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Research paper

Hybrid deep learning framework for enhanced target tracking in video surveillance using CNN and DRNN-GWO

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Abstract

The growing demand for advanced security solutions has driven significant progress in video surveillance technologies in recent years. A critical component of modern surveillance systems is the ability to accurately track and monitor targets in dynamic environments. In this paper, we present a computer vision-based target-tracking system designed to enhance the efficiency of video surveillance operations. The proposed approach employs hybrid deep learning algorithms for the detection and tracking of targets within video frames. Initially, recorded video footage from surveillance cameras is input into the system, where each frame undergoes preprocessing to enhance quality. A Convolutional Neural Network (CNN) is then utilized to extract spatial features from the preprocessed frames, enabling the precise identification and localization of objects. The CNN also detects regions of interest and labels identified objects (e.g., persons, vehicles). We introduce a novel algorithm that combines the strengths of Deep Recurrent Neural Networks (DRNN) and Grey Wolf Optimization (GWO), referred to as DRNN-GWO. The DRNN module captures spatial and temporal dependencies within the frames to predict the future positions of tracked objects, while the GWO algorithm optimizes the hyperparameters of the DRNN to further enhance tracking performance. The proposed framework was implemented in Python. Experimental results demonstrated outstanding performance, achieving a target tracking accuracy of 99.12%, a recall of 98.75%, a precision of 99.27%, and an F-measure of 99%.

Keywords: *Convolutional Neural Network; Computer Vision Target Tracking; Grey Wolf Optimization; Deep Recurrent Neural Network; Video Surveillance.*

1. Introduction

Human behavior detection plays a crucial role in a variety of real-world applications, including intelligent video surveillance and consumer behavior analysis [1]. Video surveillance has seen widespread adoption across both indoor and outdoor environments, becoming a fundamental component of modern security systems. Over the years, surveillance cameras have proven essential in safeguarding individuals, vehicles, and property [2]. With initiatives like Digital India, the integration of advanced surveillance technologies has enhanced real-time monitoring capabilities [3]. These systems offer numerous advantages, such as reducing manpower requirements, enabling efficient and continuous monitoring, supporting modern security trends, and providing cost-effective auditing solutions [4]. Traditionally, human operators performed the task of monitoring surveillance footage. However, the sheer volume of video data makes manual monitoring impractical, leading to fatigue, omissions, and decreased system efficiency [5], [6]. Manually reviewing recorded footage to locate specific events is also time-consuming [7]. As a result, automatic detection of suspicious activities in surveillance videos has emerged as a critical research area [8]. Predicting human behavior in video surveillance systems involves intelligent techniques for identifying suspicious events [9]. Current developments leverage artificial intelligence (AI), deep learning (DL), and machine learning (ML) to create automatic and accurate behavior prediction models for high-security areas like airports, banks, railways, and examination centers [10]. AI empowers computers to mimic human decision-making, enabling faster and more accurate detection of suspicious activities [11]. ML and DL, as branches of AI, learn patterns within data to make future predictions without explicit programming [12]. The integration of computer vision and video surveillance significantly enhances public safety by employing frameworks that involve environment modeling, motion detection, tracking, behavior recognition, and multi-camera data integration [13], [14]. These frameworks require extensive pre-processing to extract meaningful features from video sequences, utilizing classification algorithms based on supervised and unsupervised learning [15]. Supervised methods rely on labeled data, while unsupervised methods discover patterns autonomously [16], [17]. Object detection and tracking, core tasks in intelligent surveillance, rely heavily on analyzing footage to monitor human behavior [18]. Despite its complexity, advancements in deep learning have made significant progress in accurately predicting and interpreting human actions in surveillance videos [19]. Recent advancements in video surveillance have emphasized the importance of automatic human behavior detection for enhancing security and monitoring systems [20]. Traditional surveillance systems relied heavily on human operators, which often led to inefficiencies due to fatigue and human error, particularly when handling large volumes of video data (Valera & Velastin, 2005; Hu et al., 2004). The limitations of manual monitoring have driven research toward automated solutions capable of identifying suspicious activities with minimal human intervention [21], [22]. Human behavior detection, a core component of intelligent surveillance, involves recognizing and interpreting complex, dynamic actions that are often context-dependent and unpredictable (Popoola & Wang, 2012). Recognizing these challenges, researchers have explored various computer vision techniques to automatically detect and classify human behaviors within video footage [23], [24]. Early methods employed handcrafted features and conventional machine learning models; however, these approaches often struggled with scalability and adaptability in real-world scenarios [25], [26]. The rise of deep learning has revolutionized this field, enabling systems to learn spatial and temporal patterns directly from raw data with significantly higher accuracy. Models such as Convolutional Neural Networks (CNNs) for feature extraction and Recurrent Neural Networks (RNNs) for sequence modeling have been extensively applied to behavior detection tasks (Chaudhry et al., 2009). These advancements have paved the way for the development of more robust and reliable intelligent surveillance systems that can automatically detect, predict, and respond to human behavior anomalies in real-time [27], [28].

2. Proposed methodology

This research introduces a hybrid deep learning and optimization-based framework for accurate object detection and tracking in video surveillance applications [29]. The proposed methodology is divided into four main phases: data collection, pre-processing, object detection, and object tracking. In the data collection phase, video footage captured by surveillance cameras is gathered and fed into the system for further analysis. In the pre-processing phase, the quality of the video frames is enhanced through a series of operations, including frame resizing to standard dimensions, noise reduction to remove unwanted artifacts, contrast enhancement to highlight critical features, and background elimination to focus on moving objects [30], [31]. The object detection phase employs a Convolutional Neural Network (CNN) to extract spatial features from the pre-processed frames. The CNN identifies objects within each frame, establishes regions of interest (ROIs) around them, and classifies them into predefined categories such as persons, vehicles, or animals [32], [33]. This enables precise localization and labeling of targets across the video sequences. Following detection, the object tracking phase is conducted using the proposed Deep Recurrent Neural Network optimized with Grey Wolf Optimization (DRNN-GWO) model [34], [35]. The DRNN is responsible for learning and maintaining the spatial-temporal relationships of the detected objects over consecutive frames, enabling accurate tracking. Simultaneously, the Grey Wolf Optimization (GWO) algorithm is integrated to fine-tune the hyperparameters of the DRNN, improving the model's tracking performance, accuracy, and computational efficiency [36], [37]. The combined DRNN-GWO approach leverages the strengths of deep learning for sequence prediction and the optimization capabilities of GWO, leading to superior tracking accuracy, reduced error rates, and faster processing times compared to conventional methods [38], [39]. Fig. 1 depicts the architecture of the proposed system.

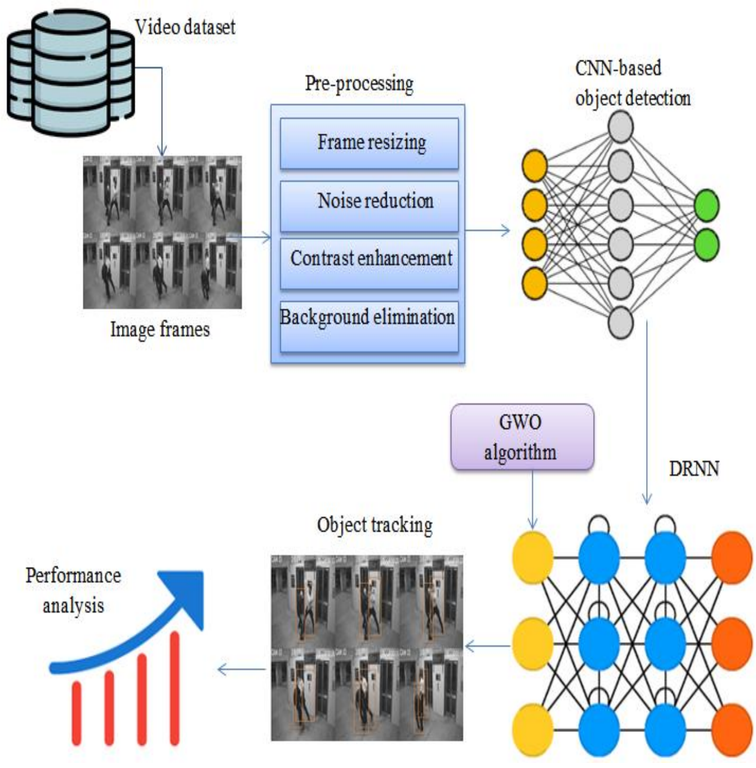

Fig. 1: Proposed System Architecture.

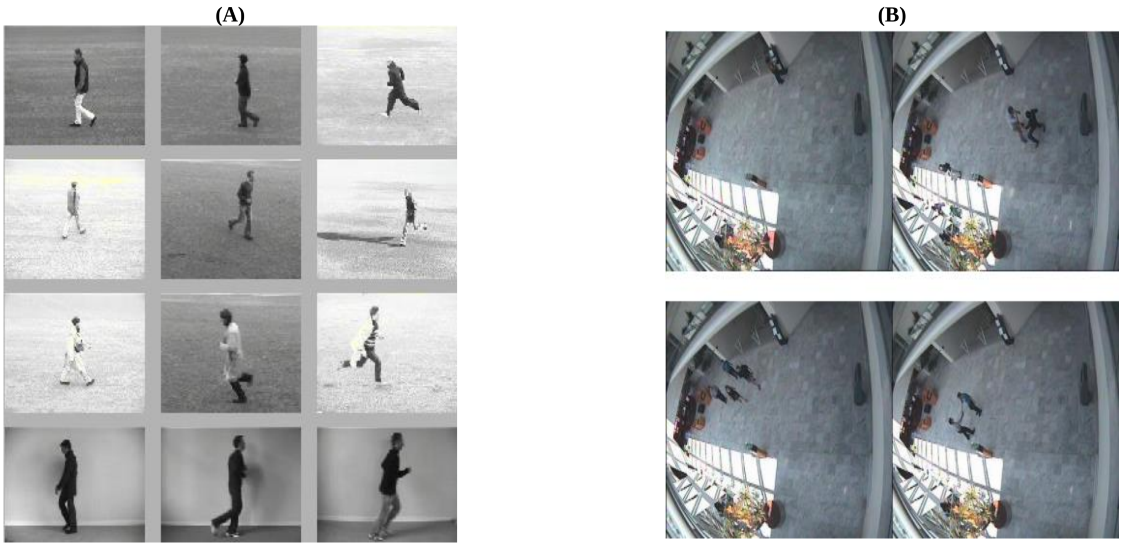

Fig. 2: Video Sequences from Datasets: (A) KTH, (B) CAVIAR.

Pre-processing plays a vital role in enhancing the effectiveness of object detection and tracking in video surveillance systems. Initially, videos were decomposed into individual frames. During the frame resizing process, the dimensions of each frame were standardized, ensuring uniformity across the dataset [40], [41]. This resizing step is critical for maintaining input consistency and optimizing the performance of deep learning models, while also enhancing computational efficiency. Following resizing, noise reduction was applied to eliminate unwanted artifacts and distortions commonly present in raw frames. Spatial filtering techniques were used, where filters directly manipulate pixel values to smooth out irregularities and reduce noise. Once noise was minimized, contrast enhancement was performed to further improve image quality [42], [43]. This was achieved using histogram equalization, which redistributes pixel intensity values to enhance the contrast and make important features more distinguishable. The final pre-processing step involved background elimination, where static elements were isolated and removed from the frames, allowing the system to focus solely on dynamic and moving objects [44], [45]. These pre-processing techniques collectively ensured that high-quality frames were fed into the next stage. Fig. 2 (a, b) depicts video sequences from the KTH and CAVIAR databases. The object detection phase was carried out using a Convolutional Neural Network (CNN), which is specifically designed to process structured grid data such as images. In this work, the CNN model extracts spatial features from the enhanced frames, identifies Regions of Interest (ROIs), and classifies detected objects into categories like humans, vehicles, and more [46], [47].

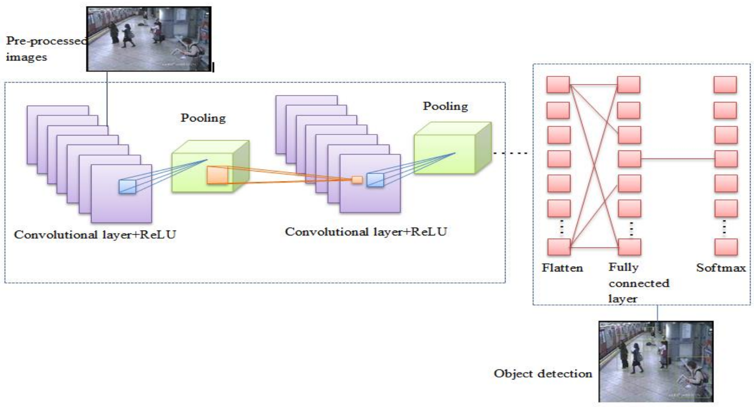

Fig. 3: CNN Architecture.

CNNs have been widely recognized for their exceptional capabilities in tasks such as pattern recognition, image classification, and other computer vision applications. A typical CNN architecture comprises three essential layers: convolutional layers, pooling layers, and fully connected (FC) layers. Convolutional layers apply kernel filters to the input frames, capturing local patterns and spatial relationships [48]. The resulting feature maps are then processed through pooling layers, which down-sample the data while preserving crucial information. Finally, the fully connected layers integrate the extracted features to produce the final classification output. For object detection, the CNN is employed to identify and localize objects within the pre-processed frames. This process involves segmenting the images into multiple regions, classifying the content within each region, and accurately adjusting bounding boxes around the detected objects. The initial step in object detection is the convolutional operation, where a kernel filter is slid across the frames to capture important local features [49]. Through this sliding mechanism, the kernel learns to recognize essential patterns such as edges, textures, and color gradients, resulting in the generation of a feature map that represents these learned characteristics. Following object detection, object tracking is carried out using the proposed DRNN-GWO algorithm, a hybrid approach that combines Deep Recurrent Neural Networks (DRNN) with the Grey Wolf Optimizer (GWO), integrating deep learning with meta-heuristic optimization strategies. In this system, the DRNN handles the tracking tasks, while GWO fine-tunes the DRNN's parameters to enhance overall tracking performance. Fig. 3 shows the CNN architecture. The DRNN is specifically designed to process sequential data, distinguishing itself from other models through its ability to retain past outputs in its internal memory—an essential feature for effective target tracking in video surveillance. A DRNN consists of multiple recurrent layers, with the output from one layer serving as the input to the next. This layered structure enables the network to capture complex temporal patterns necessary for predicting the future movements of detected objects. The number of recurrent layers can be adjusted based on the problem's complexity. The architecture of the DRNN is made up of three primary components: an input layer, recurrent layers, and an output layer, all interconnected through neurons. These neurons share feedback connections involving weights and biases. The input layer receives object-detected frames from the CNN, while the output layer generates the final tracking predictions. The recurrent layers act as memory units, where each unit contains memory cells with self-feedback loops, allowing the network to store and update temporal state information over time. This memory capability enables the DRNN to model long-term dependencies within sequential input data. For the object tracking task, the DRNN predicts the future positions of the detected objects based on the temporal information. In this work, an LSTM (Long Short-Term Memory) variant of the RNN architecture was used. LSTM units, with their internal memory cells, can maintain information over extended periods, making them highly effective for tracking moving objects across video frames. To further optimize the tracking performance, the GWO algorithm is utilized to fine-tune the hyperparameters of the DRNN. By continually adjusting these parameters, GWO enhances the learning capability and stability of the DRNN, leading to improved accuracy and efficiency in object tracking throughout the developed system. Fig. 4 depicts the flowchart of the presented algorithm.

3. Results and discussion

This research introduces a novel hybrid approach in computer vision, aimed at achieving precise target detection and tracking in video surveillance environments. The proposed system integrates the strengths of deep learning methods, meta-heuristic optimization strategies, and advanced computer vision techniques. The implementation of the developed framework was carried out using Python version 3.7.8 on a 64-bit Windows 10 platform. For validation purposes, two publicly accessible datasets, KTH and CAVIAR, were employed. The system's performance was assessed using several evaluation metrics, including accuracy, error rate, precision, computational time, recall, and F-measure. The details of the implementation settings and specifications are outlined in Table 1. The key aim of the training and testing phase was to progressively enhance the model's accuracy and tracking efficiency through iterative optimization. To facilitate this, the dataset was partitioned into a training set and a testing set in an 80:20 ratio. The effectiveness of the model during these stages was monitored by analyzing the loss and accuracy trends throughout the training process. The model's training and testing accuracy are graphically depicted in Fig. 5. The model's Training and testing loss are depicted in Fig.6. In this evaluation, the performance of the developed system is compared with traditional approaches such as CNN, DCNN, LSTM, SVM, DBN, and EL-CNN. When applied to object or target tracking, these conventional methods achieved accuracies of 90.41%, 91.55%, 93.78%, 85.44%, 89.65%, and 91.33%, respectively. In contrast, the proposed model achieved a significantly higher accuracy of 99.12%. This impressive result demonstrates the superior performance of the proposed system, underscoring its effectiveness and reliability in accurately tracking targets in video surveillance scenarios. The findings emphasize the advantages of integrating deep learning techniques and optimization algorithms, which enhance the precision of object detection and target tracking. The evaluation of the system's accuracy with the traditional algorithms is presented in Fig. 7. To validate the precision of the developed methodology, a comparison was made with existing object-tracking algorithms. The traditional models—CNN, DCNN, LSTM, SVM, DBN, and EL-CNN—achieved precision rates of 90.24%, 90.91%, 94.87%, 86.98%, 89.52%, and 93.76%, respectively. In contrast, the proposed method demonstrated a higher precision of 99.27%, highlighting its efficiency in accurately detecting positive instances (objects) within video frames. The comparative precision results are presented in Fig. 8, showcasing the proposed algorithm's enhanced performance. This increase in precision suggests that the new approach significantly reduces false negatives, thereby minimizing unnecessary alarms in practical surveillance environments.

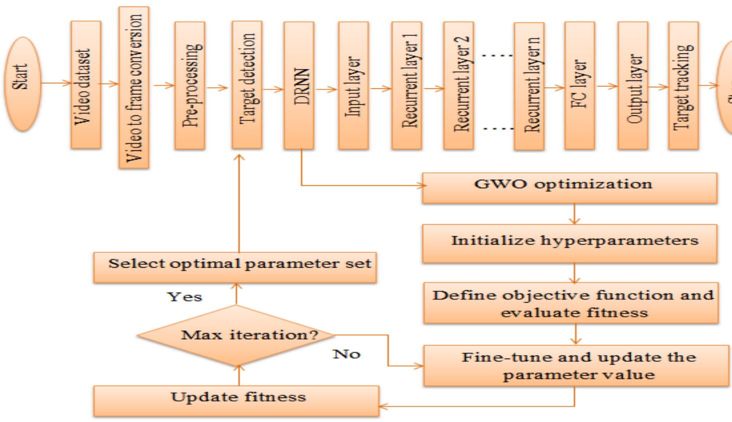

Fig. 4: Flowchart of the Developed Work.

Table 1: Implementation Parameters and Specification

Parameters	Specification
Database	KTH, CAVIAR datasets
Training %	80
Testing %	20
Classifier	DRNN
Optimizer	GO
Epoch	140
Initial learning rate	0.001

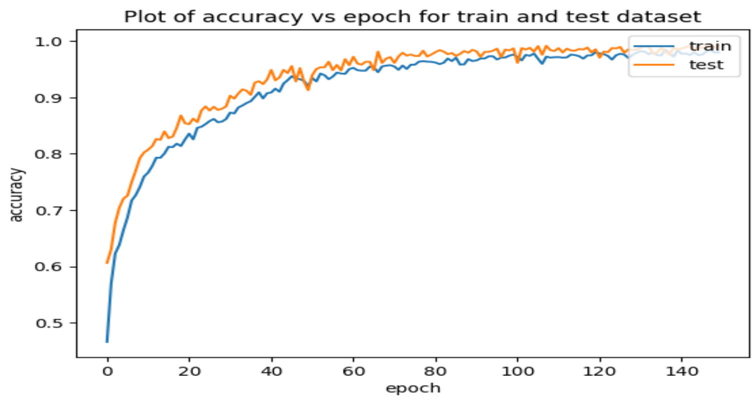

Fig. 5: Training and Testing Accuracy.

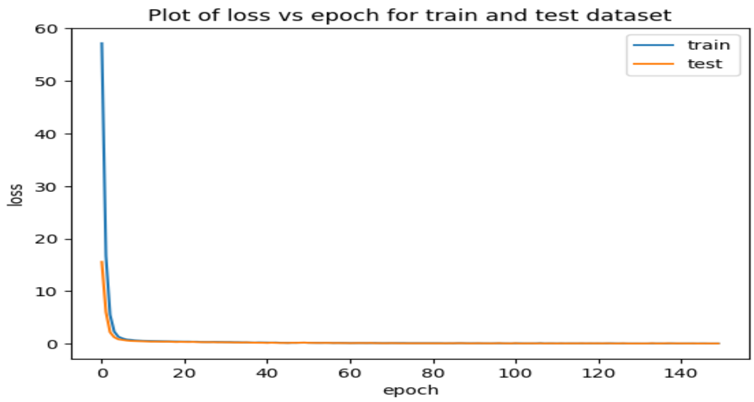

Fig. 6: Training and Testing Loss.

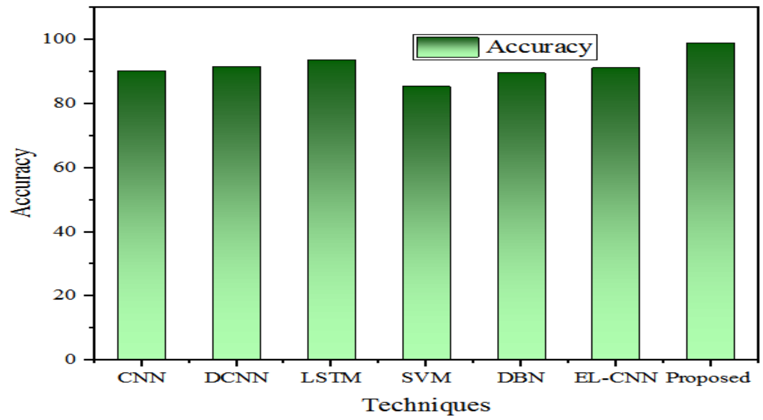

Fig. 7: Accuracy Comparison.

Next, the recall of the proposed method was evaluated against conventional tracking techniques. Recall measures the system's ability to correctly identify relevant instances for object tracking. The existing models—CNN, DCNN, LSTM, SVM, DBN, and EL-CNN—achieved recall values of 91.45%, 91.27%, 95.20%, 86.51%, 88.97%, and 92.54%, respectively. However, the proposed approach achieved a higher recall rate of 98.75%, demonstrating a superior capacity for recognizing objects in video frames. This comparative evaluation of recall is illustrated in Fig. 9. The F-measure, which balances precision and recall, was calculated for the developed system and compared with the conventional techniques. The existing models earned F-measures of 90.83%, 91.84%, 95.05%, 86.79%, 89.35%, and 93.15%, respectively. In comparison, the proposed method achieved an F-measure of 99%, signifying its ability to provide a balanced and robust performance while minimizing both false positives and false negatives. This exceptional F-measure performance is depicted in Fig. 10, highlighting the effectiveness of the developed system in real-world surveillance applications. Finally, the error rates of the various tracking techniques were analyzed. Conventional algorithms, such as CNN, DCNN, LSTM, SVM, DBN, and EL-CNN, had error rates of 4.70%, 4.88%, 3.27%, 10.54%, 9.65%, and 4.72%, respectively. In contrast, the developed framework demonstrated a remarkably low error rate of only 0.88%, illustrating its ability to minimize both false positives and false negatives. This low error rate is further emphasized in Fig. 11, underscoring the system's accuracy and reliability in video surveillance applications. Finally, the computational time of the developed method was compared with that of existing techniques, as shown in Fig. 12. Conventional techniques, including CNN, DCNN, LSTM, SVM, DBN, and EL-CNN, recorded computational times of 6.11s, 5.98s, 6.63s, 8.12s, 8.43s, and 7.52s, respectively. In contrast, the developed approach demonstrated a significantly lower computational time of 4.21s, highlighting its efficiency in processing video frames for object tracking. The comparative analysis of the developed method and existing techniques is presented in Table 2. This table summarizes key performance metrics such as accuracy, precision, recall, F-measure, error rate, and computational time for each method. The conventional techniques—CNN, DCNN, LSTM, SVM, DBN, and EL-CNN—are compared alongside the proposed method, showcasing the superior performance of the developed approach across all evaluated parameters, including achieving the highest accuracy, precision, recall, F-measure, and the lowest error rate and computational time. This table clearly demonstrates the advantages of the proposed algorithm in video surveillance applications.

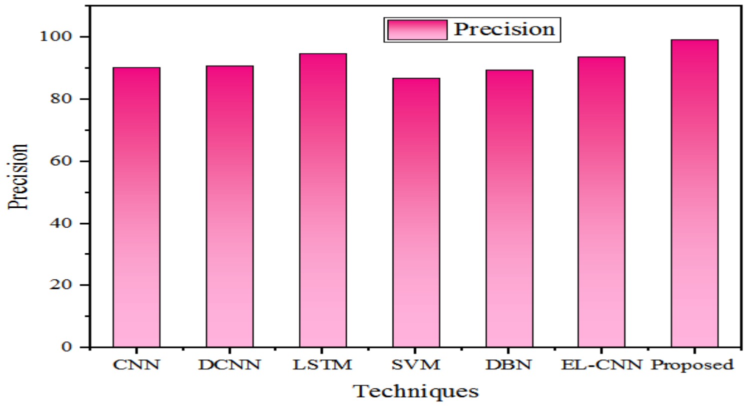

Fig. 8: Precision Comparison.

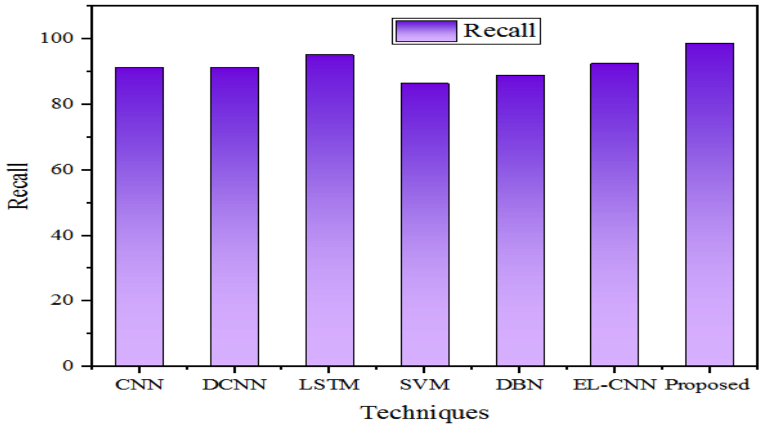

Fig. 9: Recall Comparison.

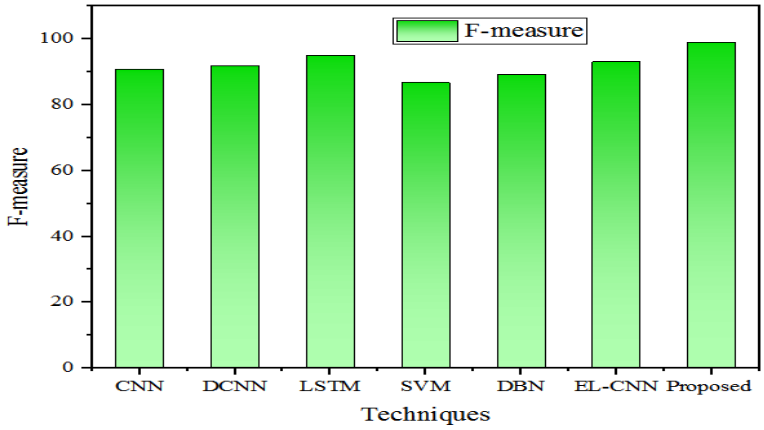

Fig. 10: F-Measure Comparison.

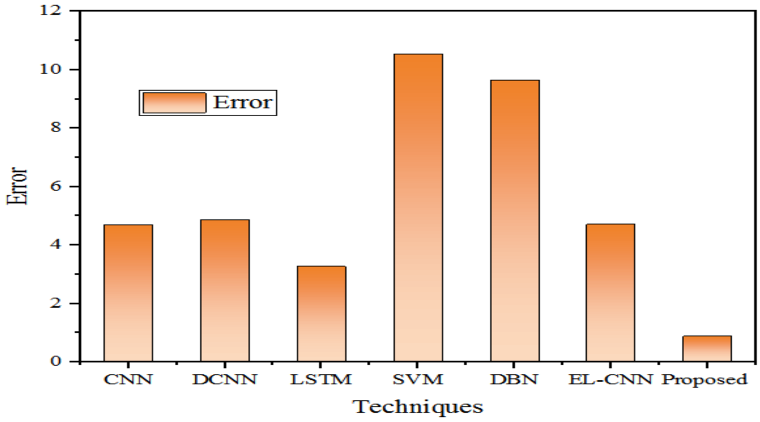

Fig. 11: Error Comparison.

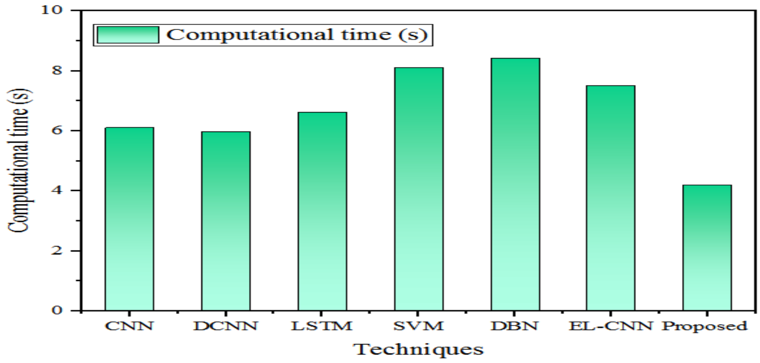

Fig. 12: Computational Time Comparison.

Table 2: Comparative Analysis

Techniques	Accuracy	Precision	Recall	F-measure	Error	Computational time
CNN	90.41	90.24	91.45	90.83	4.70	6.11
DCNN	91.55	90.91	91.27	91.84	4.88	5.98
LSTM	93.78	94.87	95.20	95.05	3.27	6.63
SVM	85.44	86.98	86.51	86.79	10.54	8.12
DBN	89.65	89.52	88.97	89.35	9.65	8.43
EL-CNN	91.33	93.76	92.54	93.15	4.72	7.52
Proposed	99.12	99.27	98.75	99	0.88	4.21

4. Conclusion

In conclusion, the developed object-tracking methodology outperforms traditional techniques such as CNN, DCNN, LSTM, SVM, DBN, and EL-CNN across multiple performance metrics, including accuracy, precision, recall, F-measure, and error rate. The proposed model demonstrated exceptional results, achieving 99.12% accuracy, 99.27% precision, 98.75% recall, and a 99% F-measure, significantly surpassing the conventional methods. Additionally, the developed system showed a minimal error rate of 0.88% and reduced computational time, with an impressive processing time of 4.21 seconds. These findings validate the robustness, efficiency, and effectiveness of the proposed algorithm, making it a promising solution for real-time object tracking in video surveillance. By minimizing false positives and false negatives while optimizing performance, this approach is well-suited for practical applications where accurate and reliable tracking is crucial.

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