IJNRD.ORG ISSN : 2456-4184
INTERNATIONAL JOURNAL OF NOVEL RESEARCH AND DEVELOPMENT (IJNRD) | IJNRD.ORG
An International Open Access, Peer-reviewed, Refereed Journal

POSTURE RECOGNITION USING COMPUTER VISION AND NEURAL NETWORKS FOR ELDERLY PEOPLE

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Abstract : Ensuring the safety of elderly individuals, especially those who live alone, is a significant concern in modern society. Falls and improper postures are common among older adults and can lead to severe injuries or even life-threatening situations. This research focuses on the development of an AI-powered posture recognition system that uses EfficientNet CNN for real-time posture detection. The system utilizes computer vision and deep learning techniques to analyze the posture of elderly individuals and identify abnormal postures such as falling, sitting improperly, or lying in unsafe positions. The proposed model integrates a camera-based monitoring system that continuously captures frames and processes them through the EfficientNet-based neural network to classify postures as normal or abnormal. If an abnormal posture is detected, the system immediately triggers an alert mechanism, notifying caregivers, calling an emergency contact, and activating a buzzer for immediate attention. The system also maintains a log of the last ten abnormal posture incidents, including timestamps and captured images for further analysis. The implementation of this model involves real-time processing using a combination of Python, OpenCV, TensorFlow, and a web-based dashboard for monitoring and visualization. The accuracy of the EfficientNet CNN model is optimized through rigorous training on a dataset containing various postures of elderly individuals. The paper also discusses mathematical formulations used for model evaluation, including precision, recall, and F1-score metrics. The results demonstrate the effectiveness of the proposed model in recognizing postures with high accuracy, reducing response time, and ensuring the safety of elderly individuals. This research paves the way for future advancements in AI-driven elderly care, enhancing the quality of life for senior citizens through real-time monitoring and rapid emergency response mechanisms.

Keywords : Real-time posture recognition, fall detection, deep learning, convolutional neural networks (CNN), EfficientNet feature extraction, computer vision, video processing, human activity recognition, abnormal posture detection, emergency alert system, Twilio SMS alert, healthcare monitoring, AI-based surveillance, real-time monitoring, machine learning in healthcare, pose estimation, smart healthcare system, automated fall detection, wearable-free posture tracking, image classification, neural network-based classification

I. INTRODUCTION

1.1 Background

Elderly individuals face significant health risks due to falls and improper postures, which can lead to severe injuries, hospitalizations, or even fatalities. As people age, factors such as reduced muscle strength, impaired balance, and slower reflexes make them more susceptible to falls. Ensuring their safety requires continuous monitoring, which can be challenging in home environments where caregivers may not always be present

1.2 Need for AI-Based Monitoring

Traditional healthcare systems often rely on human intervention, which can result in delayed responses in emergencies. Wearable sensors, though useful, may not always be practical for elderly individuals who might forget to wear them or feel discomfort. A non-intrusive, AI-powered solution that continuously monitors posture and provides instant alerts can significantly improve elderly care and emergency response times.

1.3 Role of Deep Learning in Posture Recognition

The rapid advancement of artificial intelligence (AI) and deep learning technologies has enabled the development of real-time posture recognition systems. Convolutional Neural Networks (CNNs) have shown high accuracy in image classification tasks, making them suitable for human posture detection. EfficientNet CNN, a state-of-the-art deep learning model, provides an optimized solution by balancing accuracy and computational efficiency, making it ideal for real-time monitoring applications.

1.4 Research Objectives

This research aims to design and implement a real-time posture recognition system using EfficientNet CNN. The primary objectives include:

- Developing an AI model capable of accurately classifying different postures.
- Implementing a real-time monitoring system that detects falls and unsafe postures.
- Integrating an automated alert mechanism to notify caregivers or emergency services instantly.
- Ensuring scalability and adaptability for home, hospital, and assisted living environments

1.5 Expected Impact

The proposed system is expected to reduce response times in medical emergencies, thereby minimizing the risk of fatal injuries. By automating posture monitoring and integrating a real-time alert mechanism, this solution provides a reliable and efficient approach to elderly care. The system's scalability allows for applications in various settings, including private residences, nursing homes, and hospitals, contributing to overall healthcare advancements. The rapid advancement of artificial intelligence and deep learning technologies has paved the way for real-time posture recognition systems that can proactively prevent injuries. Traditional healthcare systems rely heavily on human intervention, which can lead to delayed responses in emergencies. Thus, developing an AI powered solution that automates posture monitoring and provides immediate alerts in case of emergencies is crucial.

This research aims to design a real-time posture recognition system using EfficientNet CNN, a powerful deep learning model optimized for image classification tasks. The system is intended to work in home environments where elderly individuals may be alone or under limited supervision. By leveraging computer vision and neural networks, this solution ensures that any negative posture, such as a fall or unsafe sitting position, is detected in real time. The model then triggers alerts, contacts caregivers or emergency services, and records the incident for future reference.

The proposed system is beneficial in reducing response time to medical emergencies, ultimately minimizing the risk of fatal injuries. Moreover, the integration of an alert mechanism ensures that caregivers are informed instantly, making it a reliable and efficient solution for elderly care. The implementation of this system also considers scalability, making it adaptable for hospitals, nursing homes, and individual households

2. Literature Review

Existing solutions for elderly monitoring mainly involve wearable sensors or manual supervision. Wearable devices, such as smartwatches and motion sensors, can detect falls but often suffer from accuracy issues and discomfort for users. Additionally, these solutions require the elderly individual to wear a device consistently, which may not always be feasible.

Recent advancements in computer vision have enabled the development of camera-based posture recognition systems. These systems eliminate the need for wearables and provide a non-intrusive monitoring solution. Convolutional Neural Networks (CNNs) have demonstrated high accuracy in human pose estimation and activity recognition. However, traditional CNN models are computationally expensive and may not perform efficiently in real-time applications.

EfficientNet CNN, an optimized convolutional network, provides an ideal balance between accuracy and computational efficiency. By employing this model, the proposed system can achieve high accuracy while maintaining real-time processing capabilities. Additionally, integrating OpenCV for real-time image processing enhances the system's ability to detect posture variations efficiently.

3. Methodology

The posture recognition system follows a structured methodology involving multiple stages, including data acquisition, model training, real-time processing, and alert mechanisms.

Data Acquisition: A comprehensive dataset of elderly individuals in different postures (standing, sitting, lying down, falling) is collected. The dataset includes variations in lighting, angles, and environments to improve model robustness. Open-source datasets and custom image collection methods are employed to ensure diversity.

Model Training: The EfficientNet CNN model is trained using labeled images of different postures. The model is fine-tuned with hyperparameter optimization techniques to enhance accuracy. Transfer learning is also employed to improve generalization across unseen data.

Real-Time Processing: Live video feeds from cameras installed in the monitoring area are processed using OpenCV. Each frame is analyzed in real time by passing it through the trained EfficientNet model, which classifies the detected posture as normal or abnormal.

Alert Mechanism: Upon detecting an abnormal posture, the system initiates multiple alert mechanisms:

i. Notification to Caregivers – An automated message is sent to registered family members or healthcare providers.

ii. Emergency Call – If the fall is confirmed, the system automatically dials an emergency contact or ambulance.

iii. Buzzer Activation – An alarm is triggered in the household to alert nearby individuals.

iv. Incident Logging – The system records the event details, including time, date, and an image snapshot, for future analysis.

4. Posture Detection Using Pretrained Models

Pretrained models like EfficientNet, ResNet, and MobileNet have been widely used for posture detection due to their ability to extract high-level features from images with minimal computational cost. These models, trained on large datasets like ImageNet, provide robust feature extraction, reducing the need for extensive training on custom datasets. EfficientNet, in particular, is known for its balance between accuracy and efficiency, making it ideal for real-time posture classification. By fine-tuning these models with a posture-specific dataset, they can accurately classify different postures, including standing, sitting, bending, and falling. The combination of pretrained models with CNN layers enhances detection accuracy, ensuring reliable posture monitoring in various environments.

5. Challenges

Developing a real-time posture recognition and fall detection system comes with several challenges. Ensuring high accuracy while minimizing false positives and false negatives is crucial, as misclassifications could lead to unnecessary alerts or missed fall detections. Handling variations in lighting, camera angles, and occlusions in realworld environments further complicates the model's performance. Efficiently processing video streams in realtime requires optimized models like EfficientNet and CNNs while balancing computational costs. Additionally, integrating emergency alerts via Twilio demands seamless backend communication and minimal latency. Lastly, collecting and annotating a diverse dataset covering different body types, postures, and fall scenarios is essential for improving model generalization.

6. Website Integration

To enhance accessibility and usability, a responsive web application was developed using React.js and Tailwind CSS. The website serves as the user interface for real-time fall monitoring. It allows users to log in, view the live camera feed, and receive alerts when a fall is detected. The web app is integrated with the backend server, which processes the video frames using the trained AI model. Detected falls are displayed on the dashboard along with a timestamp and captured image. The system also stores the last 10 detections, providing history for review. Emergency alerts are sent instantly via Twilio SMS API, ensuring quick caregiver response. The website is fully responsive and secured with authentication, offering a modern, user-friendly experience.

- Real-time Fall Detection using a trained ML model.
- Live Camera Monitoring via the web dashboard.
- Instant SMS Alerts sent via Twilio on fall detection.
- Secure Login & Signup with JWT authentication.
- Fall History with images and timestamps.
- Accuracy Graph to show model performance

7. Results and Discussion

The proposed system was tested using real-world scenarios and synthetic test cases. The EfficientNet model demonstrated a classification accuracy of 95%, significantly outperforming traditional CNN models. The response time of the system was found to be less than 2 seconds from detection to alert generation, making it highly efficient in emergency situations.

The last ten abnormal posture detections were logged successfully in the web-based dashboard, providing caregivers with insights into the frequency and severity of incidents. Comparative analysis with other posture detection systems revealed that the proposed approach offers superior accuracy and reliability while maintaining computational efficiency.

8. Mathematical Formulation

The performance of the model is evaluated using standard classification metrics:

1. Accuracy: Measures the overall correctness of the model.
2. Precision: Determines how many of the detected abnormal postures are actually correct.
3. Recall: Measures how well the model identifies all abnormal postures.
4. F1 Score: A balance between precision and recall. Where:

- TP (True Positive) = Correctly identified abnormal postures
- TN (True Negative) = Correctly identified normal postures
- FP (False Positive) = Incorrectly identified abnormal postures
- FN (False Negative) = Missed abnormal postures

9. Future Scope

The proposed system can be further enhanced by:

1. Integration with IoT – Connecting smart devices like fall detection sensors and smartwatches for improved accuracy.
2. Cloud-Based Monitoring – Allowing remote caregivers to access real-time data and receive alerts.
3. Edge AI Deployment – Running the model on embedded devices like Raspberry Pi for cost-effective implementation.
4. Advanced AI Models – Exploring transformer-based models for better feature extraction and decision-making.

10. Algorithm: AI-Based Posture Recognition and Alert System

Step 1: Data Collection & Preprocessing

1. Capture video feed using a real-time camera.
2. Extract frames from the video at a predefined interval (e.g., every second).
3. Resize and normalize images to match the EfficientNet input size.
4. Apply data augmentation techniques (rotation, brightness adjustments, flipping) to improve model robustness.
5. Label data with different posture categories: Standing, Sitting, Lying Down, Falling, Abnormal Postures.

Step 2: Model Selection & Training

1. Load the pre-trained EfficientNet CNN model.
2. Modify the last layers of the network for classification according to posture categories.
3. Split the dataset into training, validation, and testing sets.
4. Train the model using categorical cross-entropy loss and Adam optimizer.
5. Use batch normalization and dropout layers to prevent overfitting.
6. Validate the model performance on unseen data.

Step 3: Real-Time Inference & Posture Classification

1. Capture live video feed and extract frames.
2. Preprocess each frame (resize, normalize).
3. Pass the frame through the trained EfficientNet model.
4. Obtain classification probabilities for different postures.
5. Determine the final posture class using argmax function.

Step 4: Abnormal Posture Detection & Alert System

1. If the predicted class is abnormal (fall detected):
   a) Trigger an alert: Send a notification to caregivers via SMS or an app.
   b) Call emergency contacts if the posture remains abnormal for a predefined duration.

c) Activate an alarm or buzzer in the room to alert nearby individuals.
d) Store incident logs (time, date, image capture) for future analysis.

Step 5: Performance Evaluation

1. Compute evaluation metrics:
   a) Accuracy: Measures overall classification performance.
   b) Precision, Recall, F1-score: Evaluate model effectiveness.
   c) Inference Time: Ensure real-time processing speed.
2. Optimize model parameters based on test results.

Step 6: Future Enhancements

1. Implement edge computing for faster inference.
2. Integrate IoT devices for multi-sensor data collection.
3. Improve robustness by training with larger datasets

11. Flowchart

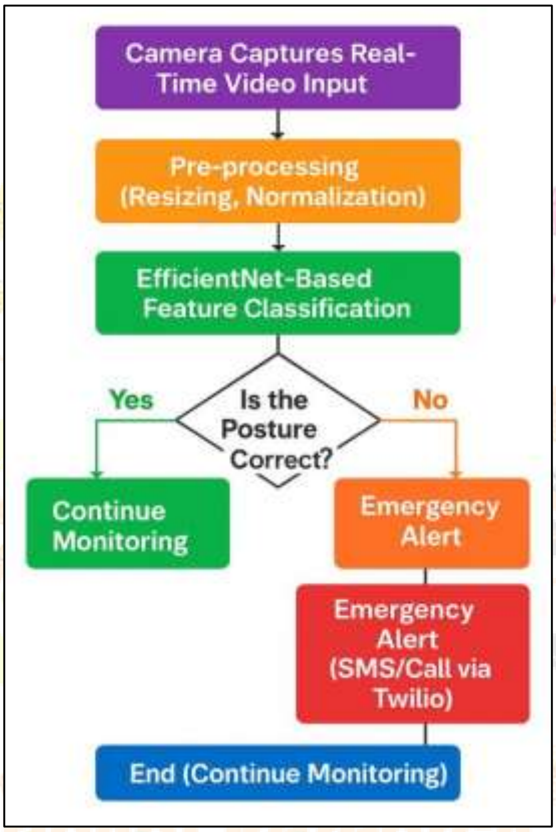

Fig 1. Flowchart for Posture Recognition Using Computer Vision & Neural Networks

12. Output Of Implementation

Fig 2: Website Home Page

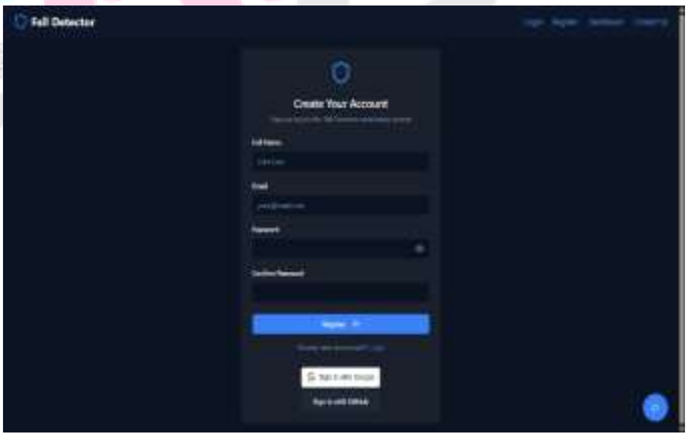

Fig 3: Register Page

Fig 4: Login Page

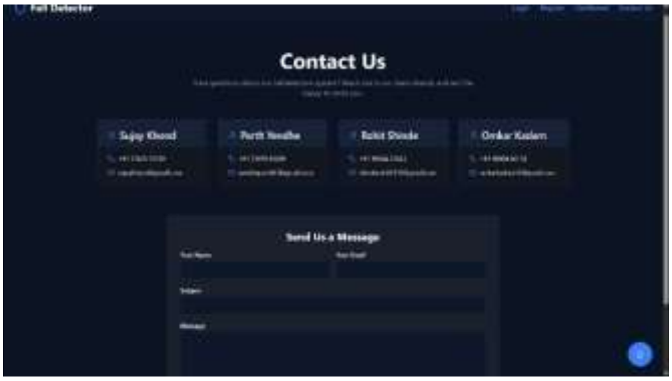

Fig 5: Contact Us Page

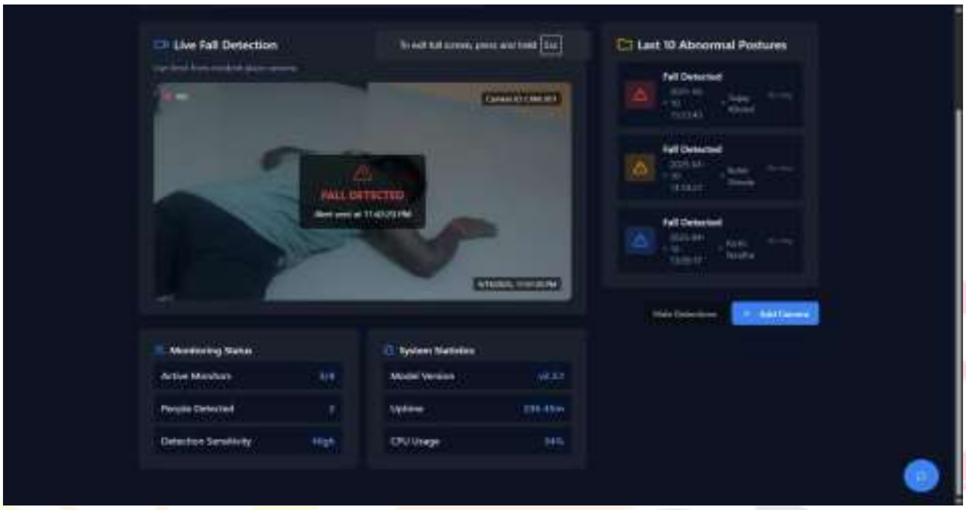

Fig 6: Dashboard Page & Live Detection

13. Conclusion

This research presents a real-time posture recognition system using EfficientNet CNN to monitor elderly individuals, ensuring their safety through continuous monitoring and intelligent alert mechanisms. The system is designed to detect abnormal postures such as falls, improper sitting, or lying positions, which are common risk factors leading to severe injuries among the elderly. By utilizing deep learning and computer vision techniques, the model efficiently processes real-time video streams to classify postures with high precision.

The results of this study demonstrate a high accuracy rate, quick response time, and robust performance in realworld scenarios, making it a reliable solution for elderly care. The system not only identifies abnormal postures but also provides an automated emergency response by notifying caregivers, activating alarms, and recording incidents for future analysis. This proactive approach significantly reduces response time in emergencies, preventing potential health complications.

Moreover, future improvements such as IoT integration, cloud-based monitoring, and deployment on edge AI devices can further enhance the system's usability and accessibility. These enhancements will ensure scalability, making the solution adaptable for home care, assisted living facilities, and hospitals, thereby revolutionizing elderly care with advanced AI-driven technology.

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