International Journal of Research in Engineering and Science (IJRES)
ISSN (Online): 2320-9364, ISSN (Print): 2320-9356
www.ijres.org Volume 12 Issue 3 ǁ March 2024 ǁ PP. 374-383

Human Assault Recognition Using Human Activity Information System With AI

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Abstract
Recognizing human activities from video sequences or still images is a challenging task due to problems, such as background clutter, partial occlusion, changes in scale, viewpoint, lighting, and appearance. Human Activity Recognition plays a significant role in human-to-human and human-computer interaction. Manually driven system are highly time consuming and costlier. So, to design a Human activity recognition system becomes a need for this current world scenario. In this project, KTH video dataset is used for designing the system. Preprocessing technique is used to extract the certain frames. In feature extraction process, Pixel and Optical flow feature extraction techniques are used to extract the features. Data visualization method is used for visualize the feature extraction. The deep learning algorithm such as Spatio-Temporal Net is then used to determine and classify the activities of a human. We can provide this efficient model as an application to road surveillance as such a camera module fixed in the road to perform constant surveillance. The camera on recognizing abnormality in the humans such as fights, etc., an alert notification is sent to the police. A mobile application is developed using react native which will be held by the police to which, the camera on recognizing abnormal actions from a human an alert notification is sent and live streaming is enabled. Thus, this project successfully provides a Human activity recognition model incorporating AI to the cameras which can be used in real time applications such as a solution to prevent and provide evidence of an abnormal detection in road.

Keywords: *Bag-of-Words (BOW), Human activity recognition, Deep learning, Real-time deployment, Dual Stacked Autoencoders, Spatio-Temporal Nets, Surveillance*

Date of Submission: 12-03-2024 Date of acceptance: 27-03-2024

I. INTRODUCTION

Video cameras, or closed-circuit television (CCTV), are becoming a more and more widespread feature of American life. Fears of terrorism and the availability of ever-cheaper cameras have accelerated the trend even more. The use of sophisticated systems by police and other public security officials is particularly troubling in a democratic society. In lower Manhattan, for example, the police are planning to set up a centralized surveillance centre where officers can view thousands of video cameras around the downtown - and police-operated cameras have proliferated in many other cities across America in just the past several years. The implicit justification for the recent push to increase video surveillance is the threat of terrorist attacks. But suicide attackers are clearly not deterred by video cameras - and may even be attracted to the television coverage cameras can ensure - and the expense of an extensive video surveillance system such as Britain's - which sucks up approximately 20 percent of that nation's criminal justice budget - far exceeds the limited benefits that the system may provide in investigating attacks or attempted attacks after the fact. The real reason cameras are usually deployed is to reduce much pettier crimes. But it has not even been demonstrated that they can do that. In Britain, where cameras have been extensively deployed in public places, sociologists studying the issue have found that they have not reduced crime.

Human activity recognition, or HAR[1], is a challenging time series classification task. It involves predicting the movement of a person by deep domain expertise and methods from signal processing to correctly engineer features from the raw data in order to fit a machine learning model. Recently, deep learning methods such as convolutional neural networks and recurrent neural networks have shown capable and even achieve state-of-the-art results by automatically learning features from the data collected. Human activity recognition, or HAR[1] for short, is a broad field of study concerned with identifying the specific movement or action of a person based on data. Movements are often typical activities performed indoors, such as walking, sleeping, standing, and sitting. They may also be more focused activities such as those types of activities performed in a kitchen or on a factory floor[4]. The data may be remotely recorded, such as video, or other wireless methods.

Alternately, data may be recorded directly on the subject such as by carrying custom hardware or smart phones that have accelerometers[3]and gyroscopes. Historically, data for activity recognition was challenging and expensive to collect, requiring custom hardware. Now smart phones and other personal tracking devices used for fitness and health monitoring are cheap and ubiquitous. As such, data from these devices is cheaper to collect, more common, and therefore is a more commonly studied version of the general activity recognition problem.

The problem is to predict the activity given a snapshot of data. Generally, this problem is framed as a univariate or multivariate time series classification task. It is a challenging problem as there are no obvious or direct ways to relate the recorded data to specific human activities and each subject may perform an activity with significant variation, resulting in variations in the recorded data. The intent is to record data and corresponding activities for specific subjects, fit a model from this data, and generalize the model to classify the activity of new unseen subjects from their data.

Human activity recognition (HAR) from video sequences or images is a challenging task with diverse applications in modern society. Traditional methods often rely on handcrafted features and conventional clustering algorithms, which exhibit limitations in scalability, accuracy, and real-time deployment. To address these challenges, this paper proposes a novel approach to HAR leveraging deep learning techniques and efficient deployment strategies. The importance of HAR lies in its ability to automate processes, enhance security measures, and improve human-computer interaction. However, existing systems face challenges such as background clutter, partial occlusion, and varying environmental conditions, which hinder their effectiveness in real-world scenarios. The proposed system aims to overcome these challenges by integrating advanced deep learning algorithms with streamlined deployment mechanisms. The proposed system introduces the DSAFEC method, which leverages Dual Stacked Autoencoders to embed features and perform clustering efficiently. By adopting a soft clustering approach and utilizing BOW construction, the system enhances the robustness and scalability of HAR models. Furthermore, integration with Spatio-Temporal Nets enables accurate classification of human activities, ensuring reliable performance across diverse datasets.

One of the key advantages of the proposed system is its capability for real-time deployment. By integrating with mobile applications, the system enables prompt alert notifications and live streaming, enhancing its utility in surveillance and security applications. Moreover, the cost-effectiveness of the system makes it accessible for a wide range of applications, including road surveillance and public safety measures. Human Activity Recognition (HAR) is a critical aspect of modern surveillance and interaction systems, finding applications in various domains such as healthcare, security, and smart environments.

II. METHODOLOGY

In this project, we are going to determine the human activity recognition by which we can effectively identify the human activity in road by which if an abnormal action can be determined. So, the first step in the project will be collecting the dataset from KTH video dataset and then we will be separating these datasets into training as well as testing dataset where the testing dataset will be kept separate and the training dataset will be used to train the model. Then these datasets are pre-processed using different techniques to align the datasets into single dimensions. After data preprocessing, in feature extraction process, Pixel and Optical flow feature extraction techniques are used to extract the features. Then, Data Visualization method is used for visualize the feature extraction. After Data Visualization, we will be ready for training with the architecture. The deep learning algorithm such as Spatio-Temporal Net is then used to determine and classify the activities of a human. We can provide this efficient model as an application to road surveillance as such a camera module fixed in the road to perform constant surveillance. The camera on recognizing abnormality in the humans such as fights, etc., an alert notification is sent to the police. A mobile application is developed using react native which will be held by the police to which, the camera on recognizing abnormal actions from a human an alert notification is sent and live streaming is enabled. Thus, this project successfully provides a Human activity recognition model incorporating AI to the cameras which can be used in real time applications such as a solution to prevent and provide evidence of an abnormal detection in road.

A) Human Activity Collection

Human activity collection module is the process of collecting various activities that will be processed by the system for performing deep learning process. The KTH video database containing six types of human actions (walking, jogging, running, boxing, hand waving and hand clapping) performed several times by 25 subjects in four different scenarios. The database contains 2391 sequences. All sequences were taken over homogeneous backgrounds with a static camera with 25fps frame rate. The sequences were down sampled to the spatial resolution of 160x120 pixels and have a length of four seconds in average.

A Humanactivity collection is a collection of data. Deep Learning has become the go-to method for solving many challenging real-world problems. It’s definitely by far the best performing method for computer vision tasks. The image above showcases the power of deep learning for computer vision. With enough training, a deep network can segment and identify the “key points” of every person in the image. These deep learning machines that have been working so well need fuel lots of fuel; that fuel is data. The more labelleddata available, the better our model performs. The idea of more data leading to better performance has even been explored at a large-scale by Google with a dataset of 300 million images. When deploying a Deep Learning model in a real-world application, data must be constantly fedto continue improving its performance. And, in the deep learning era, data is very well arguably the most valuable resource. There are three steps of collecting data

i. Scraping from the Web

Manually finding and downloading images takes a long time simply due to the amount of human work involved. The task probably has some kinds of common objects are to be detected. And so that becomes the keyword for web-scraping. It also becomes the class name for that object. From the sounds of it this is of course very easy for a task such as image classification where the images annotations are quite coarse. To get those, it’s best to use some really great image annotation tools that are already out there. The paper shows how to create a model that, given a rough set of polygon points around an object, can generate the pixel labels for segmentation. Deep extreme cut is also quite similar except they use only the four extreme points around the object. This will then give some nice bounding box and segmentation labels. Another option is to use an existing image annotation GUIs. Label someone very popular where one can draw both bounding boxes and set polygon points for segmentation maps. Amazon Mechanical Turk is also a cheap option.

ii. Third-party Websites:

Since data has become such a valuable commodity in the deep learning era, many start-ups have started to offer their own image annotation services they’ll gather and label the data. Given a description of what kind of data and annotations needed. Mighty is one that has been doing self-driving car image annotation and has become pretty big in the space were at CVPR 2018 too. Payment AI are less specialized than Mighty AI, offering image annotation for any domain. They also offer a couple more tools such as video and landmark annotations.

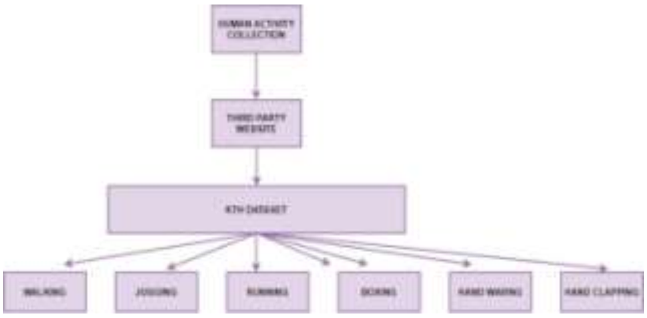

Figure 1 - Human activity Collection

B) Data Preprocessing

Data preprocessing is a process of preparing the raw data and making it suitable for a deep learning model. It is the first and crucial step while creating a deep learning model. More recently, data preprocessing techniques have been adapted for training deep learning models and AI models and for running inferences against them. Data preprocessing transforms the data into a format that is more easily and effectively processed in data mining, deep learning and other data science tasks. The techniques are generally used at the earliest stages of the deep learning and AI development pipeline to ensure accurate results.

Deep learning has truly come into the mainstream in the past few years. Deep learning uses neural nets with a lot of hidden layers (dozens in today’s state of the art) and requires large amounts of training data. These models have been particularly effective in gaining insight and approaching human-level accuracy in perceptual tasks like vision, speech, language processing. The theory and mathematical foundations were laid several decades ago. Primarily two phenomena have contributed to the rise of deep learning a) Availability of huge data-sets/training examples in multiple domains and b) Advances in raw compute power and the rise of efficient parallel hardware.Building an effective neural network model requires careful consideration of the network architecture as well as the input data format. The most common image data input parameters are the number of images, image height, image width, number of channels, and the number of levels per pixel. Typically, there are 3 channels of data corresponding to the colours Red, Green, Blue (RGB) Pixel levels are usually [0,255].

For this exercise let's choose the following values

- number of images = 100
- image width, image height =100
- 3 channels, pixel levels in the range [0–255]

Uniform aspect ratio: One of the first steps is to ensure that the images have the same size and aspect ratio. Most of the neural network models assume a square shape input image, which means that each image needs to be checked if it is a square or not, and cropped appropriately. Cropping can be done to select a square part of the image, as shown. While cropping, we usually care about the part in the center.

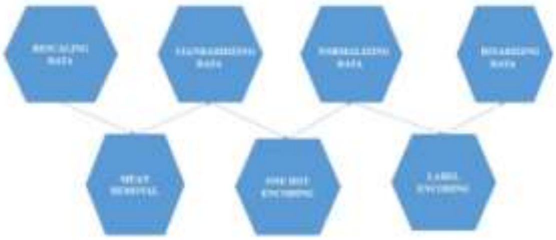

Figure 2 - Data pre-processing

C) Feature Extraction

Feature extraction refers to the process of transforming raw data into numerical features that can be processed while preserving the information in the original data set. It yields better results than applying machine learning directly to the raw data.

Feature extraction can be accomplished manually or automatically:

- Manual feature extraction requires identifying and describing the features that are relevant for a given problem and implementing a way to extract those features. In many situations, having a good understanding of the background or domain can help make informed decisions as to which features could be useful. Over decades of research, engineers and scientists have developed feature extraction methods for images, signals, and text. An example of a simple feature is the mean of a window in a signal.
- Automated feature extraction uses specialized algorithms or deep networks to extract features automatically from signals or images without the need for human intervention. This technique can be very useful when you want to move quickly from raw data to developing machine learning algorithms. Wavelet scattering is an example of automated feature extraction. requires significant expertise before one can build effective predictive models.

In this project, optical flow method and spatio temporal method are used in feature extraction.

Optical flow, or motion estimation, is a fundamental method of calculating the motion of image intensities, which may be ascribed to the motion of objects in the scene. Optical-flow methods are based on computing estimates of the motion of the image intensities over time in a video.

Spatial features capture the change in space due to the movement, whereas temporal features represent time factors during the movement. The spatiotemporal features tell us where the object is at a particular instant of time in the frame.

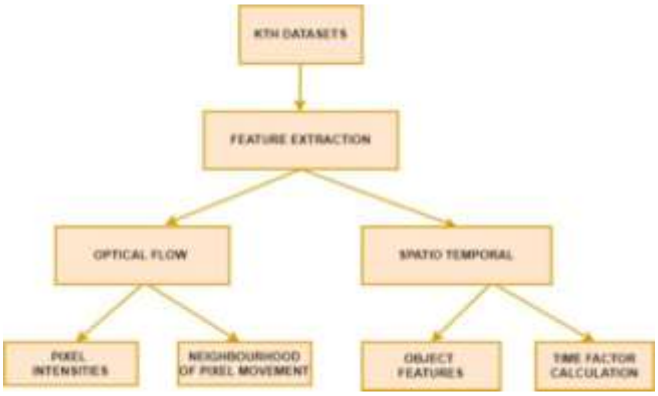

Figure 3 - Feature Extraction

D) Data Visualization

Data visualization is the graphical representation of information and data. By using visual elements like charts, graphs, and maps, data visualization tools provide an accessible way to see and understand trends, outliers, and patterns in data. Additionally, it provides an excellent way for employees or business owners to present data to non-technical audiences without confusion. In the world of Big Data, data visualization tools and technologies are essential to analyze massive amounts of information and make data-driven decisions.

Advantages

Our eyes are drawn to colors and patterns. We can quickly identify red from blue, and squares from circles. Our culture is visual, including everything from art and advertisements to TV and movies. Data visualization is another form of visual art that grabs our interest and keeps our eyes on the message. When we see a chart, we quickly see trends and outliers. If we can see something, we internalize it quickly. It's storytelling with a purpose. If you've ever stared at a massive spreadsheet of data and couldn't see a trend, you know how much more effective a visualization can be.

Some other advantages of data visualization include:

- Easily sharing information.
- Interactively explore opportunities.
- Visualize patterns and relationships.

The importance of data visualization is simple: it helps people see, interact with, and better understand data. Whether simple or complex, the right visualization can bring everyone on the same page, regardless of their level of expertise. It's hard to think of a professional industry that doesn't benefit from making data more understandable. Every STEM field benefits from understanding data—and so do fields in government, finance, marketing, history, consumer goods, service industries, education, sports, and so on.

General Types of Visualizations:

- **Chart:** Information presented in a tabular, graphical form with data displayed along two axes. Can be in the form of a graph, diagram, or map.
- **Table:** A set of figures displayed in rows and columns.
- **Graph:** A diagram of points, lines, segments, curves, or areas that represents certain variables in comparison to each other, usually along two axes at a right angle.
- **Geospatial:** A visualization that shows data in map form using different shapes and colors to show the relationship between pieces of data and specific locations.
- **Infographic:** A combination of visuals and words that represent data. Usually uses charts or diagrams.
- **Dashboards:** A collection of visualizations and data displayed in one place to help with analyzing and presenting data.

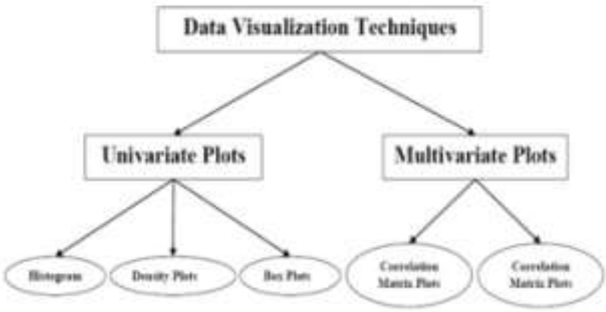

Figure 4 - Data Visualization

E) Training with the deep learning algorithm

After Data Visualization, it will be fed for training with the deep learning algorithm such as Spatio-Temporal Net is used to determine and classify the activities of a human.

Spatio-temporal graphs are made of static structures and time-varying features, and such information in a graph requires a neural network that can deal with time-varying features of the graph. Neural networks which are developed to deal with time-varying features of the graph can be considered as Spatio-temporal graph neural networks.

Spatio-temporal networks are spatial networks whose topology and parameters change with time. These networks are important due to many critical applications such as emergency traffic planning and route-finding services and there is an immediate need for models that support the design of efficient algorithms for computing the frequent queries on such networks. Neural networks which are developed to deal with time-varying features of the graph can be considered as Spatio-temporal graph neural networks. These neural networks are developed to perform time series analysis using the time-varying features of the graph.

Spatiotemporal interpolation is the problem of estimating the unknown values of some property at arbitrary spatial locations and times, using the known values at spatial locations and times where measurements were made. In spatiotemporal interpolation the estimated property varies with both space and time, with the assumption that the values are closer to each other with decreasing spatial and temporal distances. Spatiotemporal interpolation is used in spatiotemporal databases, which record spatial locations and time instances together with other attributes that are dependent on space and time.

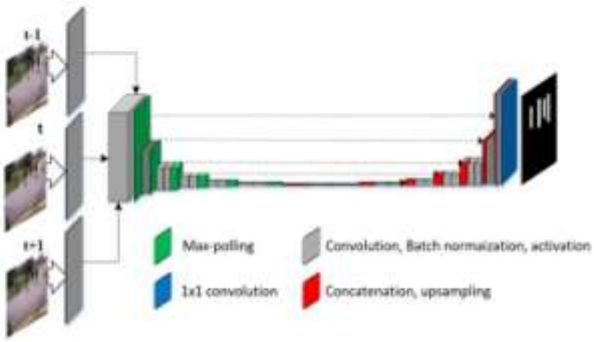

Figure 5:Spatio-Temporal Net architecture

F) Validation and Evaluation

After training with deep learning algorithms, it will validate and evaluate the datasets. Validation in deep learning is like an authorization or authentication of the prediction done by a trained model. While on the other hand, evaluation in deep learning refers to assessment or test of entire deep learning model and its performance in various circumstances. It involves assessment of machine learning model training process and how accurate is the predictions given in different situations.

G) Assault Activity Prediction

The main purpose of this research work is to find the best prediction model i.e., the best Deep Learning techniques which will determine and classify the activities of a human. We can provide this efficient model as an application to road surveillance as such a camera module fixed in the road to perform constant surveillance. The camera on recognizing abnormal detection from the humans such as fights, etc., an alert notification is sent to the police. A mobile application is developed using react native which will be held by the police to which, the camera on recognizing abnormality in the humans an alert notification is sent and live streaming is enabled. Thus, this project successfully provides a Human activity recognition model incorporating AI to the cameras which can be used in real time applications such as a solution to prevent and provide evidence of an abnormal detection in road.

H) Mobile Application Development

In this project react native is used for mobile app development.

React Native is a framework that builds a hierarchy of UI components to build the JavaScript code. It has a set of components for both iOS and Android platforms to build a mobile application with a native look and feel. Mobile development has witnessed unprecedented growth. According to statistics, mobile applications will generate an estimated 188 billion U.S. dollars in revenue via app stores, advertising and in-app purchases by the year 2020. Single and business users require high-standard apps with flawless performance, multiple screens, easy navigation and good design. On the other side, high-performing, good quality native apps are very time-consuming to develop compared to cross-platform apps that provide faster development but compromise on performance and support. React Native seems to be a viable solution for building high-quality apps in a short time with the same performance and user-experience standards that native apps provide.

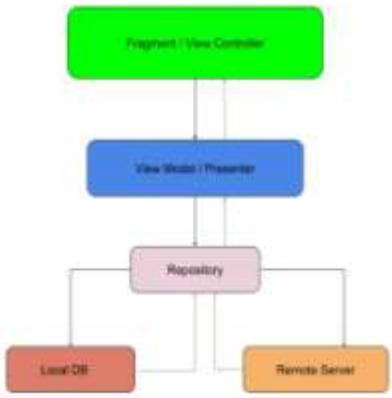

Figure 6 - Mobile App Development

The architecture of React Native helps us in structuring a project for a multi-platform mobile application, keeping the logic of the business in a reusable and maintained sub-module. In some projects, we can see that the containers could be important to be in the core module but that depends on the applications. React Native uses different mechanisms to create an efficient, consistent and reusable visual identity for the applications.

III. EXPERIMENTAL RESULT

We have used videos from the KTH video dataset for designing the system and the dataset contains six types of human actions (walking, jogging, running, boxing, hand waving and hand clapping) performed several times by 25 subjects in four different scenarios which is also used to calculate the performance of our projected technique for the prediction of human assault. Performance is measured in terms of ACC (accuracy), Recall, PRE (precision), support and F1-score.

The below figure shows that the classification report of trained spatio-temporal net algorithm classification report shows how well trained model is performed which is represents by four metrics such as precision,recall,f1-scoore and when we see below results model is performed well on training and testing data.

	precision	recall	f1-score	support
violence	1.00	1.00	1.00	457
handclapping	1.00	0.99	1.00	170
handwaving	1.00	1.00	1.00	210
jogging	0.90	0.84	0.87	102
running	0.87	0.88	0.88	68
walking	0.96	0.98	0.97	186
accuracy			0.98	1193
macro avg	0.95	0.95	0.95	1193
weighted avg	0.98	0.98	0.98	1193

Figure 7 - Classification report

The below figure shows that the confusion matrix of trained spatio temporal net algorithm.confusion matrix shows how well trained model is classified each class correctly.which is represents by four terms such as True Positive,False Positive,False Negative and True Negative when we see below results model is classified each class exactly.

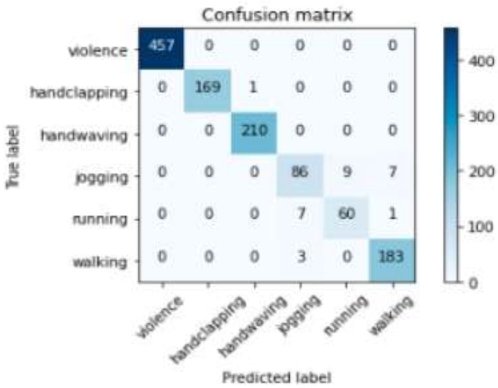

Figure 8 - Confusion Matrix

IV. RESULT

The database contains 2391 sequences. All sequences were taken over homogeneous backgrounds with a static camera with 25fps frame rate. The sequences were downsampled to the spatial resolution of 160x120 pixels and have a length of four seconds in average.

We have used videos that had been cropped to 80x60 pixels in order to compare and classify the symptoms. This classifier has been trained to recognize assault and provide results

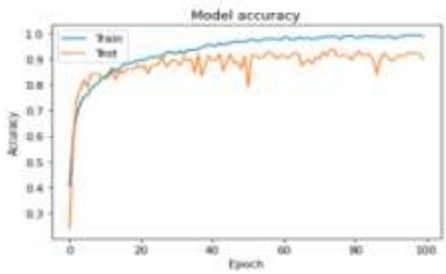

FIGURE 9: ACCURACY OF THE MODELS

As a result, the graph figure 9 illustrates the accuracy attained by these models.

Table 1: Result table showing achieved values of all the performance metrics.

Performance parameters	Results
Accuracy	0.98%
Precision	100%
Recall	100%
F1-score	100%
Support	457

In the process of training the model, the sample dataset was further split into four internal subgroups of samples. Each epoch is split into two parts: one for testing and one for the training routine. Both "acc" and "loss" denote positive values, with "acc" standing for positive values and "loss" for negative values. The models' accuracy and loss are shown in the graphs below.

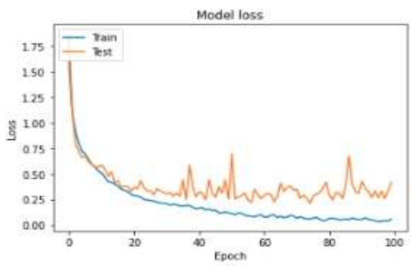

FIGURE 10: LOSS FOR THE MODELS

The misclassification that occurs during implementation is analysed using the Confusion matrix displayed in Figure 11. Each row displays an event from the prediction class, and each column displays an event from the real class.

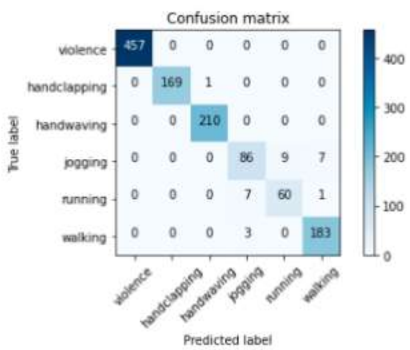

FIGURE 11: CONFUSION MATRIX

The confusion matrix of trained spatio temporal net algorithm.confusion matrix shows how well trained model is classified each class correctly.which is represents by four terms such as True Positive,False Positive,False Negative and True Negative when we see below results model is classified each class exactly. Classes that have been correctly classified are shown on diagonals. Both the misclassified classes and the misclassified objects are displayed in this matrix.

FIGURE 12: LOGIN & LIVE STREAMING (HOME PAGE)

V. CONCLUSION

In conclusion, this project has been successfully implemented a human action recognition and human gesture recognition system which can automatically recognize the human activity in road by which if an abnormal action can be determined using the deep learning approach. The algorithm such as Spatio-Temporal Net is used to determine and classify the activities of a human. KTH video dataset is used for designing the system and the dataset contains six types of human actions (walking, jogging, running, boxing, hand waving and hand clapping) performed several times by 25 subjects in four different scenarios. Using which we have developed a system to prevent and provide evidence of an abnormal detection in road. We have developed a react native application so that we can view the live streaming with a notification when an abnormal activity in road from a human.

In the coming future, we review the application of the safety and secure technology to effectively monitoring the human assault in public places and it can promote for all type of recognitions with more accuracy. In this field there are more chance to develop or convert this project in many ways. The accuracy of the prediction will be increased by using different efficient techniques and algorithms. Thus, this project has an efficient scope in coming future where manual predicting can be converted to computerized production in a cheap way.

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