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A SURVEY ON VIDEO ANALYTICS SYSTEM USING DEEP LEARNING

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ABSTRACT: Intelligent video analytics systems have fundamentally altered how we manage and analyze video data, paving the way for applications in a wide range of industries such as security and surveillance, healthcare, autonomous vehicles, and smart cities. Deep learning is an artificial intelligence subfield that has lately emerged as an efficient way for resolving tough video interpretation challenges. This survey study provides a thorough examination of the most recent and cutting-edge approaches and tactics for the development of intelligent video analytics systems using deep learning. We investigate the applications of these systems, as well as the challenges and opportunities that lie ahead, and provide an outline of the main components involved in such systems.

Keywords: *Video Processing, Machine Learning, Deep Learning, , intelligent video surveillance.*

1. INTRODUCTION

Significant advances in video analytics have made it feasible to extract important insights and information from video data in recent years. The combination of advanced video analytics and deep learning techniques has shown to be a game changer in a variety of industries, including surveillance, healthcare, autonomous vehicles, and smart cities. The purpose of this study is to provide a complete evaluation of existing methodology and approaches for constructing intelligent video analytics systems based on deep learning. This summary will be presented in the form of a research paper.

Intelligent video analytics entails extracting, analyzing, and comprehending data from video streams autonomously. Object detection and monitoring, activity recognition, behavior analysis, video summarization, and real-time processing are all part of it. Traditional video analytics solutions usually rely on manually generated features and predetermined criteria, both of which may be limited in their ability to handle massive amounts of different video data. Deep learning, on the other hand, has emerged as a powerful paradigm for learning and extracting meaningful representations from raw video data automatically. This is made possible through the use of deep neural networks.

Video surveillance systems have experienced a full transformation in recent years, becoming used not just in private settings (such as retail malls and arenas), but also in public settings (such as transit hubs and municipal streets). Both live video recording and observation can help prevent crimes, resolve problems, and gather evidence for prosecution. Despite the prevalence of CCTV recording technology (servers, cameras, display walls, and network infrastructure), video analysis remains mostly a human job [1] [5]. It is impossible that a fixed number of administrators could monitor every television broadcast utilizing many cameras on a continuous basis. The human factors challenges of visual overload, vigilance, changing vision impairment, and occupational distraction would make this activity more challenging. In a number of security scenarios, including infrastructure activity centers (such as airports and transportation networks), video is deployed reactively. Receiving a report on a suspicious person or object, receiving a warning through a hidden cable, or receiving an automatic alarm from the video system itself are the most typical means for alerting an administrator. The administrator must next identify relevant cameras, locations, and time frames in order to analyze the event [8].

The act of monitoring a region in order to keep track of any activity is referred to as surveillance. In an ideal society, all private and public locations would be inspected to improve safety precautions. Closed Circuit Television (CCTV) cameras, on the other hand, produce massive amounts of visual data. The thoroughness of the surveillance revealed some unusual incidents on these tapes. Among the main roles of video surveillance are recognizing inappropriate behavior, disasters, accidents, and other types of situations. It is actively scanning through the enormous amount of available data for observation in order to find any problems. The monitoring-relevant frequency of anomalous events may be quite low in compared to the frequency of common occurrences.

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As a result, physically analyzing these data to find unusual events is time-consuming and potentially labor-intensive [12-15]. In the realm of observation, peculiarity recognition refers to the process of inspecting a region for examples of behavior that depart from the norm. The basic structure of existing video frameworks is depicted in Figure 1.

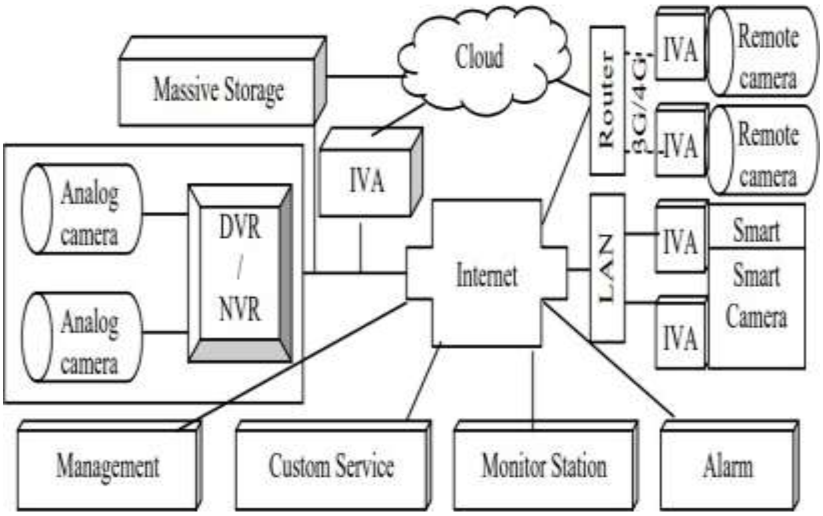

Figure 1: Architecture of Intelligent VideoSurveillance System

Existing strategies that rely on the practical knowledge of security personnel As a method of observation, keeping vigil 24 hours a day, seven days a week is neither beneficial nor helpful. Assume that even if a person is carrying a knife or other weapon in a crowded area, security personnel may not notice it because they cannot see it with their unaided eyes. The congested environment makes it difficult for them to do so. Therefore, there was a need for a system that could solve this problem in the long term, a system that could take into account the number of people in the case and distinguish between safe and dangerous actions. This would make the job of security personnel easier and result in a more cautious and effective surveillance cycle [16–18]. These structures are beneficial in historical districts, airport terminals, signaling systems, and banks. The use of computer vision and machine learning is required to discover oddities in records. The following option, which will combine machine learning and video training, will not only help automate the cycle of observation, but it will also reduce human error and neglect in various security-related areas.

Deep learning models, particularly convolutional neural networks (CNNs), recurrent neural networks (RNNs), and transformer models, have performed exceptionally well in a variety of video analysis tasks. CNNs excel at determining the spatial properties of video frames, whereas RNNs and transformer models excel at determining temporal relationships and enabling the modeling of long-term sequences. Not only have these methods made accurate and rapid video analysis possible, but they have also accelerated discovery in a vast array of application areas.

Smart video analytics employs deep learning in a variety of crucial ways. Incorporating these technologies into surveillance and security systems makes it possible to detect threats and anomalous behavior in real time and to identify faces, thereby making the public safer. Intelligent video analytics are gaining popularity in the medical industry. These techniques assist in keeping note of what patients are doing, determining what they are doing, and even determining if they have fallen. All of these factors contribute to improved patient care. Video analysis is crucial for autonomous vehicles to learn their environment, identify obstacles, and anticipate potential dangers. The use of video analytics in smart cities makes it possible to enhance traffic flow, monitor public areas, and make cities safer.

However, a number of issues must be resolved before intelligent video analytics systems employing deep learning can be developed and utilized. Because deep learning models typically require large amounts of labeled training data, insufficient data and the need for large labeled datasets pose a significant problem. Real-time processing and the ability to expand are also issues. This is due to the fact that video analytics systems must deal with and analyze video inputs in real time while efficiently utilizing computer resources. Concerns have been expressed regarding the ability to comprehend and explain the decisions made by deep learning models, particularly in areas where accountability and transparency are crucial. Concerns regarding ethics and privacy, as well as the possibility of assaults, must also be considered when discussing video analytics systems.

Without the proper metrics and benchmark datasets, it is impossible to evaluate the performance of intelligent video analytics systems. The evaluation factors should be able to quantify the systems' precision, dependability, and efficacy. The benchmark datasets should be comprehensive, representative, and challenging enough to facilitate equitable comparisons and encourage additional development.

2. RELATED WORK

Work by multiple authors is portrayed as an action to locate, identify, and evaluate all publications, studies, explorations, and distributions on a particular topic.

Anala M.R. et al. [1] have developed a system that can detect out-of-the-ordinary behavior and alert the client. There are numerous items that are not typical, making it difficult to define abnormalities. Examples include explosions, street accidents, attacks, shootings, and other incidents that are rarely witnessed but have a significant impact on public safety. This framework can differentiate between an explosion, a street accident, a gunshot, and a battle, thereby reducing the number of possible outcomes. These classes' audio was used to construct the model. Utilizing the UCF Crime Collection. Before you can learn about designs from records, you must have knowledge of space and the globe. Long Short-Term Memory (LSTM) networks learn to recognize the groups while Convolutional Neural Networks (CNN) classify spatial highlights. Using a CNN-LSTM model, the characterization is 85% accurate.

Siruruang Phatchuay et al. [2] estimated the cost of observing and classifying the behavior of pupils at the research center. While studying a subject, participate in activities. The camera was trained on the children, and computer vision was used to identify their features. Face recognition occurs when multiple video camcorders (MVC) are used to observe the behavior of individuals. In addition, the framework will make it simple for the Lecturer to recognize when students exhibit odd behavior. Assents, and to determine how keen students are to study more, 20 percent of the exam is administered if possible during school hours.

Kang Hao Cheong et al. [3] developed a low-priced and efficient method for automating, counting, and monitoring all human traffic on camera video transfers using computational item recognition. Two programming methodologies are analyzed, along with their construction. Additionally, approval is demonstrated in both controlled and uncontrolled real-world situations. The execution provides simulated individuals with automatic video investigation and tracking, removing manual tasks that employees are typically required to perform. The outcomes demonstrate enhanced performance in real-world scenarios.

Marianne DeAngelus et al. Despite substantial investments in increasing the quantity and quality of cameras, the burden on video managers to evaluate and extract useful information from video has only increased. Video administrators must perform a great deal of manual inspection as part of their daily duties, including viewing recordings, searching for abandoned items, and classifying data from multiple cameras. FOVEA is designed to interact with existing surveillance systems, unlike other devices that require video data to be sent or, at the very least, sorted prior to viewing. On-demand apparatus can be added to any video transfer without the need for additional instruments. This study examines the technical methodologies, elementary mathematics, and consequences of a video administrator's duties.

The system developed by Gargi Desai et al. [5] detects video transfer, stores the data, and ultimately sends out alarms. Therefore, no additional sensors are necessary. Using the cameras themselves, the objective is to quickly identify incidents and send alerts to hospitals or medical services, ensuring that the resources needed to save lives are available in a timely manner. Other goals include locating and reporting as many non-compliant vehicles as possible, monitoring for limited street zones and traffic signal violations, and locating and arresting lawbreakers. In addition, the proposed framework would organize the categories of vehicles whose use of a street unexpectedly increases. Thus, future roadway development can be based on the categories of vehicles that typically utilize them, resulting in a more efficient flow of traffic. In order to complete the above-mentioned duties, this study will employ calculations such as Background Subtraction, Morphological Changes, and numerous other fundamental concepts. The plan is to use technology to integrate numerous disparate elements into one intelligent system. The project will reduce the cost of street security systems and ensure that they are completely automated.

Mandar S. Munagekar et al. [6] discussed how to determine when a theft occurs in a closed environment and how to capture a thief efficiently.This work employs a Canny edge detection technique to prevent theft. As this method provides complete security by allowing you to detect and report any anomalous movement, it is the most secure option. In addition, the proposed framework does not waste memory by monitoring inconsequential movements. In conclusion, this conserves disk capacity.

The primary objective of the study by Virender Singh et al. [7] is to progressively identify anger and aggression symptoms, which aids in distinguishing atypical situations from routine ones. We plan to utilize multiple Deep Learning models (CNN and RNN) to identify and organize high growth levels in the casing. If there is a threat, we can send out an alert that identifies the suspicious behavior at a specific time.

Ashish Singh Patel et al. The work described in this article was tested at rice storage depots in Chhattisgarh, India, with promising results.

In their survey, Tasriva Sikandar et al. [9] provided information on anomaly detection, highlights, framework structure and strategy, image acquisition, test determination, execution investigation, and venture finance. In addition, the study evaluates the tests in terms of their applicability, validity, and utility in distinct situations such as ATM usage. An irrefutable video monitoring system based on image processing techniques has yet to be discovered, although ATM holds a great deal of promise. In the future, the findings of this audit could assist scientists in developing dynamic and versatile observation frameworks capable of detecting and preventing ATM fraud.

Zhenfeng Shao et al. [10] developed a new method for processing and utilizing massive quantities of surveillance video data based on event detection and alerting signals from front-end smart cameras. The strategy consists of three components: intelligence for unusual events, intelligent capacity for reconnaissance video, and rapid recuperation for proof recordings. This exhaustively examines the ephemeral spatial affiliation analysis of odd occurrences in numerous locations. The proposed results demonstrate that the proposed method can reliably forewarn of security threats before they occur, significantly reduce the amount of additional space required for recorded video, and significantly speed up the recovery of evidence video pertaining to specific suspects.

Karpathy et al. (2017) provide a thorough evaluation of deep learning algorithms for video analysis, such as action recognition, activity detection, and video captioning. The limitations and opportunities of using deep learning models to analyze video are discussed, along with the most significant advancements in the field.

(2018) Ji, S., Xu, and colleagues This survey study discusses the classification and characterization of videos using deep learning. It discusses datasets, evaluation methods, and the difficulties associated with video classification and captioning employment.

X. Peng et al. (2018) This study examines deep learning algorithms for video analysis. It covers video captioning, video object detection, and video summarization. Architectures, datasets, metrics for determining how well something functions, and problems associated with deep learning-based video analysis are discussed.

D. Tran et al., 2019 This extensive research article examines a variety of deep learning for video analytics-related topics. It offers a comprehensive examination of several tasks, including object detection, action recognition, and video comprehension. The paper discusses architectures, datasets, evaluation criteria, and issues pertaining to the application of deep learning to evaluate video.

3. COMPONENTS OF AN INTELLIGENT VIDEO ANALYTICS SYSTEM

An intelligent video analytics system is made up of several key components. These components work together to process and analyze video data in an efficient manner. These components are as follows:

1. Video Data Acquisition and Preprocessing:

This step involves gathering video data from various sources, such as cameras or video streams, and then preparing it. This system may be able to integrate with video capture devices, IP cameras, or video streaming platforms. Preprocessing phases include video stabilization, frame alignment, noise reduction, and resolution normalization to ensure that the data can be processed properly.

2. Deep Learning Architectures for Video Analysis:

Deep learning architectures are critical components in the process of extracting usable information from video data. CNNs, or Convolutional Neural Networks, are often used for image-based activities that occur within video frames. Recurrent Neural Networks, or RNNs, and Transformer models, on the other hand, are used to capture temporal dependencies that occur over successive frames.

3. Object Detection and Tracking:

Object detection is the process of identifying and locating objects of interest inside video frames. The process of determining where an object has been in a sequence of frames is known as tracking. This methodology incorporates methods such as region proposal methods and approaches that are either anchor-based or anchor-free. The goal of object tracking is to keep track of how things move from one frame to the next and to assign them unique identities. Tracking algorithms use methods such as Kalman filters, correlation filters, and deep learning trackers.

4. Activity Recognition and Behavior Analysis:

The practice of recognizing and comprehending human actions or activities inside video sequences is known as activity recognition. The process of evaluating human behavior is known as behavior analysis. Deep learning models, such as CNNs and RNNs, are trained to recognize specific events or behaviors by being fed labeled datasets during training. Behavior analysis is the process of inferring higher-level information from lower-level behaviors, such as detecting aberrant behavior or evaluating crowd behavior.

5. Video Summarization and Understanding:

Most Critical Information Approaches to video summarizing aim to reduce lengthy videos into shorter summaries or key highlights while retaining the most significant information. It comprises selecting sample frames or segments based on saliency, variety, or importance metrics. For a more in-depth understanding of the video's content, "video understanding" demands the use of higher-level analytic techniques like "semantic segmentation," "scene understanding," or "video captioning."

6. Real-time Processing and Scalability Considerations:

Two of the most significant factors for real-time video analytics systems are efficient processing and scalability. Optimization tactics, hardware accelerators (such as GPUs or TPUs), and parallel processing are used to address the computational requirements of deep learning models. It is common practice to leverage cloud-based architectures and distributed computing systems when scaling a system to accommodate huge amounts of video data.

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The interaction between each component of an intelligent video analytics system and the other components results in the formation of an end-to-end video analysis pipeline. It's also feasible that the components will have feedback loops, in which one component's output influences the behavior of another. The ultimate goal is to gain meaningful insights from video data analysis, provide credible forecasts, and enable decision-making based on such estimates.

4. DEEP LEARNING TECHNIQUES FOR VIDEO ANALYSIS

Deep learning allows models to learn from raw video data without the need for feature creation, which has revolutionized video analysis. Several important deep learning approaches are used in video analysis. Notable examples include:

1. Convolutional Neural Networks (CNNs):
CNNs are frequently used to perform tasks involving images in video frames, such as object detection, image classification, and image meaning extraction. Using convolutional layers, pooling layers, and non-linear activation functions, CNNs can learn to describe visual features in a hierarchical manner. CNNs can be employed on single frames or in conjunction with temporal modeling approaches to obtain motion information for video analysis.

2. Recurrent Neural Networks (RNNs):
RNNs are designed to model sequential data and are adept at determining how video sequences differ in time. They maintain secret states that function as memory and allow them to analyze information repeatedly. RNNs that overcome the vanishing gradient problem include Long Short-Term Memory (LSTM) and Gated Recurrent Unit (GRU). RNNs excel at tasks such as recognizing activities, captioning videos, and predicting what will happen in videos.

3. 3D Convolutional Neural Networks (3D CNNs):
3D CNNs improve on regular 2D CNNs by directly capturing information about space and time from video input. These models can learn information in both space and time by using 3D neural layers. 3D CNNs are useful for tasks such as identifying activities in videos, where motion dynamics are critical for accurate categorization. They are, however, more complicated to program and use more memory than 2D CNNs.

4. Transformer Models:
While transformer models were originally designed to analyse natural language, they have also showed great potential in video analysis activities. These models employ self-attention mechanisms to identify long-term dependencies inside or between video frames. Transformer-based solutions have performed well in tasks such as identifying activities in videos, captioning videos, and answering video-related queries.

5. Generative Models:
Variational Autoencoders (VAEs) and Generative Adversarial Networks (GANs) are two generative models used in video analysis for tasks such as video synthesis, video inpainting, and outlier detection. VAEs can learn hidden models of video frames and create new frames that look authentic. By competing a generator network against a discriminator network, GANs learn to produce realistic video patterns.

Combining and integrating these deep learning approaches into video analysis pipelines can aid in a variety of tasks such as object detection, activity recognition, video summarization, and more. By employing deep learning in an intelligent manner, video analytics systems can reach cutting-edge performance and extract meaningful information from video data.

5. CHALLENGES AND OPEN RESEARCH DIRECTIONS

Intelligent video analytics that use deep learning are now experiencing a lot of challenges, which is why researchers are looking into uncharted territory. Here is a list of the most important issues to think about and research:

1. Data Scarcity and Annotation Challenges:
Deep learning models for video analytics may require a huge amount of named training data, which might be difficult to find. The lack of data and annotations is a problem. The acquisition and annotation of cinematic content, on the other hand, can be costly

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and time-consuming. The issue of insufficient data, as well as the creation of effective techniques for organizing it, such as learning with little or no aid or on one's own, are both major research subjects.

2. Real-time Processing and Resource Constraints:

Real-time processing and resource constraints For applications such as espionage and self-driving cars, real-time video analysis is critical. This method of processing limits the available resources. Deep learning models can require a lot of processing power, and maintaining video streams in real time can be difficult since it requires a lot of processing power and can cause delays. Among the key areas of focus are the development of efficient algorithms, the deployment of hardware acceleration, and the strengthening of deep learning models for real-time processing.

3. Interpretability and Explainability:

Deep learning models are usually viewed as "black boxes," making it difficult to understand how they make decisions and function. In the field of video analytics, where accountability and openness are highly prized, evaluating deep learning models and explaining how they generated their predictions is critical.

4. Ethical Considerations and Privacy Concerns:

Because video analytics systems evaluate private visual data, they present ethical and privacy problems. Future research should focus on ensuring that video analytics are utilized properly, resolving privacy concerns, and developing techniques to protect any personal information contained in video data.

5. Robustness and Adversarial Attacks:

Deep learning models are subject to adversarial attacks, in which small changes can throw off the predictions of the models. Important areas of research include making deep learning models that are immune to these kinds of attacks, looking into ways to defend against them, and studying how vulnerable video analytics systems are to adversarial attacks.

6. Transfer Learning and Generalization:

Deep learning models that are trained on a single dataset may not do well in new settings or situations they haven't seen before. Important directions for study are to look into transfer learning techniques, domain adaptation methods, and make models that can be used across different video datasets or domains.

7. Multimodal Video Analysis:

Video data often includes other types of data, like voice, text, or sensor data. Integration of multiple modalities for comprehensive video analysis and use of multimodal fusion techniques are two ways to improve performance and get a better knowledge of what is going on in a video.

8. Human-Centric Video Analysis:

Adding human-centric analysis, such as the ability to recognize emotions, understand social behavior, or predict purpose, can make video analytics systems more personalized and aware of their surroundings. Human-centered video analysis tries to figure out how people act and what they want to do by looking at video data..

9. Lifelong and Continual Learning:

Video analytics systems should be able to adapt to changing environments, new video data, and changing jobs and learn from them. Research on methods for lifelong and continuous learning, such as incremental learning, few-shot learning, and online adaptation, is important for making video analytics systems that change and get better over time.

Using deep learning to make intelligent video analytics systems will get better and be used by more people if these problems are solved and these study directions are explored. It will make video analysis more accurate, reliable, and responsible. This will open up new possibilities for uses in many different areas.

6. CONCLUSION

In conclusion, the use of deep learning methods has changed the field of intelligent video analytics by making it possible to process, analyze, and understand video data in new ways. This survey study gave a general overview of the parts, methods, applications, problems, and future directions for creating intelligent video analytics systems based on deep learning. When we talked about the most important parts of these systems, we talked about video data preprocessing and acquisition, deep learning architectures for video analysis, object detection and tracking, activity recognition and behavior analysis, activity summarization and understanding, real-time processing, and issues with scalability. Some of the deep learning methods that were looked into were Convolutional Neural Networks (CNNs), Recurrent Neural Networks (RNNs), 3D CNNs, Transformer models, and Generative models. Object detection, activity recognition, video synthesis, and finding strange things have all been done very well with these methods.

The survey study went into detail about how intelligent video analytics can be used in sports analytics, entertainment, self-driving cars, healthcare tracking, surveillance and security systems, and smart cities. These uses have a big impact on how safety is improved, healthcare is improved, self-driving cars are made possible, and urban areas are made better. Also, a number of problems and directions for future research were pointed out. These included the difficulty of annotating sparse data, limited resources and real-time processing, problems with understanding and explaining, privacy and ethics, robustness and adversarial attacks, transfer learning, and multimodal video analysis. Taking care of these problems and studying these areas will help clever video analytics systems grow and be used by more people.

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