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Performance Analysis of Fall Detection in Elderly Care System Based on Video Image Processing

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Abstract

Video processing consists of signal processing employing statistical analysis and video filters to extract information or perform video manipulation. Basic video processing techniques include trimming, image resizing, brightness and contrast adjustment, and fade in and fade out, among others. In this work ,the comparison of three methods like **HFE-CNN-VR, LSTM-RNN, QWLMC-ABC are compared with the performance analysis metrics.**

Introduction

Since 2000, life expectancy has grown by five years as a result of medical advancements. Elderly people (8.5 percent of the world's population) will grow to 20 percent by 2050, according to the World Health Organization (WHO). In light of these changes, several nations are implementing healthy aging policies to enable the elderly to lead an active and autonomous life. One of the greatest problems, but also a wonderful potential, for society in the next several decades, is to ensure that the elderly have active and healthy aging (AHA). Recently, the idea of AHA has been classified as a comprehensive concept that aims to improve the quality of life (QoL) of the aging population while improving possibilities for health, involvement, and safety. Over the past few decades, the elderly population of the country has been a major source of concern for policymakers. A wide range of ailments and diseases afflict this elderly population, and their prognoses are bleak. Elderly people's health issues have grown increasingly urgent, and falls are the most prevalent mishaps that frequently need medical treatment.

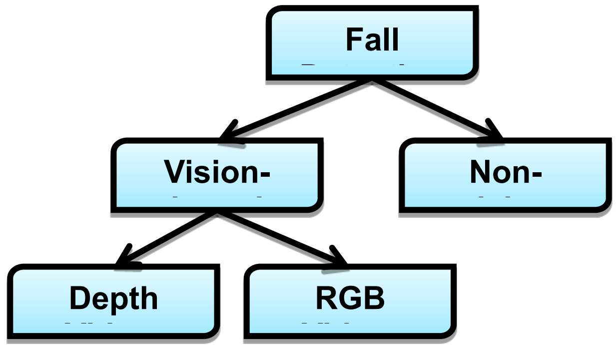

Figure 1 Categorization of fall detection

Vision-based fall detection systems have historically been implemented in ambient systems. Figure 1 illustrates the concept of vision-based system architecture. Home assistive/care systems are increasingly using cameras due to their numerous advantages over other sensor-based systems. More than one motion can be captured by a single camera, requiring less intrusion.

Litrature review

Sumiya et al. (2015) mentioned that detecting a human fall and alerting its observers is the goal of our mobile robot design. Using a Yujin Robot Kobuki, a Microsoft Kinect sensor, and a personal computer (PC), the mobile robot can recognize people and be controlled by them. The sensor is mounted on the robot so that it may follow the target in harmony, which simplifies the robot and improves the accuracy of fall detection. By moving with the robot, the sensor can decrease blind spots.

Tan et al. (2018) offered a health monitoring system that can identify an older person's unintentional fall. Both sound and accelerometer-based detections are used by the FD technique to determine if a real fall has occurred. Accurate fall detection is only possible with accelerometer-based fall detection. It’s been proven that utilizing an accelerometer separately is not adequate to reliably identify a fall, as the accelerometer wrongly calculates ADL and wrongly labels them as falls. A fall's vibration can be detected by the sound sensor, however, sound pressure alone is not a reliable sign of a fall. Using their signals, an FD system based on fuzzy logic is created to infer the occurrence of a legitimate fall through the use of a genuine fall identified by the accelerometer and a sound pressure measured during the subsequent fall. Using the fuzzy logic approach, this article shows that the algorithm can reduce the number of erroneous fall detections each day, related to the accelerometer-only FD technique.

Kong et al. (2019) mentioned that the development of an elderly fall detection IoT system based on HOG-SVM is being considered. A deep sensor is used instead of an RGB camera to get binary images of aged individuals for privacy and to withstand fluctuations in light intensity. Using Microsoft Kinect SDK, the SDK detects and tracks people, and the noise reduction algorithm reduces undesired noise. A histogram of the oriented gradient is used to extract characteristics of individuals from the denoised binary pictures, and a liner SVM is used to identify the fall status of the images. The IoT system sends an alarm to the clinic or family members if a patient falls. This research generates a database of 3500 images.

FD model development has included extensive study including senior citizens, as described by Thilo et al. (2016). Users should be involved in health technology development to better meet their wants and preferences and make these devices easier to use daily.

Liu et al. (2020) mentioned that infrared array sensors are used to suggest a non-contact method of detecting the status of the human body, which has the benefit of low price, is simple to deploy and is very accurate. By focusing on suspicious locations of body fall through basic placement, the system seeks to accomplish real-time implementation while reducing the amount of data that has to be examined.

Analysis of Fall Detection Methods

Hybrid Feature Extraction and CNN Classifier Used for VR Technology

Hybrid feature extraction-CNN can be utilized in the context of VR (Virtual Reality) technology to recognize and categorize objects, people, and other aspects in virtual environments[8]. This can be helpful for a number of purposes, such as generating VR-based training simulations or realistic and immersive VR encounters.

Hybrid feature extraction-CNN used for VR technology (HFE-CNN-VR) in fall event detection is a combination of two different techniques used in computer vision and virtual reality technologies. Algorithm 1 shows the Hybrid Feature Extraction-CNN used for VR technology (HFE-CNN-VR). The hybrid feature extraction technique involves combining multiple types of feature extraction methods, such as statistical, texture-based, and shape-based methods, to create a more robust feature representation of an image or video frame. CNN is a deep learning technique commonly used in image and video processing, which involves learning hierarchical representations of features from raw pixel values. The VR technology is used to simulate an environment in which a fall event can occur, and the HFE-CNN-VR technique is used to detect the fall event by analyzing the image or video frames captured from the simulated environment. The combination of these techniques results in a more accurate and reliable fall detection system.

Algorithm 1: HFE-CNN-VR Method

1. Initialize the HFE-CNN-VR model with appropriate hyper parameters.
2. Define the input layer of the model to accept image data.
3. Apply a set of convolutional filters to extract high-level features from the input image.
4. Use a pooling layer to reduce the dimensionality of the extracted features.
5. Add a second set of convolutional filters to extract additional features from the pooled output.
6. Use another pooling layer to further reduce the dimensionality of the second set of features.
7. Flatten the output of the second pooling layer.

8. Apply a fully connected layer to the flattened output to classify the input image.
9. Train the model using a dataset of VR images and corresponding labels.
10. Test the model on new VR images to evaluate its performance.

HFE-CNN-VR Method - Input data frame using UR fall dataset

Figure 2 : Sample videos from UR-Fall dataset

The input frame, which is from the UR fall dataset, is displayed in Figure 2.

Parameters	HFE-CNN-VR
Accuracy	80 %
Precision	62 %
Recall	90 %
F1-score	71%

Table 1 Performance analysis of HFE-CNN-VR using UR-Fall dataset

Table 1 has been filled with the results of a performance analysis of the current HFE-CNN-VR approach using the UR-Fall dataset.

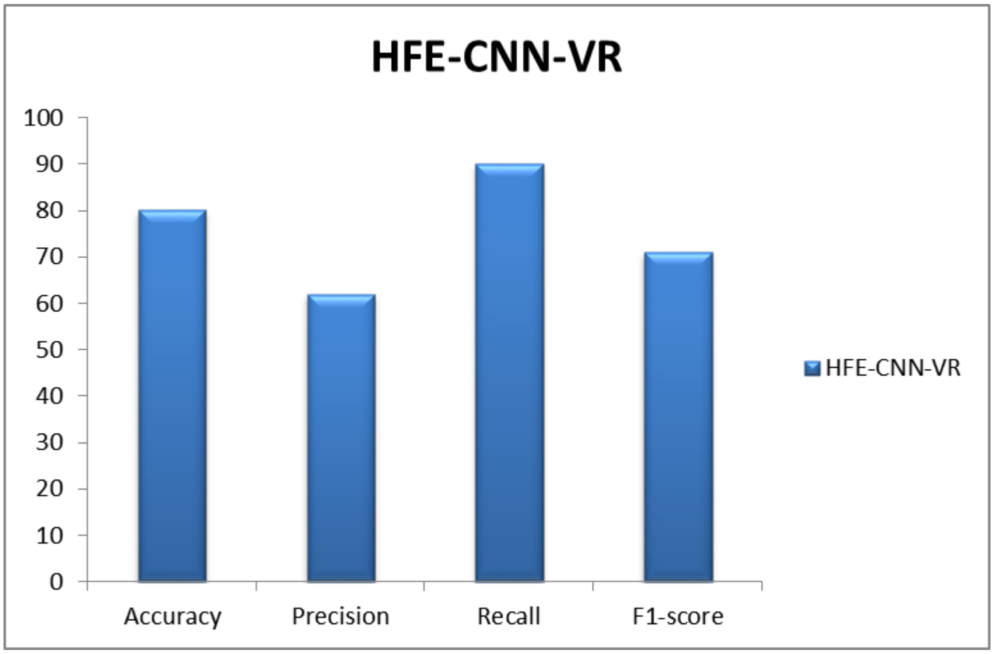

Figure 3 Performance analysis of HFE-CNN-VR using UR-Fall dataset

The HFE-CNN-VR approach is graphically depicted in Figure 3

4.3 Two Branch Stacked LSTM Based RNNs (LSTM-RNN)

A type of recurrent neural network architecture known as two-branch stacked LSTM-based RNNs processes sequential data using two parallel branches of stacked LSTM layers. LSTM, is a kind of RNN with the goal of managing long-term dependencies and avoiding the vanishing gradient problem. The input, output, and forgets gates in an LSTM cell regulate the information flow through the cell [7]. The input pattern is divided into two streams and processed by a different set of stacked LSTM layers in a two-branch stacked LSTM-based RNN. The output from each branch is then combined and either used as the final output or passed on to the following layer. When the input data has various aspects or modalities that must be handled individually, this form of architecture can be helpful. For instance, the input sequence for natural language processing could include both audio and text data. The model can more accurately capture the subtleties of each form of data and generate projections by analyzing each modality independently. All things considered, two-branch stacked LSTM-based RNNs are a potent sort of neural network design that may be applied to a number of sequential applications for data processing.

In fall event detection, the input data is usually time-series sensor data collected from wearable devices or cameras. Algorithm 2 shows the LSTM-RNN method. The LSTM-RNN can take this time-series data as input and learn the temporal patterns of the sensor data to identify falls accurately. The LSTM-RNN model has the ability to handle long-term dependencies by remembering information over long periods. It can selectively remember or forget information based on the relevance of the input data, which makes it suitable for fall event detection. The model can be trained on a labeled dataset of fall and non-fall events to learn the patterns of the

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sensor data associated with falls. During testing, the model can classify new sensor data as a fall or non-fall event based on the learned patterns.

Algorithm 2: LSTM-RNN Method

1. Initialize the LSTM cell with random weights and biases.
2. Input a sequence of data into the LSTM cell.
3. Compute the forget gate, input gate, and output gate activations.
4. Compute the cell state and hidden state activations.
5. Pass the hidden state through a fully connected layer with softmax activation.
6. Compute the loss between the predicted and actual output.
7. Backpropagate the error through the network and update the weights and biases using an optimizer.
8. Repeat steps 2-7 for a specified number of epochs.
9. Evaluate the performance of the LSTM-RNN on a held-out test set.
10. Use the trained LSTM-RNN to make predictions on new data.

LSTM-RNN Method - Input data frame using UR fall dataset

Figure 4 : Sample videos from UR-Fall dataset

Figure 4 shows that the input frame taken from UR fall dataset.

Parameters	LSTM-RNN
Accuracy	89
Precision	81
Recall	73
F1-score	81

Table 4.2 Performance analysis of LSTM-RNN using UR-Fall dataset

Performance analysis of the existing LSTM-RNN method using UR-Fall dataset has been debited in Table 4.2.

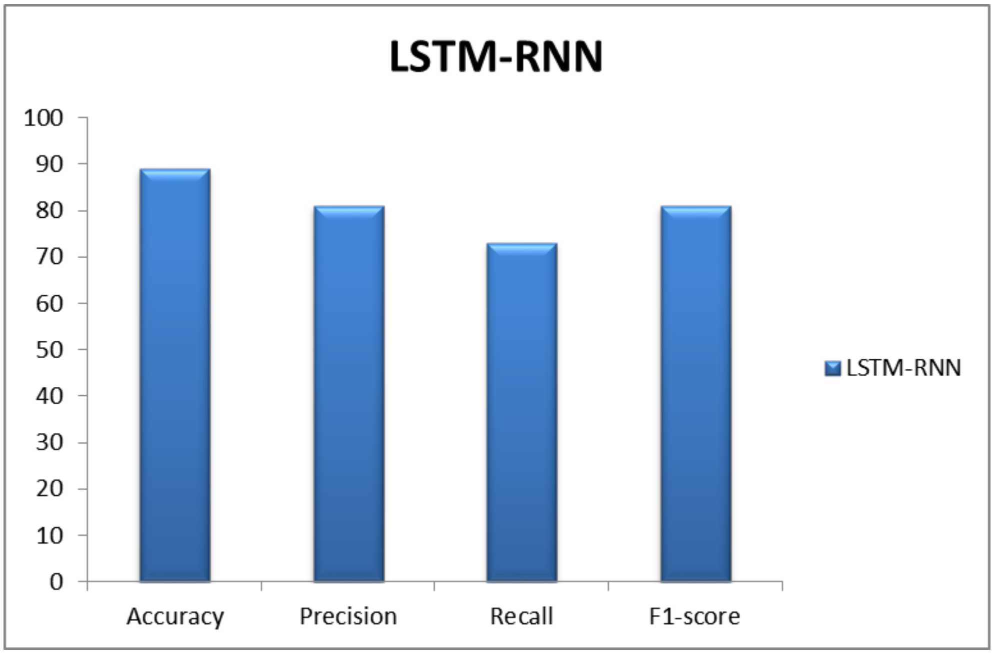

Figure 5 Performance analysis of LSTM-RNN using UR-Fall dataset

Figure 5 gives the graphical representation of LSTM-RNN method.

Quasi-Wang-Landau Monte Carlo sampling with approximate Bayesian computation (QWLMC-ABC)

Quasi-Wang-Landau Monte Carlo sampling with approximate Bayesian computation (QWLMC-ABC) is a computational method used in statistical physics and Bayesian inference. It involves using a modified version of the Wang-Landau Monte Carlo algorithm to perform a more efficient exploration of the parameter space of a model. In the context of fall event detection, QWLMC-ABC could be used to identify the parameters of a statistical model that best fit the observed fall data. This could include variables such as the age and mobility status of the faller, environmental factors such as the type of flooring or lighting conditions, and other relevant features [6].

The ABC component of the method involves using approximate Bayesian computation to estimate the likelihood of different parameter values, based on the observed fall data. This is done by simulating the model with different parameter values and comparing the simulated data to the observed data. The parameter values that produce simulated data that is closest to the observed data are considered to be the most likely.

Quasi-Wang-Landau In computational physics and statistics, respectively, Monte Carlo sampling (QWLMC-ABC) and approximate Bayesian computation are two distinct methods employed. To solve issues in both sectors, they can be integrated.

The Wang-Landau algorithm, a Monte Carlo sampling technique, is used to determine density of states of a physical entity. QWLMC-ABC is a variation of this approach. The number of configurations or states of the system that have the same amount of energy is described by a function called the density of states. By altering the system's energy landscape so that each state is sampled equally, the Wang-Landau algorithm can be used to estimate the density of states. When the energy landscape is too complex to sample all states evenly, the QWLMC-ABC variation is used, which achieves a comparable outcome by employing a semi series of energy values.

A variable or collection of parameters' posterior distribution can be roughly estimated using the statistical inference method in the presence of some observed data. When calculating the probability function, which connects the parameters to the data, is challenging or impossible, this method is frequently utilized. Instead, ABC simulates data from the model using a range of parameter values and contrasts it with the data that was actually observed. The parameter choices that result in simulated data that closely resembles the observed data are kept and applied to roughly approximating the prior probability.

When the system under study has parameters that are challenging to predict from data, QWLMC-ABC and ABC are combined. With some observed data, ABC can be used to approximate the posterior distribution of these parameters, and QWLMC-ABC can be used to construct a set of plausible parameter values. These two methods can be combined to explore a variety of physical phenomena and mathematical analysis.

Algorithm 3: QWLMC-ABC Method

1. Set the initial values for the parameters of interest and the inverse temperature beta.
2. Initialize the histogram H (E) for the energy levels E.
3. Generate an initial configuration X and calculate its energy E(X).
4. Set the acceptance probability A(X, Y) to 1.
5. Choose a random perturbation Y of the configuration X
6. Calculate the energy E(Y) of the perturbed configuration.
7. If $\mathrm{E(Y)} > E(X)$, set $\mathrm{A(X, Y)} = \exp(-\mathrm{beta} * (\mathrm{E(Y)} - \mathrm{E(x)}))$ to be the acceptance probability.
8. Generate a random number r between 0 and 1.
9. If $r <= \mathrm{A(X, Y)}$, accept the perturbation and update the histogram H(E) for E(X) and E(Y). Otherwise, reject the perturbation and update the histogram H (E) only for E(X).
10. Repeat steps 3-9 until the histogram H (E) satisfies the stopping criterion, such as a prescribed flatness or the number of iterations exceeding a maximum value. Use the histogram H (E) to compute the posterior distribution of the parameters by ABC.

QWLMC-ABC Method - Input data frame from UR-Fall dataset

Figure 6 : Sample videos from UR-Fall dataset

Figure 6 shows that the input frame taken from UR fall dataset.

Parameters	QWLMC-ABC
Accuracy	81
Precision	53
Recall	61
F1-score	56

Table 4.3 Performance analysis of QWLMC-ABC using UR-Fall dataset

Performance analysis of the existing QWLMC-ABC method using UR-Fall dataset has been debited in Table 4.3

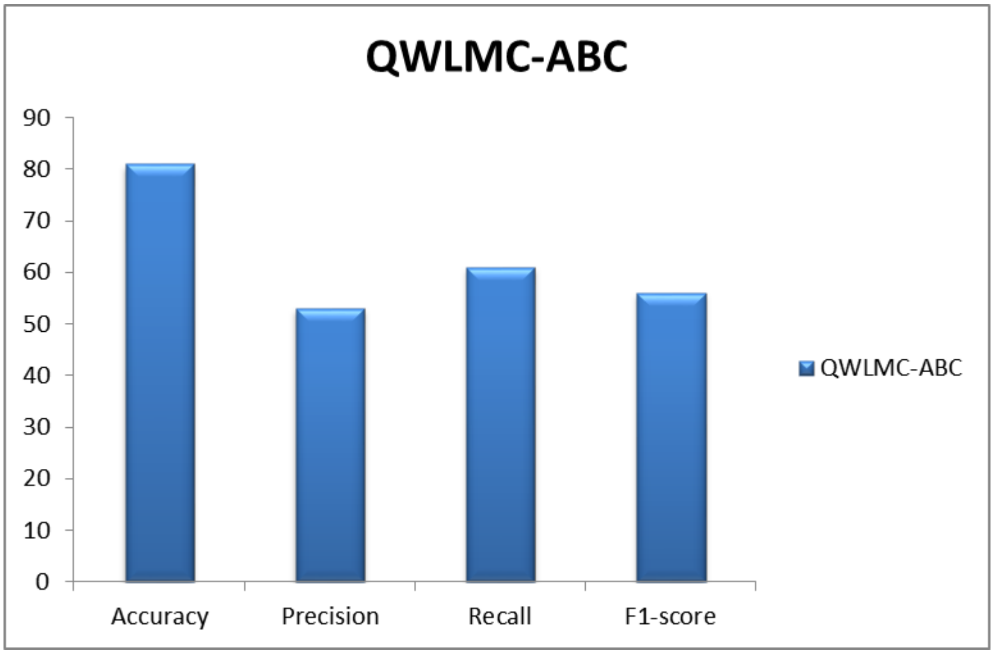

Figure 7 Performance analysis of QWLMC-ABC using UR-Fall dataset

Figure 7 gives the graphical representation of **QWLMC-ABC** method.

Result and Discussion

Table 4.4 Comparative analysis of the fall detection methods

Parameters	**Fall Detection Methods**		
	HFE-CNN-VR	**LSTM-RNN**	**QWLMC-ABC**
Accuracy	80	89	81
Precision	62	81	53
Recall	90	73	61
F1-score	71	81	56

Performance analysis of the fall detection method using UR-Fall dataset has been debited in Table 4.4

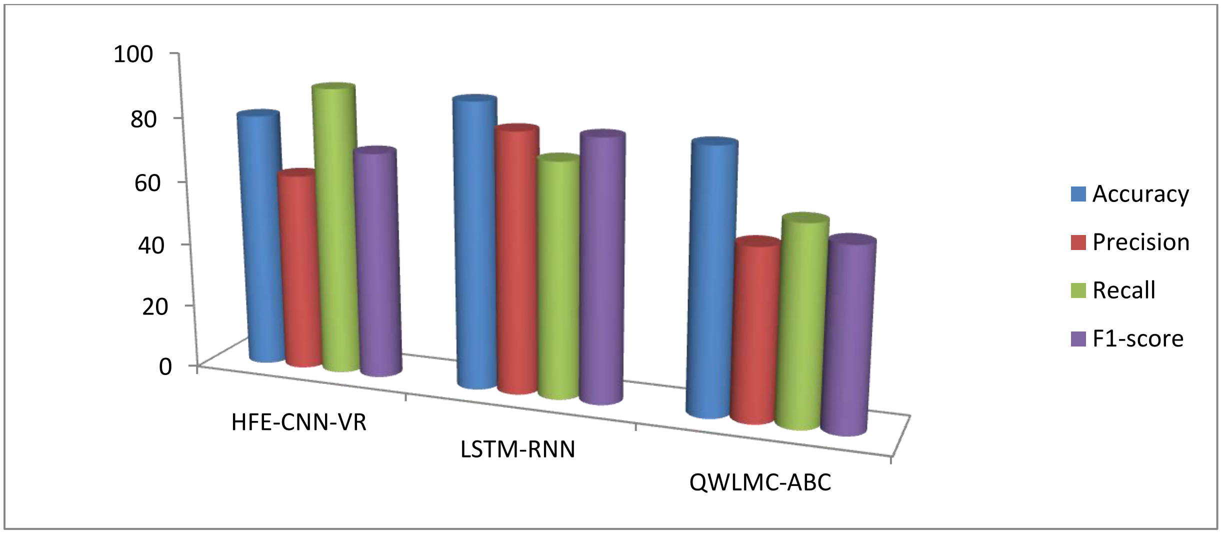

Figure 8 Performance analysis of QWLMC-ABC using UR-Fall dataset

Figure 8 Graphical representation of fall detection methods.

Conclusion

In this work, performance analysis of three existing approach Hybrid Feature Extraction-CNN used for VR technology (HFE-CNN-VR), Two Branch Stacked LSTM Based RNNs (LSTM-RNN), Quasi-Wang-Landau Monte Carlo sampling with approximate Bayesian computation (QWLMC-ABC) are used to compared to the accuracy. The goal is to identify the fall event and non-fall events.

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Authors Profile

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