DOI：10.20033/j.1003-7241.(2026)03-0001-08

基于图像识别的跌倒检测研究进展

宋晓晓，谢明璐

（海军青岛特勤疗养中心 医学工程科，山东 青岛 266071）

摘　要：采用文献综述与对比分析法，系统性综述基于图像识别的跌倒检测研究进展，剖析其实际应用中的核心挑战与未来需求，通过梳理技术现状为研究者提供参考。首先对跌倒行为进行分类；其次重点分析跌倒识别算法的鲁棒性，即应对复杂光照、遮挡、背景干扰的能力；最后，以多个公开数据集为基准，对比不同算法的关键性能指标，如准确率、召回率、精确率、F_1 评分等。分析结果表明，在众多模型中，时空图卷积网络的骨架动作识别模型（ST-GCN）性能较为突出，在多个数据库中 F_1 评分高达 100%。虽然以 ST-GCN 为代表的算法在受控环境下表现良好，但技术实用化仍面临三大挑战：1）算法鲁棒性与泛化性不足，难以适应复杂真实场景；2）隐私保护约束，视频监控在私密场所的应用受限；3）应用场景单一，与报警、医疗等系统的集成闭环尚未完善。未来需着力提升算法泛化能力、探索隐私保护计算新方法，并推动多模态融合的智能监测系统研发。

关键词：跌倒检测；图像识别；跌倒分类；时空图卷积网络（ST-GCN）；鲁棒性；跌倒数据库

中图分类号：TP391　　**文献标志码**：A　　**文章编号**：1003-7241(2026)03-0001-08

Research progress on fall detection based on image recognition

SONG Xiaoxiao, XIE Minglu

(Medical Engineering Department, Navy Qingdao Special Servicemen Recuperation Center, Qingdao 266071, Shandong, China)

Abstract: This study aims to systematically review the research progress in image recognition-based fall detection, analyze the core challenges and future requirements for its practical application, and provide a reference for researchers by synthesizing the current state of technology. A literature review and comparative analysis were adopted. Firstly, fall behaviors were classified. Secondly, the robustness of fall detection algorithms was analyzed, focusing on their ability to handle complex lighting, occlusion, and background interference. Finally, multiple public datasets were used as benchmarks to compare key performance metrics of different algorithms, such as accuracy, recall, precision, and F_1-score. The analysis indicates that, among various models, the skeleton-based action recognition model utilizing the spatial-temporal graph convolutional network (ST-GCN) demonstrates superior performance, achieving an F_1-score of up to 100% on several databases. Although algorithms represented by ST-GCN perform well in controlled environments, their practical deployment faces three major challenges: 1) insufficient algorithmic robustness and generalization, making adaptation to complex real-world scenarios difficult; 2) privacy protection constraints, limiting the application of video surveillance in private settings; 3) limited application scenarios, with a lack of integrated closed-loop systems incorporating alarm and healthcare services. Future work should focus on enhancing algorithmic generalization capabilities, exploring new privacy-preserving computing methods, and promoting the development of intelligent monitoring systems based on multimodal fusion.

Keywords: fall detection; image recognition; fall classification; spatial-temporal graph convolutional network(ST-GCN); robustness; fall dataset

人们在日常生活中面临着由生理机能衰退、复杂环境和意外行为等多重因素引发的跌倒风险。跌倒在医学上被定义为“身体因失去平衡控制而意外地非自主触地事件”[1]，其后果在老年群体中尤为严峻。第七次全国人口普查数据显示，我国 65 岁及以上人口已达 1.91 亿，占总人口 13.5%[2]，且该比例随老龄化加剧持续攀升。世界卫生组织统计表明，跌倒是全球 65 岁以上老年人伤害致死的第二大诱因，约 28%-35% 的老年人每年经历至少一次跌倒事件[3]。由此导致的髋部骨折、颅脑损伤等并发症，不仅降低患者生活质量，更造成年均超千亿元的直接医疗支出[4]。

如图 1 所示，当前跌倒检测技术主要有 3 种。一是基于可穿戴设备的生物力学监测，如惯性传感器[5]、智能手环[6]等，该技术虽具有高灵敏度却受限于用户依从性差、长期佩戴不适等问题；二是基于环境传感器的声波或压力感知系统[7-8]，该技术尽管能够保护用户的隐私但存在空间覆盖盲区，降低了跌倒的识别；三是基于图像识别的智

收稿日期：2025-02-27；**录用日期**：2025-03-19

作者简介：宋晓晓（1996—），女，硕士，技师，研究方向：医学信息处理。

通信作者：谢明璐（1984—），女，硕士，主管技师，研究方向：软件与理论。

引用本文：宋晓晓，谢明璐. 基于图像识别的跌倒检测研究进展[J]. 自动化技术与应用，2026,45(3):1-8.(SONG Xiaoxiao, XIE Minglu. Research progress on fall detection based on image recognition[J]. Techniques of Automation and Applications, 2026,45(3):1-8.)

能监控技术[9-10]，基于摄像头捕捉人体姿态变化，为判断跌倒提供丰富的数据依据，这种非接触式跌倒识别技术场景适应性更强，获取的人体姿态信息可用于跌倒事件的全流程分析。特别是随着深度神经网络在图像应用领域的发展，基于图像识别的跌倒检测系统具有多重优势。通过迁移学习，可利用现有安防监控基础设施实现低成本部署[11]；时空卷积网络与图卷积网络的融合应用，使算法对典型跌倒姿态的识别准确率提升至96%以上[12-13]；针对低光照环境开发的对抗生成网络数据增强技术，有效克服了传统光流法在夜间监护场景的性能衰减难题[14-15]。基于图像识别的跌倒检测技术能够实现监控覆盖下的多目标的跌倒检测，极大地降低了监测成本。

本文基于图像识别的跌倒检测技术研究进展，通过系统梳理该领域主要算法的核心文献，深入剖析三大关键问题：1）跌倒行为分类；2）对比分析不同跌倒图像数据库算法的 F_1 评分；3）跌倒识别算法在遮挡、低光照、背景干扰、多人场景中的鲁棒性差异，为实际应用场景算法选型提供参考。

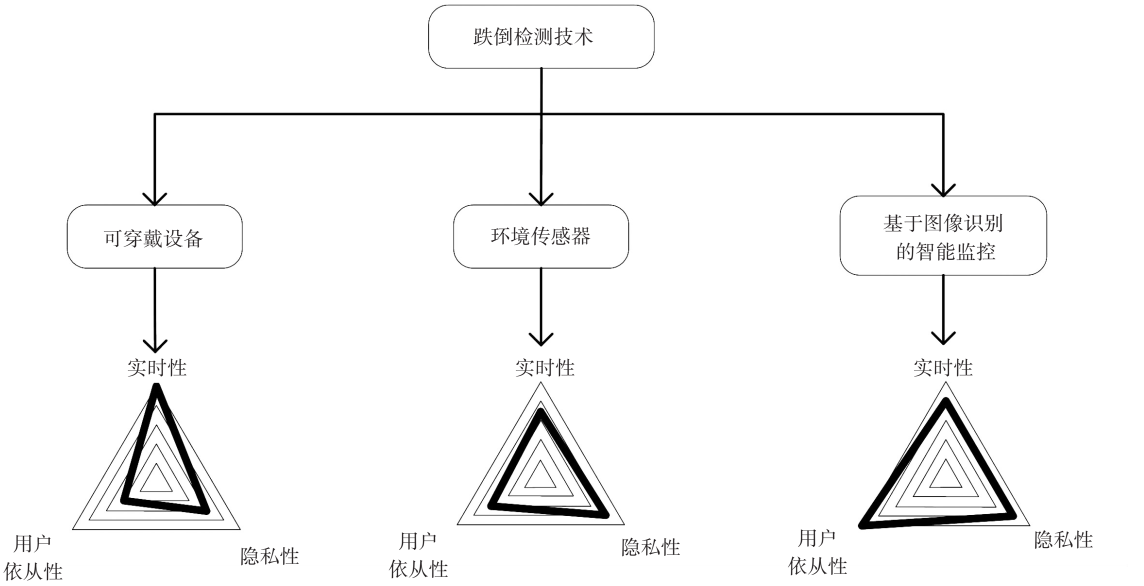

图 1 跌倒检测技术分类与对比示意图

Fig. 1 Classification and comparison diagram of fall detection technologies

1 跌倒行为分类

跌倒行为依据其生理病理机制、动力学特征及损伤等级，对检测算法提出了不同的要求。本文基于临床医学标准（Morse 跌倒评估量表）[16]和图像处理需求，如表 1 所示，从生理病理机制、运动学特征以及损伤分级 3 个维度构建了跌倒行为的分类体系，并分析了其与图像识别检测算法的关联性。

表 1 跌倒行为分类

Tab. 1 Classification of falling behavior

分类依据	跌倒类型	生物力学标识	算法关联参数
生理病理机制	自发性跌倒	股四头肌肌力显著下降[17]	肌电信号[18]
	外因素跌倒	足底滑移距离较大[19]	动态背景光流补偿[20]
运动学特征	前倾跌倒	膝关节屈曲角较大且躯干倾角持续较大[21]	时间和空间跌倒检测鲁棒性[22-25]
	后倾跌倒	髋关节触地速度较快[26]	坐姿-跌倒双流判别模型[27-28]
	侧倾跌倒	骨盆侧移距离较大且加速度较高[29]	基于图像分割的多目标分离算法[30]
损伤分级	轻度跌倒	表皮损伤面积小	运动模式滤波（排除宠物跌倒）[8]
	重度跌倒	髋部冲击力较大	倒地姿态持续监测[31]

1.1 基于生理病理机制的跌倒分类

跌倒行为根据生理病理机制的不同，可以分为自发性跌倒和外因性跌倒。自发性跌倒主要由年龄相关衰退、神经性疾病和药源性失衡引起，如老年人由于肌肉衰减综合征，股四头肌肌力显著下降，增加了坐立转换时后倾跌倒的风险[17]，有研究提出应用肌电图提取股四头肌肌力显著下降特征识别此类跌倒[18]。帕金森病患者的步态冻结导致垂直加速度突变引起跌倒[32]，而糖尿病周围神经病变则会升高足底触觉阈值，延迟滑移检测引起跌倒[33]。此外，药物如苯二氮䓬类也可能导致姿势调节反应时间延长，增加跌倒风险[34]。外因性跌倒则通常由外部环境因素导致的跌倒，例如地面湿滑、障碍物、光线不足等[19]，

通过动态背景光流补偿算法实现外因性跌倒的识别[20]。

1.2 基于运动学特征的姿态分类

跌倒行为的运动学特征包括前倾跌倒、后倾跌倒和侧倾跌倒。前倾跌倒的特点是膝关节屈曲角较大且躯干倾角持续较大[21],这需要算法具备遮挡鲁棒的时空注意力网络来准确检测[22-25]。后倾跌倒则涉及髋关节触地速度较快[26],需要基于坐姿-跌倒双流判别模型来区分跌倒与正常坐姿[27-28]。侧倾跌倒的特点是骨盆侧移距离较大且加速度较高,需要基于图像分割的多目标分离算法来处理多人场景下的目标粘连问题[29-30]。

1.3 基于损伤严重度的医学分级

跌倒行为的损伤严重度可以根据《国际疾病分类》第十一版(ICD-11)标准分为轻度和重度[35]。轻度跌倒通常仅涉及表皮损伤,而重度跌倒则可能导致骨折等严重损伤。对于轻度跌倒,算法需要排除宠物跳跃、摔倒等类似于人类的跌倒误报,提高特异性[8];对于重度跌倒,算法需要区分倒地静止与睡眠姿态,提高准确率[31]。

上述多维度分类体系揭示了跌倒行为在生理诱因、运动学表征与损伤后果间的复杂耦合关系,对图像识别算法的优化具有重要的指导价值。

2 图像识别在跌倒检测中的应用

2.1 图像识别跌倒检测技术概述

2.1.1 传统图像识别跌倒

在跌倒检测的早期阶段,传统图像识别方法主要依赖于人工运动特征提取,常用的方法包括基于光流场的运动估计、背景差分法、人体关节关键点检测与姿态分析,以及基于轮廓特征与形态学分析的目标表征方法。光流法基于图像亮度和梯度,能够有效捕捉突发运动以此识别跌倒,其在实时环境下检测率达到92.52%[36]。该方法实时性强,但对于复杂场景会干扰光流的计算。背景差分基于高斯混合模分离运动目标,在静态场景下识别率可达97.3%[37],但该方法对光照变化敏感,且需要固定摄像头位置,应用场景存在局限性。基于图像分析人体关键点的姿态判断是否跌倒,通过提取髋关节中心的下降速度、人体中心线与地面的角度以及人体的宽度与身体外部矩形比例等人体的骨骼信息,跌倒识别率达到97%[28]。此方法具有较高的识别精度,场景适应性强,但对图像的质量要求高,检测速度受限。基于图像的轮廓和形状也可以检测跌倒,某研究集中于识别坐下并站在椅子上时发生的跌倒,其识别准确率为95.96%[10]。该方法实时性好,但对于多人图像,容易出现轮廓重叠或混淆,影响检测准确性。这些方法的局限性在于依赖人工阈值设定,泛化性较差。

2.1.2 基于机器学习的跌倒识别

随着机器学习和深度学习的兴起,跌倒检测技术迎来了显著突破。在机器学习中,跌倒检测主要依赖于人工特征提取和传统分类器。有研究对卷积神经网络(convolutional neural networks,CNN)、支持向量机(support vector machine,SVM)、*K*近邻和长期记忆神经网络(long short-term memory,LSTM)在3种步态模式分类中检测跌倒,发现SVM在步态模式分类中的精度最高,达到94.9%[38]。还有研究应用随机森林从图像中的非骨架部分识别跌倒,对动态数据的识别率达到了96%[39]。此外,有研究提出了基于联邦学习和极端学习机器的跌倒检测方法,对于老年人的跌倒识别率超过了96%[40]。这些研究展示了机器学习方法在跌倒检测中的应用潜力,但其性能往往受限于人工提取特征的能力,在实际应用中面临一定挑战。

深度学习方法能够自动提取特征并进行分类,显著提升了跌倒检测的性能。有研究提出一种基于CNN的跌倒检测方法,通过从两个连续的RGB图像中提取光流的时间来提取的时间特征进行检测,该方法的准确性达到88.55%[41]。有研究结合光流和人类姿势同时提取运动和外观特征检测跌倒,在公开数据库上取得了较高的准确率[42]。有研究提出了一种基于3DCNN的跌倒检测方法,该算法基于多级图像融合以突出运动差异,达到了99.03%的准确性[43]。此外,有研究结合了注意力机制(attention mechanism)的深度学习模型和CNN的优点,提出了一种多尺度特征融合的跌倒检测模型,显著提升了复杂场景下的检测性能[44-45]。这些研究表明,深度学习方法在跌倒检测任务中具有显著优势,尤其是在特征提取和复杂场景处理方面。

2.2 图像跌倒检测算法对比

2.2.1 跌倒图像数据库

如表2所示,基于图像和视频的跌倒数据库在样本规模、数据多样性、场景复杂性上差异显著。样本量方面,CAUCAFall Dataset(20002样本)和NTU RGB+D Fall Detection Dataset(2 160样本)数据量大,适合深度学习模型训练。数据模态方面,NTU RGB+D Fall Detection Dataset同步提供RGB、深度、红外、骨骼关节点4类数据,适用于多模态研究;UP - Fall Dataset整合视觉与传感器数据的跨模态关联特性。场景复杂性方面,TST Fall Detection Dataset v2和Fall Event Dataset模拟医院、家庭多人交互场景,涵盖多视角跌倒方向与遮挡干扰,提升了数据的环境泛化性。Fall Event Dataset还包含易混淆动作,利于提升分类器抗干扰能力。而SDU Fall Dataset和Le2i Dataset局限于实验室单人场景,数据多样性依赖姿态估计和时间同步传感器的辅助信息。

当前数据库发展呈两个方向:Synthetic Fall Dataset构建复杂室内外场景,结合多摄像头与光照变化参数提升虚拟数据真实性;NTU RGB+D Fall Detection Dataset和Multiple Cameras Fall Dataset通过跨视角采集与多设备同步,为算法在视角迁移和传感器失效场景下的鲁棒性评估提供基础。但现有数据库普遍存在现实场景覆盖率不足问题,尤其在动态遮挡、极端光照等边缘条件下样本稀缺,制约跌倒检测算法实际应用。

表 2　基于图像和视频的跌倒数据库

Tab. 2　Fall database based on images and videos

数据库	样本量	跌倒事件数	采集背景	其他
UR-Fall Dataset[46]	70	30	实验室模拟日常活动,单人场景	光照变化、提供时间同步的加速度计数据
SDU Fall Dataset[47]	540	90	实验室模拟日常活动	提供人体姿态估计的3D骨骼坐标
UP-Fall Dataset[48]	561	255	实验室模拟日常活动	提供RGB相机、深度相机和传感器数据
Le2i Fall Dataset[49]	191	143	实验室模拟日常活动	提供视频的时间戳和标签
Multiple Cameras Fall Dataset[50]	192	96	实验室模拟日常活动	背景干扰、多摄像头
Synthetic Fall Dataset[51]	848	424	模拟室内外环境(超市、街道、楼梯)	多摄像头,光照变化、遮挡场景、摄像头角度
CAUCA Fall Dataset[52]	20 002	6 421	模拟摔倒	遮挡场景、光照变化
TST Fall Detection Dataset v2[53]	264	132	模拟医院/家庭环境,多人交互场景	不同跌倒方向(前倾、侧倾、后倾),遮挡场景
NTU RGB+D Fall Detection Dataset[54]	2 160	560	实验室模拟家庭/医院环境	1)提供RGB、深度、红外和骨骼关节点4类数据。2)包含跨视角(水平/俯视)和跨主体泛化测试集
Fall Free Dataset[55]	391	208	实验室模拟日常活动	光照变化
Fall Event Dataset[24]	220	145	模拟大厅、广场等人多的场所	1)多摄像头。包含前倾跌倒、侧倾跌倒、后倾跌倒;包含摔倒事件:弯腰、下蹲和趔趄。2)拍摄视野、距离、光照、背景变化,遮挡场景

2.2.2　不同数据库 F_1 评分对比

为了能够精准量化算法在复杂场景下的鲁棒性差异,本文分析了主要干扰源对算法性能的影响,其影响因素主要包括目标遮挡、低光照、背景干扰、多人场景等。本研究采用以下评估指标对算法性能进行评估。

准确率(Accuracy)是指成功预测的结果占总样本的百分比。

$$\mathrm{Accuracy}=\frac{\mathrm{TP}+\mathrm{TN}}{\mathrm{TP}+\mathrm{TN}+\mathrm{FP}+\mathrm{FN}} \tag{1}$$

召回率(Recall)表明跌倒被正确检测到的结果百分比。

$$\mathrm{Recall}=\frac{\mathrm{TP}}{\mathrm{TP}+\mathrm{FN}} \tag{2}$$

精确率(Precision)是指跌倒和非跌倒均被正确检测到的结果百分比。

$$\mathrm{Precision}=\frac{\mathrm{TP}}{\mathrm{TP}+\mathrm{FP}} \tag{3}$$

式中,TP指正确检测到跌倒的数量,TN指正确检测到非跌倒的数量,FP指错误检测到跌倒的数量,FN指错误检测到非跌倒的数量。

F_1 评分(F_1-Score)是机器学习中衡量分类模型综合性能的核心指标,其为精确率与召回率的调和平均数,计算公式为

$$F_1\text{-Score}=2\times\frac{\mathrm{Precision}\times\mathrm{Recall}}{\mathrm{Precision}+\mathrm{Recall}} \tag{4}$$

过度追求精确率可能导致漏检风险,而盲目提升召回率则易引发误警。F_1-Score通过调和二者,提供了一种鲁棒的综合评价标准,评估算法在复杂多源数据库下的泛化能力。

表3是基于数据库差异的算法 F_1 评分对比分析,通过对多组算法与数据库组合的深入研究,发现结合图卷积网络和时间卷积网络的骨架动作识别的模型ST-GCN(spatial temporal graph convolutional networks)在跌倒检测中表现出色,在多个数据库中 F_1-Score高达100%,但在数据复杂或样本分布差异大的UP-Fall Dataset中 F_1-Score降至93%。多模态数据融合可提升模型鲁棒性,在UR-Fall Dataset中,结合图像与加速度计数据的算法 F_1 达97.98%,高于纯图像方法。此外,数据库的特定挑战,如复杂背景、低分辨率图像等,会显著影响算法 F_1-Score。

在FallFree数据库中,ST-GCN和时间注意力组合算法模型的 F_1-Score达100%,高于普通ST-GCN;而在TST Fall Detection v2中,ST-GCN算法更优。IMEFD-ODCNN和SSOA-VAE组合模型通过特征增强与异常检测提升性能,在多个数据库中 F_1 超99%;而Transformer在有限数据下效率不如图卷积。数据集标注与样本平衡影响性能评估:当数据存在类别不平衡时,准确率可能虚高,如在Le2i Fall Dataset中,sigma-lognormal和SVM的准确率高于 F_1-Score。跨数据库泛化能力依赖数据融合,多源数据融合可增强模型适应性,UR-Fall、SDU、IMVIA等联合数据训练的时序卷积自编码器 F_1-Score达98%;而单一数据库训练的算法泛化能力弱,如ROI-threshold在SDU中 F_1-Score仅66.67%。

表3　基于数据库差异的算法 F_1 评分对比

Tab. 3　Comparison of F_1-scores for algorithms based on database differences

数据库	算法	Precision/%	Recall/%	Accuracy/%	F_1-Score	干扰因素
UR-Fall Dataset	U-Net[56]	—	100	—	—	光照
UR-Fall Dataset	V2V-PoseNet+SVM[57]	—	93	96.55	—	光照
UR-Fall Dataset	ST-GCN[58]	100	100	100	1	光照
UR-Fall Dataset	IMEFD-ODCNN+SSOA-VAE[59]	99.72	99.55	99.57	0.9938	光照
UR-Fall Dataset	WOADTL-AFD[60]	—	99.58	99.36	0.9912	光照
UR-Fall Dataset	GSTCAN[12]	99.86	—	99.74	0.9855	光照
UR-Fall Dataset	(CNN2D + CNN1D) (Images)+CNN1D (Accelerometer)[61]	99.4	96.6	99.56	0.9798	光照
UR-Fall Dataset	Yolo-OpenPose[62]	97.33	96.67	97.33	0.9778	光照
UR-Fall Dataset	C4.5[63]	—	96.22	97.36	0.976	光照
UR-Fall Dataset	Sigma-Lognormal +SVM[64]	95	97	99.6	0.9599	光照
UR-Fall Dataset	Transformer[44]	—	—	95.45	0.9476	光照
UR-Fall Dataset	YOLOv3+CNN+The Attention Guides LSTM[24]	94.8	91.4	—	0.9307	光照
UR-Fall Dataset	ROI-threshold[47]	100	81	90	0.895	光照
TST Fall Detection Dataset v2	Skeletal Joints+SVM[65]	—	—	92.2	—	遮挡
TST Fall Detection Dataset v2	ST-GCN[66]	100	100	100	1	遮挡
TST Fall Detection Dataset v2	YOLOv4 + Temporal Information Processing[67]	99.24	98.48	98.86	0.9886	遮挡
TST Fall Detection Dataset v2	ST-GCN+ Temporal Attention[68]	—	85	89.58	0.875	遮挡
UP-Fall Dataset	CNN2D[61]	99.9	100	99.99	0.9995	—
UP-Fall Dataset	2D CNN[69]	96.91	83.08	95.64	0.9743	—
UP-Fall Dataset	ST-GCN[58]	99	92	98.62	0.93	—
UP-Fall Dataset	Transformer[44]	—	—	99.03	0.9235	—
Multiple Cameras Fall Dataset	U-Net[56]	—	100	—	—	背景干扰
Multiple Cameras Fall Dataset	IMEFD-ODCNN+SSOA-VAE[59]	99.68	99.85	99.76	0.9965	背景干扰
Multiple Cameras Fall Dataset	WOADTL-AFD[60]	—	99.48	99.48	0.9948	背景干扰
NTU RGB+D Fall Detection Dataset	ST-GCN[66]	—	—	92.91	—	—
NTU RGB+D Fall Detection Dataset	3D Pose+Dilated Convolution[54]	97.47	94.25	99.83	0.9583	—
FallFree Dataset	ST-GCN+ Temporal Attention[68]	100	100	100	1	光照
FallFree Dataset	ST-GCN[66]	—	97.5	97.33	0.975	光照
Le2i Fall Dataset	Sigma-Lognormal +SVM[64]	97	97.2	98	0.971	—
Le2i Fall Dataset	Yolo-OpenPose[62]	97.65	97.73	96.91	0.9708	—
Le2i Fall Dataset	SSHFD-SH + FallNet2d3d[70]	90.08	89.92	—	0.8999	遮挡
Synthetic Dataset	Mask R-CNN[51]	—	—	—	0.976	光照、遮挡
Fall Event Dataset	YOLOv3+CNN+The Attention Guides LSTM[24]	89.8	83.5	—	0.8654	光照、遮挡、背景干扰、多人场景
SDU Fall Dataset	ROI-Threshold[47]	100	50	83.3	0.6667	—
UR-Fall Dataset+a portion of the Le2i Fall Dataset	Background Subtraction-Based Detector+BlazePose[71]	89.73	89.66	89.99	0.9002	光照
UR-Fall Dataset+SDU Fall Dataset+IMVIA Dataset +Thermal Dataset + Toyota SmartHome	Temporal Convolutional Hourglass Autoencoder[72]	—	96	98	—	光照

注：表示该单元格在文献中无数值。

3 挑战与讨论

本文从技术瓶颈、伦理约束和应用场景3个维度，深入探讨了跌倒检测领域面临的主要挑战。

3.1 鲁棒性与泛化性技术瓶颈

在技术层面，算法的鲁棒性与泛化性问题是核心难题。例如，复杂环境中的遮挡问题、动态背景干扰和低光照条件，均显著影响了算法的准确率。研究显示，当目标人体被遮挡时，基于骨架关键点的算法性能下降导致识别失败[73-74]；此外，低光照下模型性能的衰退同样不容忽视[75-76]。同时，实验室与现实场景之间的差距以及跨数据库的泛化能力不足，也限制了技术的实际应用效果[77-78]。总结而言，技术瓶颈问题要求寻找更具鲁棒性的算法，并提高其在不同场景下的泛化能力。

3.2 伦理与隐私争议

监控合规性的要求与紧急情况下的实际需求之间存在冲突，而数据偏见风险则可能导致某些群体的检测敏感度下降。例如，《通用数据保护条例》要求对监控数据进行匿名化处理，但这样的处理方式可能会增加漏检率，同时也存在法律方面的风险[79]。这些问题需要平衡技术的有效性与伦理的合规性，确保技术的可持续发展。

3.3 应用场景局限性

当前算法在医疗方面的应用仍有不足，且缺乏连续风险评估机制，无法预测跌倒。同时，多模态融合系统在理论上性能优越，但在实践中由于设备同步误差等技术问题，其性能反而可能下降[80-81]。综上所述，跌倒检测技术的应用场景局限性要求开发更为精准和可靠的系统，以满足实际应用需求。

4 结论

通过本文的分析，发现ST-GCN在跌倒检测中性能最好，但遮挡鲁棒性仍是关键挑战。其次，像智能地板[82]、智能手环[6]等设备的使用虽然减少了检测延迟，但采集到的数据质量对检测结果产生较大影响；同时隐私保护措施虽降低了隐私泄露风险，但也影响了检测精度。算法创新和技术突破仍是精确检测跌倒的关键。无监督域适应[83]、因果推理模型[84]的探索以及联邦学习[85]架构和可解释性增强技术[86]的发展，将极大地提高跌倒检测的精确率。同时，临床转化的重点应关注跌倒的预测和老龄化的适应性，以满足不同护理等级的需求。整体而言，未来的研究需要在保证技术性能的同时兼顾伦理合规性、实际应用场景的适应性以及临床转化的实际价值。

参考文献

[1] WANG S, LIU X, PAI Y C. Limb collapse or instability? Assessment on cause of falls[J]. Annals of Biomedical Engineering, 2019(47): 767-777.

[2] 中华人民共和国国家统计局. 2020年第七次全国人口普查主要数据公报(第5号)[DB/OL]. (2021-05-11). https://www.stats.gov.cn/sj/tjgb/rkpcgb/qgrkpcgb/202302/t20230206_1902005.html

[3] SHARIF S I, AL-HARBI A B, AL-SHIHABI A M, et al. Falls in the elderly: assessment of prevalence and risk factors[J]. Pharmacy Practice (Granada), 2018, 16(3):1206.

[4] DENG R, LI B, QIN M, et al. The characteristics and risk factors of fatal falls among adults aged 60 and above in Southwest China[J]. Scientific reports, 2024, 14(1):7020.

[5] ZHENG L, ZHAO J, DONG F, et al. Fall detection algorithm based on inertial sensor and hierarchical decision[J]. Sensors, 2022, 23(1):107.

[6] QU J, QIAO N, SHI H, et al. Convolutional neural network for human behavior recognition based on smart bracelet[J]. Journal of Intelligent & Fuzzy Systems, 2020, 38(5):5615-5626.

[7] CHEN D, WONG A B, WU K. Fall detection based on fusion of passive and active acoustic sensing[J]. IEEE Internet of Things Journal, 2023, 11(7): 11566-11578.

[8] SINGH A, REHMAN S U, YONGCHAREON S, et al. Sensor technologies for fall detection systems: a review[J]. IEEE Sensors Journal, 2020, 20(13):6889-6919.

[9] YAO C B, LU C T. Dynamic tracking and real-time fall detection based on intelligent image analysis with convolutional neural network[J]. Sensors, 2024, 24(23):7448.

[10] LU K L, CHU E T H. An image-based fall detection system for the elderly[J]. Applied Sciences, 2018, 8(10):1995.

[11] AHMED S, IRFAN S, KIRAN N, et al. Remote health monitoring systems for elderly people: a survey[J]. Sensors, 2023, 23(16):7095.

[12] EGAWA R, MIAH A S M, HIROOKA K, et al. Dynamic fall detection using graph-based spatial temporal convolution and attention network[J]. Electronics, 2023, 12(15):3234.

[13] YANG J, HE Y, ZHU J, et al. Fall detection method for infrared videos based on spatial-temporal graph convolutional network[J]. Sensors, 2024, 24(14):4647.

[14] TANG G, NI J, CHEN Y, et al. An improved CycleGAN-based model for low-light image enhancement[J]. IEEE Sensors Journal, 2023, 24(14):21879-21892.

[15] CHO S W, BAEK N R, KOO J H, et al. Semantic segmentation with low light images by modified CycleGAN-based image enhancement[J]. IEEE Access, 2020(8):93561-93585.

[16] SCHWENDIMANN R, DE GEEST S, MILISEN K. Evaluation of the Morse Fall Scale in hospitalised patients[J]. Age and Ageing, 2006, 35(3):311-313.

[17] GRANACHER U, ZAHNER L, GOLLHOFER A. Strength, power, and postural control in seniors: considerations for functional adaptations and for fall prevention[J]. European Journal of Sport Science, 2008, 8(6):325-340.

[18] DA SILVA D A, BRANCO N F L C, DE ANDRADE MESQUITA L S, et al. Electromyography and dynamometry in the prediction of risk of falls in the elderly using machine learning tools[J]. Biomedical Signal Processing and Control, 2024(88):105635.

[19] YUNUSOVA V. Reducing the risk of falls in elderly patients and the prevention of falls in an in-patient and out-patient setting[D]. Ternopil: Horbachevsky Ternopil National Medical University, 2022.

[20] NOUREDANESH M. An intelligent ambulatory fall risk assessment method based on the detection of compensatory balance reactions and environmental factors[D]. Waterloo, Ontario, Canada: University of Waterloo, 2022.

[21] MATSUMOTO H, OKUNO M, NAKAMURA T, et al. Fall incidence and risk factors in patients after total knee arthroplasty[J]. Archives of Orthopaedic and Trauma Surgery, 2012(132):555-563.

[22] SHIN J, MIAH A S M, EGAWA R, et al. Fall recognition using a three stream spatio temporal GCN model with adaptive feature aggregation[J]. Scientific Reports, 2025, 15(1):10635.

[23] KONG Y, HUANG J, HUANG S, et al. Learning spatiotemporal

representations for human fall detection in surveillance video[J]. Journal of Visual Communication and Image Representation, 2019 (59): 215-230.

[24] FENG Q, GAO C, WANG L, et al. Spatio-temporal fall event detection in complex scenes using attention guided LSTM[J]. Pattern Recognition Letters, 2020(130):242-249.

[25] YU X, WANG C, WU W, et al. A Real-time skeleton-based fall detection algorithm based on temporal convolutional networks and transformer encoder[J]. Pervasive and Mobile Computing, 2025(107):102016.

[26] PAVOL M J, OWINGS T M, FOLEY K T, et al. Mechanisms leading to a fall from an induced trip in healthy older adults [J]. The Journals of Gerontology Series A: Biological Sciences and Medical Sciences, 2001, 56(7):M428-M437.

[27] PATEL M, PAVIC A, GOODWIN V A. Wearable inertial sensors to measure gait and posture characteristic differences in older adult fallers and non-fallers: a scoping review[J]. Gait & Posture, 2020(76): 110-121.

[28] CHEN W, JIANG Z, GUO H, et al. Fall detection based on key points of human-skeleton using openpose[J]. Symmetry, 2020, 12 (5):744.

[29] MOON Y, SOSNOFF J J. Safe landing strategies during a fall: systematic review and meta-analysis[J]. Archives of physical medicine and rehabilitation, 2017, 98(4):783-794.

[30] YAO C, HU J, MIN W, et al. A novel real-time fall detection method based on head segmentation and convolutional neural network [J]. Journal of Real-Time Image Processing, 2020(17):1939-1949.

[31] HSIAO R S, CHEN T X, BITEW M A, et al. Sleeping posture recognition using fuzzy *C*-means algorithm[J]. Biomedical Engineering Online, 2018(17):1-19.

[32] BLOEM B R, HAUSDORFF J M, VISSER J E, et al. Falls and freezing of gait in Parkinson's disease: a review of two interconnected, episodic phenomena[J]. Movement Disorders: Official Journal of the Movement Disorder Society, 2004, 19(8):871-884.

[33] REEVES N D, ORLANDO G, BROWN S J. Sensory-motor mechanisms increasing falls risk in diabetic peripheral neuropathy[J]. Medicina, 2021, 57(5):457.

[34] DE GROOT M H, VAN CAMPEN J P C M, MOEK M A, et al. The effects of fall-risk-increasing drugs on postural control: a literature review[J]. Drugs & Aging, 2013(30):901-920.

[35] HARRISON J E, WEBER S, JAKOB R, et al. ICD-11: an international classification of diseases for the twenty-first century[J]. BMC Medical Informatics and Decision Making, 2021, 21(Sup. 6):206.

[36] MOHAMED N A, ZULKIFLEY M A. Moving object detection via TV-L1 optical flow in fall-down videos[J]. Bulletin of Electrical Engineering and Informatics, 2019, 8(3): 839-846.

[37] BHAVANI K D, UKRIT M F. Human fall detection using gaussian mixture model and fall motion mixture model[C]//2023 5th International Conference on Inventive Research in Computing Applications (ICIRCA). Piscataway: IEEE, 2023:1814-1818.

[38] CHEN B, CHEN C, HU J, et al. Computer vision and machine learning-based gait pattern recognition for flat fall prediction [J]. Sensors, 2022, 22(20):7960.

[39] ABOBAKR A, HOSSNY M, NAHAVANDI S. A skeleton-free fall detection system from depth images using random decision forest[J]. IEEE Systems Journal, 2017, 12(3): 2994-3005.

[40] YU Z, LIU J, YANG M, et al. An elderly fall detection method based on federated learning and extreme learning machine (fed-ELM) [J]. IEEE Access, 2022(10): 130816-130824.

[41] MENACHO C, ORDOÑEZ J. Fall detection based on CNN models implemented on a mobile robot[C]//2020 17th international conference on ubiquitous robots (UR). Piscataway: IEEE, 2020: 284-289.

[42] FEI K, WANG C, ZHANG J, et al. Flow-pose net: an effective two-stream network for fall detection[J]. The Visual Computer, 2023, 39 (6): 2305-2320.

[43] ALANAZI T, MUHAMMAD G. Human fall detection using 3D multi-stream convolutional neural networks with fusion[J]. Diagnostics, 2022, 12(12): 3060.

[44] NÚÑEZ-MARCOS A, ARGANDA-CARRERAS I. Transformer-based fall detection in videos[J]. Engineering Applications of Artificial Intelligence, 2024, 132: 107937.

[45] CHEN H, GU W, ZHANG Q, et al. Integrating attention mechanism and multi-scale feature extraction for fall detection[J]. Heliyon, 2024, 10(10):e31614.

[46] MARTÍNEZ-VILLASEÑOR L, PONCE H, BRIEVA J, et al. UP-fall detection dataset: a multimodal approach[J]. Sensors, 2019, 19(9):1988.

[47] SASE P S, BHANDARI S H. Human fall detection using depth videos [C]//2018 5th International Conference on Signal Processing and Integrated Networks (SPIN). Piscataway: IEEE, 2018:546-549.

[48] MARTÍNEZ-VILLASEñOR L, PONCE H, BRIEVA J, et al. UP-fall detection dataset: a multimodal approach[J]. Sensors, 2019, 19(9): 1988.

[49] GASPARRINI S, CIPPITELLI E, SPINSANTE S, et al. A depth-based fall detection system using a Kinect © sensor[J]. Sensors, 2014, 14(2):2756-2775.

[50] AUVINET E, ROUGIER C, MEUNIER J, et al. Multiple cameras fall dataset[J]. DIRO-Université de Montréal, Tech Rep, 2010, 1350: 24.

[51] ZHERDEV D, ZHERDEVA L, AGAPOV S, et al. Producing synthetic dataset for human fall detection in AR/VR environments[J]. Applied Sciences, 2021, 11(24): 11938.

[52] GUERRERO J C E, ESPAÑA E M, AÑASCO M M, et al. Dataset for human fall recognition in an uncontrolled environment[J]. Data in brief, 2022, 45: 108610.

[53] CIPPITELLI E, GAMBI E, GASPARRINI S, et al. TST fall detection dataset v2. [J/OL]. IEEE data port, (2015-01-06). https://ieee-dataport.org/documents/tst-fall-detection-dataset-v2.

[54] CHEN Z, WANG Y, YANG W. Video based fall detection using human poses[C]// CCF Conference on Big Data. Singapore: Springer Nature Singapore, 2021:283-296.

[55] ALZAHRANI M S, JARRAYA S K, SALAMAH M A, et al. FallFree: multiple fall scenario dataset of cane users for monitoring applications using kinect [C]//2017 13th International Conference on Signal-Image Technology & Internet-Based Systems (SITIS). Piscataway: IEEE, 2017:327-333.

[56] LI S, SONG X. Future frame prediction network for human fall detection in surveillance videos[J]. IEEE Sensors Journal, 2023, 23 (13): 14460-14470.

[57] ALAOUI A Y, TABII Y, THAMI R O H, et al. Fall detection of elderly people using the manifold of positive semidefinite matrices[J]. Journal of Imaging, 2021, 7(7): 109.

[58] GALVAO Y M, PORTELA L, FERREIRA J, et al. A framework for anomaly identification applied on fall detection[J]. IEEE Access, 2021, 9:77264-77274.

[59] VAIYAPURI T, LYDIA E L, SIKKANDAR M Y, et al. Internet of things and deep learning enabled elderly fall detection model for smart homecare[J]. IEEE Access, 2021, 9: 113879-113888.

[60] ALMALKI N, ALNFIAI M M, AL-WESABI F N, et al. Deep transfer learning driven automated fall detection for quality of living of disabled persons [J]. Computers, Materials & Continua, 2023, 74(3):6719.

[61] GALVÃO Y M, FERREIRA J, ALBUQUERQUE V A, et al. A multimodal approach using deep learning for fall detection[J]. Expert

Systems with Applications, 2021, 168:114226.

[62]WANG B H, YU J, WANG K, et al. Fall detection based on dual-channel feature integration[J]. IEEE Access, 2020, 8: 103443-103453.

[63]NAHIDUZZAMAN M, TASNIM M, NEWAZ N T, et al. Machine learning based early fall detection for elderly people with neurological disorder using multimodal data fusion[C]//International Conference on Brain Informatics. Cham: Springer International Publishing, 2020: 204-214.

[64]DENTAMARO V, IMPEDOVO D, PIRLO G. Fall detection by human pose estimation and kinematic theory [C]//2020 25th international conference on pattern recognition (ICPR). Piscataway: IEEE, 2021:2328-2335.

[65]MALDONADO-MENDEZ C, HERNANDEZ- MENDEZ S, TORRES-MUÑOZ D, et al. Fall detection using features extracted from skeletal joints and SVM: preliminary results [J]. Multimedia Tools and Applications, 2022, 81(19): 27657-27681.

[66]KESKES O, NOUMEIR R. Vision-based fall detection using ST-GCN [J]. IEEE Access, 2021, 9: 28224-28236.

[67]LI R, LI D, ZHANG M. A Real-time fall detection system using ToF depth images[C]//2022 IEEE 10th International Conference on Smart City and Informatization (iSCI). Piscataway: IEEE, 2022:41-48.

[68]MAI C T H, DUNG D T P, DUC P L A, et al. Skeleton-based fall detection using computer vision [C]// International Conference on Cooperative Design, Visualization and Engineering. Cham: Springer Nature Switzerland, 2023: 158-167.

[69]ESPINOSA R, PONCE H, GUTIÉRREZ S, et al. A vision-based approach for fall detection using multiple cameras and convolutional neural networks: a case study using the UP-Fall detection dataset[J]. Computers in biology and medicine, 2019, 115: 103520.

[70]ASIF U, VON CAVALLAR S, TANG J, et al. SSHFD: single shot human fall detection with occluded joints resilience[M]//ECAI 2020: 24th European Conference on Artificial Intelligence. Amsterdam: IOS Press, 2020: 2656-2663.

[71]WANG Y, DENG T. Enhancing elderly care: efficient and reliable real-time fall detection algorithm [J]. Digital Health, 2024, 10: 20552076241233690.

[72]WAHLA S Q, GHANI M U. Visual fall detection from activities of daily living for assistive living[J]. IEEE Access, 2023, 11: 108876-108890.

[73]CAO Z, HIDALGO G, SIMON T, et al. Openpose: realtime multi-person 2D pose estimation using part affinity fields [J]. IEEE transactions on pattern analysis and machine intelligence, 2019, 43(1): 172-186.

[74]PENG K, ROITBERG A, YANG K, et al. Delving deep into one-shot skeleton-based action recognition with diverse occlusions[J]. IEEE Transactions on Multimedia, 2023, 25: 1489-1504.

[75]ZI X, CHATURVEDI K, BRAYTEE A, et al. Detecting human falls in poor lighting: object detection and tracking approach for indoor safety [J]. Electronics, 2023, 12(5): 1259.

[76]GUTIÉRREZ J, MARTIN S, RODRIGUEZ V H, et al. Fall detection in low-illumination environments from far-infrared images using pose detection and dynamic descriptors [J]. IEEE Access, 2024, 12: 41659-41675.

[77]XU T, ZHOU Y, ZHU J. New advances and challenges of fall detection systems: a survey[J]. Applied Sciences, 2018, 8(3): 418.

[78]FULA V, MORENO P. Wrist-based fall detection: towards generalization across datasets[J]. Sensors, 2024, 24(5): 1679.

[79]ANDREW J, BAKER M. The general data protection regulation in the age of surveillance capitalism[J]. Journal of Business Ethics, 2021, 168: 565-578.

[80]KOSHMAK G, LOUTFI A, LINDEN M. Challenges and issues in multisensor fusion approach for fall detection[J]. Journal of Sensors, 2016, 2016(1): 6931789.

[81]WANG X, ELLUL J, AZZOPARDI G. Elderly fall detection systems: a literature survey[J]. Frontiers in Robotics and AI, 2020, 7: 71.

[82]ALHARBI H A, ALHARBI K K, HASSAN C A U. Enhancing elderly fall detection through iot-enabled smart flooring and ai for independent living sustainability[J]. Sustainability, 2023, 15(22): 15695.

[83]LIU X, YOO C, XING F, et al. Deep unsupervised domain adaptation: a review of recent advances and perspectives[J]. APSIPA Transactions on Signal and Information Processing, 2022, 11(1):e25.

[84]WANG Z. CausalBench: a comprehensive benchmark for evaluating causal reasoning capabilities of large language models[C]//Proceedings of the 10th SIGHAN Workshop on Chinese Language Processing (SIGHAN-10). Kerrville: Association for Computational Linguistics, 2024: 143-151.

[85]ZHANG C, XIE Y, BAI H, et al. A survey on federated learning [J]. Knowledge-Based Systems, 2021, 216: 106775.

[86]ARRIETA A B, DÍAZ-RODRÍGUEZ N, DEL SER J, et al. Explainable artificial intelligence (XAI): concepts, taxonomies, opportunities and challenges toward responsible AI[J]. Information fusion, 2020(58):82-115.