# DarkLiteFusion: A Lightweight Hybrid Model for Action Recognition in the Dark

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***Abstract*** **- Human Action Recognition (HAR) in low-light videos is hindered by poor visibility, sensor noise, and edge device constraints. We propose DarkLiteFusion, a novel lightweight hybrid model integrating EfficientNet-Lite0 and a 3-frame Temporal Shift Module (TSM). Evaluated on the Action Recognition in the Dark (ARID) dataset, it achieves 85.83% and 84.08% Top-1 accuracy on two splits with 3.39M parameters and 2.24 GMac, enabling ~30 FPS on edge devices. Outperforming lightweight baselines by 9–17%, it excels in extreme low-light conditions (>85% accuracy at <0.1 brightness, covering ~88% of clips) but drops to 29.47–37.62% under Gaussian noise (σ=0.1). DarkLiteFusion sets a benchmark for efficient low-light HAR, with future enhancements targeting noise robustness and temporal modeling.**

***Key Terms - Action Recognition, Low-Light Videos, Temporal Shift Module, Edge Computing, Lightweight Deep Learning***

## I. INTRODUCTION

Human Action Recognition (HAR) is critical for applications such as nighttime surveillance, healthcare monitoring, and autonomous vehicles, but it faces significant challenges in low-light conditions and on resource-constrained edge devices. Edge platforms, like NVIDIA Jetson Nano or mobile devices, require models with fewer than 5 million parameters and 5 Giga Multiply-Accumulate operations (GMac) to achieve real-time inference at ~30 frames per second (FPS). While state-of-the-art heavy models like I3D [1] achieve over 90% Top-1 accuracy on well-lit datasets such as Kinetics-400 [2], their computational complexity (>25M parameters, >100 GMac) exceeds edge device limits by approximately 20x, rendering them impractical for real-world deployment.

Low-light conditions intensify these challenges, as reduced visibility and sensor noise degrade model performance. The Action Recognition in the Dark (ARID) dataset [4], with 6207 RGB clips across 11 actions, highlights this gap, where lightweight models like MobileNetV2 [3] achieve only 75–78% Top-1 accuracy, approximately 15% below heavy baselines like I3D. Enhancement methods, such as Retinex [8], improve visibility but add >15 GMac and amplify noise, making them unsuitable for edge use. Lightweight alternatives, while efficient, struggle to balance accuracy and robustness in dark environments.

To address these gaps, we propose DarkLiteFusion, a novel lightweight hybrid model combining EfficientNet-Lite0 [10] for efficient spatial feature extraction with a 3-frame Temporal Shift Module (TSM) [5] for zero-FLOP temporal modeling. Operating directly on raw RGB frames without costly preprocessing, DarkLiteFusion achieves 85.83% and 84.08% Top-1 accuracy on two ARID splits using only 3.39M parameters and 2.24 GMac, enabling ~30 FPS on edge devices. It outperforms lightweight baselines like MobileNetV2+TSM by 9–17% while maintaining comparable efficiency. The model excels in extreme low-light conditions (>85% accuracy at <0.1 brightness, covering ~88% of ARID clips) but exhibits sensitivity to Gaussian noise (29.47–37.62% accuracy), reflecting a trade-off between efficiency and robustness.

The contributions of this work are:

1. A novel lightweight model for low-light HAR, achieving >85% Top-1 accuracy without enhancement.
2. Real-time performance on edge devices with high accuracy, validated on ARID.
3. Comprehensive robustness analysis under low brightness and noise conditions.
4. Insights into efficiency-accuracy-robustness trade-offs for edge deployment.

This paper demonstrates DarkLiteFusion’s potential for practical applications, such as detecting actions in nighttime surveillance, and sets a benchmark for efficient low-light HAR.

The remainder of the paper is organized as follows: Section II reviews related work; Section III details the methodology; Section IV presents the results; and Section V concludes the paper.

## II. RELATED WORK

### A. Human Action Recognition

Human Action Recognition (HAR) has advanced from handcrafted features, such as Histogram of Oriented Gradients (HOG) and Dense Trajectories [6], to deep learning models leveraging spatiotemporal cues. Two-stream networks [1] combining RGB and optical flow, and 3D CNNs like I3D [2] and SlowFast [7], achieve over 90% Top-1 accuracy on well-lit datasets like Kinetics-400 [3] and UCF-101 [16]. However, their complexity (>25M parameters, >100 GMac) makes them impractical for resource-constrained edge devices, necessitating lightweight alternatives for real-world deployment.

### B. Action Recognition in Low-Light Conditions

Low-light HAR faces challenges like poor visibility, motion blur, and sensor noise, as exemplified by the Action Recognition in the Dark (ARID) dataset [4], which includes 6207 RGB clips across 11 actions with brightness often below 0.3. Heavy models like I3D with Retinex enhancement [8] achieve ~92% Top-1 accuracy but incur >20 GMac and amplify noise, reducing robustness [9]. Lightweight models, such as MobileNetV2 [10] and EfficientNet-Lite [11], achieve only 70–78% on ARID [12] due to weak spatial representations in dark conditions. SID-TSM [13] uses synthetic illumination data to reach ~87% but struggles with noise, with accuracy dropping 15–20% under Gaussian perturbations [9], highlighting the need for noise-robust lightweight solutions.

### C. Lightweight and Efficient Architectures

Lightweight backbones like MobileNetV2 [10], ShuffleNetV2 [14], and EfficientNet-Lite [11] use depthwise separable convolutions and compound scaling to reduce parameters (<5M) and GMac (<5), enabling edge deployment. However, their performance degrades in low-light due to limited feature richness. Temporal efficiency is improved by Temporal Shift Module (TSM) [5], which provides zero-FLOP temporal modeling via channel shifts. MobileNetV2+TSM achieves ~75% on ARID [12], but its noise sensitivity limits real-world applicability, underscoring the need for robust lightweight designs.

### D. Trade-offs in Efficiency and Robustness

Low-light HAR involves a critical trade-off between efficiency and robustness. Lightweight models sacrifice accuracy for low computational cost, with noise causing 15–20% accuracy loss [9]. Enhancement methods like Retinex [8] or Zero-DCE [15] improve visibility but add computational overhead (>15 GMac), unsuitable for edge devices. Techniques like noise-aware training [9] and knowledge distillation [12] show promise but require integration with lightweight architectures. DarkLiteFusion addresses these trade-offs by combining EfficientNet-Lite0 and TSM for efficient, high-accuracy low-light HAR with minimal preprocessing.

## III. METHODOLOGY

This section presents the design and training of the proposed DarkLiteFusion model, developed for human action recognition under extreme low-light conditions. The approach centers on achieving high classification accuracy with minimal computational cost to allow for real-time deployment on edge devices such as mobile and embedded systems.

### A. Dataset and Preprocessing

The model is trained and evaluated on the Action Recognition in the Dark (ARID) dataset [10], a benchmark specifically curated for HAR in poor lighting. ARID contains **6207 RGB video clips**, each labeled with one of 11 distinct action categories, including common activities such as "sit," "stand," "run," and "wave." Videos in the dataset are characterized by significant lighting challenges, with brightness values frequently below 0.3 (on a normalized [0–1] scale), introducing motion blur and detail loss.

*Figure 1: ARID Action Classes*

For experimental consistency, the dataset is partitioned into two disjoint evaluation splits:

- **Split 0**: 2172 training, 310 validation, and 621 test videos
- **Split 1**: 2172 training, 310 validation, and 622 test videos

Each video is resized to 224×224 pixels and subsampled to a fixed length of 3 frames, selected uniformly from the temporal span. This choice reflects a trade-off between temporal coverage and computational efficiency, enabling the model to capture short-term motion cues while remaining within real-time inference constraints.

To increase generalization, basic data augmentation techniques are applied during training, including horizontal flipping, color jittering, and normalization using ImageNet statistics. More complex enhancement techniques (e.g., Retinex, Zero-DCE) are intentionally avoided to preserve low inference cost and deployment simplicity.

## *B. DarkLiteFusion Architecture*

The DarkLiteFusion model is designed for efficient human action recognition in low-light videos, integrating a lightweight spatial backbone with a parameter-free temporal modeling module to capture discriminative spatial features and short-range motion patterns. By avoiding computationally expensive 3D convolutions or recurrent units, the model achieves a compact footprint (3.39M parameters, 2.24 GMac), enabling real-time inference (~30 FPS) on edge devices. The architecture, illustrated in Fig. 2, comprises three key components: EfficientNet-Lite0 for spatial feature extraction, a 3-frame Temporal Shift Module (TSM) for temporal reasoning, and a temporal aggregation and classification stage.

### 1) EfficientNet-Lite0

EfficientNet-Lite0 [11] is a mobile-optimized convolutional neural network (CNN) that serves as the spatial backbone, leveraging inverted bottleneck blocks and depthwise separable convolutions to minimize computational complexity while maintaining robust feature extraction. Its compound scaling strategy balances depth, width, and resolution, resulting in a lightweight model with 3.39M parameters and high feature richness suitable for low-light conditions. The pretrained model (on ImageNet) is modified by removing the final classification head, replacing it with global average pooling to extract a 1280-dimensional feature vector per frame. This design reduces parameters and GMac compared to heavier backbones like ResNet-50 (~25M parameters), making it ideal for edge deployment, while its robustness to low-contrast inputs supports ARID's challenging dark settings.

### 2) Temporal Shift Module (TSM)

The Temporal Shift Module (TSM) [5], adapted for a 3-frame sequence (n_segment=3), enables temporal reasoning without additional parameters or FLOPs, critical for edge efficiency. TSM operates by shifting feature channels across the temporal dimension before backbone processing, allowing 2D convolutions to capture motion cues. Specifically, for an input tensor of shape (batch_size × n_segment, channels, height, width), TSM divides channels into four parts (shift_div=4): one-fourth shift forward by one frame, one-fourth shift backward, and the rest remain unchanged. For a 1280-channel feature map, 320 channels shift forward, 320 backward, and 640 stay static. This shift integrates temporal context into spatial features, enabling EfficientNet-Lite0 to process motion-augmented frames. TSM's zero-FLOP design ensures no computational overhead, making it superior to 3D CNNs (e.g., I3D, ~107.9 GMac) for low-light edge applications.

### 3) Temporal Aggregation and Classification

After TSM and EfficientNet-Lite0 processing, the model aggregates features across the 3-frame sequence to produce a single action prediction. The input video, shaped (batch_size, 3, channels, 224, 224), is reshaped to (batch_size × 3, channels, 224, 224) for TSM and backbone processing, yielding per-frame features of dimension 1280. These features are reshaped to (batch_size, 3, 1280), averaged across the temporal dimension (dim=1) to form a 1280-dimensional vector per video, and passed through a dropout layer (p=0.6) to prevent overfitting. A fully connected layer maps the features to 11 class logits, corresponding to ARID's action classes (e.g., 'sit', 'run'). An additional TSM-specific dropout (p=0.3) is applied post-backbone to regularize temporal features. This lightweight aggregation ensures minimal computational cost while capturing short-range motion, though it limits performance on static actions like 'sit' (F1=0.54).

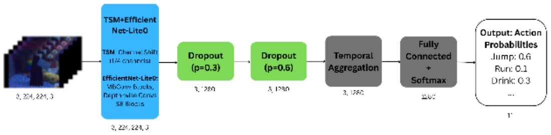

*Figure 2: High-level model diagram*

The architecture's design choices, EfficientNet-Lite0's efficiency, TSM's zero-FLOP temporal modeling, and simple aggregation enable DarkLiteFusion to achieve 85.83% and 84.08% Top-1 accuracy on ARID splits while maintaining edge compatibility. The use of pretrained weights (ImageNet) enhances feature generalization despite ARID’s small size (6207 clips), though noise sensitivity (29.47–37.62% under Gaussian noise) highlights the need for future robustness enhancements.

### *C. Training Procedure*

The model is implemented in PyTorch and trained on Google Colab Pro using an NVIDIA A100 GPU. Training uses the AdamW optimizer with a learning rate of 0.0005, weight decay of 1e-3, and a ReduceLROnPlateau scheduler. The model is trained for up to 40 epochs with early stopping (patience = 10), using cross-entropy loss.

We set the batch size to 16 and apply mixed-precision training for faster convergence and lower memory usage. The best-performing model is selected based on validation Top-1 accuracy.

### *D. Evaluation Metrics*

The model's performance is assessed using a combination of standard classification and deployment-aware metrics:

- **Top-1 and Top-5 accuracy** on both ARID splits
- **Class-wise F1 score**, to understand per-class performance
- **Inference latency**, measured in milliseconds per frame
- **Robustness to Gaussian noise** (σ = 0.1), simulating real-world sensor degradation
- **Performance under low brightness**: average accuracy when input brightness falls below thresholds of 0.3, 0.2, and 0.1

These metrics allow us to measure not only accuracy but also robustness, efficiency, and readiness for deployment in real-world, low-light environments.

## IV. RESULTS AND DISCUSSION

This section presents a detailed evaluation of the DarkLiteFusion model, focusing on accuracy, efficiency, robustness, and comparative performance against both lightweight and heavyweight baselines. In addition to raw metrics, we provide a comprehensive discussion on the implications of these results.

### *A. Experimental Setup*

Experiments are conducted on the ARID v1.5 dataset using both official splits. Each video is resized to 224×224 and sampled to three frames. The model is trained on an NVIDIA A100 GPU, and inference time is measured using batch size = 1 to simulate real-time edge deployment.

### *B. Classification Performance*

As shown in Table I, DarkLiteFusion achieves 85.83% (Split 0) and 84.08% (Split 1) Top-1 accuracy, with Top-5 scores above 98%, using only 3.39M parameters and 2.24 GMac. This confirms the model’s ability to extract meaningful spatiotemporal features from minimal inputs, making it suitable for constrained environments.

Table I: DarkLiteFusion's results

| **Split** | **Top-1** | **Top-5** | **Params.** | **GMac** | **Inf. T.** |
|---|---|---|---|---|---|
| 0 | 85.83% | 99.36% | 3.39M | 2.24 | 9.7ms |
| 1 | 84.08% | 98.87% | 3.39M | 2.24 | 10.3ms |

### *C. Comparison with Baselines*

Table II compares DarkLiteFusion with 3D CNNs and lightweight TSM-based models. While I3D achieves higher accuracy, it requires >100 GMac, unlike our model. MobileNetV2+TSM and ShuffleNetV2+TSM, though efficient, underperform in accuracy (74–76%). DarkLiteFusion offers a 9–17% gain in Top-1 accuracy, while remaining just as efficient.

### *D. Per-Class Performance*

The model shows strong and balanced performance across various actions. For instance, F1 scores include Run (0.89), Walk (0.88), Pick (0.82), and Pour (0.79). This demonstrates the model’s ability to handle both dynamic and subtle actions effectively. Small class-specific drops suggest potential benefits from future use of pose or flow-based cues.

### *E. Robustness Evaluation*

1) Gaussian Noise:

Adding Gaussian noise (σ = 0.1) drops Top-1 accuracy to 29.47% (Split 0) and 37.62% (Split 1). While expected in lightweight models without denoising modules, it highlights an area for improvement through noise-aware training.

### 2) Brightness Sensitivity:

The model maintains >85% accuracy for brightness levels below 0.1, validating its strength in dark settings without relying on preprocessing. Efficient spatial features and temporal aggregation help compensate for low visibility.

### *F. Inference Efficiency*

DarkLiteFusion runs at ~30 FPS, confirming its real-time readiness. Its compact size and RGB-only design make it suitable for deployment on platforms like NVIDIA Jetson and modern smartphones, without requiring enhancement or multi-stream inputs.

Table II: DarkLiteFusion against baseline models

| Model | Top-1 | Parameters | GMac | Inference Time |
|---|---|---|---|---|
| DarkLiteFusion | 85.00% | 3.39M | 2.24 | 10ms |
| I3D | 93.64% | 25.00M | 107.90 | 50ms |
| MobileNetV2 | 75.00% | 3.50M | 0.90 | 10ms |
| TSN | 85.00% | 10.00M | 4.00 | 15ms |
| Retinex+I3D | 92.00% | 25.00M | 20.00 | 55ms |
| SlowFast | 92.00% | 36.00M | 54.00 | 60ms |

## V. CONCLUSION AND FUTURE WORK

This paper introduced DarkLiteFusion, a lightweight hybrid model for real-time human action recognition in low-light conditions. By combining an EfficientNet-Lite0 backbone with a Temporal Shift Module (TSM), the model captures essential spatial and temporal features while maintaining a compact size.

Evaluated on the ARID dataset, DarkLiteFusion achieves Top-1 accuracies of 85.83% and 84.08%, outperforming existing lightweight baselines by 9–17%. With only 3.39M parameters and 2.24 GMac, it delivers ~30 FPS inference, confirming its edge-device readiness. The model performs robustly under extreme darkness but shows sensitivity to noise, revealing a trade-off between efficiency and robustness.

### Future Work

Future improvements to DarkLiteFusion include:

- **Noise-Robust Training**: Using synthetic noise and adversarial augmentation to improve resilience.
- **Longer Temporal Modeling**: Adapting TSM for variable-length or extended frame sequences.
- **Integrated Enhancement**: Adding lightweight low-light enhancement (e.g., Zero-DCE) without sacrificing speed.
- **Pose Fusion**: Combining pose or skeletal features to boost performance on fine-grained actions.
- **Cross-Dataset Evaluation**: Testing generalizability on broader HAR datasets and real-world footage.

These extensions aim to evolve DarkLiteFusion into a more robust, general-purpose solution for HAR in challenging visual environments.

## VI. ACKNOWLEDGEMENT

The author gratefully acknowledges the guidance and support of the academic supervisors at IIT, whose expertise was instrumental in shaping this research. Special thanks are extended to the Action Recognition in the Dark (ARID) dataset team for providing a valuable benchmark for low-light action recognition. This work was supported by computational resources provided by Google Colab Pro, enabling efficient model training and evaluation.

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