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HUMAN ACTIVITY RECOGNITION BY USING ARTIFICIAL INTELLIGENCE

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Abstract - Since these machine learning approaches have been so successful in extracting and learning from activity datasets, they have lately attracted a lot of attention from researchers looking into Activity Recognition (AR) issues. From old-school, feature-based machine learning algorithms built by heurists to newer, hierarchically self-evolving deep learning algorithms, the methodologies cover the gamut. Despite researchers' best efforts, augmented reality (AR) remains a difficult challenge in unmanaged smart settings. In the real world, augmented reality systems face a number of obstacles caused by the activity data's complicated, volatile, and chaotic character. We provide a thorough review of the current state of augmented reality (AR) systems, as well as the fundamental issues and difficulties related to them, as well as a survey of the most up-to-date machine learning and data mining methods used in AR. In an effort to pinpoint potential avenues for future activity identification research, we also detail the latest developments and state-of-the-art methods in this field.

Keyword: - Activity Recognition, Data Mining, Machine Learning, Transfer Learning, Deep Learning, Active Learning, Wearable Sensors.

I. INTRODUCTION

The chapter delves into the fundamental idea and covers all the necessary details. One significant area of computer vision is human activity identification, which involves the automatic detection of human actions in video footage. Human activity recognition has had tremendous growth in the last decade, in line with societal expectations to build a range of critical applications such as smart surveillance, gadgets to improve the quality of life for the elderly, and human-computer interfaces. The area of action recognition is slowly but surely progressing beyond the identification of basic human motions like walking and running, and towards the recognition of complicated realistic human activities involving several people and things. In particular, methods that used spatio-temporal aspects have shown promising outcomes in activity identification in real-world settings throughout the last five years. These methods get their inspiration from the effectiveness of scale-invariant local patch features in object identification; they use the three-dimensional video volume created by joining picture frames along the time axis to extract sparse local features. Actions (like films) may be effectively classified using the bag-of-words paradigm, which disregards feature placements.

Nevertheless, a crucial component of human activity analysis is omitted by the majority of the current activity identification methods. Prior studies, like the ones mentioned, have mostly dealt with human activity recognition after the fact, after the whole video sequence has been seen. As a result, these methods aren't well-suited for detecting incomplete actions in video streams early on. Identifying a human's (e.g., criminal's) planned conduct before they completely execute it is a need in many real-world settings. Recognising the absence of certain items after their theft, for instance, could not have any practical use in a monitoring setting. If the system could anticipate the continuing theft activities as early as feasible using live video observations, it might be more beneficial in preventing theft and catching the perpetrators. Similarly, for an autonomous car to successfully avoid an accident, its vision system must be able to foresee the impending collision and intervene in time to prevent harm. Traditional sequential models, such hidden Markov models (HMMs), may be extended to approximatively solve the prediction issue, but they are ill-suited to contemporary high-dimensional characteristics that provide a sparse discontinuous picture of the video. It is essential to provide a novel approach to activity prediction that can identify a partially completed activity in a video that just shows the beginning of the activity. Formally defined in this work as an inference of the current activity given temporally imperfect information, activity prediction is shown in Figure 1. This study presents novel approaches for activity prediction and introduces the concept of activity prediction. Our goal is to pave the way for the development of an AI system capable of real-time early identification from live video broadcasts. We provide a probabilistic formulation of the prediction issue and talk about new approaches to effectively estimate the activity's continuing state, which solves the problem. In this research, we provide two novel approaches to human activity prediction that can handle incomplete activity films. The posterior probability of "which activity has progressed to which point of the activity" is computed using these approaches and the available data. We use 3-D XYT spatio-temporal characteristics that are robust against noise, dynamic backgrounds, and scale shifts. By simulating the evolution of activity feature distributions with more observational data, we developed a technique to activity prediction we termed integral bag-of-words. The activities are represented by integral histograms, which are built using training data.

video clips. Also, the prediction algorithm is enhanced to take into account the sequential structure established by video characteristics, and a novel recognition technique called the dynamic bag-of-words approach is created. We use a dynamic programming approach to calculate structural similarities between activity models and partial data.

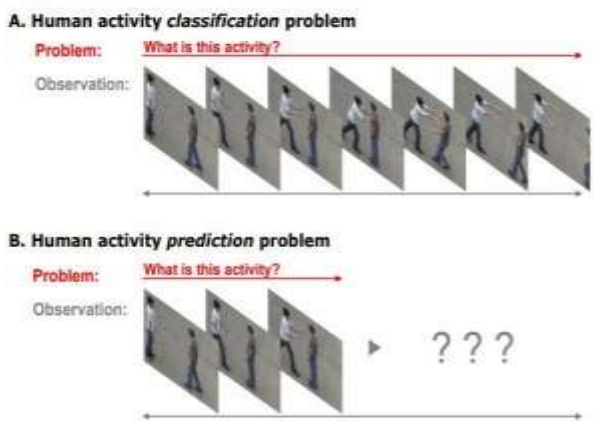

Fig. 1.1. A comparison between the activity classification problem and the activity prediction problem.

In contrast to the classification task, a system is required to infer the ongoing activity before fully observing the activity video in the prediction task.

Digital activity video has become Associate in nursing integral a part of lifestyle and other image processing application. It's well-known that activity video improvements a lively topic in computer vision has received a lot of attention in recent years. The aim is to boost the visual look of the activity video, or to supply a "better" rework illustration for future machine-driven activity video process, like analysis, detection, segmentation, and recognition. Moreover, it helps analyses background info that's essential to know object behavior while not requiring costly human visual examination. There square measure varied applications wherever digital activity video is no inheritable , processed and used, like investigation, general identification, criminal justice systems, civilian or military activity video process. Additional and additional activity video cameras square measure wide deployed in several eventualities e.g. Public places, production Plants, domestic investigation systems etc. Most of the activity video cameras add the outdoors which implies the standard of activity video depends on the climatic conditions. The camera and activity video investigation systems square measure expected effective altogether lighting and climatic conditions, however the bulk of those cameras weren't designed for slow-lighting, so the poor capture quality of activity video camera makes the activity video unusable for several applications in unhealthy conditions e.g. dark night, soaking rain, significant snow and fog. Over the last many decades, there are substantial capability enhancements in digital cameras as well as resolutions and sensitivity. Despite these enhancements, however, fashionable digital cameras square measure still restricted in capturing high dynamic vary pictures in low-light conditions. These cameras usually place confidence in automatic exposure management to capture pictures of high dynamic vary, however the longer exposure time usually results motion blur. In addition, image sequences captured in low-light conditions usually have low signal -to-noise magnitude relation (SNR). Once the illumination is extremely low, the extent of noise becomes comparatively beyond the signal, therefore standard De-Noising techniques cannot be applied. Design an efficient and quick low lighting activity video improvement could be a difficult drawback. Several approaches square measure developed for enhancing low-light activity video but most of them think about activity video from moderately dark conditions.

Aim to develop a novel framework to enhance activity video from extremely low-light environments. Method consists of temporal noise reduction, contrast enhancement and de-noising. The Software tool used is MATLAB.

Activity video segmentation is a ways of dividing a movie into meaningful segments. It a process of labelling independently moving image process [1]. In activity video segmentation there are foreground and background. Foreground is an object and background is a noise. Activity video segmentation result could be a Binary image and Probabilistic image. Binary image which only containing

Foreground only and Probabilistic image likelihood of each pixel of each pixel being foreground.

There are two approaches for activity video segmentation:

1. Motion Based
2. Colored Based

Activity video segmentation generalizes this concept to the grouping of pixels into spatio-temporal regions that exhibit coherence in both appearance and motion. Such segmentation is useful for several higher-level vision tasks such as activity recognition, object tracking, content-based retrieval, and visual enhancement.

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II. THE ACTIVITY VIDEO-OBJECT SEGMENTATION PROBLEM

Activity video-object segmentation seeks to isolate relevant things within a given scene from the surrounding environment. In order to tackle this issue, it is essential to establish a clear definition of relevant items and the proper form for object masks. In reality, however, there is still the basic issue of achieving a clear description of activity video objects. This section sorts the definitional issues that were engaged into two categories: those that were physical (arising from the picture generation) and those that were semantic. Here are the physical issues:

Handling reflections is really very similar to dealing with object shadows. But reflections are trickier to work with as the reflected pictures' appearance is dependent on the reflecting surface's physical characteristics and the reflection itself isn't always related to the item.

The object's form may also be altered due to occlusions. Returning the masks of obscured objects to their original forms is an application-specific decision.

Objects that are partly transparent or constructed of translucent materials may give the impression of being partially see-through. Thin structures, such as hair or fabric, can also give the impression of being partially see-through. A combination of foreground and background colours is always present in pixels around the edges of an item. Rather than only generating a binary object mask, the segmentation method has to calculate an alpha-channel mask that determines the translucency factor for each pixel in order to simulate the transparency. While it is impossible to get precise alpha-channel information from a single picture, techniques based on heuristics have been suggested.

III. OBJECTIVE

In this section, we present our human activity prediction methodology named integral bag-of-words. The major difference between the approach introduced in this section and the previous approaches is that our approach is designed to efficiently analyze the status of ongoing activities from video streams. In first discuss the video features used by ANN method. Next, our new probabilistic activity prediction methodology is presented in Subsection by ANN.

IV. PROBLEM IDENTIFICATION

- **HUMAN ACTIVITY CLASSIFICATION:**

The objective of human activity classification is to assign a fixed number of classes to the provided movies, which are testing videos. The system must deduce the activity label Ap from a video observation O, which consists of picture frames from 0 to t, and assign it to the video based on its best guess. A number of classifiers, such as support vector machines (SVMs) and K-nearest neighbours (K-NNs), have been widely used in earlier methods. The use of activity categorization algorithms for the localization of activities from continuous video streams often made use of sliding windows approaches.

- **HUMAN ACTIVITY PREDICTION:**

The problem of human activity prediction is defined as an inference of unfinished activities given temporally incomplete videos. In contrast to the activity classification, the system is required to make a decision on ‘which activity is occurring’ in the middle of the activity execution. In activity prediction, there is no assumption that the ongoing activity has been fully executed. The prediction methodologies must automatically estimate each activity’s progress status that seems most probable based on the video observations, and decide which activity is most likely to be occurring at the time.

V. PROBLEM FORMULATION

The activity prediction issue is formulated in this section using probabilistic methods. To start, we provide a quick overview of our probabilistic interpretation of the human activity categorization issue from before. We next compare and contrast the prior activity categorization issue with the new human activity prediction challenge and structure it accordingly.

Here is how we proceed: ANN uses local characteristics that are three-dimensional and space-time in order to forecast human actions. In order to provide descriptors that reflect local motions happening in a video, a spatio-temporal feature extractor (e.g. [16, 4]) finds interest locations with noticeable motion changes. Before finding 3-D volume patches with noticeable motion changes, the feature extractor transforms a movie into a three-dimensional XYT volume by joining picture frames along the time axis. For every local patch, a descriptor is calculated by adding up the gradients inside the patch. Our approach then sorts the retrieved local features into several kinds according to how they look (i.e., the values of the feature vectors). "Visual words" describe these kinds, which are basically collections of characteristics. Forming visual words from attributes derived from sample movies is achieved using the k-means clustering technique. Consequently, out of the k visual words, one corresponds to each identified feature in a movie.

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VI. PROPOSED METHOD

The process begins with the entry of a raw activity video. Whatever device can capture activity video, whether it a live camera, a recorded file, or something else entirely, may serve as the activity video source. Some blurring or noise may be present in this unprocessed action video. The action video undergoes preprocessing to eliminate these blur or noise components. A series of frames may be used to depict an activity video. The preprocessing processes include extracting frames from the activity video sequentially.

Frame Extraction: These method are also called Preprocessing. In this approach extract image from applied input activity video. Hence Provide various sample image then to converting image in particular size format.

Image to convert Gray scale: In this step input sample image like as colored image to converting gray scale image. This processes gives a color contrast input image sample.

K-Mean Clustering: By using K-means Clustering method change to the input image into clustered output image. The clustered output image enhance the image pixel quality with gives a L*a*b form blue colored image. Approach gives a segmented output in colored image.

Watershed segmentation method: Watershed segmentation method enhancement of boundaries region with separate for object and image surface contour. Now Fundamental segmentation technique for distingue image and colored based region for equal saturation RGB. Segmentation are different type but watershed segmentation one of the part to provide RGB based segmentation. Output of Segmentation image find MSE parameter in terms of noise with collect different segmentation output and also find out different image parameter in tabulated form.

ANN: ANN method is minimize the MSE parameter by using iteration and Trained data set. ANN work on three input like as trained data, Sample and target data sample. Hence iteration work in terms of Layred based. Hidden layer to arranged output in terms of validation and performance basis. Multiple training minization of MSE and increase performance criteria. The performance parameter ideally follow linearity input and output data sets.

Results of sample image: In a sample image results to gives in terms of MSE and PSNR. Find out image Entropy and Standard deviation. Ideally Entropy increase then PSNR are also increase and Decrease of MSE and Standard Deviation.

Minimization of MSE Parameter with ANN

Reducing picture noise, handling rule-free image processing and image fission issues, and replacing ineffective or ineffective old methods are all areas where artificial neural networks have shown exceptional strength. found inside the boxed picture of the activity video that was examined. A number of imaging-related application fields make full use of the ANN's fault-tolerant features and parallel design to solve challenges involving picture parameters like MSE and PSNR. Pattern recognition, segmentation, compression, colour representation, and other areas of image processing all make use of artificial neural networks. These networks also aid in feature extraction-based recognition methods, such as classification, clustering, and feature selection, among other essential features for improving image quality. AIs typically consist of three layers: input, hidden, and output.

For the purpose of approximating functions that are often unknown, computer models modelled after biological neural networks are known as artificial neural networks (ANNs). In particular, they draw inspiration from neuronal activity and the electrical impulses that neurons transmit between the brain's input (such as visual information or nerve endings in the hand), processing, and output (such as a response to temperature, light, or touch). Research into the mechanisms by which neurons convey meaning is an active field of study.[1]references 2 and 3[4] Despite their apparent lack of complexity, the vast majority of artificial neural networks are quite good at what they set out to do, such as classification and segmentation. For instance, to represent ever-changing populations and ecosystems, some ANNs are designed as adaptive systems.

A wide range of topologies and learning techniques are available for use in neural networks, which may be either hardware-based (representing neurons by physical components) or software-based (computer models).

Artificial Neural Networks 3.1 Real time applications two major advantages of ANNs are applicable to a wide variety of problems and are relatively easy to use. This review has concentrated on applications of ANNs to image processing problems, which were reported in the scientific literature. However, as the field matured, ANNs have gradually found their way into a large range of applications. The ANN-based application systems are

1. Industrial inspection: quality and process control, e.g., the detection of defect objects in the production of steel, textiles, fruit, vegetables, plants or other food products.

2. Document processing: computerized reading of machine-generated and hand-written text used for, e.g., automatic processing of forms and mail sorting.

3. Identification and authentication: e.g., license plate recognition, fingerprint analysis and face identification and verification.

4. Medical diagnosis: e.g., screening for cervical cancer or breast tumor.

5. Defense: various navigation and guidance systems, target recognition systems, etc.

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PROPOSED METHOD STEPS:

0.) we take input and output

- X as an input matrix
- y as an output matrix

1.) We initialize weights and biases with random values (This is one time initiation. In the next iteration, we will use updated weights, and biases). Let us define:

- wh as weight matrix to the hidden layer
- bh as bias matrix to the hidden layer
- wout as weight matrix to the output layer
- bout as bias matrix to the output layer

2.) We take matrix dot product of input and weights assigned to edges between the input and hidden layer then add biases of the hidden layer neurons to respective inputs, this is known as linear transformation:

hidden_layer_input= matrix_dot_product(X,wh) + bh

3) Perform non-linear transformation using an activation function (Sigmoid). Sigmoid will return the output as 1/(1 + exp(-x)).

hiddenlayer_activations = sigmoid (hidden_layer_input)

4.) Perform a linear transformation on hidden layer activation (take matrix dot product with weights and add a bias of the output layer neuron) then apply an activation function (again used sigmoid, but you can use any other activation function depending upon your task) to predict the output

output_layer_input = matrix_dot_product (hiddenlayer_activations * wout) + bout*output = sigmoid(output_layer_input)*

All above steps are known as "Forward Propagation"

5.) Compare prediction with actual output and calculate the gradient of error (Actual – Predicted). Error is the mean square loss = ((Y-t)^2)/2

E = y – output

6.) Compute the slope/ gradient of hidden and output layer neurons (To compute the slope, we calculate the derivatives of non-linear activations x at each layer for each neuron). Gradient of sigmoid can be returned as x * (1 – x).

slope_output_layer = derivatives_sigmoid(output) *slope_hidden_layer = derivatives_sigmoid(hiddenlayer_activations)*

7.) Compute change factor (delta) at output layer, dependent on the gradient of error multiplied by the slope of output layer activation

*d_output = E * slope_output_layer*

8.) At this step, the error will propagate back into the network which means error at hidden layer. For this, we will take the dot product of output layer delta with weight parameters of edges between the hidden and output layer (wout.T).

Error_at_hidden_layer = matrix_dot_product(d_output, wout.Transpose)

9.) Compute change factor (delta) at hidden layer, multiply the error at hidden layer with slope of hidden layer activation

*d_hiddenlayer = Error_at_hidden_layer * slope_hidden_layer*

10.) Update weights at the output and hidden layer: The weights in the network can be updated from the errors calculated for training example(s).

wout = wout + matrix_dot_product(hiddenlayer_activations.Transpose, d_output)*learning_rate
wh = wh + matrix_dot_product(X.Transpose,d_hiddenlayer)*learning_rate learning_rate: The amount that weights are updated is controlled by a configuration parameter called the learning rate)

11.) Update biases at the output and hidden layer: The biases in the network can be updated from the aggregated errors at that neuron.

- bias at output_layer =bias at output_layer + sum of delta of output_layer at row-wise * learning_rate
- bias at hidden_layer =bias at hidden_layer + sum of delta of output_layer at row-wise * learning_rate

*bh = bh + sum(d_hiddenlayer, axis=0) * learning_rate bout = bout + sum(d_output, axis=0)*learning_rate*

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Steps from 5 to 11 are known as "Backward Propagation"

One forward and backward propagation iteration is considered as one training cycle. As I mentioned earlier, when we train second time then update weights and biases are used for forward propagation.

VII. RESULT AND SIMULATION

DATASET:

For our experiments, we used the segmented version of the UT-Interaction dataset [13] containing videos of six types of human activities: hand-shaking, hugging, kicking, pointing, punching, and pushing. The UT-Interaction dataset is a public video dataset containing high-level human activities of multiple actors. The dataset is composed of two different sets with different environments, containing a total of 120 videos of six types of human interactions. Each set is composed of 10 sequences, and each sequence contains one execution per activity. The videos involve camera jitter and/or background movements (e.g. trees). Several pedestrians are present in the videos

Figure 7.1. Example snapshots from the UT-Interaction dataset.

As well, preventing the recognition. The UT-Interaction dataset was used for the human activity recognition contest (SDHA 2010) [14], and it has been tested by several state-of-the-art methods [17, 18, 19]. We chose a dataset composed of complex activities having sufficient temporal durations, instead of testing our system with videos of periodic and instantaneous actions. Even though the KTH dataset and the Weizmann dataset have been popularly used for the action classification in previous works, they were inappropriate for our experiments: Their videos are composed of short periodic movements which only require few frames (e.g. a single frame [9]) to perform a reliable recognition.

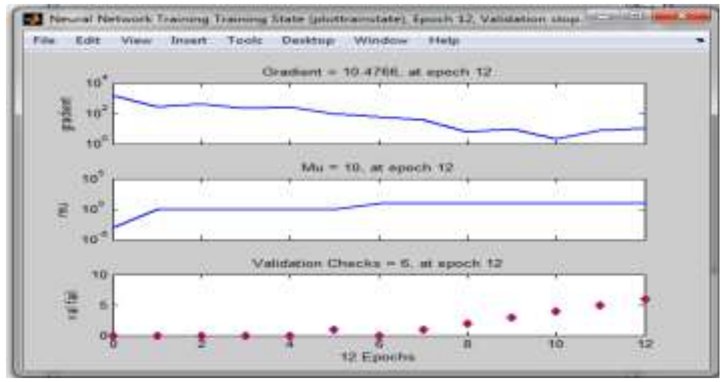
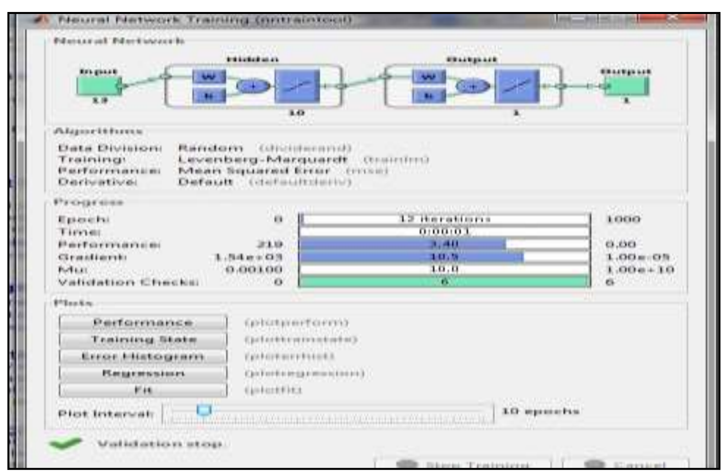


Fig.7.2 NN Training State.

Matlab software will be used for the implementation. Matlab works faster in calculation while working with activity video or image.

Why Matlab?
Matlab is intended primarily for Mathematical Computing. Matlab contains a huge collection of predefined algorithm which is used for image processing. An algorithm can be tested immediately without recompiling it again. Matlab provides an interactive environment which help you to work innovatively with your data and helps to keep track of the files and variable etc.

Fig.7.3 NN Validation State.



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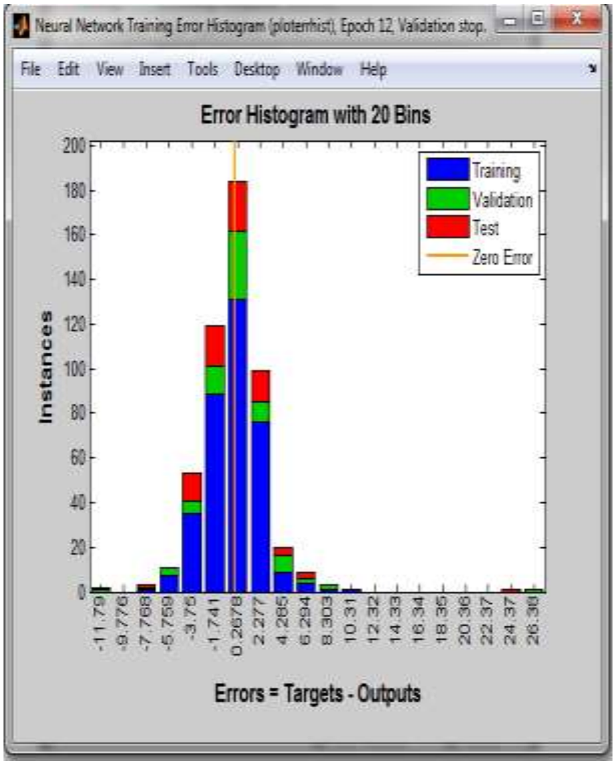

Fig.7.4 Error of histogram.

MSE Analysis represent histogram for multiple layer option. The irregular result provide to neural network. So 0.2678 Error histogram with 20 bins is the highest value of this graph represent.

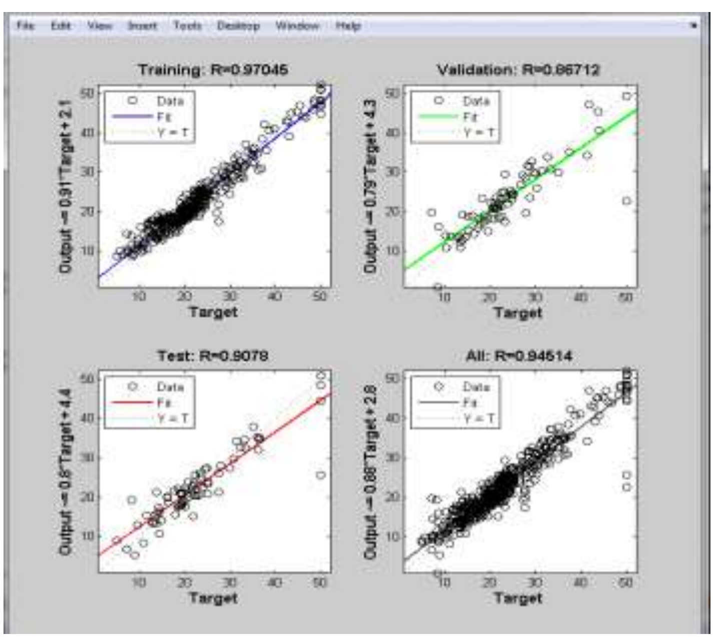

Fig.7.5 output Error.

Fig.7.6 Import data.

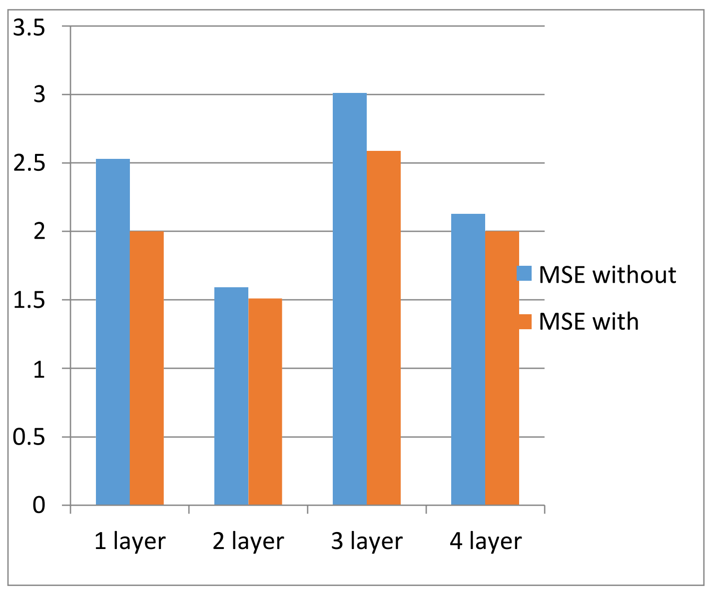

Fig.7.8 MSE Layer of Analysis Neural Network.

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Fig.7.9 Boxing Activity identification.

The previous chapter introduces the proposed methodology. This chapter describes the related future work and schedule plan of excursion.

Fig.7.10 Dialog box identification.

Table 1: Accuracy and Precision of base paper and our proposed work.

S.N.	Accuracy Base paper	Proposed ANN based Accuracy
1.	98.24	99.32

The previous chapter introduces the proposed methodology. This chapter describes the related future work and schedule plan of excursion. The previous chapter introduces the proposed methodology. This chapter describes the related future work and schedule plan of exclusion.

VIII. CONCLUSION AND FUTURE SCOPE

Finding temporal segmentation using the K-mean Clustering Approach in ANN requires obtaining spatial segmentation of each frame, as was noted in the earlier suggested scheme. The object identification approach consumes a significant amount of time due to the tedious practice of spatial segmenting every frame. For bits, this is the practicality of implementing in real time. Using the suggested spatio-temporal method, we calculate the spatial segmentation of a certain frame to lighten the computational load. The purpose of the adaption method is to raise the intensity of the image pixels and the image entropy parameter. The spatial segmentation of succeeding frames is generated by beginning with the segmentation of the provided frame. By combining frame-by-frame temporal segmentation, it is possible to detect objects in an activity video at every given frame. When using spatiotemporal formulation for spatial segmentation, a single frame is produced. An innovative ANN method is created for this specific objective. For picture segmentation, the Watershed Transform has long been a go-to method. Unfortunately, it often fails to meet the morphological and perceptually homogenous image processing criterion when applied to portions of textured images. After that, large homogenous watermarked areas are located using a marker placement method. Following the identification of areas, the Perticular segmentation technique employs a marker-driven Watershed Transform to accurately segment the images while maintaining their quality. The experimental findings show that this method is better than k-means clustering.

Hence, it's reasonable to assume that K-MEAN and ANN won't be able to detect all the peaks, and the primary goal should be to devise new strategies that can. It is well-known that in a K-MEAN based scenario, subpopulations in various multimodal performance niches remain stable. Once tested on multimodal performance, scenario algorithmic programmes based on K-MEAN and ANN might keep stable sub-populations at the various niches, allowing for the determination of all solutions or classifications. Machine load was determined to be the primary obstacle in this topic. In order to make this theme work, the focus switched to a K-MEAN predominantly focused strategy. In comparison to K-MEAN and ANN-based methods, the number of iterations required by the K-MEAN predominantly clump algorithmic programme was much lower—up to forty times lower. Additionally, systems based on K-MEAN may correctly spot all the peaks and categories.

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