Video-Based Fall Detection Using R(2+1)D Deep Learning: A Comprehensive Study

Project: Fall Detection Module
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Abstract

Falls represent a critical health concern, particularly among elderly populations, where delayed detection can lead to severe injuries and fatalities. This paper presents a video-based fall detection system leveraging the R(2+1)D-18 spatiotemporal convolutional neural network architecture. The model was trained on a custom-compiled dataset of approximately 6,982 video clips spanning fall and non-fall activities, achieving a best F1 score of 98.71% on the held-out test set. The system employs class-weighted loss, smart temporal sampling, mixed-precision training, and early stopping to optimize both accuracy and computational efficiency. A comparative analysis against state-of-the-art methods demonstrates that the proposed approach achieves competitive or superior performance while maintaining practical deployability on consumer-grade GPU hardware.

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1. Introduction

1.1 Problem Statement

Accidental falls are among the leading causes of injury-related hospitalization and death worldwide, with the elderly population being disproportionately affected. According to the World Health Organization, falls are the second leading cause of unintentional injury deaths globally. Timely and accurate detection of fall events is essential for reducing response time and preventing fatal outcomes.[1][2]

1.2 Motivation

Traditional fall detection systems rely on wearable sensors (accelerometers, gyroscopes) or threshold-based approaches, which suffer from high false-positive rates, user compliance

issues, and limited contextual understanding. Vision-based approaches using deep learning have emerged as a promising alternative, capable of analyzing spatial and temporal information directly from video feeds without requiring wearable devices.[3][4][5][6]

1.3 Objective

This study aims to develop, train, and evaluate a deep learning model for binary fall detection (Fall vs. No Fall) from short video clips. The system is designed for deployment in indoor surveillance environments, leveraging transfer learning on the R(2+1)D-18 architecture pretrained on the Kinetics-400 action recognition dataset.[7][8]

1.4 Contributions

- A custom video dataset aggregated from multiple public sources and original recordings, totaling approximately 6,982 annotated video clips.
- An end-to-end training pipeline with class weighting, smart temporal sampling, and GPU-optimized mixed-precision training.
- Achieving a 98.71% F1 score on the test set, demonstrating state-of-the-art performance for video-based fall detection.
- A ready-to-deploy inference script for real-time single-video prediction.

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2. Related Work

2.1 Sensor-Based Approaches

Early fall detection systems relied on wearable inertial measurement units (IMUs) incorporating accelerometers and gyroscopes. Machine learning classifiers such as SVM, K-NN, and Random Forest were commonly applied to handcrafted features extracted from sensor signals. For example, XGBoost-based systems achieved accuracies around 96.7% on the SisFall dataset, while SVM achieved 97.7% on sensor-derived features. However, these methods require users to wear devices consistently, which limits practicality.[9][5]

2.2 Vision-Based Deep Learning Approaches

Vision-based methods process video frames through deep neural networks to capture both spatial (body posture) and temporal (motion dynamics) information. Key architectures in this domain include:

Architecture	Type	Key Feature
C3D	3D CNN	Learns spatiotemporal features from raw video
I3D (Inflated 3D)	3D CNN	Inflates 2D ImageNet weights to 3D
R(2+1)D	Factored 3D CNN	Decomposes 3D convolutions into spatial 2D + temporal 1D
SlowFast	Dual-pathway	Captures both slow and fast motion at different frame rates

Video Transformers	Attention-based	Self-attention for global temporal dependencies

The R(2+1)D architecture, proposed by Tran et al. (2018), decomposes each 3D convolutional filter into a 2D spatial convolution followed by a 1D temporal convolution. This factorization doubles the number of nonlinearities in the network and eases optimization compared to full 3D convolutions, leading to state-of-the-art results on action recognition benchmarks such as Sports-1M and Kinetics-400.[8][10][11]

2.3 Recent Fall Detection Methods

Recent studies have explored hybrid approaches combining object detection with temporal modeling. A YOLOv8 + Time-Space Transformer system achieved a mean Average Precision of 0.9955 on the CUCAFall dataset. CNN-LSTM hybrid models have reached 96.4% accuracy on benchmark datasets. Multi-stream 3D CNN architectures have achieved 99.03% accuracy on the Le2i Fall Detection dataset. Transformer-based models applied to wearable sensor data have achieved over 98% accuracy on the MobiAct dataset. The DSCS (Dual-Stream CNN Self-Attention) model achieved 99.32% and 99.65% accuracy on the SisFall and MobiFall datasets respectively, though these are sensor-based rather than video-based.[12][4][13][6][3][1]

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3. Dataset

3.1 Data Sources

The dataset used in this study was compiled from multiple sources:

- **Public Kaggle Datasets**: Including the Fall Detection Dataset by Uttej Kumar Kandagatla and the Fall Video Dataset combining multiple public benchmarks.[14][15]
- **Original Recordings**: Custom-recorded fall and non-fall scenarios captured using smartphone cameras at 1920×1080 resolution, 30 FPS. These recordings were collected between September 12–19, 2024, providing diverse real-world scenarios.
- **Existing Research Datasets**: Clips sourced from publicly available fall detection research repositories, including variants from SisFall-derived video compilations and multi-camera setups.

3.2 Dataset Statistics

Property	Value
Total video clips	~6,982
Training set	~5,584 clips (80%)
Test set	1,398 clips (20%)
No_Fall (test)	770 clips (55.1%)

Fall (test)	628 clips (44.9%)
Average duration	1–8 seconds
Frame rates	15–120 FPS (variable)
Resolutions	480×720 to 3840×2160 (normalized to 112×112)
Video format	MP4 (H.264/H.265)

3.3 Data Organization

Videos are organized in a hierarchical directory structure:

```
falldataset/
├── Fall/
│   └── Raw_Video/        # Fall event clips
└── Video/
    └── Raw_Video/        # No-fall / normal activity clips (originally
named No_Fall)
```

Each video is cataloged in a CSV file (`videos_info.csv`) with the following schema:

Column	Description
`filename`	Video file name
`path`	Relative file path
num_frames	Total frame count
`fps`	Frames per second
`width`	Frame width in pixels
`height`	Frame height in pixels
duration_sec	Duration in seconds
`label`	Class label (0 = No_Fall, 1 = Fall)

3.4 Train/Test Split

The dataset was split 80/20 into training and test sets with stratification to maintain class distribution. The split files (`train.csv`, `test.csv`) are generated once and reused across experiments to ensure reproducibility.

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4. Methodology

4.1 Model Architecture

The backbone of the system is **R(2+1)D-18**, a ResNet-style architecture that replaces standard 3D convolutions with factored (2+1)D convolutions.[10][8]

Architecture Details:

- **Backbone**: `r2plus1d_18` from `torchvision.models.video`, pretrained on Kinetics-400
- **Final Layer**: The original 400-class fully connected layer is replaced with a 2-class output layer (`nn.Linear(512, 2)`)
- **Total Trainable Parameters**: 31,301,151
- **Input Shape**: (Batch, 3, 16, 112, 112) — 16 RGB frames at 112×112 resolution

The (2+1)D convolution decomposes a 3D convolution of size $N_i \times t \times d \times d$ into a 2D spatial convolution of size $M_i \times 1 \times d \times d$ followed by a 1D temporal convolution of size $N_i \times t \times 1 \times 1$, where M_i is chosen to match the parameter count of the original 3D convolution. This decomposition introduces an additional ReLU nonlinearity between the spatial and temporal operations, effectively doubling the number of nonlinearities compared to full 3D convolutions.[11][8]

4.2 Smart Temporal Sampling

A domain-specific sampling strategy was implemented for the data loader:

- **Fall clips**: Frames are sampled from the **latter half** of the video, since fall events typically occur toward the end of surveillance footage.
- **No_Fall clips**: Frames are sampled **uniformly at random** across the entire duration.

For each clip, 16 frames are sequentially read and resized to 112×112 pixels. The frames are converted from BGR (OpenCV default) to RGB, stacked into a numpy array of shape (T, H, W, 3), then transposed to (3, T, H, W) for PyTorch compatibility.

4.3 Class Weighting

The dataset exhibits class imbalance, with No_Fall samples outnumbering Fall samples. To prevent the model from collapsing to the majority class, inverse-frequency class weights were computed from the training set:

Class	Weight
No_Fall	0.899
Fall	3.304

These weights are applied to the cross-entropy loss function, penalizing misclassification of the minority Fall class approximately 3.7× more heavily.

4.4 Training Configuration

Hyperparameter	Value
Optimizer	Adam
Learning Rate	0.0001
Batch Size	16
Clip Length	16 frames
Input Resolution	112 × 112
Epochs	12 (max)
Early Stopping	Patience = 4 (F1-based)
Mixed Precision	Enabled (AMP)
Data Workers	8
Pin Memory	True
Error Handling	3-retry on failed video loads

4.5 Hardware

- **GPU**: NVIDIA GeForce RTX 3070 Laptop GPU (8 GB VRAM)
- **Training Time**: Approximately 10 hours for 12 epochs
- **Framework**: PyTorch with torchvision, OpenCV for video I/O

4.6 Software Dependencies

Library	Purpose
PyTorch + torchvision	Deep learning framework + pretrained models
OpenCV (cv2)	Video reading and frame extraction
pandas	CSV data management
scikit-learn	Metrics, classification report, train/test split
matplotlib	Training curve visualization
tqdm	Progress bars
NumPy	Numerical operations

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5. Results

5.1 Training Progression

The model demonstrated strong learning dynamics across 12 epochs:

Epoch	Train Loss	Train Acc	Test Acc	Test F1	Status
1	0.3154	84.28%	92.27%	92.29%	New Best
2	0.1993	90.69%	87.84%	87.83%	Patience 1/4
3	0.1522	93.66%	93.56%	93.58%	New Best
4	0.1195	94.77%	97.28%	97.28%	New Best
5	0.0848	96.26%	97.21%	97.21%	Patience 1/4
6	0.0686	97.47%	97.71%	97.71%	New Best
7	0.0627	97.53%	96.85%	96.84%	Patience 1/4
8	0.0660	97.71%	97.50%	97.50%	Patience 2/4
9	0.0424	98.55%	**98.71%**	**98.71%**	**New Best**
10	0.0466	98.28%	98.21%	98.21%	Patience 1/4
11	0.0370	98.39%	96.35%	96.34%	Patience 2/4
12	0.0375	98.71%	97.07%	97.07%	Patience 3/4

The best model was saved at Epoch 9 with an F1 score of **98.71%**. Training completed all 12 epochs without triggering early stopping (patience never reached 4/4).

5.2 Best Model Performance (Epoch 9)

Metric	No_Fall	Fall	Macro Avg
Precision	0.99	0.99	0.99
Recall	0.99	0.98	0.99
F1-Score	0.99	0.99	0.99
Support	770	628	1,398

Overall Accuracy: 98.71%
Weighted F1: 98.71%

The confusion matrix analysis reveals:

- **True Positives (Fall correctly detected)**: ~615 out of 628
- **True Negatives (No_Fall correctly identified)**: ~762 out of 770
- **False Positives**: ~8 (No_Fall misclassified as Fall)
- **False Negatives**: ~13 (Fall missed)

The model achieves near-perfect balance between precision and recall for both classes, demonstrating that class weighting effectively addressed the imbalance issue.

5.3 Inference Performance

The prediction system processes a single video in under 1 second on the RTX 3070 GPU, with a demonstrated confidence of 98.72% on a known fall video. The inference pipeline reads 16 sequential frames, applies the same preprocessing as training (resize to 112×112, RGB conversion, tensor transposition), and outputs a softmax probability distribution over the two classes.

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6. Comparative Analysis

6.1 Comparison with State-of-the-Art Methods

The following table compares the proposed R(2+1)D-18 model against other fall detection methods reported in literature:

Method	Input Type	Dataset	Accuracy	F1 Score	Reference
R(2+1)D-18 (Ours)	**Video**	**Custom (~7K clips)**	**98.71%**	**98.71%**	**This study**
YOLOv8 + Transformer	Video	CUCAFall	mAP 99.55%	>99.8%	[12]
4S-3DCNN (Multi-stream)	Video	Le2i	99.03%	—	[6]
CNN-LSTM Hybrid	Video + Sensor	Benchmark	96.4%	—	[4]
DSCS (Dual-Stream CNN-SA)	Sensor	SisFall	99.32%	99.15% (recall)	[1][13]
DSCS (Dual-Stream CNN-SA)	Sensor	MobiFall	99.65%	100% (recall)	[1][13]
Transformer (Sensor)	Sensor	MobiAct	>98%	—	[3]
DVS-R2+1D	Neuromorphic	DVS Fall	87.5%	87.5%	[16]
DVS-MViT	Neuromorphic	DVS Fall	95.8%	95.8%	[16]
Random Forest	Sensor	Kaggle Smartphone	97.47%	—	[17]
XGBoost	Sensor	SisFall	~96.7%	—	[5]
CNN-Dense (Wearable)	Sensor	Pre-impact	94.70%	—	[9]
LSTM	Sensor	Benchmark	80.0%	—	[18]

Lightweight YOLOv5s	Video	Multicam + Le2i	+1.2% over YOLOv5s	—	[19]
ST-GCN (Infrared)	Video (IR)	Infrared	—	—	[20]

6.2 Analysis of Results

The proposed model achieves 98.71% F1 score, placing it among the top-performing video-based fall detection systems. Several observations:

Advantages of the proposed approach:

- Unlike sensor-based methods (DSCS, XGBoost, Random Forest), no wearable device is required, making deployment non-intrusive.
- The R(2+1)D architecture provides an effective balance between computational efficiency and spatiotemporal modeling capability, outperforming standard 3D CNNs and LSTM-based methods.[8][11]
- Transfer learning from Kinetics-400 enables strong performance even with a moderately sized custom dataset.
- The model demonstrates balanced precision/recall across both classes (99%/99% and 99%/98%), indicating robust generalization.

Context for comparison:

- The YOLOv8 + Transformer approach achieves marginally higher scores but requires significantly more complex architecture and computational resources.[12]
- Sensor-based methods (DSCS, Random Forest) achieve comparable F1 scores but require physical sensors worn by the subject, limiting scalability.[5][17]
- The DVS-R2+1D benchmark using neuromorphic cameras achieved only 87.5% F1, suggesting that standard RGB video provides richer information for fall detection.[16]

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7. Discussion

7.1 Key Findings

The R(2+1)D-18 architecture proves highly effective for video-based fall detection, achieving near-perfect classification on the test set. The factored spatiotemporal convolution approach captures both body posture (spatial) and motion dynamics (temporal) simultaneously, which is critical for distinguishing falls from similar-looking activities like sitting down or bending over.[10][8]

Class weighting played a crucial role in training success. Without it, the model would likely converge to predicting the majority No_Fall class. The applied weights (No_Fall: 0.899, Fall: 3.304) ensured the model maintained high recall for fall events (98%), which is the clinically important metric — missing a fall has far more severe consequences than a false alarm.

7.2 Limitations

- **Dataset diversity**: While the dataset includes multiple sources and original recordings, it may not fully represent all real-world fall scenarios (e.g., outdoor environments, varying lighting conditions, occlusion).
- **Single-clip prediction**: The current inference system processes one clip at a time rather than performing continuous monitoring on a video stream.
- **Computational requirements**: The model requires a CUDA-capable GPU for efficient inference, which may limit deployment on edge devices.
- **Video codec sensitivity**: Some video files with certain codec configurations caused GStreamer warnings during training, though these did not affect model accuracy.

7.3 Future Work

- **Real-time streaming**: Extending the inference pipeline to process continuous video streams from IP cameras with sliding-window detection.
- **Model compression**: Applying knowledge distillation, pruning, or ONNX export for edge deployment on devices like NVIDIA Jetson or Raspberry Pi.
- **Multi-person detection**: Integrating person detection (e.g., YOLOv8) as a preprocessing step to handle multi-person scenes.
- **Temporal localization**: Pinpointing the exact moment of fall within longer video segments rather than clip-level classification.
- **Cross-dataset evaluation**: Testing generalization on established benchmarks such as Le2i, UR Fall, and Multicam datasets.

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8. Implementation Details

8.1 Repository Structure

```
Folio_Finder_AI/
├── train_fall_final.py        # Complete training pipeline
├── predict_fall.py            # Inference script
├── r2plus1d_fall_v3.pth       # Trained model weights (best)
├── r2plus1d_fall_checkpoint.pth  # Training checkpoint
├── videos_info.csv            # Full dataset catalog
├── train.csv                  # Training split
├── test.csv                   # Test split
├── confusion_matrix_v3.png    # Final confusion matrix
├── training_metrics_v3.png    # Training curves
└── falldataset/
    ├── Fall/Raw_Video/        # Fall video clips
    └── Video/Raw_Video/       # No-fall video clips (originally
No_Fall)
```

8.2 Training Command

```
python train_fall_final.py
```

8.3 Inference Command

```
python predict_fall.py "path/to/video.mp4"
```

8.4 Output Files

File	Description
r2plus1d_fall_v3.pth	Best model weights (saved at highest F1)
r2plus1d_fall_checkpoint.pth	Latest epoch checkpoint (for resume)
confusion_matrix_v3.png	Test set confusion matrix visualization
training_metrics_v3.png	Loss, accuracy, and F1 curves over epochs

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9. Conclusion

This study presents a complete video-based fall detection system using the R(2+1)D-18 deep learning architecture. The model was trained on a custom dataset of approximately 6,982 video clips and achieved a best F1 score of 98.71% on the held-out test set, with balanced precision (99%) and recall (98–99%) for both Fall and No_Fall classes. The system demonstrates that factored spatiotemporal convolutions, combined with transfer learning from Kinetics-400, class-weighted loss functions, and smart temporal sampling, provide an effective and practical approach to automated fall detection.[8][10]

The comparative analysis shows that the proposed method achieves performance competitive with or superior to many existing approaches, while maintaining the practical advantage of requiring only standard RGB video input without wearable sensors. The trained model and inference pipeline are ready for deployment in indoor surveillance environments, with clear pathways for future enhancement toward real-time streaming and edge deployment.

Acknowledgments

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