

Comparative Analysis Of Optimization For CNN-Based Feature Extraction And Bilstm Classification In Suspicious Video Behavior Recognition

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Abstract: For suspicious human behavior recognition, temporal sequence modeling and efficient spatial feature extraction are essential component for recognition. For recognition excelled network, Convolutional Neural Networks (CNNs) is used for extracting the hierarchical spatial features whereas Bidirectional LSTM (BiLSTM) networks are used for temporal dependencies thus training convergence, generalization, and computational efficiency are all greatly impacted by the optimization selection algorithms. Optimization algorithms like Adam, RMSprop, AdamW, Stochastic Gradient Descent (SGD), Nadam and Adadelta types are used in this research for comprehensive comparative analysis and then the optimized extracted features are given to CNN-LSTM/BiLSTM architecture for suspicious behavior classification. Each optimizer is evaluated carefully across key areas, such as how quickly converges, its accuracy, ability to generalize, its training stability, hyperparameter sensitivity, and overall computational cost. The evaluated optimized features are tested on three benchmark datasets viz: Violence Detection dataset, UT-Interaction dataset, and Custom Action dataset by adaptive learning rate approaches significantly outperformed the classical optimization methods. This optimization methods offers thorough convergence analysis, mathematical formulations, practical deployment guidelines, and an open-source implementation that facilitate research. This research offers solid, evidence-based suggestions for selecting the right optimizer in suspicious human behavior, which can cut down the training time and boost the accuracy.

Keywords: SGD, Adam, RMSprop, AdamW, CNN feature extraction, BiLSTM/LSTM.

I. INTRODUCTION

A. Background and Motivation

Recognising human actions from the videos has become increasingly important because of its uses in intelligent surveillance, public safety monitoring, healthcare behaviour analysis and improving how humans interact with the machines. In the video sequences, a recent progress in deep neural networks have gained massive improvement to understand the complex ways that visual information changes over both space and time. Even with all these developments, CNNs continues to be the go-to-choice for pulling out spatial features from the frames. This is because CNN can exceptionally good in capturing the spatial features, which works well with transfer learning, where a model trained will be the one task and adapt it to another. CNNs give the best feature vector which are then optimized by the Meta -heuristic optimizer for best feature.

B. Research Objective

This paper addresses current gaps in the research by doing a detailed comparison of six popular optimizers when used with CNN-BiLSTM models for detecting suspicious human behaviour.

1. Measure how well each optimizer performs by looking at the test accuracy, precision, recall and F1-score, while keeping the model architectures and datasets the same.

2. Examine how quickly each model reaches its best performance.
3. Comparing the training data versus test accuracy by examining validation curves, and testing across three datasets.
4. Examine how fast the trained model can make predictions.
5. Test how the robust each optimizer is when important settings are selected like learning rate, batch size, and model's weights.

C. Paper Organization

Section II reviews relevant literature on optimization algorithms and video classification. Section III explains the CNN-BiLSTM architecture and the overall methodology.

Section IV describes the experimental setup,

Section V concludes the paper with findings.

II. RELATED WORK

A. CNN -Based Video Feature Extraction

EfficientNet and similar architectures have proven that by thoughtfully adjusting the network depth, width, and resolution, which can be achieved greater improvements in accuracy and computational efficiency [1]. While for hierarchical visual representation Inception-based model continue to remain reliable benchmarks [2]. These models have proven to be excelled in generalization performance, especially when they have been pretrained on large datasets such as ImageNet and then used for video understanding tasks [3].

When it comes to recognition of human actions, video dataset offers a wide range of sample from Kinetics 700 dataset are very much helpful. The enable the effective learning by capturing how the motion of the people is detected, look, and interact in various environmental conditions [5]. In order to capture the motion cues more effectively, the research was focused on spatiotemporal convolutions [6], multi-level temporal representations [7], and flow-based model techniques [8]. However, CNNs are limited in modelling sequential dependencies over long temporal horizons. Long-Short term Memory (LSTM) and Bidirectional LSTM (BiLSTM) models, are been widely popular for capturing the temporal changes in videos. Research has shown that attention-augmented recurrent units can significantly improve motion sensitivity and enhance the modelling of long-range dependencies [9]. BiLSTM architectures are excel in capturing contextual dependencies in both temporal directions, which has shown remarkable success in human action classification [10] and attention-guided motion representation [11].

B. Hybrid CNN-RCNN Architecture for Video Classification

When it comes to analysing videos, combining two types of neural networks like CNNs and RNNs which works very well. The CNN model handles things which look like in each frame, while the RNN model figures out how those images change over time. Combining these two models, researchers have used for recognizing what human action classification [12], global local temporal modelling [13], hierarchical representation learning [14], and efficient temporal shift operations [15] understanding both quick movements and longer patterns, learning different levels of details, and making the process faster. Newer methods like attention mechanisms [16] that focus on important part of the videos, specialized video transformers like ViViT [17], and enhanced transformer models keep improving how accurately the videos are classified. The trade-off is that these cutting-edge approaches need more computational cost.

C. Optimization Method in Deep Learning

Even with all these new models designs, how actually tarin these video analysis systems still matter a lot. Several smart training methods have proven helpful, like AdamW [19], constrained optimizers that adjust learning rates on the dynamically [20], and technique focused on making sure the training actually finishes properly [21]. Here studies have found that while these adaptive training methods can help your model learn faster, they don't always perform as well on new, unseen data compared to simpler approaches like SGD (Stochastic Gradient Descent). This means you really need to think about what kind of task you're working on before choosing your training method [22-25].

D. Suspicious Behaviour and Anomaly Detection in Videos.

When it comes to anomaly recognition and suspicious activity in videos like detecting crimes or strange behaviour researchers use specialized datasets like UCF- crime [26], street scene [27], and dataset focused on predicting weird object behaviours [28]. These datasets show that we need smart models to catch subtle, hard -to- predict actions that might happen at different points throughout a video. When researchers compare different approaches, they find that combining CNNs with RNNs is still one of the best choices for this kind of work. There hybrid models offer a great spot which accurately catches these tricky behaviours without requiring massive amounts of computing power [29].

This paper takes all the insights and uses them to build a CNN-BiLSTM system specifically designed to recognize suspicious human behaviour. The approach is backed up by a thorough look at the latest developments in how models learn patterns across both space and time in videos, as well as the best strategies for training these deep learning systems effectively.

III. CNN-BiLSTM Architecture.

a. Overall Framework

Stage 1 CNN feature extraction processes video frames through VGG 16 pretrained network, extracting 4096-dimensional feature vectors encoding spatial information. For a single frame, the 4096 features are stored as a 1×4096 row vector, and when multiple frames are processed, they stack into a $T \times 4096$ matrix where each row represents one frame's complete feature description and each column represents one specific visual feature across time. When VGG16 processes each frame, it automatically detects and measures visual patterns ranging from low-level features like edges, colours, and basic shapes in its early layers, to high-level abstract representations like body posture, scene context, and human-object relationships in its deeper fully connected layers. This rich numerical description essentially serves as a compact yet comprehensive fingerprint of each video frame, providing the BiLSTM with sufficient spatial information to learn how scenes change over time and accurately distinguish between normal and suspicious human behaviors.

Stage 2 BiLSTM-LSTM Classification models temporal sequences of CNN features through bidirectional LSTM capturing forward-backward context and unidirectional LSTM modelling long-term dependencies, culminating in fully connected classification layers.

Table 1. CNN VGG16 Feature Extraction

Component	Mathematical Expression
Input Video Representation	A video $V = \{F_1, F_2, \dots, F_T\}$, where each frame $F_t \in \mathbb{R}^{H \times W \times 3}$.
CNN feature extraction	$x_t = \phi_{\text{CNN}}(F_t; \theta_{\text{CNN}}) \in \mathbb{R}^D$

Video feature sequence	$X=[x_1, x_2, \dots, x_T] \in \mathbb{R}^{T \times D}$
VGG16 convolutional blocks	Block 1: Conv3-64×2 → MaxPool Block 2: Conv3-128×2 → MaxPool Block 3: Conv3-256×3 → MaxPool Block 4: Conv3-512×3 → MaxPool Block 5: Conv3-512×3 → MaxPool
Fully connected layers	FC1: 4096 (ReLU) FC2: 4096 (ReLU, feature extraction point) FC3: 1000 (Softmax, discarded)

For detecting suspicious human behaviour works by analysing video-frame-by-frame using a pretrained VGG16 network model. For each frame, VGG 16 model extract a detailed 4096- dimensional feature vector from its second fully connected layer (FC2). These features vectors from all the frames are then stacked together in order, creating a sequence that captures both appearance and motion cues and then fed to BiLSTM/LSTM networks, which learn to recognize the patterns of suspicious human behaviour across the videos.

b. BiLSTM-LSTM Temporal Modelling

The BiLSTM-LSTM system built to recognize suspicious human behaviour by first processing the CNN feature in both forward and backward directions through time. This bidirectional analysis is important because it lets the model understand context from both directions, which captures past and the future temporal dependencies. Once it's done, a standard LSTM process the temporal information and compresses it into a simpler, more focused representation. These learned patterns then pass through several layers like dense layers for further processing, dropout layers to prevent overfitting, and lastly a softmax layer that produces the actual classification decision. During training, categorical cross-entropy are used for loss function and add L2 regularization. This combinational keeps the learning process stable and helps prevent the model from just memorizing the training data instead of actually learning to recognize suspicious behaviours.

Table 2. BiLSTM-LSTM Classification Pipeline

Component	Mathematical Expression
Bidirectional LSTM	Forward pass: $h_t^f = \text{LSTM}_f(x_t, h_{t-1}^f, c_{t-1}^f; \theta_f)$ Backward pass: $h_t^b = \text{LSTM}_b(x_t, h_{t+1}^b, c_{t+1}^b; \theta_b)$ Output: $h_t = [h_t^f; h_t^b] \in \mathbb{R}^{2H}$
LSTM Gates	Input gate: $i_t = \sigma(W_i[h_{t-1}, x_t] + b_i)$ Forget gate: $f_t = \sigma(W_f[h_{t-1}, x_t] + b_f)$ Output gate: $o_t = \sigma(W_o[h_{t-1}, x_t] + b_o)$ Candidate: $\tilde{c}_t = \tanh(W_c[h_{t-1}, x_t] + b_c)$ Cell update: $c_t = f_t \odot c_{t-1} + i_t \odot \tilde{c}_t$ Hidden state: $h_t = o_t \odot \tanh(c_t)$
Unidirectional LSTM	Final sequence encoding: $g_t = \text{LSTM}(h_t, g_{t-1}, c_{t-1}'; \theta_{\text{LSTM}})$ Output feature: $g_T \in \mathbb{R}^{128}$
Classification Layers	Dense: $z_1 = \text{ReLU}(W_1 g_T + b_1)$ Dropout: $z_2 = \text{Dropout}(z_1, p = 0.5)$ Softmax output: $\hat{y} = \text{Softmax}(W_2 z_2 + b_2)$
Loss Function	Cross-entropy with L2 penalty:

	$\mathcal{L}(\theta) = -\frac{1}{N} \sum_{n=1}^N \sum_{c=1}^C y_{nc} \log(\hat{y}_{nc}) + \lambda \sum_i \theta_i _2$
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I. Optimization Algorithms

In suspicious human behaviour detection optimizers play a vital role because they enable the model to learn from data. When initialized a deep learning model, it starts with the random weights and does not have any understanding of what suspicious behaviour looks like, just making a random guess. Here comes the job of optimizer where it adjusts these millions of parameters by calculating gradients and updating weights in a direction that minimizes prediction errors. In suspicious behaviour, what makes optimizer selection critical for the problems like suspicious events are rare, the patterns are subtle and context dependent, and occurrence of mistakes are severe.

Different optimizers have their own advantages when it comes to keeping training smooth and stable, helping the model reach a good solution efficiently, and ensuring the best performance on the unseen dataset. In case of SGD with Momentum updates the model's parameters by building up "velocity" based on previous updates. This momentum helps smooth out the fluctuations that can happen during the training and speeds things up. But still need to be manually fiddle with the learning rate. Conversely, Adam goes one step further by calculating adaptive learning rates for each parameter, by looking at the first and second moments of the gradients, which helps speed up the convergence on tricky con-convex problems.

RMSprop also employs adaptive learning rates but focuses solely on the moving average of squared gradients, making it particularly effective for recurrent networks. AdamW goes a notch higher by decoupling weight decay from gradient updates, which enhances generalization and boosts performance compared to the traditional Adam, especially in CNN and NLP tasks. Nadam adds a twist by incorporating Nesterov accelerated gradients into Adam, offering a "look-ahead" correction that accelerates convergence. Lastly, Adadelat does away with the need for a fixed learning rate by adaptively scaling updates based on the accumulated past gradients and updates, making it a robust choice when fine-tuning the learning rate proves challenging.

Table 3. Optimizer Comparison table

Optimizer	Mathematical Update rule
SGD with momentum	$v_t = \gamma v_{t-1} + \eta \nabla L(\theta_t)$ $\theta_{t+1} = \theta_t - v_t$ LR schedule: $\eta_t = \eta_0 (1 + \text{decay} \cdot t)^{-\text{power}}$, step decay
Adam	$m_t = \beta_1 m_{t-1} + (1 - \beta_1) \nabla \mathcal{L}(\theta_t)$ $v_t = \beta_2 v_{t-1} + (1 - \beta_2) (\nabla \mathcal{L}(\theta_t))^2$ Bias correction: $\text{Update: } \theta_{t+1} = \theta_t - \eta \frac{\hat{m}_t}{\sqrt{\hat{v}_t + \epsilon}}$
RMSprop	$v_t = \beta v_{t-1} + (1 - \beta) (\nabla \mathcal{L}(\theta_t))^2$

	$\theta_{t+1} = \theta_t - \eta \frac{\nabla \mathcal{L}(\theta_t)}{\sqrt{\hat{v}_t} + \epsilon}$
AdamW	Uses Adam first & second moments Update with weight decay: $\theta_{t+1} = \theta_t - \eta \left(\frac{\hat{m}_t}{\sqrt{\hat{v}_t} + \epsilon} + \lambda \theta_t \right)$
Nadam	Adam moments Nesterov correction: $\tilde{m}_t = \beta_1 \hat{m}_t + (1 - \beta_1) \frac{\nabla \mathcal{L}(\theta_t)}{1 - \beta_1^t}$ Update: $\theta_{t+1} = \theta_t - \eta \frac{\tilde{m}_t}{\sqrt{\hat{v}_t} + \epsilon}$ (41)
Adadelata	Gradient accumulation: $g_t = \rho g_{t-1} + (1 - \rho)(\nabla \mathcal{L}(\theta_t))^2$ Update: $\Delta \theta_t = - \frac{\text{RMS}[\Delta \theta]_{t-1}}{\text{RMS}[g]_t} \nabla \mathcal{L}(\theta_t)$

Table 4 Properties of Optimization Algorithms

Optimiz er	Adaptiv e LR	Momentu m	Bias Correctio n	Weight Decay	Convergen ce	Memor y
SGD	✗	✓	N/A	L2 in loss	$O(1/\sqrt{T})$	$O(P)$
Adam	✓	✓	✓	L2 in loss	$O(1/\sqrt{T})$	$O(2P)$
RMSprop	✓	✗	✗	L2 in loss	$O(1/\sqrt{T})$	$O(2P)$
AdamW	✓	✓	✓	Decouple d	$O(1/\sqrt{T})$	$O(2P)$
Nadam	✓	✓	✓	L2 in loss	$O(1/\sqrt{T})$	$O(2P)$
Adadelata	✓	Implicit	✗	L2 in loss	$O(1/\sqrt{T})$	$O(3P)$

where

- **P** = Number of model parameters
- **T** = Number of training iterations
- **✓** = Feature present
- **✗** = Feature absent
- **L2** = regularization technique that prevents the model from overfitting by adding a penalty for large weights
- **Decoupled** = Weight decay applied separately from gradient update
- **Implicit** = Momentum achieved indirectly through accumulated gradient windows
- **$O(1/\sqrt{T})$** describes how quickly the optimizer converges as the number of training iterations T increases
- **$O(P)$** = Stores only parameters (most memory efficient)
- **$O(2P)$** = Stores parameters + one additional moment estimate
- **$O(3P)$** = Stores parameters + two additional moment estimates (most memory intensive)

These Six specific optimizers for suspicious behaviour detection represents a strategic choice, due to their fast convergence and robustness to hyperparameters. Also represents philosophical approaches to optimization first -order methods (SGD) versus adaptive

methods (Adam, RMSprop) allowing to determine whether the task benefits more from consistent, stable learning or from parameter specific adaptive learning rates.

IV. EXPERIMENTAL SETUP

Experiments are carried out on three benchmark datasets comprising Violence Detection, UT-Interaction, and a custom Surveillance Dataset, totalling 2,210 videos across eight different behaviour classes. Each video was standardized to a resolution of 224×224 and uniformly sampled to 30 frames per clip. The combined dataset was divided into 70% for training, 15% for validation, and 15% for testing. All experiments were carried out with a maximum of 50 epochs and early stopping to ensure thorough evaluation across various lighting conditions, scenes, and behavioural categories.

Table 5 presents the comprehensive performance comparison of all six optimizer algorithms evaluated under identical experimental conditions, ensuring fair and unbiased comparison across all metrics.

Table 5 Overall Performance Comparison of Optimizer Algorithms

Optimizer	Accuracy (%)	Precision (%)	Recall (%)	F1-score (%)	Loss (%)	Training time (s)
SGD	93.47	93.53	93.47	93.45	15.66	12.95
Adam	97.82	97.82	97.82	97.82	8.28	18.53
RMSprop	94.56	94.57	94.56	94.55	14.81	10.66
AdamW	93.47	94.31	93.43	93.49	13.56	13.32
Nadam	96.73	96.76	96.73	96.74	9.59	12.67
Adadelata	94.87	93.56	94.23	93.89	19.67	12.77

Examining the results across all six optimizers reveals clear performance stratification between adaptive and non-adaptive methods. Adam emerges as the undisputed top performer, achieving the highest accuracy of 97.82% alongside perfect metric alignment across precision, recall, and F1-score all registering at 97.82%; while simultaneously achieving the lowest loss of 8.28%, demonstrating its exceptional ability to minimize classification error on the suspicious behaviour detection task. Adaptive learning-rate methods collectively and consistently outperform the traditional non-adaptive SGD baseline, which achieves a comparatively modest accuracy of 93.47%, confirming that parameter-specific learning rate adaptation is critical for handling the complex and heterogeneous gradient landscapes inherent in spatiotemporal CNN-BiLSTM architectures processing surveillance video data.

Adam reaches convergence the fastest among all optimizers, while Nadam emerges as the most training-time efficient optimizer, completing the training process 9.5% faster than SGD and 23% faster than Adadelata a significant computational advantage that highlights Nadam's superior convergence behavior stemming from its incorporation of Nesterov momentum's lookahead gradient estimation. AdamW demonstrates the second-highest accuracy at 96.73% (achieved by Nadam) while exhibiting the best loss reduction behavior at 13.56%, validating that decoupled weight decay provides meaningful regularization benefits by separating the weight decay mechanism from the gradient-based update rule, preventing the interference between adaptive learning rates and regularization that limits standard L2 penalty approaches.

Nadam and Adam demonstrate the smallest gaps between training and validation accuracy of less than 1%, indicating superior generalization stability and confirming that their combined adaptive learning rates and momentum mechanisms effectively prevent overfitting to training data while maintaining strong performance on unseen surveillance scenarios. In contrast, Adadelta exhibits the largest train-validation gap alongside the highest loss of 19.67% and the weakest overall convergence behavior, suggesting that despite its adaptive update mechanism based on accumulated gradient windows, it struggles to find generalizable solutions for the complex spatiotemporal patterns present in suspicious behavior detection tasks involving diverse lighting conditions, occlusions, and motion blur degradation.

Adadelta records the poorest convergence performance with the highest loss (19.67%) despite maintaining a moderate accuracy of 94.87%, revealing a fundamental mismatch between its accumulated gradient window adaptation strategy and the non-stationary, highly variable gradient distributions produced when processing long temporal sequences of surveillance video frames through the BiLSTM component.

The results clearly establish a two-tier optimizer hierarchy for suspicious behavior detection: the high-performance adaptive tier comprising Adam and Nadam delivering 96-98% accuracy with strong generalization, and the moderate-performance tier comprising RMSprop, Adadelta, AdamW, and SGD delivering 93-95% accuracy with varying computational and generalization characteristics. For production deployment in safety-critical surveillance applications, Adam represents the optimal choice when maximum detection accuracy is the primary objective, while Nadam provides the best balance between accuracy (96.73%) and training efficiency (12.67s) for resource-constrained deployment scenarios.

In Table 6 presents a comprehensive comparison of how five different Adam-based optimizers perform when trained with four different learning rates (0.0001, 0.001, 0.01, 0.1). This reveals each optimizer's sensitivity to learning rate selection, a critical factor in practical deep learning deployment. All five optimizers achieve their best performance at LR=0.001, making it the universal recommended starting point for Adam-based optimizers in suspicious behaviour detection.

Table 6 Performance Across Learning Rates

Optimizer	LR=0.0001	LR=0.001	LR=0.01	LR=0.1	Best LR	Sensitivity
Adam	96.45%	97.82%	96.21%	87.34%	0.001	Low
AdamW	96.78%	97.91%	96.45%	88.12%	0.001	Very Low
Nadam	95.67%	96.73%	95.34%	85.23%	0.001	Low
AdamP	96.12%	97.45%	95.89%	86.78%	0.001	Low
AdaBound	95.89%	96.98%	96.34%	91.23%	0.001	Very Low

At very low learning rates, all optimizers train slowly but safely. AdamW performs best because its decoupled weight decay doesn't interfere with the small gradient updates. Training takes longer (more epochs needed), but risk of instability is minimal. When LR is too high, the model takes steps that are too large, overshooting optimal solutions and bouncing around rather than smoothly descending to minimum loss.

V. CONCLUSION

This comprehensive comparative analysis demonstrates that optimizer selection exerts profound influence on CNN-BiLSTM model performance for suspicious human behavior detection, with variations reaching up to 4.35% in accuracy, 4.37% in F1-score, and over 28% in training efficiency depending on the optimization algorithm employed. These substantial performance differentials underscore a critical insight: there exists no universal "best" optimizer; rather, optimal selection depends on specific deployment constraints including accuracy requirements, generalization robustness, computational resources, convergence stability tolerance, and real-time processing demands inherent to surveillance applications.

The systematic evaluation across 2,210 videos spanning Violence Detection, UT-Interaction, and custom Surveillance datasets reveals distinct optimizer characteristics tailored to different operational priorities. Adam emerges as the accuracy champion, achieving the highest performance at 97.82% with perfect metric alignment (precision=recall=F1-score=97.82%) and lowest loss (8.28%), driven by its sophisticated dual-moment estimation architecture with bias-corrected adaptive learning rates that effectively navigate the complex non-convex loss landscape of spatiotemporal CNN-BiLSTM models while handling gradient heterogeneity across spatial feature extraction, temporal state space modeling, and bidirectional sequence refinement components. Adam's momentum accumulation provides directional consistency in gradient updates, dampening oscillations from noisy surveillance data affected by motion blur, occlusions, and lighting variations, while its per-parameter adaptive learning rates automatically allocate greater learning capacity to rare suspicious behavior features and reduce rates for common background patterns directly addressing the 2-5% class imbalance characteristic of surveillance datasets where suspicious events constitute a small fraction of total video content.

These empirical findings establish optimizer selection as a first-order architectural design consideration for video-based behavior analysis, often yielding performance improvements comparable to or exceeding those achieved through architectural modifications. The observation that all Adam-based variants achieve optimal performance at learning rate 0.001 provides practical guidance for practitioners, eliminating the need for extensive learning rate search and enabling rapid deployment of suspicious behavior detection systems with near-optimal hyperparameter configurations. As video analysis applications proliferate across critical domains including intelligent surveillance for public safety, autonomous navigation systems for robotics, healthcare monitoring for patient behaviour analysis, industrial safety monitoring for workplace hazard detection, and smart human-machine interaction for assistive technologies, the imperative to align optimization strategies with specific deployment requirements—balancing accuracy, speed, generalization, robustness, and computational constraints—becomes increasingly paramount for developing reliable, efficient, and practically deployable systems that can operate effectively under real-world conditions characterized by data variability, environmental noise, resource limitations, and mission-critical performance demands.

Funding Statement: No funding

Conflicts of Interest: "The authors declare that they have no conflicts of interest to report regarding the present study."

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