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Human Activity Recognition (HAR) Using Opencv

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Abstract - *Human activity recognition (HAR) systems are a rapidly evolving area of research, with the aim of recognizing and categorizing human activities using sensor-based techniques. These systems are designed to provide real-time information about individuals' activities in a given environment, with potential applications in various fields such as healthcare, sports, and entertainment. HAR systems can recognize various activities, ranging from simple actions such as walking or sitting, to complex activities like dancing or playing a musical instrument. The accuracy of recognition depends on several factors, such as the type of sensors used, their placement on the body, the sampling frequency, and the choice of machine learning algorithms.*

In healthcare, HAR systems can be used to track and monitor the physical activities of patients with chronic conditions or disabilities. In sports, they can monitor and analyze athletes' performance, while in entertainment, they can enhance the immersive experience of gaming or virtual reality applications. In conclusion, HAR systems have the potential to transform our interactions with technology and provide personalized services based on our activities and preferences. However, further research is needed to improve the accuracy and reliability of these systems and to address the ethical and privacy concerns associated with the collection and use of personal data.

Keywords—Sensors, HAR, Recognize, Healthcare

1. INTRODUCTION

Human Activity Recognition (HAR) is a rapidly growing technology that uses sensors and data processing techniques to automatically identify and understand human activities. HAR systems utilize machine learning algorithms to analyze data from sensors, such as accelerometers, gyroscopes, and magnetometers found in wearable devices, smartphones, or smart watches, to recognize and categorize different types of activities performed by individuals. This technology has several advantages, including low cost, non-invasiveness, and ease of use. It can be applied to various fields such as healthcare, sports, security, and entertainment. HAR systems can monitor physical activities, evaluate the effectiveness of therapy, and identify suspicious behaviour, among other things. For example, in healthcare, these systems can track elderly individuals' movements to detect falls or monitor their sleep patterns. In sports, HAR systems can track athletes' movements and provide feedback on their performance. In security, these systems can identify and report suspicious activities to security personnel.

Researchers are continuously developing HAR technology, exploring new techniques to enhance accuracy, reliability, and efficiency. The ultimate objective is to create a system that can recognize various human activities accurately and automatically in real-time. However, there are also ethical and data privacy concerns that need to be addressed. Overall, HAR technology has the potential to improve individuals' quality of life by providing personalized interventions, enhancing safety and security, and promoting a healthy lifestyle.

2. LITERATURE REVIEW

The paper titled "Hybrid Posture Detection Framework: Integrating Machine Learning and Deep Neural Networks" presents a novel approach to posture detection that combines machine learning algorithms and deep neural networks. The authors aim to overcome the limitations of current methods that rely on simple heuristics or use only one type of methodology. The proposed framework consists of three stages: data acquisition and pre-processing, feature extraction and selection, and classification using a deep neural network. The authors collected a dataset of posture data from subjects performing various activities and evaluated the performance of their framework. They report high accuracy and robustness, showing potential for real-time implementation. The authors suggest that the integration of different methodologies in their framework can lead to significant improvements in posture detection accuracy. They argue that their approach has the potential to advance research in this area, particularly in the context of preventing musculoskeletal disorders. However, there are potential limitations to the practical implementation of the framework. Its complexity and computational requirements could pose challenges for deployment, and there is a risk of overfitting or underfitting due to the use of deep neural networks. Additionally, the authors note that further research is necessary to determine the framework's performance in real-world scenarios. Overall, the paper highlights the potential benefits of integrating different methodologies to improve the accuracy of posture detection. The authors' proposed hybrid approach shows promising results and opens up avenues for further research. However, the limitations of the framework must be carefully considered before its practical implementation.[1]

Sánchez, González-Vidal, and García-Sáez conducted a systematic review of literature on human activity recognition (HAR) using machine learning (ML) algorithms in 2020. The article aimed to provide a detailed analysis of the most common techniques used in the field of HAR and their performance. The authors identified 171 studies that met the inclusion criteria through a structured search strategy of various scientific journals and conference proceedings databases. They classified the studies based on the type of sensor used, the type of activity identified, the ML algorithm utilized, and the performance metrics reported. Accelerometers, gyroscopes, and magnetometers were found to be the most frequently used sensors for HAR. The most commonly used ML algorithms were support vector machines, decision trees, and artificial neural networks. The studies reported accuracy, precision, recall, and F1 score as performance metrics. The authors also highlighted the challenges in the field of HAR, which included the need for robust and accurate sensors, large and diverse datasets, and better feature extraction and selection methods. In conclusion, the article provides a comprehensive overview of the current state of HAR using ML algorithms. Researchers and practitioners interested in HAR and ML can use this resource to gain insights into the most commonly used sensors and ML algorithms and to understand the challenges in the field.[2]

The paper titled "Human Activity Recognition Using Machine Learning: A Review" by Yellanki et al. provides an extensive literature survey of the current state-of-the-art approaches to human activity recognition using machine learning. The authors aim to provide a comprehensive overview of the various aspects of human activity recognition, including sensor types, feature extraction techniques, and machine learning algorithms. The paper reviews different sensor types, such as wearable sensors, smartphone sensors, and camera-based sensors, and discusses their advantages and limitations. The authors also describe various feature extraction techniques, such as statistical, frequency domain, and time-frequency domain features, and compare their effectiveness. Furthermore, the paper explores a wide range of machine learning algorithms used for human activity recognition, including decision trees, support vector machines, artificial neural networks, and deep learning algorithms. The authors analyze the advantages and disadvantages of each algorithm and compare their performance on different datasets. The paper also addresses the challenges and limitations of human activity recognition using machine learning, such as the need for large and diverse datasets, issues with data preprocessing, and the lack of standardization in evaluation metrics. These challenges could limit the practical implementation of the approaches discussed in the paper. Overall, the paper provides a comprehensive overview of the current research in human activity recognition using machine learning. The authors highlight the challenges and limitations of the existing approaches and suggest potential research directions. The paper can serve as a valuable reference for researchers and practitioners working in this area, helping them to better understand the strengths and weaknesses of different methodologies and to identify new research opportunities.[3]

Madadi, Bayat, and Argha (2020) conducted a literature review on the use of deep learning methods for human activity recognition (HAR). They discussed the limitations of traditional approaches that used handcrafted features and classification algorithms, such as the need for domain expertise and inability to handle complex data. The authors focused on deep learning methods as they can automatically learn features and handle complex data. They discussed different types of deep learning models, including CNNs, RNNs, and their variants, and reviewed the latest research in the field, categorizing them based on the type of sensor data used, such as accelerometer, gyroscope, and magnetometer. The authors also discussed the datasets commonly used for HAR research and the evaluation metrics used to measure model performance. They identified challenges in HAR using deep learning, such as the need for large and diverse datasets, handling class imbalance, and dealing with sensor noise and missing data. The authors also discussed the importance of interpretability and ethical implications of HAR. In conclusion, the authors suggested future directions for HAR research using deep learning, such as incorporating multimodal sensor data, addressing privacy concerns, and improving model interpretability. Madadi, Bayat, and Argha (2020) provided a comprehensive review of the latest research in HAR using deep learning methods, which can be a valuable resource for researchers and practitioners working in the field.[4]

Nweke et al. (2020) conducted a comparative study of deep learning techniques for human activity recognition (HAR) using wearable sensors. They reviewed the challenges of HAR, such as sensor noise and variability in human movements, and the need for real-time processing. They discussed the different sensors used for HAR and data preprocessing techniques, such as filtering and normalization, to prepare the data for analysis. They compared the performance of different deep learning architectures, including convolutional neural networks (CNNs), recurrent neural networks (RNNs), and hybrid models combining CNNs and RNNs, on several publicly available datasets. Their results showed that CNNs and RNNs are promising deep learning techniques for HAR, with CNNs performing well for time-series data and RNNs performing well for sequential data. Hybrid models combining CNNs and RNNs can leverage the strengths of both approaches and achieve higher accuracy. The authors identified the sensitivity to hyperparameters, the need for large datasets, and the computational complexity as limitations of each approach. The authors suggested that future research should focus on developing more efficient and scalable deep learning architectures for HAR and exploring the use of transfer learning and unsupervised learning techniques. Overall, their paper provides a comprehensive comparison of deep learning techniques for HAR using wearable sensors, highlighting the strengths and limitations of each approach. It can be a useful resource for researchers and practitioners interested in HAR and deep learning.[5]

In their 2019 review, Amelard, Roy, and Toth provided an extensive analysis of human activity recognition (HAR) with wearable sensors. The review emphasized the significance of HAR in various fields, including healthcare, sports, and human-computer interaction. The authors outlined the key concepts, methodologies, and challenges related to HAR, along with an overview of the various types of sensors used for HAR. The authors presented a comprehensive review of the state-of-the-art methods used for HAR, including feature extraction, classification, and sensor fusion. They discussed the advantages and limitations of each method and highlighted the need for more accurate and reliable techniques to improve the performance of HAR systems. Furthermore, the review covered the commonly used datasets for evaluating HAR algorithms, including publicly available datasets like UCI-HAR and OPPORTUNITY. The authors emphasized the importance of benchmarking and standardization in the field of HAR to facilitate comparison and reproducibility of results. In addition to the technical aspects, the review also discussed ethical considerations related to the use of wearable sensors for HAR. Privacy, consent, and data ownership were identified as crucial factors. The authors concluded that transparent and responsible data management practices are necessary to ensure the protection of individual rights. Overall, the review by Amelard et al. (2019) provides a comprehensive overview of the current state-of-the-art in HAR with wearable sensors. The authors identified a need for further research to improve the accuracy and reliability of HAR systems while addressing the ethical challenges associated with the use of wearable sensors. [6]

Chen et al. (2019) proposed a novel method for human activity recognition (HAR) using joint cross-domain feature learning and adaptive weighting deep neural networks (DNNs). The authors address the challenges of HAR, such as the variability in human movements and the need for robust feature extraction methods. Their approach uses a cross-domain feature learning method that extracts features from multiple domains, such as time-domain, frequency-domain, and spatial-domain, and integrates them into a joint feature representation. They then employ principal component analysis (PCA) to reduce the dimensionality of the features, which improves the efficiency of the learning process. To further improve the performance of their approach, the authors introduce an adaptive weighting DNN (AW-DNN) that dynamically adjusts the weights of different features based on their relevance to the activity being recognized. The AW-DNN consists of a feature weighting layer and a fully connected neural network layer. The feature weighting layer computes the weights of the input features, and the neural network layer performs classification based on the weighted features. Chen et al. evaluated the performance of their approach on two publicly available datasets, including the UCI-HAR dataset. The results showed that their method achieved higher accuracy compared to several state-of-the-art HAR methods. They also conducted sensitivity analysis and ablation study to investigate the impact of different factors on the performance of their method. In conclusion, Chen et al.'s method is a promising approach to HAR, as it combines cross-domain feature learning with adaptive weighting DNNs. This allows for the effective extraction of discriminative features from multiple domains and the dynamic adjustment of the feature weights, which results in higher accuracy in HAR. The paper provides valuable insights into the design of deep learning models for HAR and can be a useful resource for researchers and practitioners in this field.[7]

Kumar and Hossain's (2019) paper presents a method for human activity recognition (HAR) using convolutional neural networks (CNNs) with transfer learning. The authors address the challenges of HAR, including the need for robust feature extraction methods and the limited availability of labeled data. Their proposed method uses a pre-trained CNN model on Image Net and fine-tunes the last few layers on a small amount of labeled HAR data. The authors also employ data augmentation techniques to reduce overfitting and improve the model's generalization performance. Kumar and Hossain evaluate their method on two publicly available datasets, including the UCI-HAR dataset. The results show that their method achieves higher accuracy compared to several state-of-the-art HAR methods. The authors also conduct a sensitivity analysis to investigate the impact of different factors on the performance of their method. In conclusion, Kumar and Hossain's method is a promising approach to HAR, as it utilizes transfer learning from a pre-trained CNN model on ImageNet and adapts it to the HAR task. The fine-tuning and data augmentation techniques further improve the model's performance. The paper provides valuable insights into the design of deep learning models for HAR and can serve as a useful reference for researchers and practitioners in this field.[8]

Zhao and Tian's (2019) paper presents a hybrid approach for human activity recognition (HAR) using wearable sensors that combines deep learning and handcrafted feature extraction methods. Their proposed approach addresses the limitations of traditional methods that rely solely on statistical or machine learning algorithms for feature extraction and classification. The method consists of two stages: feature extraction and classification. In the feature extraction stage, the authors extract time-domain and frequency-domain features from the raw sensor data using statistical methods and a convolutional neural network (CNN) model, respectively. The extracted features are then combined using principal component analysis (PCA) to reduce the dimensionality of the data. In the classification stage, the authors use a support vector machine (SVM) model to classify the activities based on the reduced feature set. The authors evaluated their method on two publicly available datasets, including the UCI-HAR dataset. The results demonstrate that their method achieves higher accuracy compared to several state-of-the-art HAR methods, including those that use only deep learning or handcrafted features. The proposed approach improves the accuracy and robustness of HAR systems and has potential applications in healthcare, sports, and other fields. In conclusion, Zhao and Tian's hybrid approach provides a promising solution to HAR by combining the strengths of both deep learning and handcrafted feature extraction methods. The paper provides valuable insights into the design of HAR systems and can serve as a useful reference for researchers and practitioners in this field. The method's effectiveness in recognizing human activities using wearable sensors makes it a relevant contribution to the literature on HAR, with potential practical applications in various fields.[9]

The paper by Yao et al. (2018) provided a comprehensive literature review on the use of sensor-based systems for human activity recognition (HAR). HAR has gained significant attention in recent years due to its potential applications in various fields such as healthcare, sports, and security. The authors presented an overview of the fundamental concepts of HAR, including the types of sensors used, data collection methods, feature extraction, and classification techniques. They also reviewed the existing literature on HAR categorized by the types of sensors used, and discussed the advantages and limitations of each sensor type. Furthermore, the authors highlighted the latest advancements in deep learning techniques such as CNNs, RNNs, and LSTMs, and their potential applications in HAR. They emphasized the importance of addressing the challenges and open issues in HAR, such as data privacy, sensor placement, and sensor fusion. Overall, the paper provides a valuable reference for researchers and practitioners in the field of HAR. The authors stressed the need for further research in HAR to improve the accuracy and reliability of these systems.[10]

3. PROPOSED WORK DESCRIPTION

Human activity recognition is the task of identifying and categorizing different human activities based on images or sensor data such as accelerometers and gyroscopes. Two machine learning algorithms that are commonly used for human activity recognition are Random Forest and Convolutional Neural Networks (CNNs).To develop a human activity recognition system, the first step is to collect and pre-process the sensor data by removing noise and filtering. Next, relevant features are extracted from the pre-processed data using a CNN. This approach can improve the accuracy of the model as CNNs can learn and extract features from the raw sensor data. The CNN output can then be utilized as input features for the Random Forest algorithm.

Once the features are extracted using CNN, a Random Forest model is trained on the pre-processed data and extracted features. Random Forest is a powerful algorithm that can handle complex feature interactions and nonlinear relationships between features and activity classes. However, to achieve optimal performance, the number of trees, maximum depth of each tree, and other hyperparameters need to be tuned. After the model is trained, it is evaluated on a test dataset to measure its accuracy, precision, recall, and F1-score. The final step is to deploy the trained model on a mobile device or a cloud server to perform real-time activity recognition. However, it's worth noting that using a combination of CNN and Random Forest may require more computational resources and can be more complex to implement than using a single machine learning algorithm for human activity recognition.

4. SYSTEM ARCHITECTURE

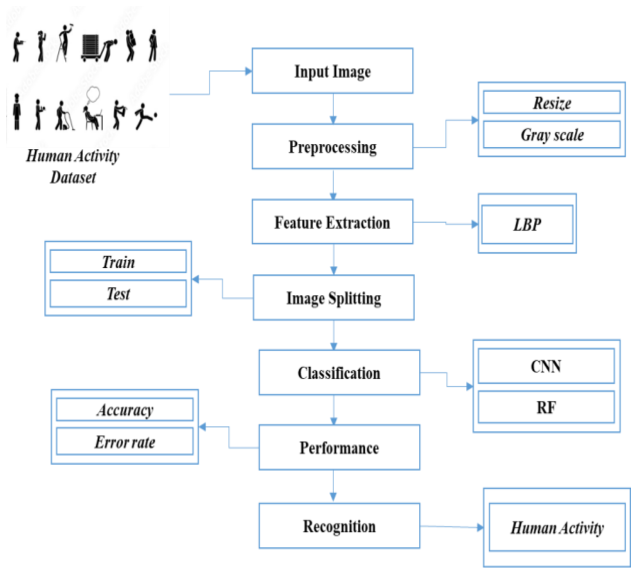

Figure 1: System Architecture

5. METHODOLOGY

In proposed system, the image dataset was taken as input of any image format. Then, we have to implement the pre-processing step. In this step, we have to resize the original image and convert the image into gray scale. Then, we have to implement the Local Binary Pattern for finding the unique features of an image. After that, use the Convolution neural network algorithm with rectifier linear unit to change the image into numerical vectors corresponding to the trained activities and pass them to Random Forest algorithm which uses the numerical vectors in contrast with the features of the trained activities to predict the output with high accuracy and prediction.

5.1 Preprocessing

In order to preprocess an image dataset for a Human Activity Recognition (HAR) system, the first step is to collect and label images of human activities. Once collected, the images are resized and normalized to ensure consistency and reduce computational complexity. Additional data augmentation techniques such as rotation, flipping, and zooming can be applied to increase the number of images and avoid over fitting. Relevant features are then extracted from the images using methods like Histogram of Oriented Gradients (HOG), Local Binary Patterns (LBP), or Convolutional Neural Networks (CNNs), followed by selecting the most representative features using techniques such as Feature Importance Ranking. The dataset is then split into training, validation, and testing sets, with the features being normalized and reduced in dimensionality. A classification model is then trained on the preprocessed data using methods Random Forests, or Neural Networks. Finally, the performance of the model is evaluated on the testing set using metrics such as accuracy, precision, and recall.

Fig. : 2 Original Image

Gray scale conversion is the process of converting a color image to black and white by extracting the luminance values of each pixel in the image. Different methods of grayscale conversion exist, including the luminance method, the average method, and the weighted average method. The luminance method computes the weighted sum of the red, green, and blue values of each pixel. The average method calculates the average of the red, green, and blue values of each pixel, while the weighted average method uses different weights to compute the average value of the color channels. The selection of the grayscale conversion method is dependent on the intended use of the image and the computational resources available.

$$ImgGray = 0.2989 * R + 0.5870 * G + 0.1140 * B$$

Fig. : 3 Gray Scale Image open CV

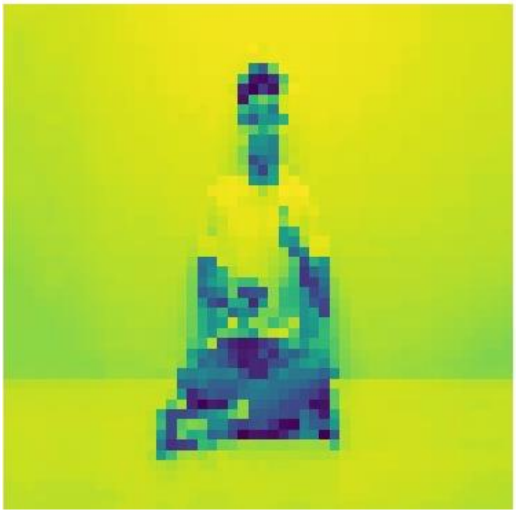

Fig. : 4 Gray Scale Image Python

5.2 Featured Extraction

Human activity recognition is the process of identifying human activities from sensor data, including image datasets. Local Binary Patterns (LBP) is a feature extraction technique that encodes the texture of an image by comparing each pixel with its neighboring pixels. To use LBP and open cv for feature extraction in image datasets, several steps can be taken. First, preprocessing is necessary to ensure all images have the same size and resolution. Then, the LBP feature vector is extracted for each image using the scikit-image library's LBP algorithm. Next, open cv can be used to create visualizations, such as histograms or scatter plots, to better understand the texture of the images. Finally, machine learning algorithms, such as Random Forest, can be used to classify the human activities based on the LBP feature vectors.

Overall, the LBP and open cv is a powerful approach to extract features and visualize the texture of image datasets for human activity recognition.

Fig. : 5 LBP open Cv

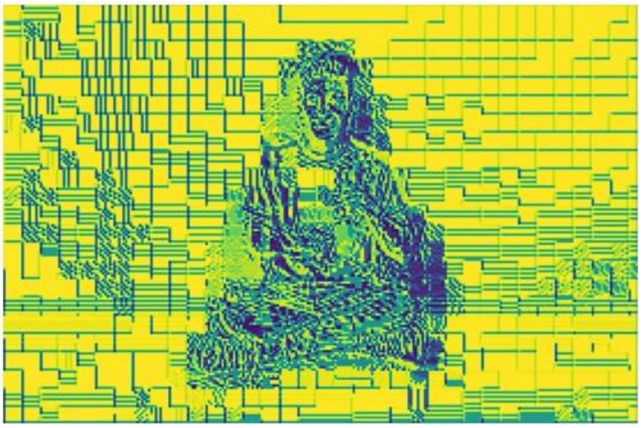

Fig. : 6 LBP Python

5.3 Data Splitting

Building a human activity recognition system involves several steps, and one crucial step is data splitting. This involves dividing the dataset into training, validation, and testing sets to ensure that the model generalizes well to new data. Typically, a split of 60% for training, 20% for validation, and 20% for testing is used, although this may vary depending on the size and complexity of the dataset.

Before training the model, the data needs to be preprocessed by normalizing, scaling, or transforming it as necessary. Once the data is ready, the model can be trained on the training set, and different models can be tried to find the best fit. The validation set is used to tune the model's and prevent over fitting. Finally, the testing set is used to evaluate the model's performance on new, unseen data. It's important to note that the splitting ratio and other factors such as class balance and temporal dependencies should also be considered when splitting the data. By following these steps and ensuring that the model is well-trained and validated, we can build a robust human activity recognition system that accurately identifies different activities. In our proposed system the system use 80% of the data is used for training and 20% of the data is used for testing.

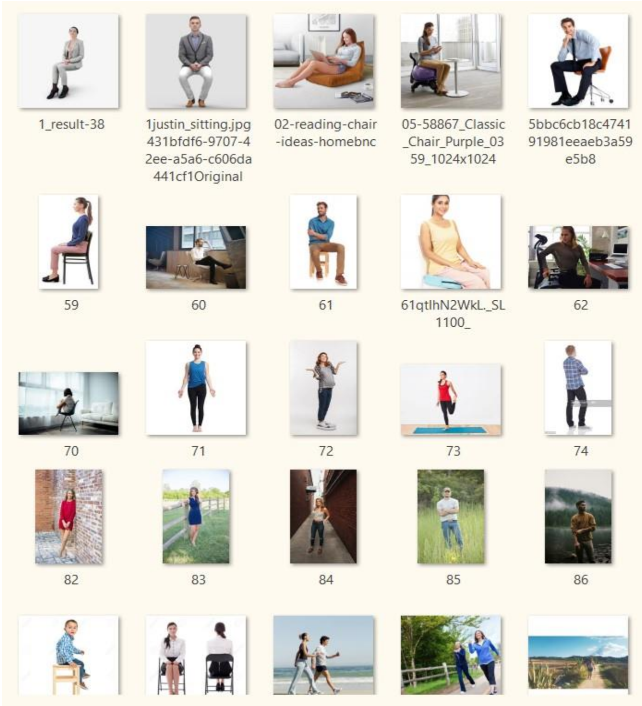

Fig. : 7Training Datasets

5.4 Classification

Human activity recognition (HAR) is the task of classifying the actions performed by a human based on sensor data, such as accelerometer and gyroscope data, collected from wearable devices. **Convolutional Neural Networks** (CNNs) are a type of deep learning model that have been shown to be effective in many computer vision tasks, including image classification, object detection, and segmentation. The first step in using CNNs for HAR is to preprocess the sensor data to create a suitable input format for the CNN. The sensor data can be represented as a time series of sensor readings, where each reading represents the acceleration or rotation in a particular direction at a particular time. The data is typically preprocessed to remove noise and perform feature extraction, such as calculating the magnitude of the acceleration or the frequency of the signal. Once the data has been preprocessed, it is transformed into a suitable input format for the CNN. Here the **dataset is collected from Kaggle** website. There are several ways to represent the data as an input to the CNN, including: Time-Distributed CNNs: In this approach, the sensor data is transformed into a sequence of feature vectors, where each vector represents the sensor readings at a particular time. The sequence of feature vectors is fed into a CNN with a time-distributed layer that applies the same set of filters to each feature vector independently. The outputs of the time-distributed layer are concatenated to form a sequence of feature maps, which are then fed into a fully connected layer for classification.

2D CNNs: In this approach, the sensor data is represented as a 2D matrix of time vs. sensor data, where the rows represent the time steps and the columns represent the different sensor readings. The 2D matrix is fed into a CNN with one or more convolutional layers that apply filters to the input data to learn spatial and temporal features. The output of the convolutional layers is then fed into one or more fully connected layers for classification.3D CNNs: In this approach, the sensor data is represented as a 3D matrix of time vs. sensor data vs. features, where the features can include accelerometer data, gyroscope data, and other sensor data. The 3D matrix is fed into a CNN with one or more 3D convolutional layers that apply filters to the input data to learn spatial and temporal features. The output of the 3D convolutional layers is then fed into one or more fully connected layers for classification.

Once the CNN has been trained on a dataset of labeled sensor data, it can be used to classify the actions performed by a human based on new sensor data. The input sensor data is transformed into the appropriate input format for the CNN, and the CNN outputs a probability distribution over the possible actions. The action with the highest probability is chosen as the predicted action. Overall, CNNs are a powerful tool for human activity recognition, and the specific approach used will depend on the characteristics of the input data and the requirements of the application.

```
Layer (type)                 Output Shape              Param #
=================================================================
input_3 (InputLayer)         [(None, 100, 100)]        0

sequential (Sequential)      (None, 32)                320032

sequential_1 (Sequential)    (None, 100, 100)          330000

=================================================================
Total params: 650,032
Trainable params: 650,032
Non-trainable params: 0
_________________________________________________________________
None
1/1 [==============================] - 3s 3s/step
1/1 [==============================] - 0s 382ms/step
==========================================
```

Fig. : 8 Passing of training data

A **Convolutional Neural Network** (CNN) is a type of neural network that is commonly used for image recognition tasks. CNNs are specifically designed to work with input data that has a grid-like structure, such as images. The network consists of several layers, including convolutional layers, pooling layers, and fully connected layers. Convolutional layers are responsible for extracting features from the input data by performing a convolution operation using filters. This process identifies important patterns and structures in the image that can be useful for recognizing characters. Pooling layers are used to down sample the output of the convolutional layers, reducing the size of the data and making the network more efficient. Fully connected layers are responsible for making predictions about the input image by using the extracted features from the convolutional and pooling layers.

```
Model: "sequential_2"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
conv2d (Conv2D)              (None, 50, 50, 16)        208

max_pooling2d (MaxPooling2D  (None, 25, 25, 16)        0
)

conv2d_1 (Conv2D)            (None, 25, 25, 32)        2080

max_pooling2d_1 (MaxPooling  (None, 12, 12, 32)        0
2D)

conv2d_2 (Conv2D)            (None, 12, 12, 64)        8256

max_pooling2d_2 (MaxPooling  (None, 6, 6, 64)          0
2D)

dropout (Dropout)            (None, 6, 6, 64)          0

flatten_1 (Flatten)          (None, 2304)              0

dense_2 (Dense)              (None, 500)               1152500

dropout_1 (Dropout)          (None, 500)               0

dense_3 (Dense)              (None, 2)                 1002

=================================================================
Total params: 1,164,046
Trainable params: 1,164,046
Non-trainable params: 0
_________________________________________________________________
```

Fig. : 9 Training Model

During training, the CNN is presented with a limited dataset of labeled images. The network then adjusts its weights through back propagation, which involves computing the gradient of the loss function with respect to the network's parameters and updating the weights accordingly. Once the CNN is trained, it can recognize characters in new images by feeding them through the network and examining the output of the fully connected layers. The label with the highest probability is typically chosen as the recognized label.

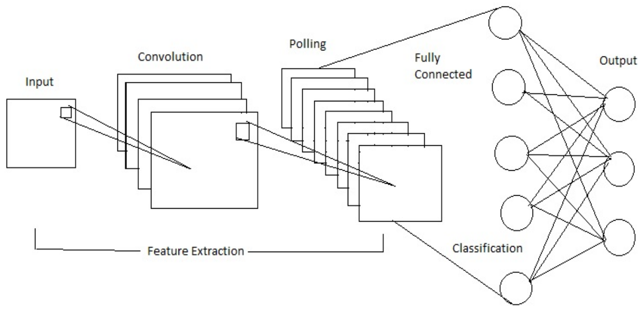

Fig. :10 CNN Architecture

Random Forest is a popular machine learning algorithm that can be used for human activity recognition from CNN (Convolutional Neural Network) features. CNNs are a type of deep learning neural network that are commonly used in computer vision applications, including human activity recognition. To use Random Forest for human activity recognition from CNN features, you would first need to train a CNN on a dataset of human activity videos or sensor data. The CNN would learn to extract meaningful features from the input data, which could then be used as inputs to a Random Forest classifier. Once you have trained the CNN and extracted features from the training data, you can train a Random Forest classifier on the features. The Random Forest classifier would learn to predict the activity label based on the input features. For example, you could experiment with different values of the number of trees, the maximum depth of the trees, and the number of features to consider at each split. Overall, using Random Forest for human activity recognition from CNN features can be an effective approach for accurately classifying human activities in real-time applications.

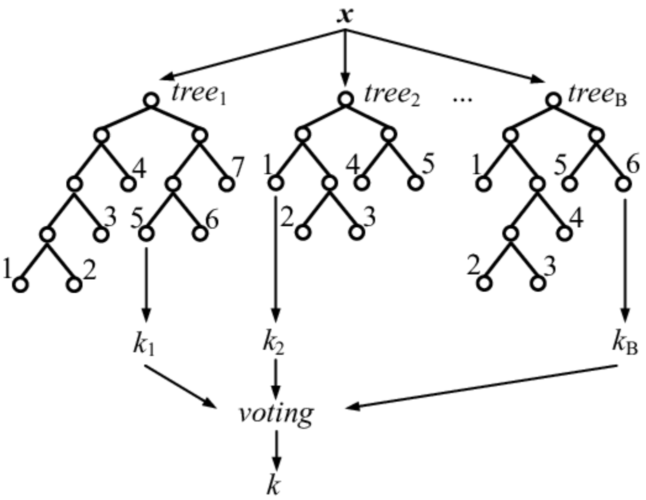

Fig. 11: Random Forest Architecture

5.5 Performance Metrics

Performance metrics play a crucial role in evaluating the effectiveness of human activity recognition systems. The accuracy, precision are commonly used metrics to measure the performance of these systems. Accuracy refers to the percentage of correctly classified instances, while precision represents the ratio of true positives to the total number of positive predictions. The Final Result will get generated based on the overall classification and prediction. The performance of this proposed approach is evaluated using some measures like, Accuracy, Error Rate.

```
---------------------------------
CONVOLUTIONAL NEURAL NETWORK (CNN)
---------------------------------

Epoch 1/5
62/62 [==============================] - 9s 57ms/step - loss: 0.6932
Epoch 2/5
62/62 [==============================] - 26s 424ms/step - loss: 0.6930
Epoch 3/5
62/62 [==============================] - 3s 55ms/step - loss: 0.6929
Epoch 4/5
62/62 [==============================] - 3s 55ms/step - loss: 0.6928
Epoch 5/5
62/62 [==============================] - 4s 57ms/step - loss: 0.6926
4/4 [==============================] - 1s 43ms/step
---------------------------------
PERFORMANCE --------> (CNN)
---------------------------------

1) Accuracy    = 94.0 %

2) Specificity =  90.0 %

3) Sensitivity =  100.0 %
```

Fig. : 12 CNN Performance

5.6 Accuracy

Accuracy of classifier refers to the ability of classifier. It predicts the class label correctly and the accuracy of the predictor refers to how well a given predictor can guess the value of predicted attribute for a new data.

$$AC= (TP+TN)/ (TP+TN+FP+FN)$$

```
Model: "sequential_3"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 resnet50 (Functional)       (None, 2, 2, 2048)        23587712

 dense_4 (Dense)             (None, 2, 2, 512)         1049088

 dropout_2 (Dropout)         (None, 2, 2, 512)         0

 dense_5 (Dense)             (None, 2, 2, 512)         262656

 dropout_3 (Dropout)         (None, 2, 2, 512)         0

 dense_6 (Dense)             (None, 2, 2, 1)           513

=================================================================
Total params: 24,899,969
Trainable params: 1,312,257
Non-trainable params: 23,587,712
_________________________________________________________________
-------------------------------------
PERFORMANCE ---------> (RESNET)
-------------------------------------

1) Accuracy    =  96.0 %

2) Specificity =  93.33333333333333 %

3) Sensitivity =  100.0 %
```

Fig. : 13 CNN+RF Performance

Output:

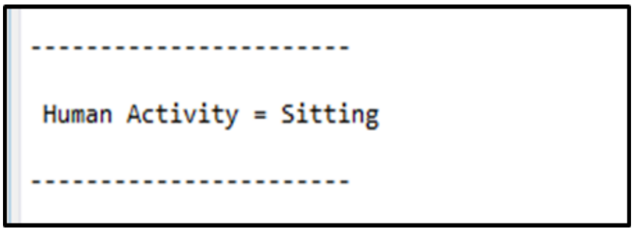

Fig. : 14 Predicted output

6. CONCLUSION

In our proposed system we have used various algorithms to perform Human Activity Recognition System. The input image is resized and preprocessed into grayscale image. Then, the preprocessed image is given as the input to implement the Local Binary Pattern (LBP) to identify the unique features of the image. The resulted image is passed into the Convolution neural network to classify according to the category. The classified image in numerical format vector is sent into the Random Forest Algorithm and the algorithm checks whether the numerical vector is in similar with the decision trees which are trained with the activities. The model is trained with sleeping, sitting, walking, stairs and standing, in future it can also be increased to recognize various activities.

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