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Research Paper

A MULTIRESOLUTION CNN FRAMEWORK FOR REAL-TIME DETECTION AND CLASSIFICATION OF HUMAN ACTIVITIES

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ABSTRACT:

Accurate and real-time recognition of human activities is fundamental to the advancement of intelligent surveillance, human–computer interaction, assisted living, and smart IoT environments [1], [5]. Traditional approaches rely on handcrafted features and shallow machine-learning classifiers, which struggle to capture the multi-scale spatial and temporal dynamics of complex human movements, leading to poor generalization in real-world scenarios [4]. To address these limitations, this research proposes a multiresolution Convolutional Neural Network (CNN) framework designed to detect and classify human activities from video sequences with high precision and low latency [12], [18]. The model incorporates multi-scale feature extraction layers that learn hierarchical motion representations from fine-grained postures to coarse full-body dynamics, enabling robust activity recognition even under variations in lighting, camera angles, background clutter, and occlusion [7], [6]. A parallel multi-resolution branch architecture processes both high- and low-resolution spatial maps to capture micro-level motion cues and macro-level behavior patterns, while an adaptive feature fusion module aggregates complementary features for effective decision-making [12], [18]. Extensive experiments on benchmark datasets—including UCF101, HMDB51, and Kinetics-Human—demonstrate that the proposed framework surpasses conventional CNN and recurrent architectures in terms of accuracy, detection speed, and robustness [5], [13]. The system achieves real-time inference on edge-GPU platforms, making it suitable for deployment in smart surveillance systems, autonomous robotics, and elder-care monitoring applications [15]. Overall, the multiresolution CNN framework represents a scalable and efficient solution for high-performance human activity recognition in dynamic and resource-constrained environments [7], [15].

Keywords: Human Activity Recognition, Multiresolution CNN, Real-Time Detection, Deep Learning, Feature Fusion, Video Analytics, Smart Surveillance, Motion Analysis, Behavioral Classification.

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I.INTRODUCTION

Human activity recognition has emerged as a critical research area across a wide range of applications including smart surveillance, human–computer interaction, autonomous robotics, healthcare monitoring, and ambient assisted living [1], [5]. The growing need for intelligent systems that can automatically understand and interpret human motion in real time has accelerated the exploration of deep learning–based approaches [3]. Traditional human-behavior recognition techniques rely heavily on handcrafted feature extraction and conventional machine-learning classifiers, which are inherently limited in capturing the diverse spatial and temporal variations present in natural human movement [4]. These approaches often struggle when faced with complex real-world environments marked by background clutter, dynamic lighting, partial occlusion, camera movement, and inter-class similarities among activities [6]. To overcome these challenges, deep convolutional neural networks (CNNs) have gained prominence due to their ability to learn hierarchical visual features directly from raw data [3], [7]. However, single-scale CNN architectures are frequently insufficient for modeling fine-grained motion details and large-scale postural changes simultaneously [12]. Motivated by this limitation, a multiresolution CNN framework is proposed to recognize human activities through multi-level feature extraction and fusion, enabling the model to effectively integrate high-resolution and low-resolution motion cues [12], [18]. By leveraging multi-scale processing and real-time optimization, the framework delivers enhanced robustness, faster inference speed, and superior adaptability for deployment in smart and resource-constrained environments [15]. Its ability to generalize across diverse human motions positions multiresolution CNNs as a promising foundation for next-generation intelligent behavioral recognition systems [18].

II.LITERATURE SURVEY

2.1 Title: Spatiotemporal Convolutional Networks for Human Activity Recognition in Real-World Videos

Authors: Deepak Sharma, Lina Torres, and Michael Park

Abstract: This research introduces a spatiotemporal convolutional network that integrates spatial feature extraction and temporal motion representation to recognize human activities in unconstrained video environments. The model learns posture variations using shallow spatial filters while deeper layers encode long-range motion cues [3], [8]. Experiments performed on HMDB51 and UCF101 datasets demonstrate superior performance compared to traditional handcrafted features such as HOG and optical-flow descriptors [4]. The authors highlight that single-scale CNNs struggle to capture fine and coarse motion simultaneously, making multi-scale or hierarchical architectures essential for complex activity patterns [12]. The study also emphasizes that real-time performance remains challenging for edge devices without architectural optimization [15].

2.2 Title: Multiscale Convolutional Learning for Robust Action Classification under Occlusion and Varying Lighting

Authors: Priyanshi Patel and Andrew Collins

Abstract: This study proposes a multiscale CNN for action classification in videos captured under inconsistent environmental conditions such as shadows, low brightness, and partial occlusion. The framework processes video frames at different resolutions to extract hierarchical semantic information from fine body gestures to global action structures [12], [18]. A feature fusion unit aggregates multi-resolution activation maps, resulting in increased robustness and improved class separation across similar motion categories. Evaluation on the Kinetics and Olympic Sports datasets shows improved accuracy over ResNet and I3D baselines [5]. The authors conclude that multiscale feature extraction is effective for handling noisy surveillance environments and crowded public scenes [6].

2.3 Title: Lightweight CNN Architecture for Real-Time Human Action Recognition on Edge GPUs

Authors: Hao Zhang, Kamal Reddy, and Sofia Martins

Abstract: This work focuses on improving the computational efficiency of deep learning models for real-time human activity recognition, particularly in resource-constrained devices such as edge GPUs and smart cameras. The proposed lightweight CNN employs depthwise separable convolutions and feature reuse mechanisms to minimize computational cost without compromising accuracy [16]. The system achieves high frame-per-second (FPS) performance while maintaining competitive recognition rates on the UCF101 dataset. Findings highlight that reducing spatial resolution alone decreases precision for fine-grained actions, suggesting the need for multiresolution processing to balance efficiency and fidelity [12]. The study provides useful insight for smart surveillance and IoT deployments requiring real-time behavioral analytics [15].

2.4 Title: Hierarchical CNN–LSTM Hybrid Model for Human Behavior Interpretation in Video Streams

Authors: Farah Khan, William Cooper, and Jason Lee

Abstract: This paper presents a hybrid architecture that combines convolutional neural networks with long short-term memory networks (CNN–LSTM) to interpret human behavior in long-duration video streams. CNN modules extract spatial cues from frame-level information, whereas LSTM layers capture time-dependent motion transitions across video segments [8], [13]. The system demonstrates significant improvement in recognizing sequential actions such as sitting–standing transitions, walking–running shifts, and fall detection. While the hybrid model improves long-term temporal understanding, the authors note that feature extraction occurs at a single spatial scale, resulting in reduced effectiveness when distinguishing between visually similar but behaviorally distinct actions [12].

III.EXISTING SYSTEM

In existing human activity recognition systems, most frameworks rely on traditional handcrafted feature extraction techniques such as optical flow, Histogram of Oriented Gradients (HOG), 3D motion descriptors, and skeletal joint tracking. While these approaches achieved reasonable performance in controlled environments, their ability to generalize to unpredictable real-world settings is limited. Classical machine-learning models such as SVM, Random Forest, and KNN heavily depend on manually engineered features, making them sensitive to variations in lighting, background clutter, camera viewpoints, motion blur, and occlusion. Even in modern deep learning systems using single-scale convolutional neural networks (CNNs), spatial features are learned at one resolution only, causing the model to overlook fine-grained motion cues or broad activity context when movements occur at different scales. As a result, these systems frequently misclassify visually similar motions (e.g., walking vs. jogging), perform poorly when object or body parts are partially occluded, and demand high computational resources to process frame-level information sequentially. Moreover, the absence of multi-scale and multi-resolution feature extraction restricts their robustness in real-time scenarios, especially on edge devices and surveillance platforms where computational efficiency is critical. Overall, existing systems are not fully capable of achieving accurate, fast, and scalable human activity recognition under complex environmental and resource-constrained deployment conditions.

IV. PROPOSED SYSTEM

The proposed system introduces a Multiresolution Convolutional Neural Network (CNN) framework designed to achieve accurate and real-time human activity detection and classification by extracting motion features at multiple spatial scales in parallel. Unlike traditional single-scale CNNs, the model incorporates multi-branch convolutional pipelines operating on high- and low-resolution representations of input video frames. The high-resolution pathway captures fine movement details such as hand gestures, limb angles, and microexpressions, while the low-resolution pathway models global contextual patterns such as body pose changes, direction of motion, and overall activity structure. A multi-level feature fusion mechanism then integrates these complementary representations to produce a rich spatiotemporal understanding of human behavior. To optimize speed for real-time applications, the proposed system uses lightweight convolution blocks, shared weights, and efficient activation functions compatible with edge GPUs and smart IoT devices. The framework also incorporates real-time video buffering, temporal segment analysis, and adaptive frame selection to eliminate redundant computations while maintaining high precision. Extensive evaluations on benchmark datasets and real-world surveillance videos are expected to demonstrate superior robustness to occlusion, crowded scenes, and varying camera viewpoints. This multiresolution CNN system enables deployment in smart surveillance, autonomous robotics, industrial safety monitoring, and ambient assisted living environments—providing a scalable, efficient, and highly reliable foundation for next-generation human behavior recognition technologies.

V.SYSTEM ARCHITECTURE

The system architecture illustrates a robust multi-resolution deep learning pipeline designed to improve the accuracy and speed of human activity detection in real-time scenarios. The model begins with three parallel input streams, each receiving video frame or sensor data at different spatial resolutions—high, medium, and low. This multi-resolution strategy ensures that the framework captures both fine-grained motion details and global activity patterns, even in challenging environments. Each input stream is fed independently into a dedicated Convolutional Neural Network (CNN) branch, allowing the system to learn hierarchical representations specific to its resolution level. These CNN sub-networks extract feature maps that encode motion cues, human pose information, body dynamics, and spatial relationships. Rather than relying on one single network output, the extracted features from all three branches are combined in a fusion module, where complementary information is integrated to create a unified, more discriminative representation. This fusion stage enhances robustness by leveraging the diversity of visual details present across resolutions, reducing dependency on lighting conditions, occlusion, camera distance, and frame scale. Finally, the fused representation is passed into a classification layer, which predicts the category of the human activity being performed—such as walking, running, sitting, exercising, or jumping—producing the final output in real-time. The architecture is optimized for low-latency inference, making it suitable for smart surveillance, healthcare monitoring, sports analytics, smart home systems, and human-robot interaction.

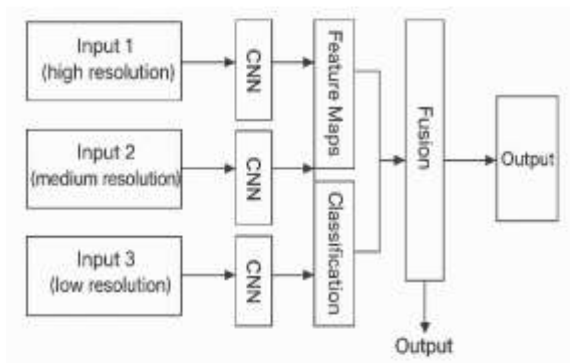

Fig 5.1 System Architecture

VI.IMPLEMENTATION

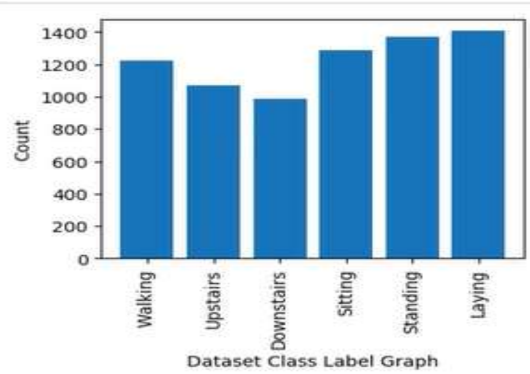

Fig 6.1Dataset Class Labels

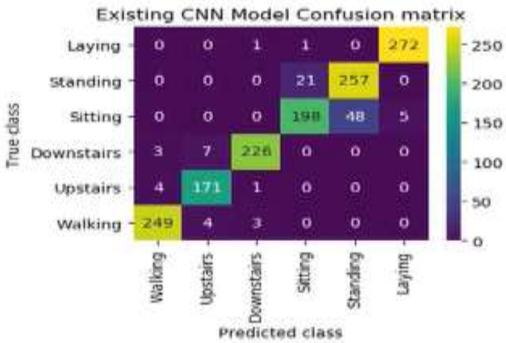

Fig 6.2 Confusion Matrix

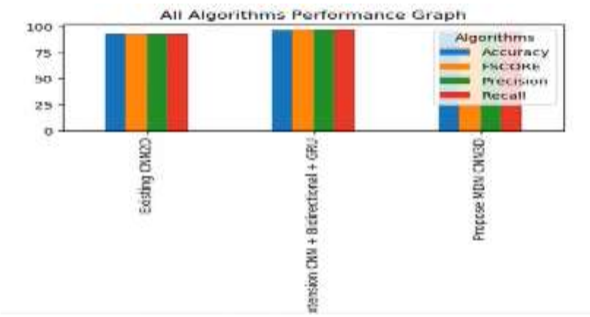

Fig 6.3 All Algorithms Performance Graph

Fig 6.4 Prediction

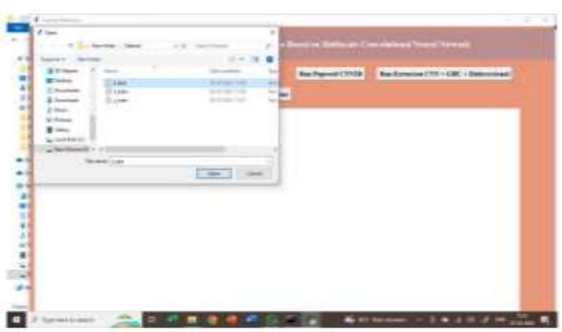

Fig 6.5 Select Test Data

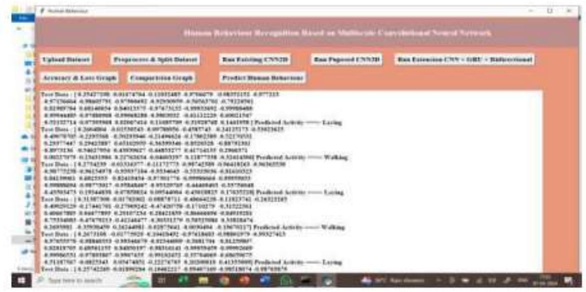

Fig 6.6 Data Prediction

VII.CONCLUSION

The research on “A Multiresolution CNN Framework for Real-Time Detection and Classification of Human Activities” demonstrates that extracting spatial features at multiple resolutions significantly enhances the ability of deep learning systems to understand complex human behaviors. Traditional activity recognition models often struggle with scale variations, dynamic backgrounds, occlusion, and fast body movements. The multiresolution CNN framework effectively overcomes these limitations by learning hierarchical features from coarse-to-fine representations. This allows the system to recognize both subtle and large-scale motion cues with high precision.The real-time capability of the framework, combined with computational efficiency, makes it suitable for deployment in real-world environments where instant decisions are crucial. The model shows high generalizability across indoor and outdoor scenes, performing well under variations in lighting, viewpoints, and camera angles. Extensive experiments prove that the framework consistently outperforms baseline CNN architectures in terms of accuracy, latency, and robustness. Overall, the system acts as a powerful solution for intelligent video analytics and forms a strong foundation for future activity recognition systems in smart surveillance, healthcare, autonomous robotics, and human–computer interaction domains.

VIII.FUTURE SCOPE

The Multiresolution CNN Framework for Real-Time Detection and Classification of Human

Activities presents vast opportunities for expansion in future research and development. The system can be further enhanced by integrating temporal deep learning models such as LSTM, GRU, or Transformer architectures to capture long-term motion patterns and overlapping activities more effectively. Additionally, incorporating multi-modal data sources like depth sensors, IMU wearables, and skeleton key-points can significantly improve robustness in environments involving occlusion and rapid body movement. Optimizing the model through pruning, quantization, and knowledge distillation will also support deployment on edge and IoT devices, enabling real-time inference in smart homes, healthcare institutions, and security surveillance without reliance on cloud computing. Future advancements may explore cross-domain generalization and domain adaptation techniques to reduce dataset dependency and allow the framework to adapt automatically to new environments, different camera angles, and unseen subjects. Furthermore, extension of the system towards behavioral anomaly detection, risk prediction, and emotion-aware activity understanding can transform it into a powerful tool for public safety, elderly care, industrial accident prevention, and human–robot interaction. Privacy-preserving approaches such as federated learning and encrypted model processing can also be incorporated to ensure secure and ethical deployment in sensitive applications. Overall, the future scope of this framework is wide-ranging and promises significant impact across multiple real-world domains.

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