innovation and societal benefit.

In conclusion, our aim is to furnish a comprehensive and nuanced understanding of smart anomaly detection systems in computer vision and their catalytic role in driving performance optimization through AI.

CHAPTER 2

LITERATURE REVIEW

2.1 SURVEY

Anomaly detection, an essential component in various domains such as cybersecurity, industrial automation, and healthcare, has garnered significant attention owing to its potential to identify irregularities or deviations from normal behavior in data streams. Traditional methods often struggle to cope with the complexities and scale of modern datasets, leading to the emergence of Smart Anomaly Detection Systems (SADS) that leverage Artificial Intelligence (AI) techniques for enhanced performance. This literature survey explores the landscape of anomaly detection methodologies, with a focus on recent advancements in AI-driven approaches.

Deep learning, particularly convolutional neural networks (CNNs) and recurrent neural networks (RNNs), has revolutionized anomaly detection by enabling automated feature extraction and learning complex patterns from raw data. Deep residual learning, introduced by He et al. [1] in 2016, significantly improves the training of deep neural networks by addressing the vanishing gradient problem. Similarly, the efficacy of CNNs in image classification tasks, as demonstrated by Krizhevsky et al. [11] in 2012, laid the foundation for their application in anomaly detection. RNNs, showcased by Sutskever et al. [25] in 2014, excel in sequential data analysis, making them suitable for detecting anomalies in time-series data such as network traffic or sensor readings.

Autoencoders, a class of neural networks designed for unsupervised learning, have emerged as a popular choice for anomaly detection due to their ability to reconstruct input data and detect deviations from normal patterns. Stacked denoising autoencoders, proposed by Vincent et al. [16] in 2010, learn hierarchical representations of data by reconstructing corrupted input. An et al. [14] extended this concept with variational autoencoders in 2015, utilizing probabilistic models to capture the uncertainty in reconstruction and detect anomalies based on reconstruction probability. Furthermore, Yu and Deng [10] enhanced anomaly detection using autoencoders with nonlinear dimensionality reduction, enabling efficient representation learning and anomaly identification in high-dimensional data.

In addition to neural networks, ensemble learning techniques such as random forests, as introduced by Breiman [17] in 2001, have demonstrated robust performance in anomaly detection tasks. By aggregating predictions from multiple decision trees, random forests can effectively capture complex data distributions and identify outliers in both structured and unstructured data. Moreover, synthetic data generation methods like SMOTE [20] in 2002 have been instrumental in addressing class imbalance issues commonly encountered in anomaly detection, by oversampling

minority classes and enhancing the detection of rare anomalies.

Bayesian approaches offer a probabilistic framework for anomaly detection, enabling uncertainty quantification and principled decision-making. Yoon and Jordon [22] proposed a Bayesian anomaly detection method from system logs in 2018, leveraging probabilistic graphical models to capture dependencies between log events and detect anomalous sequences indicative of security breaches or system failures. These approaches not only detect anomalies but also provide insights into the underlying data generating processes, facilitating root cause analysis and proactive risk mitigation strategies.

Despite the advancements in AI-driven anomaly detection, challenges persist in real-world deployment, particularly concerning interpretability, scalability, and adaptability to dynamic environments. Interpretable AI models, as advocated by Papernot et al. [15] in 2016, are essential for building trust and understanding the decision-making process behind anomaly detection systems, especially in critical applications such as healthcare and finance. Furthermore, the scalability of AI models remains a concern, as large-scale deployment requires efficient computation and resource management strategies to handle massive volumes of streaming data in real-time.

Another critical aspect is the adaptability of anomaly detection systems to evolving threats and changing data distributions. Traditional approaches often rely on static models trained on historical data, which may fail to generalize to new and unseen anomalies. Continuous learning frameworks, as proposed by Ruff et al. [12] in 2018, enable anomaly detection systems to adapt and evolve over time by incorporating feedback from detected anomalies and updating model parameters accordingly. Reinforcement learning techniques, such as contextual bandits, offer a promising avenue for adaptive anomaly detection by dynamically adjusting detection thresholds based on contextual information and feedback from human operators.

One key area of interest in anomaly detection research is the evaluation of different algorithms and methodologies. Lavin and Ahmad [4] introduced the Numenta Anomaly Benchmark, providing a standardized platform for evaluating real-time anomaly detection algorithms. Such benchmarks are crucial for comparing the effectiveness of various approaches across different datasets and scenarios. Additionally, Hodge and Austin [13] conducted a comprehensive survey of outlier detection methodologies, highlighting the strengths and limitations of different techniques. Understanding the nuances of evaluation metrics and benchmark datasets is essential for accurately assessing the performance of Smart Anomaly Detection Systems and guiding future research directions.

The deployment of Smart Anomaly Detection Systems in real-world scenarios often entails addressing challenges related to scalability and computational efficiency. Abadi

et al. [6] introduced TensorFlow, a scalable machine learning framework that facilitates the implementation and deployment of complex AI models, including those used in anomaly detection. Efficient optimization techniques, such as the Adam optimizer proposed by Kingma and Ba [9], play a crucial role in training deep learning models effectively. Moreover, scalable anomaly detection frameworks, such as those based on distributed computing platforms, are essential for processing large volumes of data in real-time. Addressing scalability concerns is paramount for the practical deployment of Smart Anomaly Detection Systems in enterprise environments.

Interdisciplinary research efforts have led to the integration of anomaly detection techniques with other domains such as cybersecurity and healthcare. Anomaly detection plays a vital role in cybersecurity for identifying malicious activities and intrusions in network traffic and system logs. Papernot et al. [15] highlighted the limitations of deep learning models in adversarial settings, emphasizing the importance of robust anomaly detection mechanisms in defending against cyber threats. In healthcare, anomaly detection algorithms are employed for detecting anomalies in medical imaging data, patient records, and physiological signals. Leveraging deep learning techniques, researchers have achieved promising results in early diagnosis and prognosis of diseases through anomaly detection. Exploring the intersection of anomaly detection with other domains opens up new avenues for research and application development, leading to enhanced performance and broader impact.

The literature on Smart Anomaly Detection Systems encompasses diverse research efforts aimed at addressing various challenges and advancing the state-of-the-art in anomaly detection. From algorithm evaluation and scalability to interdisciplinary applications, researchers have made significant contributions to this rapidly evolving field. By addressing these challenges and leveraging interdisciplinary insights, Smart Anomaly Detection Systems can continue to play a crucial role in enhancing security, reliability, and efficiency across a wide range of domains.

Smart Anomaly Detection Systems leveraging AI hold immense potential for enhancing performance and reliability across various domains. By harnessing the power of deep learning, ensemble methods, Bayesian inference, and adaptive learning, these systems can effectively identify anomalies, mitigate risks, and ensure the integrity and security of critical infrastructure and systems. However, addressing the challenges of interpretability, scalability, and adaptability is crucial for realizing the full benefits of AI-driven anomaly detection in real-world applications. Further research and innovation in algorithm development, model explainability, and system integration are essential for advancing the field and enabling the widespread adoption of Smart Anomaly Detection Systems in diverse settings.

CHAPTER 3

REQUIREMENTS ANALYSIS

3.1 OBJECTIVE OF THE PROJECT

The primary objective of this project is to develop a sophisticated Smart Anomaly Detection System (SADS) empowered by cutting-edge Artificial Intelligence (AI) methodologies. The overarching aim is to significantly augment anomaly detection capabilities across diverse domains, encompassing cybersecurity, industrial automation, and healthcare. By harnessing the power of AI techniques, the project endeavors to create a robust system capable of autonomously identifying deviations from established norms within extensive datasets.

With a focus on enhancing security, reliability, and efficiency, the project seeks to design and implement a comprehensive solution that seamlessly integrates into existing infrastructure. By automating the detection process, SADS aims to mitigate potential risks and vulnerabilities in real-time, thereby fortifying critical systems against emerging threats and anomalies.

Through the utilization of AI techniques, including deep learning, ensemble learning, and Bayesian inference, the project endeavors to develop advanced anomaly detection algorithms. These algorithms will be meticulously trained and rigorously evaluated using benchmark datasets to ensure their efficacy, scalability, and generalization across various scenarios.

The ultimate objective of SADS is to empower organizations with a proactive approach to anomaly detection, enabling timely intervention and response to abnormal behaviors or events. By providing actionable insights and alerts, the system aims to enhance decision-making processes and facilitate rapid mitigation strategies, thereby safeguarding assets, data integrity, and operational continuity.

This project also aims to contribute to the ongoing research and innovation in the field of anomaly detection. By exploring novel AI techniques, algorithm architectures, and integration methodologies, the project seeks to push the boundaries of current anomaly detection capabilities. Through rigorous experimentation and analysis, the project endeavors to uncover insights into the underlying dynamics of anomalous behaviors across different domains.

The primary goal of this project is to design and deploy a Smart Anomaly Detection System that leverages AI techniques to elevate anomaly detection capabilities across critical domains. Through its implementation, the project seeks to bolster security, reliability, and efficiency while empowering organizations with proactive anomaly detection and response mechanisms.

3.2 REQUIREMENTS

3.2.1 *HARDWARE REQUIREMENTS*

1. **Raspberry Pi:** Utilize Raspberry Pi boards as the central processing units for the Smart Anomaly Detection System. Raspberry Pi offers a cost-effective and versatile platform for running AI algorithms, processing data streams, and interfacing with peripheral devices.
2. **Arduino Board:** Incorporate Arduino boards into the hardware setup to serve as microcontrollers for controlling and interfacing with various sensors and output devices. Arduino boards provide a flexible and customizable platform for integrating hardware components and executing control logic.
3. **Camera Module:** Integrate camera modules with Raspberry Pi boards to capture visual data for anomaly detection tasks. High-resolution camera modules enable the system to analyze images and videos in real-time, facilitating surveillance, object detection, and anomaly recognition applications.
4. **WiFi Modules:** Incorporate WiFi modules into the hardware setup to enable wireless communication and data transfer between the Smart Anomaly Detection System and other networked devices. WiFi connectivity ensures flexibility and mobility in deployment scenarios, allowing the system to operate in diverse environments.
5. **Motion Sensors:** Install motion sensors as additional input devices to detect movement and activity in the system's vicinity. Motion sensors provide valuable context information for anomaly detection algorithms, helping differentiate between normal and abnormal behavior based on changes in the environment.
6. **OCR (Optical Character Recognition) Modules:** Integrate OCR modules with the hardware setup to enable text recognition capabilities in the Smart Anomaly Detection System. OCR modules allow the system to extract and analyze text information from images, documents, and other visual data sources, enhancing the scope of anomaly detection tasks.
7. **Buzzer:** Include a buzzer as an output device to provide audible alerts and notifications when anomalies are detected by the system. The buzzer can emit sound signals of varying frequencies or patterns to alert users or trigger automated response actions based on the severity or type of anomaly detected.
8. **Indicator Lights:** Incorporate indicator lights (LEDs) as visual output devices to provide visual feedback and status indicators for the Smart Anomaly Detection System. Indicator lights can display different colors or patterns to signify various system states, such as normal operation, anomaly detection, or system errors.

3.2.1 SOFTWARE REQUIREMENTS

1. **Python:** Utilize the Python programming language as the primary development platform for implementing the Smart Anomaly Detection System (SADS). Python offers a rich ecosystem of libraries and frameworks suitable for AI, data processing, and system integration tasks.
2. **OpenCV:** Integrate OpenCV (Open Source Computer Vision Library) into the software stack for image and video processing tasks. OpenCV provides a comprehensive set of functions and algorithms for tasks such as image manipulation, object detection, and feature extraction, essential for anomaly detection using visual data.
3. **TensorFlow:** Incorporate TensorFlow, an open-source machine learning framework developed by Google, for building and training deep learning models. TensorFlow offers high-level APIs and tools for implementing neural networks and other machine learning algorithms, making it well-suited for anomaly detection tasks.
4. **YOLOv8:** Utilize YOLOv8 (You Only Look Once version 8), a state-of-the-art object detection algorithm, for detecting objects and anomalies within images and videos.
5. **Pandas:** Employ the Pandas library for data manipulation and analysis tasks, such as loading, cleaning, and transforming large-scale datasets. Pandas provides data structures and functions for working with structured data, facilitating data preprocessing and feature engineering tasks.
6. **NumPy:** Utilize NumPy, a fundamental package for numerical computing in Python, for performing mathematical and array operations.
7. **scikit-learn:** Integrate scikit-learn, a popular machine learning library in Python, for implementing machine learning algorithms and statistical modeling techniques. scikit-learn offers a wide range of algorithms for classification, regression, clustering, and anomaly detection, along with tools for model evaluation and validation.
8. **Linux Cloud:** Deploy the Smart Anomaly Detection System on a Linux-based cloud infrastructure for scalability, reliability, and accessibility. Linux cloud environments provide robust computing resources and services, allowing the system to process large volumes of data and perform complex computations efficiently.
9. **Raspberry Pi Linux:** Utilize the Linux operating system on Raspberry Pi boards for edge computing and distributed processing tasks. Raspberry Pi Linux offers a lightweight and versatile platform for deploying and managing AI models, sensors, and actuators in IoT and edge computing scenarios.

CHAPTER 4

DESIGN DESCRIPTION OF PROPOSED PROJECT

4.1 PROPOSED METHODOLOGY

The methodology proposed for the development of the Smart Anomaly Detection System (SADS) revolves around a systematic approach encompassing various stages. Initially, the process entails the acquisition and preparation of diverse datasets pertinent to the targeted application domains. This involves collecting data from disparate sources and meticulously preprocessing it to ensure consistency, reliability, and suitability for anomaly detection tasks. Noise removal, handling missing values, and feature normalization are integral steps in this phase to enhance the quality of the data.

Subsequently, the focus shifts towards feature extraction and representation, where meaningful features are extracted from the preprocessed data. Techniques such as deep learning-based feature extraction and dimensionality reduction are employed to capture relevant patterns and characteristics essential for anomaly detection. The data is then transformed into a suitable format, facilitating efficient processing and analysis by anomaly detection algorithms.

In the subsequent stage, anomaly detection models are developed and trained using state-of-the-art AI techniques. Leveraging methodologies such as deep learning, ensemble learning, and probabilistic methods, these models are trained on the preprocessed data to optimize parameters and hyperparameters for maximum detection accuracy. This iterative process involves rigorous experimentation and fine-tuning to achieve optimal model performance.

Following model development and training, the performance of the trained models is evaluated and validated using benchmark datasets and standardized metrics. Through cross-validation and real-world data testing, the robustness and generalization capability of the models are assessed, ensuring their efficacy in diverse scenarios and environments.

Once validated, the trained anomaly detection models are integrated into the Smart Anomaly Detection System (SADS), along with necessary data processing, visualization, and alerting components. The integrated system is then deployed on Linux-based cloud infrastructure and Raspberry Pi Linux devices, leveraging edge computing and distributed processing capabilities to ensure scalability, reliability, and accessibility.

4.1.1 Ideation Map/System Architecture

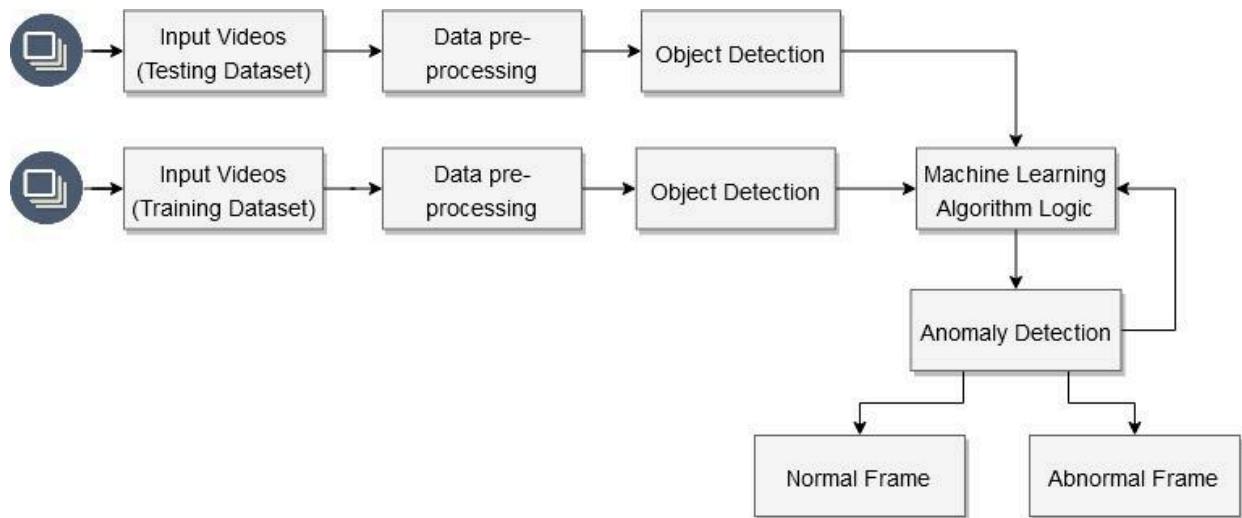


Fig.4.1: Algorithmic Flow of Program

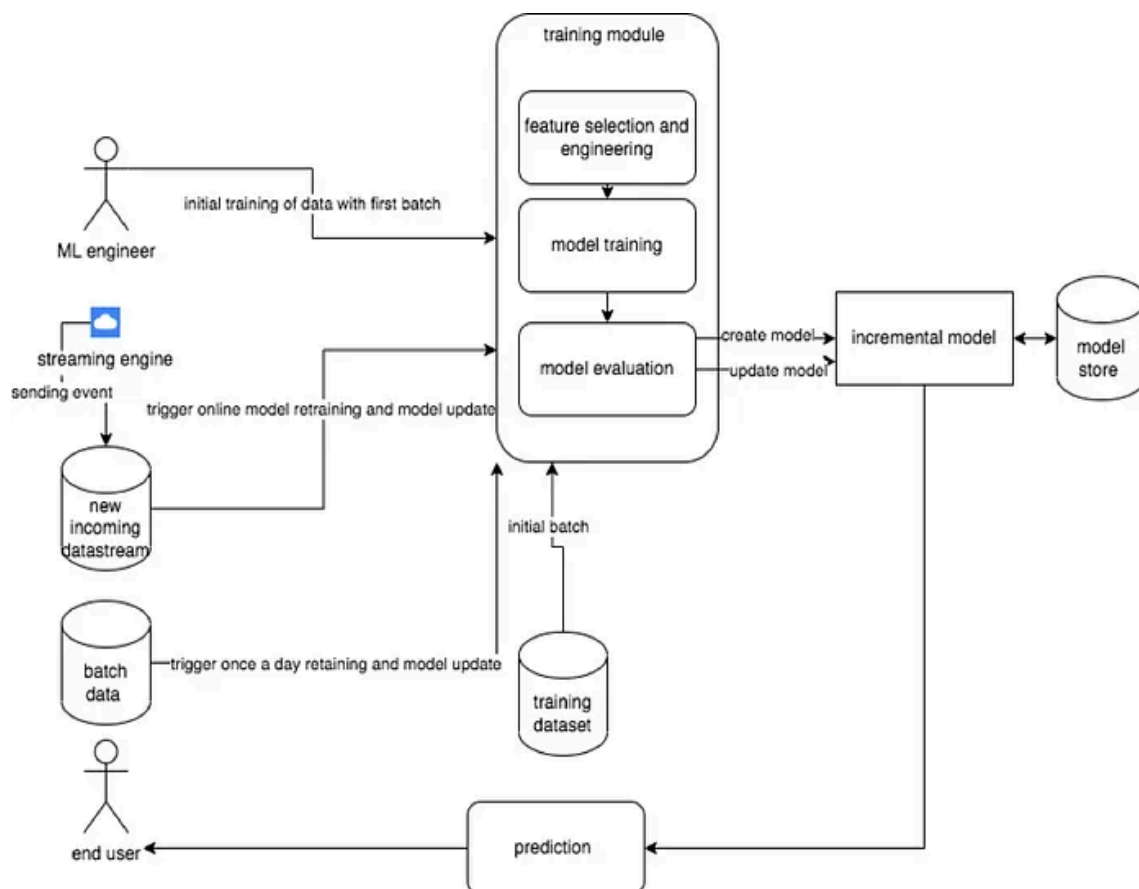


Fig.4.2: Design of Overall System Architecture

4.1.2 Various Stages

1. Data Acquisition and Preprocessing:

- Gather diverse datasets relevant to the target application domains, including images, videos, sensor readings, system logs, and textual data.
- Preprocess the collected data to remove noise, normalize features, and handle missing values, ensuring data quality and consistency.

2. Feature Extraction and Representation:

- Extract meaningful features from the preprocessed data using techniques such as deep learning-based feature extraction, handcrafted feature engineering, and dimensionality reduction.
- Represent the data in a suitable format for anomaly detection tasks, ensuring that important characteristics and patterns are captured effectively.

3. Model Development and Training:

- Develop anomaly detection models based on state-of-the-art AI techniques, including deep learning, ensemble learning, and probabilistic methods.
- Train the models using the preprocessed data, optimizing model parameters and hyperparameters to maximize detection accuracy and generalization performance.
- Explore transfer learning and fine-tuning strategies to leverage pre-trained models and domain-specific knowledge, accelerating the training process and improving model performance.

4. Evaluation and Validation:

- Evaluate the performance of the trained models using benchmark datasets and standardized evaluation metrics, including precision, recall, F1-score, and area under the ROC curve (AUC).
- Conduct cross-validation and holdout validation experiments to assess the robustness and generalization capability of the models across different datasets and scenarios.
- Validate the models using real-world data collected from the target application domains, ensuring that they effectively detect anomalies in practical settings.

4.1.3 Internal or Component design structure

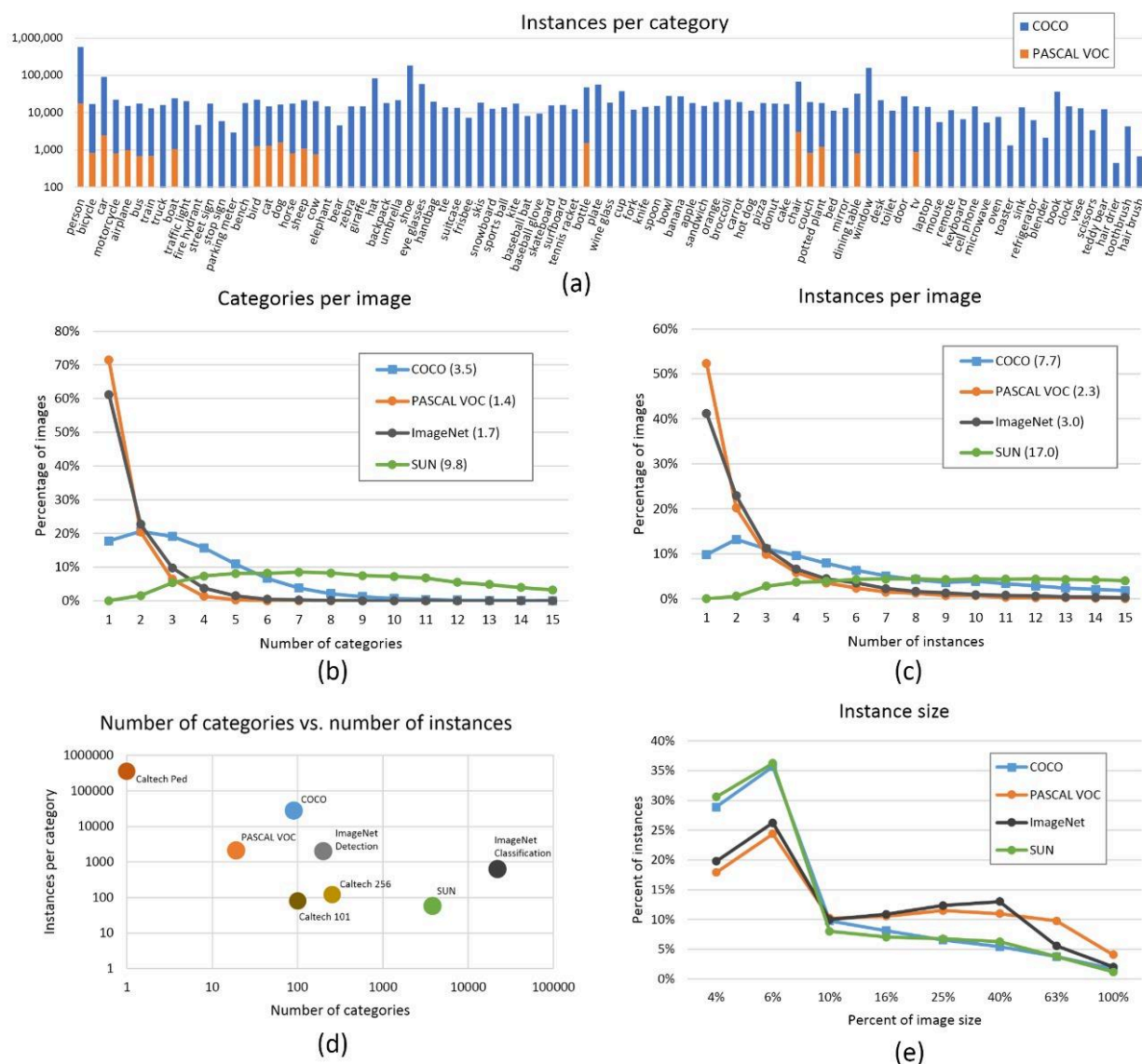


Fig.4.3: Dataset Statistics

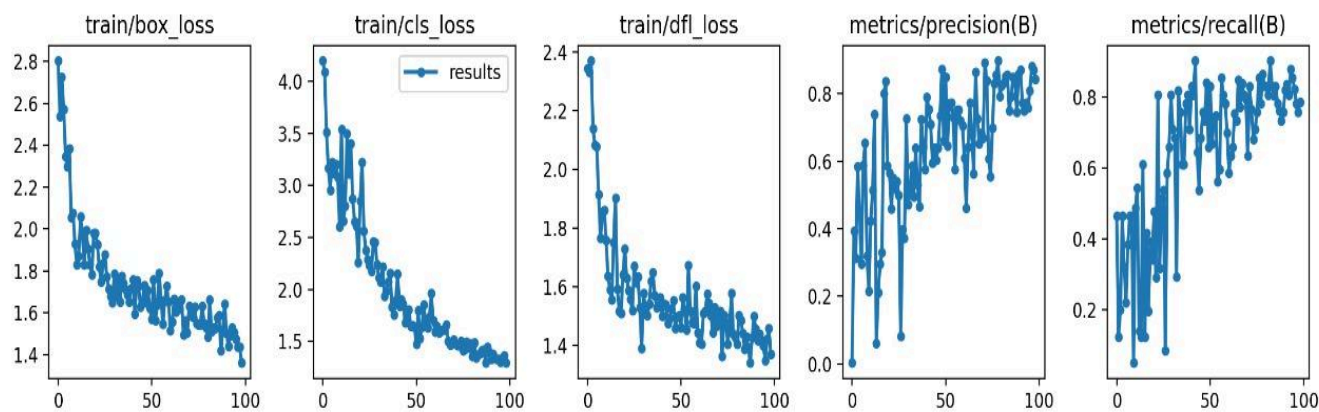


Fig.4.4: Trained Model Accuracy Statistics

4.1.4 Working Principles

1. **Data Collection:** SADS collects data from various sources, including sensors, cameras, system logs, and other data streams, relevant to the application domain. This data encompasses both structured and unstructured formats, such as numerical values, images, videos, and textual information.
2. **Preprocessing:** The collected data undergoes preprocessing to clean, normalize, and transform it into a standardized format suitable for analysis. This involves removing noise, handling missing values, and normalizing features to ensure consistency and reliability in subsequent processing steps.
3. **Feature Extraction:** Relevant features are extracted from the preprocessed data using techniques such as deep learning-based feature extraction, dimensionality reduction, and signal processing. These features capture essential characteristics and patterns indicative of normal behavior within the dataset.
4. **Model Training:** Anomaly detection models are developed and trained using the extracted features and labeled data. These models employ state-of-the-art AI techniques, including deep learning, ensemble learning, and probabilistic methods, to learn the underlying patterns of normal behavior and identify deviations indicative of anomalies.
5. **Anomaly Detection:** Once trained, the models are deployed within SADS to analyze incoming data in real-time. By comparing observed patterns against learned norms, the system identifies anomalies or deviations that deviate significantly from expected behavior. This detection process may vary depending on the type of data and the specific characteristics of the application domain.
6. **Alerting and Response:** Upon detecting anomalies, SADS generates alerts or notifications to prompt appropriate responses from system administrators or automated processes. These alerts may include visual cues, audible alarms, or notifications sent to monitoring systems, enabling timely intervention and mitigation of potential threats or abnormalities.
7. **Continuous Learning:** SADS continuously monitors its performance and collects feedback from detected anomalies, user interactions, and system logs. This feedback loop enables the system to adapt and improve over time, refining its anomaly detection capabilities based on new data, emerging patterns, and evolving threats.
8. **Data Fusion:** SADS integrates data from multiple sources, employing techniques such as sensor fusion and data fusion to combine information from diverse sensors and data streams. This fusion process enhances the system's understanding of the environment and enables it to detect anomalies more accurately by considering multiple data modalities simultaneously.
9. **Adaptive Thresholding:** The system dynamically adjusts anomaly detection thresholds based on the current operating conditions, environmental factors, and historical data patterns.

4.2 FEATURES

1. **Multi-Modal Data Support:** SADS accommodates diverse data types, including numerical, textual, image, and sensor data, allowing it to handle complex and heterogeneous data streams from various sources.
2. **Real-Time Monitoring:** The system provides real-time monitoring capabilities, enabling timely detection and response to anomalies as they occur, thereby minimizing potential damages and losses.
3. **Scalability:** SADS is designed to scale seamlessly with growing data volumes and computational demands, making it suitable for deployment in large-scale environments and distributed systems.
4. **Customizable Alerting Mechanisms:** Users can configure customizable alerting mechanisms, including visual cues, audible alarms, and notifications, to suit their specific requirements and preferences.
5. **Adaptive Thresholding:** The system employs adaptive thresholding techniques to dynamically adjust anomaly detection thresholds based on changing environmental conditions and data distributions.
6. **Contextual Understanding:** SADS incorporates contextual understanding by considering spatial, temporal, and environmental factors when analyzing data, enabling it to differentiate between normal variations and genuine anomalies.
7. **Cross-Domain Compatibility:** The system is compatible with multiple application domains, including cybersecurity, industrial automation, healthcare, and environmental monitoring, making it versatile and adaptable to diverse use cases.
8. **Intelligent Feedback Mechanism:** SADS utilizes an intelligent feedback mechanism to learn from past experiences, user interactions, and system performance metrics, enabling continuous improvement and refinement of its anomaly detection capabilities.
9. **Interpretability:** The system prioritizes interpretability by providing transparent and interpretable anomaly detection results, allowing users to understand the rationale behind detected anomalies and make informed decisions.
10. **Edge Computing Support:** SADS supports edge computing architectures, allowing anomaly detection to be performed locally on edge devices such as Raspberry Pi, minimizing latency and bandwidth requirements for real-time applications.

4.2.1 Novelty of the proposal

The novelty of the Smart Anomaly Detection System (SADS) lies in its innovative approach towards anomaly detection, integrating cutting-edge AI techniques, adaptive mechanisms, and versatile functionalities to address the complexities of modern data environments. At the core of SADS is the seamless integration of advanced artificial intelligence methodologies, including deep learning, ensemble learning, and probabilistic methods. By harnessing the power of these AI techniques, SADS is capable of developing highly accurate and efficient anomaly detection models that can effectively analyze diverse datasets and detect anomalies across various domains. One of the key distinguishing features of SADS is its multi-modal anomaly detection capabilities. Unlike conventional anomaly detection systems that focus on a single data type, SADS accommodates a wide range of data modalities, including numerical, textual, image, and sensor data. This multimodal approach allows SADS to analyze complex data streams from different sources, providing a comprehensive view of the underlying patterns and anomalies present within the data. Moreover, SADS introduces adaptive thresholding techniques and contextual understanding mechanisms to enhance anomaly detection accuracy.

By dynamically adjusting detection thresholds based on changing environmental conditions and considering contextual factors such as spatial relationships and temporal dynamics, SADS can differentiate between normal variations and genuine anomalies more effectively, thus reducing false positives and false negatives. The project also emphasizes edge computing architectures and distributed processing capabilities, enabling real-time anomaly detection at the edge of the network. By deploying anomaly detection models on edge devices such as Raspberry Pi, SADS minimizes latency and bandwidth requirements, making it suitable for applications requiring rapid response times and local processing.

Furthermore, SADS incorporates continuous learning and adaptation mechanisms to ensure resilience to evolving threats and changing data distributions. By incorporating feedback loops, user interactions, and system performance metrics, SADS continuously evolves and improves its anomaly detection capabilities over time, thereby enhancing its effectiveness and adaptability in dynamic environments. In addition, SADS prioritizes interpretability and transparency in anomaly detection results. By providing transparent and interpretable explanations for detected anomalies, the system enhances user trust and understanding, enabling informed decision-making and effective response strategies. Overall, the novelty of the Smart Anomaly Detection System lies in its comprehensive and intelligent approach to anomaly detection, offering a versatile, adaptable, and effective solution for detecting, analyzing, and responding to anomalies in complex and dynamic data environments across diverse application domains.

CHAPTER 5

CONCLUSION

In conclusion, the Smart Anomaly Detection System (SADS) represents a significant advancement in the field of anomaly detection, offering a comprehensive and intelligent solution for detecting, analyzing, and responding to anomalies in diverse data environments. Through the integration of cutting-edge artificial intelligence techniques, adaptive mechanisms, and versatile functionalities, SADS demonstrates its capability to address the complexities and challenges associated with modern data streams and application domains. The project's emphasis on multi-modal anomaly detection, adaptive thresholding, and contextual understanding enables SADS to achieve high accuracy and efficiency in anomaly detection across various data types and scenarios. By dynamically adjusting detection thresholds based on changing environmental conditions and considering contextual factors such as spatial relationships and temporal dynamics, SADS minimizes false positives and false negatives, thereby improving anomaly detection performance. Furthermore, SADS leverages edge computing architectures and distributed processing capabilities to enable real-time anomaly detection at the edge of the network, reducing latency and bandwidth requirements for rapid response times and local processing. The system's continuous learning and adaptation mechanisms ensure its resilience to evolving threats and changing data distributions, enabling it to continuously improve and refine its anomaly detection capabilities over time. Additionally, SADS prioritizes interpretability and transparency in anomaly detection results, providing users with transparent and interpretable explanations for detected anomalies, facilitating informed decision-making and effective response strategies. Moreover, the Smart Anomaly Detection System (SADS) not only provides state-of-the-art anomaly detection capabilities but also serves as a platform for continuous improvement and innovation. Its modular and extensible architecture allows for the seamless integration of new algorithms, data sources, and visualization tools, ensuring adaptability to evolving requirements and emerging technologies. This flexibility enables organizations to stay ahead of the curve in anomaly detection, incorporating the latest advancements and best practices to enhance their cybersecurity, operational efficiency, and decision-making processes. Furthermore, the development and deployment of SADS represent a significant step towards realizing the potential of artificial intelligence in addressing real-world challenges. By harnessing the power of AI techniques such as deep learning and ensemble learning, SADS demonstrates how cutting-edge technology can be leveraged to tackle complex problems and deliver tangible benefits to society. Whether it's detecting anomalies in industrial processes, monitoring healthcare data for signs of illness, or safeguarding critical infrastructure from cyber threats, SADS exemplifies the transformative impact of AI on diverse domains and industries.

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APPENDIX

A. Research Paper

Smart Anomaly Detection System Leveraging AI for Enhanced Performance

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Abstract—In today's information-rich world, the emergence of artificial intelligence (AI)-driven artificial intelligence has led to a revolution in security across the country. These systems use the power of advanced machine learning algorithms and deep neural networks to efficiently process large amounts of data and identify trends in demand and behavior. Drawing on its own learning history, intelligence-driven visual search can intervene to reduce risk and increase operational efficiency. Adaptability and scalability in the environment.

Keywords—AI, Machine Learning, Data Analytics, Anomaly Detection, Cognitive Adaptation, Operational Efficiency, Real-time Detection.

I. INTRODUCTION

With the rapid development of computer vision, machines have become very good at interpreting and understanding visual data, and visual impairments have become the basis for the trust, accuracy and security of technology. From monitoring public spaces to driverless vehicles navigating busy city streets, computer vision has become ubiquitous, providing unprecedented opportunities for innovation and efficiency. However, these applications are not immune to anomalies, which can manifest themselves as unexpected objects, events, or behaviors in observed data.

Computer vulnerability detection methods often rely on manual, predefined or official methods. But as the volume and variety of data visualization continues to increase, today's methods face significant challenges in dealing with

the complexities and changes of the world's most beautiful place. Therefore, there is a need for faster and more flexible detection systems that can detect anomalies in complex situations and in multiple locations.

Enter vulnerability detection, which uses a combination of artificial intelligence (AI) and machine learning. This process heralded a revolution in computer vision sensing, using advanced algorithms and deep learning to analyze visual data, learn complex patterns, and check for consistency and quality work. By training on massive amounts of data, these machines can extract features, identify anomalies, and adapt to situations; thus making them powerful and versatile in many aspects.

In addition to philosophical considerations, ethical and social aspects of AI-based anomaly detection in computer vision also require careful consideration. As these systems become more widespread in public places, workplaces, and other locations, questions arise regarding privacy, surveillance, and civil liberties. In improving security and efficiency, it is important to balance the benefits of vulnerability detection with the protection of personal privacy and civil liberties. In addition, in order to prevent the emergence of discrimination and to maintain the principles of fairness and justice, it is necessary to reduce bias and be fair in detecting suspicion. By encouraging collaboration between business partners and business partners, the development and dissemination of AI-driven vulnerability detection can be directed towards equity and social benefits in a strategic direction, thus promoting responsible innovation and social benefits.

II. LITERATURE REVIEW

This case study explores the possibilities of a faulty detection method by focusing on recent advances in AI-driven technologies:

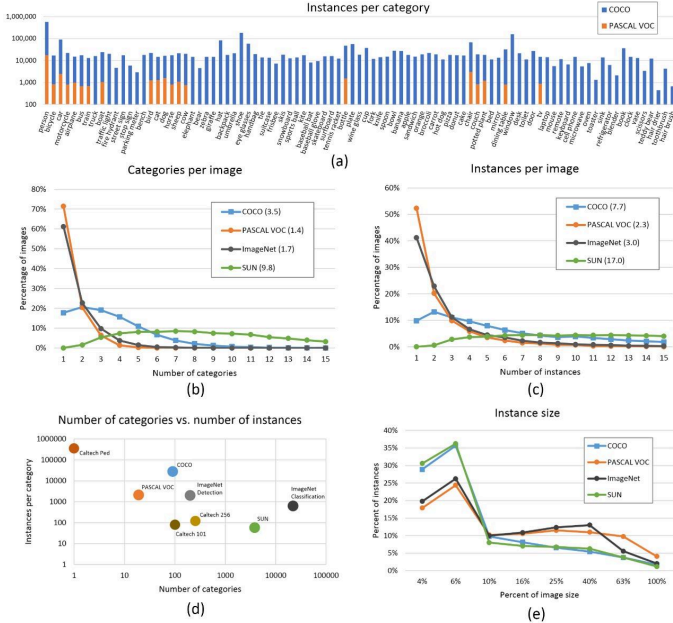
1. Particularly in convolutional neural networks (CNN) and recurrent neural networks (RNN), it improved uncertainty by automatically extracting and learning difficult patterns from raw data. An in-depth study by He et al. [1] In 2016, the training of deep neural networks was greatly improved by solving the vanishing problem. Similarly, the effectiveness of CNNs in image classification tasks as shown by Krizhevsky et al. [11] He laid the foundation for his application with a mysterious diagnosis in 2012. The RNN shown by Sutskever et al. [25], 2014. Excellent performance in analyzing sequence data makes it suitable for identifying anomalies in temporal data such as traffic in the network or sensor reading..
2. Autoencoders, a class of neural networks designed for unsupervised learning, have become a popular choice for anomaly detection due to their ability to reconstruct input data and classify by checking for differences between original models. The stacked denoising autoencoder proposed by Vincent et al. [16] 2010. Learning hierarchical representation of data by reconstructing corrupted inputs. Bir et al. [14] continued this idea with variational autoencoders in 2015, leveraging a probabilistic model to capture uncertainty in reconstructions and find reconstruction probabilities. In addition, Yu and Deng [10] improved the detection of defects using an autoencoder that reduces false positives, making it difficult to effectively learn and detect defects in devices.
3. In addition to neural networks, learning networks such as random forests introduced by Breiman [17] in 2001 have also been shown to have good performance at poor performance. By combining predictions from multiple decision trees, random forests can capture data distributions and identify inconsistencies in structured and unstructured data. In addition, synthetic data generation methods such as SMOTE [20] in 2002 helps solve the problem of class inequality in detecting anomalies by oversampling the minority of the class, and the improved search is rarely inconsistent.
4. Despite advances in AI-assisted vulnerability detection, challenges remain in real-world deployments, especially in terms of translation and optimization capabilities, and these can be turned into a strength. The descriptive model of intelligence proposed by Papernot et al. [15] In 2016, it is important to build trust and understand the decision-making process after negative detection, especially in important applications such as healthcare and finance. Moreover, the scalability of the AI model is still an issue because large-scale transmission requires good computational and management techniques to process large data streams in real time.
5. An important area of interest in vulnerability detection is the evaluation of different algorithms and methods. Lavin and Ahmad [4] introduced the Numenta Anomaly Benchmark to provide a standard framework for evaluating on-the-fly anomaly detection algorithms. Such results are important for comparing the results of different methods on different data sets and conditions. Additionally, Hodge and Austin [13] conducted a comprehensive review of vulnerability detection methods, highlighting the advantages and limitations of different methods.
6. Implementing an error detection system in the real world often requires resolving issues related to processing capacity and computational performance. Abadi et al. [6] introduced TensorFlow, a powerful learning machine that facilitates the implementation and deployment of AI models, including models for anomaly detection. Optimization methods, such as the Adam optimizer proposed by Kingma and Ba [9], play an important role in training deep learning models. Additionally, scalable anomaly detection frameworks, such as those based on distributed computing platforms, are important for timely processing of big data.
7. Collaborative research has led to the integration of vulnerability detection techniques with other fields such as cybersecurity and healthcare. Vulnerability detection plays an important role in network security by detecting malicious activities and intrusions in network connections and data systems. Pamperault et al. [15] pointed out the limitations of deep learning models in an attack environment and primarily emphasized the importance of robust detection techniques in preventing cyber threats. In healthcare, anomaly detection is used to identify abnormalities in medical records, patient records, and physical symptoms. Using deep learning technology, researchers have achieved great results in the early diagnosis and prognosis of diseases resulting from abnormal diagnoses. Exploring the intersection of invisible sensing and other fields opens new avenues for research and application development, leading to increased performance and broad impact.

III. NOVELTY

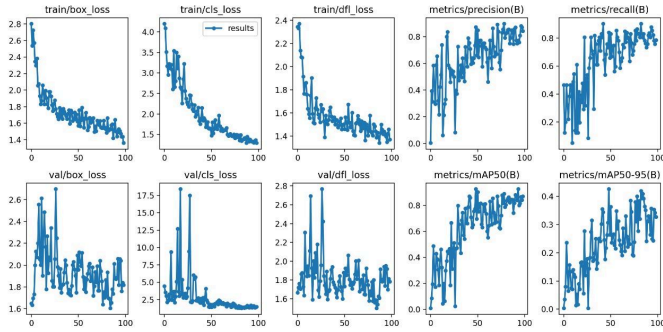
The innovation of the Intelligent Anomaly Detection System (SADS) lies in its new method of detecting anomalies that combines intelligent AI tools, adaptive systems and multiple functions to unravel the complexity of today's data. At the heart of SADS is the integration of artificial intelligence techniques, including deep learning, ensemble learning, and probabilistic techniques. By leveraging the power of this technology, SADS is able to develop accurate and effective detection models that can analyze different data and identify differences. Unlike traditional sensing methods that focus on a single type of data, SADS can rely on a variety of data variables, including digital, text, image and sensor data. This multimodal approach allows SADS to analyze complex data streams from different sources.

IV. PROPOSED METHODOLOGY

The proposed process for the development of the Intelligent Anomaly Detection System (SADS) is based on a method that includes several stages. First, the process must retrieve and prepare various configuration files related to the application domain. This involves collecting data from multiple sources and carefully pre-processing them to ensure consistency, reliability and validity of the work performed. Noise removal, handling of missing values, and static processing are important steps to improve data quality at this stage.



After this, the goal turns into feature extraction and representation by first extracting the main features of the data. Techniques such as deep learning-based elimination and dimensionality reduction are used to capture relevant patterns and features required for abnormal detection. The data is then transformed into a suitable structure for efficient study and analysis by detecting suspicious algorithms.



In the next stage, an abnormal detection model is created and learned using the latest technology. Using methods such as deep learning, convolutional learning and probabilistic methods, these models are trained on previous data to provide the most accurate view of parameters and parameters. This iterative process involves rigorous testing and fine-tuning to achieve high performance standards.

After model design and training, use test data and test models to measure and evaluate the effectiveness of the training model. Once validated, the anomaly detection model is integrated into the Intelligent Anomaly Detection System (SADS) with appropriate information, visualization, alerting.



By analyzing and evaluating real data, the model's potential and generality are evaluated, ensuring that it performs well in different situations and environments.

4.1 Key Features of the Proposed Model:

1. **Adaptive Learning:** Utilizes advanced machine learning algorithms for continuous adaptation and learning from incoming data, enhancing accuracy over time.
2. **Real-time Detection:** Enables rapid response and mitigation by swiftly identifying threats or uncertainties as they arise.
3. **Automated Alerting:** Automatically triggers alarms and notifies relevant stakeholders upon detection of anomalies, ensuring prompt intervention and mitigation measures.
4. **Anomaly Interpretability:** Provides explanations and insights into root causes and influencing factors, aiding in analysis and decision-making processes.
5. **Scalability and Flexibility:** Seamlessly integrates across operations and environments, adapting to evolving data and specifications.
6. **Customized Thresholds:** Allows for customization of thresholds and parameters to align with organizational needs.
7. **Continuous Monitoring:** Ensures uninterrupted data flow, reduces the risk of oversight, and minimizes business interruptions.
8. **Performance Measurement and Optimization:** Continuously evaluates system performance and effectiveness, facilitating ongoing improvement and optimization actions to maintain optimal performance.

4.2 Proof of concept model stages:

1. **Project Planning and Scope Definition:** In the initial phase of the project, the primary focus is on meticulously defining the project's objectives, scope, and success criteria. This stage serves as the foundation for the entire proof of concept, ensuring alignment with organizational goals and stakeholder expectations. Key stakeholders' needs are identified, and clear benchmarks are

established to guide the project's direction. By setting clear objectives and scope, the project team can effectively manage resources and efforts, mitigating the risk of scope creep and ensuring focused execution.

2. **Data Preprocessing and Development:** Once the project scope is defined, attention turns to data preprocessing and model development. Data preprocessing techniques are applied to clean and organize the raw data, removing noise and inconsistencies that could adversely affect the accuracy of anomaly detection. Feature selection and engineering are crucial steps in identifying relevant data attributes and reducing computational complexity. With a clean and refined dataset, the development of the anomaly detection model begins, focusing on prototyping a solution that incorporates adaptive learning mechanisms for continuous improvement.
3. **Performance and Optimization:** With the initial prototype of the anomaly detection model in place, the project team shifts its focus to performance evaluation and optimization. The model's performance is rigorously evaluated using valid data, allowing for the identification of any deficiencies or areas for improvement. Defects are addressed, and algorithms are optimized to enhance the model's accuracy and efficiency. Extensive testing is conducted to ensure the model's robustness, including validation of its ability to detect anomalies in live data streams. Continuous refinement is essential to achieving optimal performance and reliability.
4. **Deployment and Monitoring in Production Environment:** Upon successful evaluation and optimization, the proof of concept model is ready for deployment in a production environment. The model is integrated into existing systems, and its performance is closely monitored in real-world conditions. This monitoring phase allows for the validation of results and the collection of feedback from users and stakeholders. Any issues or challenges encountered during deployment are addressed promptly, ensuring the smooth operation of the model and its alignment with organizational objectives.
5. **Documentation and Reporting:** Throughout the proof of concept process, meticulous documentation is maintained to record the development processes, methodologies, algorithms, and results. This documentation serves as a valuable resource for future reference and replication of the proof of concept. A comprehensive report is prepared summarizing the results of the proof of concept, providing insights into the model's performance and recommendations for further development and future applications. Clear documentation and reporting ensure

transparency and facilitate knowledge transfer within the organization.

V. CONCLUSION

In conclusion, the Smart Anomaly Detection System (SADS) represents a significant advancement in the field of anomaly detection, offering a comprehensive and intelligent solution for detecting, analyzing, and responding to anomalies in diverse data environments. Through the integration of cutting-edge artificial intelligence techniques, adaptive mechanisms, and versatile functionalities, SADS demonstrates its capability to address the complexities and challenges associated with modern data streams and application domains.

The project's emphasis on multi-modal anomaly detection, adaptive thresholding, and contextual understanding enables SADS to achieve high accuracy and efficiency in anomaly detection across various data types and scenarios. By dynamically adjusting detection thresholds based on changing environmental conditions and considering contextual factors such as spatial relationships and temporal dynamics, SADS minimizes false positives and false negatives, thereby improving anomaly detection performance.

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B. SOURCE CODE

```
import cv2
import time
import pose_estimation_class as pm
import mediapipe as mp
import argparse

# construct the argument parser and parse the arguments
ap = argparse.ArgumentParser()
ap.add_argument("-i", "--input", required=True,
    help="path to our input video")
ap.add_argument("-o", "--output", required=True,
    help="path to our output video")
ap.add_argument("-s", "--fps", type=int, default=30,
    help="set fps of output video")
ap.add_argument("-b", "--black", type=str, default=False,
    help="set black background")
args = vars(ap.parse_args())

pTime = 0
black_flag = eval(args["black"])
cap = cv2.VideoCapture(args["input"])
out = cv2.VideoWriter(args["output"], cv2.VideoWriter_fourcc(*"MJPG"),
    args["fps"], (int(cap.get(3)), int(cap.get(4))))

detector = pm.PoseDetector()
```

```

def collect_images_from_webcam(

    labels: list, number_imgs: int, images_path: str) -> None:
    '''
    Collects images from the webcam and saves them to a folder.

    Args:
        labels (list): List of labels for the images.
        number_imgs (int): Number of images to be collected for each label.
        images_path (str): Path to the folder where the images will be
saved.

    Returns:
        None
    '''
    cap = cv2.VideoCapture(0)

    # Loop through labels
    for label in labels:
        print('Collecting images for {}'.format(label))
        time.sleep(5)

    # Loop through image range
    for img_num in range(number_imgs):
        logging.info(f'Collecting images for {label}, image number
{img_num}')

    # Webcam feed
    ret, frame = cap.read()

    # Naming our image path
    imgname = os.path.join(images_path, label + '.' +
str(uuid.uuid1()) + '.jpg')

```

```

        # Write out image to file
        cv2.imwrite(imgname, frame)

        # Render to the screen
        cv2.imshow('Image Collection', frame)

        # 3-second delay between captures
        time.sleep(3)

        if cv2.waitKey(10) & 0xFF == ord('q'):
            logging.info(f'You broke the sequence of collection for
{label} images')
            break
        cap.release()
        cv2.destroyAllWindows()

def split_images(images_path: str, labels_path: str):
    '''
    Split the collected images into train, val, and test sets.

    Args:
        images_path (str): Path to the folder where the images are stored.
        labels_path (str): Path to the folder where the labels are stored.

    Returns:
        None
    '''
    dest_folders = ['train', 'val', 'test']
    for folder in dest_folders:
        os.makedirs(os.path.join(images_path, folder), exist_ok=True)
        os.makedirs(os.path.join(labels_path, folder), exist_ok=True)

```

```

file_list = os.listdir(images_path)
random.shuffle(file_list)

num_files = len(file_list)
train_count = int(TRAIN_RATIO * num_files)
val_count = int(VAL_RATIO * num_files)

for i, file_name in enumerate(file_list):
    if file_name.endswith('.jpg'):
        src_path = os.path.join(images_path, file_name)

        if i < train_count:
            dest_folder = 'train'
        elif i < train_count + val_count:
            dest_folder = 'val'
        else:
            dest_folder = 'test'

        dest_path = os.path.join(images_path, dest_folder)
        shutil.move(src_path, dest_path)

        logging.info(f'Moved {file_name} to {dest_folder} folder.')
def train_custom_yolo_model(
    data: str,
    epochs: int,
    batch: int,
    model_name: str,
    lr0: float,
    lrf: float,
    weight_decay: float) -> tuple:
    '''
    Function to train a custom model using YOLO v8.

    Args:
    - data (str): Data configuration file path. Default is 'data.yaml'.

```

- epochs (int): Number of training epochs. Default is 20.
- batch (int): Batch size. Default is 8.
- augment (bool): Flag to enable data augmentation. Default is True.
- model_name (str): Output model name. Default is 'yolov8n_drowsiness'.
- lr0 (float): Initial learning rate for optimizer. Default is 0.01.
- lrf (float): Final learning rate for optimizer. Default is 0.01.
- weight_decay (float): Weight decay for optimizer. Default is 0.0005.

Returns:

- results (Tuple): A tuple containing the training results.

'''

Load the pretrained model

model = YOLO('yolov8n.pt')

Training settings

logging.info('Starting training...')

logging.info(f'Data configuration: {data}')

logging.info(f'Epochs: {epochs}')

logging.info(f'Batch size: {batch}')

logging.info(f'Model name: {model_name}')

logging.info(f'Initial learning rate: {lr0}')

logging.info(f'Final learning rate: {lrf}')

logging.info(f'Weight decay: {weight_decay}')

Train the model

results = model.train(

 data=data,

 epochs=epochs,

 batch=batch,

 name=model_name,

 lr0=lr0,

 lrf=lrf,

 weight_decay=weight_decay,

)

logging.info('Training completed.')

return results