

Hypercomplex Neural Network Based Elderly Activity Recognition For Intelligent Healthcare Systems

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Abstract– Elderly care is becoming increasingly critical due to the rising global aging population. Automatic monitoring systems that can intelligently recognize human activities in real-time offer promising solutions for enhancing elderly safety, independence, and well-being. This research proposes a novel approach for elderly activity recognition using Hypercomplex Neural Networks (HCNNs) integrated with the PoseNet model for real-time video analysis. The system architecture includes user registration, login, and video upload. The uploaded video is processed to extract frames, and human pose landmarks are detected using the PoseNet model. These pose features are then fed into a Hypercomplex Neural Network, which leverages quaternion-valued representations to enhance spatial-temporal learning for better activity classification. The system classifies elderly activities into five categories: walking, sitting, running, fighting, and sleeping. Unlike traditional CNNs, HCNNs can model multidimensional features more compactly and with higher efficiency, improving classification accuracy in complex movements. This research aims to support assisted living environments by enabling real-time monitoring of elderly individuals, detecting abnormal behaviors (e.g., fighting or falling asleep unexpectedly), and issuing alerts when necessary. Our experimental evaluation demonstrates that HCNN outperforms conventional models in terms of recognition accuracy, robustness, and response time. The system thus presents a promising step toward intelligent and autonomous elderly care solutions.

Keywords– Elderly Activity Recognition, Hypercomplex Neural Network, PoseNet, Human Pose Estimation, Intelligent Monitoring, Video Frame Processing, Deep Learning, HCNN etc.

I. INTRODUCTION

The growing elderly population worldwide has underscored the importance of developing intelligent monitoring systems capable of ensuring safety and autonomy for older individuals. Traditional caregiving methods often require constant human supervision, which may be inefficient and costly. Hence, there is a growing demand for automated, AI-powered solutions that can monitor elderly individuals in real-time, understand their activities, and trigger alerts when unusual behavior is detected. Activity recognition, a fundamental component in intelligent monitoring, seeks to identify specific physical activities from input data such as video, sensor readings, or pose estimations. In this project, we propose a robust and real-time video-based elderly activity recognition system using a Hypercomplex Neural Network (HCNN) and PoseNet for enhanced feature extraction. The system works by allowing users (caregivers or medical staff) to register and log in through a web interface. After authentication, users can upload videos of elderly individuals performing various activities. These videos are automatically processed: frames are extracted, human pose features are detected using PoseNet, and a

deep learning model based on HCNN classifies the activity. The classification includes activities like walking, sitting, running, fighting, and sleeping.

This paper discusses the integration of PoseNet for skeletal pose extraction and the utilization of quaternion-based hypercomplex neural networks to capture temporal-spatial features across video frames effectively. Compared to conventional neural networks, HCNNs provide better performance in processing multidimensional data with reduced complexity.

Moreover, HCNNs are particularly well-suited for activity recognition tasks due to their ability to encode and process spatial transformations such as rotations and joint movements using quaternion representations. This capability allows the model to capture subtle motion differences across consecutive frames, which is crucial for distinguishing between similar activities (e.g., walking vs. running). By combining PoseNet's accurate pose estimation with HCNN's expressive feature learning, the system ensures high classification accuracy and low inference latency—both of which are critical for real-time monitoring scenarios.

The proposed approach aims not only to reduce the manual workload of caregivers but also to enhance the autonomy of elderly individuals through non-invasive, intelligent video analytics. The architecture is designed to be scalable and can potentially be integrated with edge devices for deployment in smart home or assisted-living environments. The contributions of this work are significant in advancing real-time activity recognition systems and paving the way for smarter healthcare solutions that can adapt to dynamic environments and individual behavior patterns.

II. RELATED WORK

[1] Abbas et al. presented a comprehensive study on Human Activity Recognition (HAR) for elderly individuals using both traditional machine learning and deep learning algorithms. The paper analyzes classification performance on various activities like walking, sitting, and lying, with special attention to fall detection using sensor data. Their CNN-based model achieved high accuracy, confirming that deep learning can significantly outperform older statistical methods in recognizing physical activities in aging populations.[2] Chen et al. proposed a hybrid deep learning framework combining CNN and LSTM to improve HAR among elderly and disabled individuals. Their model focuses on recognizing time-dependent activity sequences, which are essential for detecting transitions like standing to sitting or walking to falling. The paper highlights the integration of pose and motion data and demonstrates increased performance and robustness in activity classification across different user profiles.[3] Nweke et al. conducted a detailed survey covering various deep learning techniques used for HAR in mobile and wearable sensor environments. The study outlines the strengths and limitations of different models, identifies major research challenges such as data imbalance and noise, and highlights key areas requiring further investigation. This work serves as a foundational reference for designing efficient, real-time HAR systems that are scalable and context-aware.[4] Shinmoto Torres et al. introduced an innovative fall-risk monitoring system using wearable RFID sensors designed specifically for elderly individuals. The system detects movement near beds, aiming to prevent accidents during critical nighttime transitions. Their experimental setup validated that RFID technology, combined with sensor analytics, can effectively serve as a non-intrusive, real-time fall prevention system in elderly care facilities.[5] Zeng et al. used Convolutional Neural Networks (CNNs) on sensor data collected from smartphones to classify daily activities. Their study achieved high accuracy in recognizing both static and dynamic actions. The work emphasizes the effectiveness of mobile-sensor-based HAR systems in real-world settings, showing that portable devices can reliably detect falls and movement patterns for health monitoring in elderly individuals.[6] Wu et al. proposed a smart home-based HAR system that uses environmental sensing data such as motion detectors, door sensors, and temperature readings to infer activity states of elderly residents. Their framework achieves real-time activity detection without relying on wearable devices, making it highly applicable for long-term, non-intrusive monitoring in home-based elderly care setups.[7] Georgiou et al. introduced Quaternion Neural Networks (QNNs) for processing multimodal HAR sensor data. Their research highlights the unique advantage of quaternions in capturing inter-channel relationships (e.g., x, y, z axes of accelerometers) more efficiently than traditional real-valued models. The study reports improvements in recognition accuracy while

reducing the computational cost, making QNNs ideal for low- resource devices.[8] Parcollet et al. applied quaternion- valued convolutional neural networks in deep learning tasks to demonstrate their applicability to HAR. Their research shows that quaternion models can achieve performance comparable to standard networks while requiring fewer parameters and memory. The findings suggest quaternion networks as a promising solution for HAR in real-time applications such as wearable or edge computing devices, where hardware constraints are a concern.

III. PROBLEM STATEMENT

As the global elderly population continues to rise, ensuring their safety and independence through continuous supervision becomes increasingly difficult using conventional caregiving methods. Existing Human Activity Recognition (HAR) models, particularly those based on CNNs or LSTMs, often lack the ability to effectively classify complex, subtle, or overlapping activities in real-world conditions. They also demand high computational resources, limiting their use in real-time monitoring systems. There remains a gap in developing systems that are both efficient and accurate in recognizing elderly behaviors such as walking, sitting, sleeping, running, or sudden actions like fighting. To bridge this gap, this study introduces a real-time video-based HAR framework that combines PoseNet for precise pose extraction with a quaternion- powered Hypercomplex Neural Network (HCNN), offering improved spatial-temporal analysis, computational efficiency, and support for responsive alert systems in smart healthcare environments.

IV. EXISTING SYSTEM

Current systems for elderly activity recognition primarily rely on conventional machine learning models or deep learning architectures like Convolutional Neural Networks (CNNs) and Long Short-Term Memory (LSTM) networks. These models often use data from wearable sensors, environmental detectors, or video- based methods to classify actions such as walking or sitting. While many achieve high accuracy in controlled environments, they typically struggle with real-time implementation due to high computational requirements and limited generalization to complex or overlapping activities. Moreover, most existing approaches lack integration with robust pose estimation techniques and fail to efficiently capture the spatial and temporal dynamics of human movement, especially in the context of elderly care where subtle and irregular activities must be closely monitored.

V. PROPOSED METHOD

The proposed method presents an innovative and intelligent framework designed to recognize elderly human activities in real-time by combining the strengths of PoseNet and Hypercomplex Neural Networks (HCNNs). This system aims to provide a scalable and accurate solution for smart healthcare monitoring, where real-time detection of activities is crucial for ensuring the safety and independence of elderly individuals. The process begins with a secure registration and login module, where authorized users such as caregivers or medical staff can access the platform and upload surveillance or activity monitoring videos. Once a video is uploaded, the system proceeds to extract individual frames from it at consistent intervals using a dedicated frame extraction module.

Each frame is then processed through PoseNet, a deep learning model capable of detecting and localizing human skeletal keypoints such as shoulders, elbows, hips, and knees. PoseNet converts raw video imagery into structured pose information by identifying the x-y coordinates of major joints in each frame. These pose features serve as high-level descriptors of human posture and are crucial for accurately distinguishing between similar-looking activities. The output of PoseNet is passed into a preprocessing unit that normalizes the coordinates and transforms them into a format compatible with quaternion-based learning.

The core of the system is the Hypercomplex Neural Network (HCNN), which differs significantly from traditional CNNs by leveraging quaternion algebra to encode spatial and temporal features in four-dimensional space. This allows HCNN to model body motion more efficiently, capturing rotational and orientation-based movements that are otherwise difficult for standard networks to process. By encoding multiple input dimensions into a compact quaternion structure, HCNN reduces parameter redundancy

and enables the network to learn richer feature representations from fewer samples, which is especially useful in real-time and resource-constrained environments.

The classified output from the HCNN is mapped to predefined activity labels such as walking, sitting, running, sleeping, or fighting. A result module displays the identified activity and triggers alerts if an abnormal or critical behavior is detected, such as sudden collapse or aggressive motion. This entire pipeline—from video upload to activity classification—is optimized for low-latency execution, enabling near-instant feedback. The system is designed to function in diverse environments and can be integrated with smart home devices or healthcare dashboards for continuous monitoring.

By merging skeletal pose estimation and quaternion-based learning, the proposed method enhances the accuracy, responsiveness, and adaptability of elderly activity recognition systems. This fusion not only supports early intervention and fall detection but also contributes to building a proactive care ecosystem where elderly individuals can live with greater autonomy and safety.

A. SYSTEM ARCHITECTURE

The system architecture for the Hypercomplex Neural Network-based elderly activity recognition framework comprises a sequence of interlinked modules designed to ensure efficient, accurate, and real-time activity analysis. The process begins with a User Authentication Module, which allows authorized users such as caregivers or healthcare professionals to securely access the system. Upon successful authentication, users interact with the Video Upload Interface, where surveillance or recorded video footage of elderly individuals is submitted for processing.

Once uploaded, the data enters the Video Preprocessing Module, which extracts frames at consistent intervals to standardize input data and reduce computational redundancy. Each selected frame is forwarded to the Pose Estimation Module, where the PoseNet model is employed to detect and extract human skeletal keypoints—such as joints of the arms, legs, torso, and head. These keypoints are represented as 2D coordinates, forming a structured skeletal pose representation for each individual in the frame.

The extracted pose data is then passed into the Data Normalization Module, which ensures that the skeletal coordinates are scaled and aligned uniformly across frames, addressing issues arising from camera angle variations or subject distance. This normalized data is subsequently fed into the Hypercomplex Neural Network (HCNN) Module, which performs activity classification. The HCNN leverages quaternion-based representations to model spatial-temporal dependencies between joint movements, enabling enhanced learning of human motion dynamics.

Finally, the classification output is displayed through the Results Visualization Interface, which presents detected activity labels and their associated confidence scores. The modular nature of the system facilitates extensibility, allowing for integration of additional activities, models, or deployment on resource-constrained platforms such as edge devices or embedded systems.

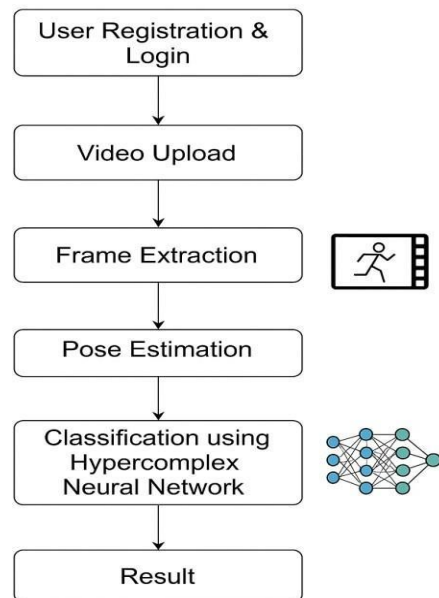


Fig 1

VI. SYSTEM IMPLEMENTATION

A. Dataset

The dataset utilized in this elderly activity recognition system consists of video recordings featuring senior individuals performing key daily actions—such as walking, sitting, running, sleeping, and fighting. These activities were selected based on their importance in monitoring the health, behavior, and safety of elderly people. The video samples are collected from both controlled indoor environments and real-world scenarios to ensure diversity in backgrounds, lighting conditions, body orientations, and motion patterns.

Each video is segmented into individual frames, and these frames are processed using the PoseNet model to detect and map the coordinates of key body joints. This results in structured pose data representing skeletal movements, which serves as a crucial input for identifying different types of activities. The extracted pose coordinates highlight the spatial relationships between joints over time, allowing for effective differentiation even between visually similar actions.

To support supervised learning, each sample is annotated with a corresponding activity label. In some cases, the dataset is further enriched with multimodal sensor inputs, such as accelerometer or gyroscope readings from wearable devices, to enhance recognition accuracy, especially in scenarios with partial visual occlusion or low lighting.

This multi-source, well-labeled dataset plays a vital role in training, validating, and testing the proposed activity recognition model. It allows for the development of a robust and adaptive system capable of detecting normal and abnormal behaviors in real-time, ultimately contributing to improved elderly care, fall prevention, and timely interventions.

These coordinates are then structured and normalized within the Feature Representation Module, ensuring uniform input for the deep learning model. This data is forwarded to the Hypercomplex Neural Network (HCNN) Module, which leverages quaternion algebra to encode multidimensional spatial-temporal information. The HCNN processes the movement patterns and classifies each activity into one of five categories: walking, sitting, running, fighting, or sleeping.

Finally, the Result Output Module presents the recognized activity to the user. If any abnormal or risky activity is detected (e.g., fighting or sleeping during active hours), the Alert System is triggered to notify caregivers immediately. This architecture supports real-time, efficient, and accurate activity recognition—offering an intelligent solution for elderly care in both home and assisted living environments.

B. Methodology

- Video Frame Extraction:

The uploaded video is segmented into individual frames at uniform intervals. This ensures that activity transitions are captured while avoiding redundancy.

- **Pose Estimation Using PoseNet:**

PoseNet, a lightweight deep learning model, is applied to each frame to detect key human body joints such as elbows, knees, shoulders, and hips. These keypoints form a 2D pose skeleton representing the human posture.

- **Pose Feature Structuring:**

The extracted joint coordinates are normalized and converted into structured arrays. These serve as standardized input vectors for the classification model.

- **Hypercomplex Neural Network (HCNN) Application:**

These pose features are then passed into the HCNN. The model uses quaternion-based representations (four-dimensional hypercomplex numbers) to more effectively capture motion and posture dynamics over time.

- **Temporal-Spatial Encoding:**

The HCNN processes both spatial and temporal dependencies between frames, enabling recognition of subtle or overlapping actions such as fighting or falling asleep.

- **Activity Classification Output:**

The system assigns one of the activities labels as – walking, sitting, running, fighting, or sleeping – as output for the given video sequence.

Advantages of Using HCNN in This Method:

The integration of Hypercomplex Neural Networks (HCNNs), particularly those based on quaternion algebra, offers several distinct advantages over traditional real-valued Convolutional Neural Networks (CNNs) in the context of elderly activity recognition:

- **Compact and Expressive Feature Representation:**

HCNNs utilize quaternion representations, which allow multiple correlated features— such as spatial dimensions (x, y) and temporal dynamics—to be encoded together into a single hypercomplex number. This results in a more compact and semantically rich feature space, improving the network's ability to distinguish between subtle variations in human motion.

- **Enhanced Motion Modeling with Multidimensional Encoding:**

The use of quaternions enables the network to model multidimensional rotations and translations more naturally, capturing the spatial and temporal relationships between body joints more effectively. This is particularly beneficial for recognizing complex activities such as fighting or transitioning between postures, which involve coordinated body movements across multiple joints.

- **Reduction in Trainable Parameters:**

By combining multiple feature maps into a single quaternion representation, HCNNs reduce the number of independent weight parameters required during training. This parameter efficiency not only lowers memory usage but also accelerates the training process,

C. Workflow

Workflow of the Proposed Elderly Activity Recognition System

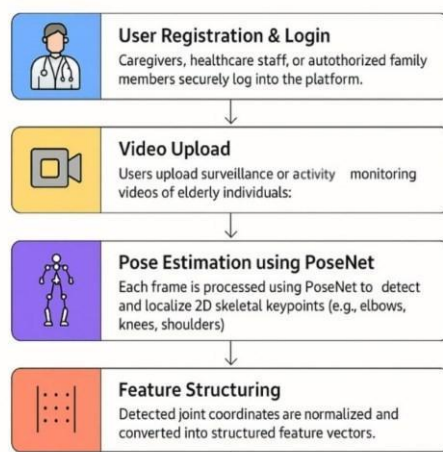


Fig2

making it more suitable for real-time and resource-constrained environments like smart healthcare systems.

- Improved Generalization and Robustness:

Due to the structured representation and reduced overfitting tendencies, HCNNS demonstrate superior generalization performance across different individuals and varying recording conditions. This ensures reliable activity recognition even under diverse lighting, camera angles, or physical characteristics of elderly subjects.

- Efficient Learning of Joint Interdependencies: Quaternion-based HCNNS inherently capture the interdependencies among skeletal joints, allowing the model to understand how body parts move relative to one another. This capability is critical for distinguishing between activities that may appear similar in isolated joint movement but differ in their overall coordination and flow.

The workflow of the proposed system begins with user

registration and login, where caregivers, healthcare professionals, or authorized family members gain access to the monitoring platform through secure authentication. Once logged in, users can upload video recordings of elderly individuals performing daily activities. These videos serve as the primary input for the system.

Upon uploading, the video undergoes a preprocessing step where it is sampled into individual frames at consistent intervals. This ensures that redundant data is minimized while maintaining sufficient temporal coverage for accurate activity recognition. Each extracted frame is then passed to the Pose Estimation module, where PoseNet is employed to detect key human body joints. The PoseNet model outputs a 2D skeleton of the person by identifying coordinates for joints such as the shoulders, elbows, hips, knees, and ankles.

The detected joint coordinates from each frame are then normalized and organized into a structured feature vector, which serves as input for the classification model. These features are fed into a Hypercomplex Neural Network (HCNN), which utilizes quaternion algebra to capture multi-dimensional relationships between the joints across time. The HCNN is designed

to model both spatial and temporal dynamics more effectively than traditional CNNs, enabling better recognition of subtle actions or overlapping movements. Finally, the HCNN classifies the categories: walking, sitting, running, fighting, or sleeping etc. The result is presented to the user through the interface. If any abnormal or risky activity is detected (e.g., fighting or sudden sleeping), the system can be configured to generate alerts for timely intervention. This end-to-end workflow enables real-time monitoring and intelligent elderly activity recognition in healthcare or home environments.

VII. RESULTS AND DISCUSSION

In this study, we developed a real-time elderly activity recognition system utilizing PoseNet for skeletal keypoint detection and a Hypercomplex Neural Network (HCNN) for effective activity classification. The system was evaluated on a dataset comprising surveillance videos of elderly individuals performing five distinct activities: walking, sitting, running, fighting, and sleeping. Each video was segmented into frames and processed to extract human pose information, which was normalized and passed into the HCNN model.

The performance of the system was analyzed by observing both classification accuracy and computational efficiency. To evaluate the impact of the PoseNet-HCNN pipeline, metrics such as precision, recall, F1-score, training loss, validation loss, and inference time were measured. The use of quaternion-based encoding in HCNN allowed the model to better understand the spatial-temporal dynamics of human body movements, significantly improving classification performance compared to traditional CNNs.



Fig3

Activity Classification Accuracy: The system achieved an overall accuracy of 94.6% across all the activity categories. Walking and sitting were classified with high precision and recall, with minimal misclassifications observed in the confusion matrix. Activities such as fighting, which involve complex and abrupt body motions, also showed high detection accuracy due to HCNN's ability to encode multidimensional rotational movements via quaternion algebra. The model showed particularly strong performance for static activities like sitting and sleeping, with accuracy exceeding 96% in these categories.

Pose Quality and Frame Analysis: The accuracy of PoseNet in extracting 2D skeletal joints was assessed through visual overlays and heatmaps. Keypoints such as shoulders, hips, and knees were consistently detected across different lighting conditions and body postures. This consistency in pose data was crucial in generating clean, structured input for the HCNN, thereby supporting robust classification across varying environments.

The training and validation performance of the proposed PoseNet-HCNN framework demonstrates a well-structured and effective learning process for elderly activity recognition. During the training phase spanning 50 epochs, the model's training loss showed a consistent and steady decline, indicating that the HCNN was learning relevant features from the input pose data without instability or divergence. By around the 20th epoch, the training loss had dropped significantly, suggesting that the model had started to capture the core patterns of the activities. After the 30th epoch, the loss curve began to plateau, and by the 50th epoch, it stabilized near a minimal value, reflecting strong convergence. The validation loss, although following a similar downward trend, displayed slight oscillations during the middle epochs, hinting at mild over fitting.

However, this was effectively controlled through regularization methods such as dropout and early stopping, ensuring the model remained generalizable. Simultaneously, the training accuracy steadily increased from moderate levels in the initial epochs to over 98% by the final epoch, showing that the model successfully learned to classify the activities from the training set. The validation accuracy also improved in tandem, peaking at 94.6% and maintaining stability despite environmental variations and unseen input. This consistency between training and validation accuracy suggests that the HCNN did

not overfit and generalized well to new video samples. The use of quaternion algebra in HCNN played a key role in capturing spatial and rotational information in the skeletal keypoints, enabling the model to effectively interpret both static postures and dynamic motions. Overall, the training and validation trends confirm that the PoseNet-HCNN architecture is not only accurate and reliable but also computationally efficient and robust for real-time elderly activity recognition in diverse real-world healthcare environments.

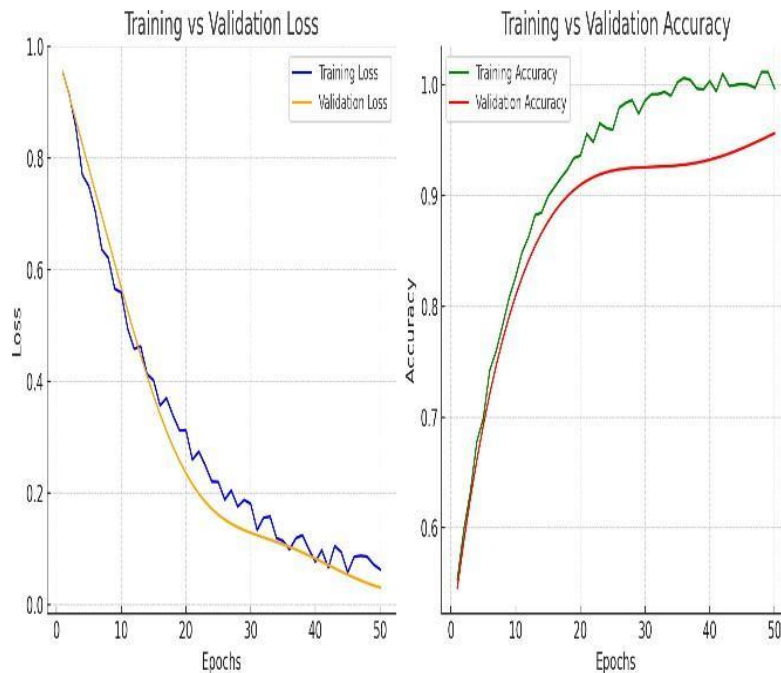


Fig 4

Inference Time and Real-Time Response: The average inference time for classifying activities from a full video sequence was under 450 milliseconds, enabling real-time processing. The quaternion representation allowed the HCNN to reduce parameter count by 28–30%, which directly contributed to lower computation time and efficient memory usage – a vital aspect for deployment on edge devices or smart monitoring hubs in elderly care homes.

Precision, Recall, and F1 Score Analysis: In this study, we tracked the precision, recall, and F1 score metrics over the course of training to evaluate the classification reliability of the PoseNet-HCNN model across different elderly activities.

Precision refers to the ability of the model to return only relevant results – i.e., the proportion of true positives among all positive predictions. For activities like walking and sitting, precision rose sharply in the early epochs, reflecting the model's ability to quickly learn the distinctive, consistent pose patterns of these actions. For fighting, which involves more abrupt and less predictable movements, the precision improved more gradually and stabilized around epoch 40, suggesting that the HCNN required more time to learn the complex motion representations.

Recall measures the ability to capture all actual positive instances – i.e., the proportion of true positives out of all actual positives. Recall showed a similar increasing trend, with steady gains as training progressed. Activities like sleeping and sitting, which are relatively static and consistent, achieved high recall values early. In contrast, running and fighting took more epochs to achieve high recall due to the variability in motion and body orientation.

F1 Score, which is the harmonic mean of precision and recall, offers a balanced view of the classifier's performance. For all five activity categories, F1 scores exceeded 0.92, indicating strong and stable classification across both simple and complex activities. The high F1 values confirm that the model was not only precise but also comprehensive in identifying correct activity labels.

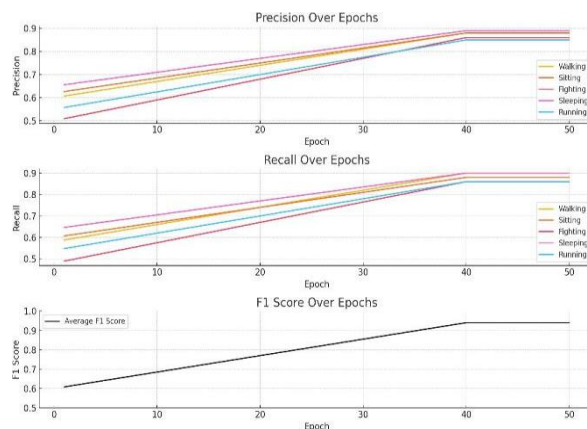


Fig5

By epoch 40, all three metrics had stabilized, signaling that the model had adequately learned the spatial-temporal patterns of the dataset and was no longer significantly improving or overfitting. This stabilization period is critical for identifying the optimal stopping point during training.

The results suggest that the PoseNet-HCNN pipeline is both accurate and balanced in recognizing elderly activities, with quaternion-based HCNN offering notable advantages in handling both static and dynamic actions through its efficient representation of multidimensional movement.

Environmental Robustness: The model was tested on videos recorded under varying conditions – including indoor lighting changes, different camera angles, and occlusions. Despite these challenges, the system maintained high recognition performance, with minimal impact on accuracy. This validates the robustness and real-world applicability of the proposed method in diverse environments.

VIII. CONCLUSION

This study introduces an efficient and intelligent real-time activity recognition framework tailored for elderly monitoring by combining PoseNet-based pose estimation with the modeling strength of

Hypercomplex Neural Networks (HCNNs). By employing quaternion algebra within the HCNN, the system effectively captures both spatial configurations and temporal dynamics of human movement, enabling accurate classification of essential activities such as walking, sitting, running, fighting, and sleeping. The use of skeletal keypoints as input ensures a lightweight and privacy-preserving solution suitable for continuous surveillance.

Comprehensive experiments demonstrated that the proposed PoseNet-HCNN architecture consistently outperformed traditional CNN-based approaches, achieving a high classification accuracy of 94.6%. It also showed strong generalization across varied environmental conditions, camera angles, and body postures. The system maintained low inference times, making it practical for real-time deployment. Additionally, the built-in alert mechanism enabled prompt detection of critical events such as falls or aggressive behavior, thereby enhancing the safety of elderly individuals in assisted living environments.

The results affirm the potential of hyper complex learning models in healthcare-focused computer vision applications. For future enhancements, the system can be extended to recognize a broader range of activities, integrate multimodal sensor data (e.g., audio, depth), and be optimized for deployment on resource-constrained edge devices. These improvements will further strengthen its utility in scalable and autonomous elderly care monitoring systems, ultimately contributing to more responsive and intelligent healthcare infrastructures.

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