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COST-EFFECTIVE VEHICLE TYPE BASED SMART PARKING SYSTEM OVER DEEP NEURAL NETWORK

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Abstract- Vehicle type recognition in surveillance images with deep learning has received important attention in various applications of intelligent transportation systems. Thus, a deep active learning method with a new query strategy is proposed in this implementation for vehicle type recognition in surveillance images. As the rate of people owning their vehicles increases, the need of parking slots to park vehicles also increases. But currently the scenario is that there are not sufficient parking slots available or there is also possibility that people are not now aware about the legal parking slots available in their locality. To overcome this problem we are going to invent video based parking system.

Keywords- *Active learning, deep learning, surveillance images, vehicle type recognition.*

I INTRODUCTION

This implementation aims to resolve this problem by reducing manual labelling in surveillance images, and then maximizing the effect of the few tagged data. Thus, a deep active learning method with a new query strategy is proposed in this implementation for vehicle type recognition in surveillance images. First, the proposed method constructs a memory space using a large-scale fully labelled auxiliary dataset collected from the Internet. Subsequently, two metrics, the similarity measurement in memory space and the entropy, are used to simultaneously emphasize the diversity and uncertainty in the query strategy. Moreover, an additional label-consistent term apart from the hyper-parameters is used to adaptively adjust the combination of the two principles in active learning. The proposed method was evaluated on the Comprehensive Cars dataset. The experimental results demonstrated that the proposed method could effectively reduce the annotation cost by up to 40% in surveillance vehicle type recognition compared with the random selection method. Recently, vehicle type recognition in surveillance images with deep learning has received important attention in various applications of intelligent transportation systems. However, annotating large-scale images from many surveillance images is tedious and time-consuming, which impedes its application in the real world.

II LITERATURE SURVEY

Patel Parin and Gayatri Pandi [1] states Traffic Monitoring is a difficult undertaking on jam-packed streets. Traffic Monitoring methods are manual, costly, time expending and include human administrators. Huge scale stockpiling and investigation of video streams were unrealistic due to constrained accessibility. Notwithstanding, it is currently conceivable to actualize object discovery and following, conduct examination of traffic designs, number plate acknowledgment and reconnaissance on video streams created by traffic checking. In Big Data, video streams (datasets) are enormous to such an extent that average database frameworks are not ready to store and examination the datasets. Putting away and preparing huge volume of information requires adaptability, Fault Tolerance and accessibility. In this manner, Big Data and Cloud figuring are two perfect ideas as cloud empowers Big Data for traffic observing utilizing Hadoop innovation with AI calculation. Examination results are put away in Hive, which is an information stockroom based over Hadoop. This information incorporates by and large traffic speed, traffic volume, and individual vehicle speed. Hive gives information rundown, question, and investigation. To dodge the necessities of path control and sensor exhibits, we propose information driven way to deal with street traffic investigation utilizing advanced video.

Shaoqing Ren et.al[2] introducing best in class object recognition systems rely upon area proposition calculations to speculate object areas. Advances like SPPnet and Fast R-CNN have diminished the running time of these discovery systems, uncovering area proposition calculation as a bottleneck. In this work, we present a Region Proposal Network (RPN) that offers full-picture convolutional highlights with the recognition arrange, along these lines empowering almost without cost district recommendations. A RPN is a completely convolutional arrange that at the same time predicts article limits and objectness scores at each position. RPNs are prepared start to finish to create highquality district recommendations, which are utilized by Fast R-CNN for location. With a basic substituting streamlining, RPN and Fast R-CNN can be prepared to share convolutional highlights.

Jeany Son et.al [3] proposed Quadruplet Convolutional Neural Networks (Quad-CNN) for multi-object following, which figure out how to partner object discoveries crosswise over edges utilizing quadruplet misfortunes. The proposed systems consider target appearances together with their transient adjacencies for information affiliation. In contrast to traditional positioning misfortunes, the quadruplet misfortune implements an extra imperative that makes transiently contiguous identifications more firmly situated than the ones with enormous transient holes. We likewise utilize a perform various tasks misfortune to mutually learn object affiliation and bouncing box relapse for better limitation. The entire system is prepared start to finish. For following, the objective affiliation is performed by minimax mark engendering utilizing the measurement gained from the proposed system. We assess execution of our multi-object following calculation on open Witticism Challenge datasets, and accomplish extraordinary outcomes.

Ying-li Tian et.al[4] introducing the increasing need for sophisticated surveillance systems and the move to a digital infrastructure has transformed surveillance into a large scale data analysis and management challenge. Smart surveillance systems use automatic image understanding techniques to extract information from the surveillance data. While the majority of the research and commercial systems have focused on the information extraction aspect of the challenge, very few systems have explored the use of extracted information in the search, retrieval, data management and investigation context. The IBM smart surveillance system (S3) is one of the few advanced surveillance systems which provides not only the capability to automatically monitor a scene but also the capability to manage the surveillance data, perform event based retrieval, receive real time event alerts thru standard web infrastructure and extract long term statistical patterns of activity. The IBM S3 is easily customized to fit the requirements of different applications by using an open-standards based architecture for surveillance.

Tong Xiao et.al [5] states Existing individual re-recognizable proof benchmarks and techniques mostly center around coordinating trimmed passerby pictures among inquiries and competitors. Be that as it may, it is unique from genuine situations where the explanations of passerby bouncing boxes are inaccessible and the objective individual should be looked from a display of entire scene pictures. To close the hole, we propose another profound learning structure for individual pursuit. Rather than separating it into two separate undertakings—walker location and individual re-recognizable proof, we together handle the two perspectives in a solitary convolutional neural system. An Online Instance Matching (OIM) misfortune capacity is proposed to prepare the system viably, which is adaptable to datasets with various characters. To approve our methodology, we gather and comment on an enormous scale benchmark dataset for individual hunt. It contains 18, 184 pictures, 8, 432 personalities, and 96, 143 walker bouncing boxes. Investigations demonstrate that our system beats other separate approaches, and the proposed OIM misfortune capacity merges a lot quicker and better than the ordinary Softmax.

Weihua Xu et.al. [6] introducing The measure of human activity video information is expanding quickly because of the development of interactive media information, which builds the issue of how to process the enormous number of human activity recordings efficiently. Along these lines, we devise a novel methodology for human activity closeness estimation in the distributed environment. The efficiency of human action similarity estimation depends on feature descriptors. Existing element descriptors, for example, Local Binary Pattern and Local Ternary Pattern can just separate surface data however can't acquire the item shape data. To determine this, we present another element descriptor; in particular Edge based Local Pattern descriptor (ELP). ELP can concentrate article shape data other than surface data and ELP can likewise manage power fluctuations. In addition, we investigate Apache Spark to perform include extraction in the disseminated condition. At long last, we present an observational adaptability assessment of the undertaking of extricating highlights from video datasets.

III ALGORITHM AND MATHEMATICAL MODEL

1] Convolutional Neural Network (CNN):-

In proposed work we are using CNN which takes video frames as a input. After getting frames from video it will processed using image processing techniques for feature evaluation. We extract different features from those images regardless of their events in it consists. By using a series of mathematical functions we are going to identify the vehicle. Every layer in CNN has capability to find out weights of images by using matrix evaluations which converts input to output with valuable functions. Layers of CNN used to identify vehicle from extracted frames and give prediction by preserving high accuracy and less time.

- Step 1- Input vehicle parking video's
- Step 2- Frame extraction from video
- Step 3- Image processing by using open-cv
- Step 4- Feature Extraction from images
- Step 5- Model generation
- Step 6- vehicle recognition
- Step 7- Alert generation in the form of voice

Four main layer working approach of CNN explained below:-

a) Convolutional Layer

We are going to extract different features of frames like pixel weight matrix calculations by using feature kernels. Perform mathematical convolutions on frames, where every function uses a unique filter. This outcome will be in different feature maps. At the end, we will collects all of these feature maps and draft them as the destination output matrix of the convolution layer.

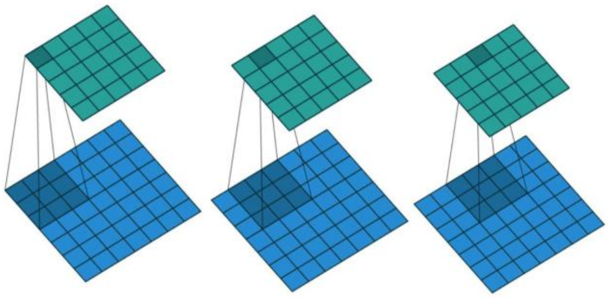

Figure 1 Convolutional Layer

b) Pooling

The expression of pooling is to constantly decrease the dimensionality to limits the number of factors and calculation in the network. This limits the time of training and maintains over fitting problem. The max Pooling extracts out the largest pixel value out of a feature. While pooling average is calculated for the average pixel value that has to be evaluated.

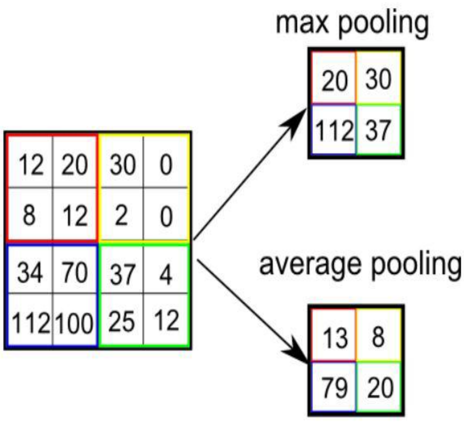

Figure 2 Pooling Layer

c) Flattening

Generally here we put the pooled feature into a single column as a sample input for further layer (transform the 3D matrix data to 1D matrix data)

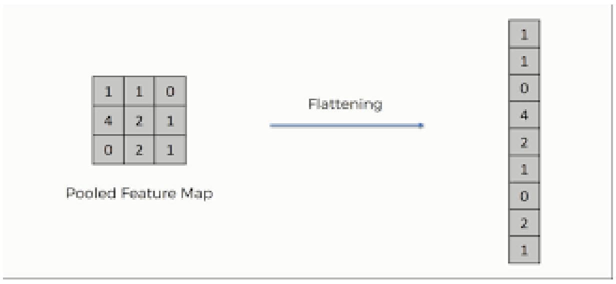

Figure 3 Flattening Matrix

d) Fully Connection

A fully connected layer has full connections of neurons to all the nodes in the previous layer.
The fusion of more neurons to evaluates accurately.

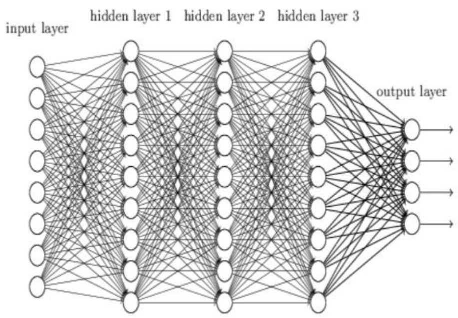

Figure 4 Fully Connected Layer

2] Mathematical Model:-

a] Testing Model 1:

Sign System:

Mathematical Model: Let us consider S as a system for Smart Parking System.

S={s, H, I, O, V,e}

INPUT:

1. S=start of program
2. H= {h1, h2, h3 ....., hn} where H is the set of video frames/images of testing dataset.
3. I= i1, i2, i3 testing image submitted by the User, i.e. vehicle sequence , parking vehicle sequences
4. O= o1, o2, o3 Set of voice outputs from the function sets, Output of desired vehicle detection, i.e. wrong vehicle detection
5. V=alert voice as a output
6. e = End of the program.

b] Training Model 2:

Set Theory

T={s, e, D, M}

Where,

s = Start of the program.

T=Train set

D=video Dataset contains {L1,L2,L3,….Ln} where L is label sets of total dataset images

L1=set of label bike data

L2= set of label car data

L3=set of label other vehicle data

M=Trained model

IV EXISTING SYSTEM APPROACH

In existing on machine learning and smart parking techniques we come on conclusion that there is not any promising solution for pre- event identification and alert generation. All alert systems are based on sensors and hardware devices which is very expensive. Existing work on video surveillance is used recorded video sequences for crime investigation which is post investigation process. In which chances of overcome risk and loss is very less. So there is need of pre-event identification systems in video surveillance and monitoring with the addition of alert generation for better accident prevention techniques. So we are working on smart parking system for giving most promising solution over existing post methods.

V PROPOSED SYSTEM APPROACH

In a proposed system, we are proposing experiment on vehicle detection and pre-alarm generation, wrong vehicle parking detection and prevention, Smart Parking by using video surveillance.

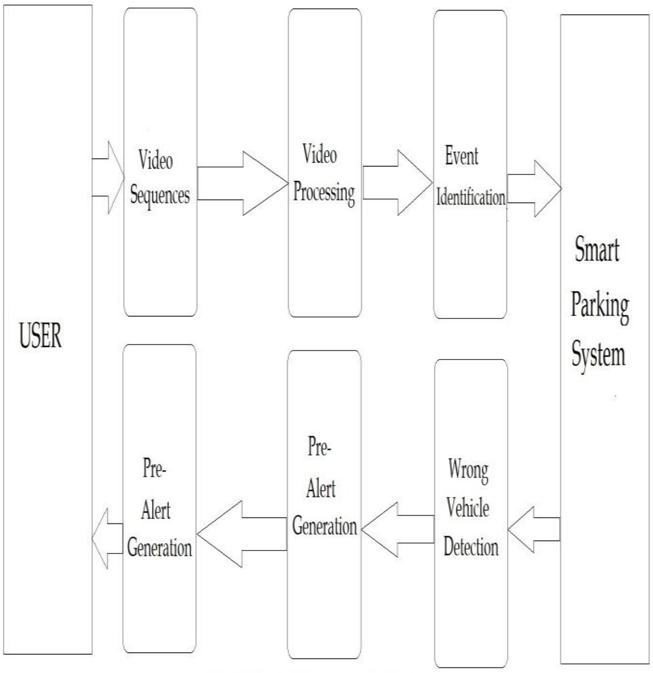

Figure 5 Block Diagram of Proposed System

In a proposed system, we have overcome existing drawbacks of post investigation techniques of video surveillance systems by providing pre alert generation system. Our work is based on machine learning techniques for video analysis with better performance and vehicle detection with advantages of alert generation. We are proposing vehicle type recognition and parking management scenario. We propose a new Convolutional neural network based wrong vehicle parking detection and alarm generation. We are going to solve existing parking problem by using python machine learning approach. We are going to develop following modules:

1) Video processing
2) Image processing
3) Feature extraction
4) Vehicle type detection
5) Alarm generation

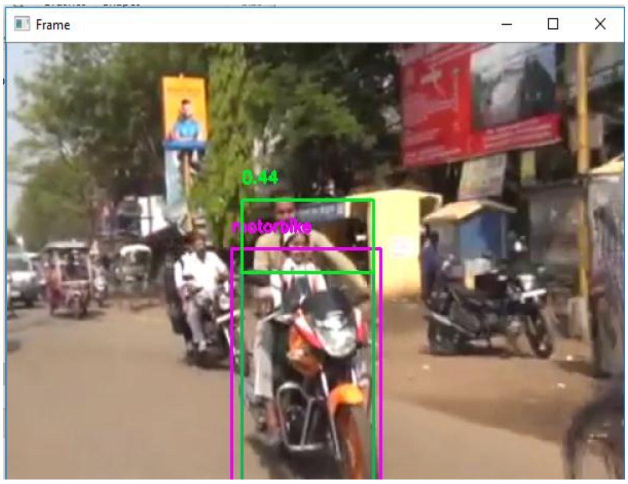

Figure 6 Motor bike recognition from video

Main motive behind this system is to give promising solution by vehicle recognition which alternatively increases prevention of wrong vehicle parking. To intensive task of monitoring parking regions as well as explore smart parking mechanism, researchers seek the advanced computer vision algorithms to develop intelligent video based smart parking systems. In proposed system, vehicle detection, vehicle type recognition, vehicle tracking.

VI RESULTS & DISCUSSION

In our experimental setup, as shown in table, the total numbers of vehicle frames collected from video data were tested. These frames go through vehicle detection framework by following feature extraction using our image processing module. Then our trained model of vehicle detection get classifies the video into car, bike and other vehicle categories. Smart parking video sequence get classified into car, bike and other vehicle categories. The common action will take on wrong vehicle detection by us after getting appropriate voice alert.

Sr. No	Category	Number of Frames
1	Positive Frames	750
2	Negative Frames	250

Table1: Classification of frames

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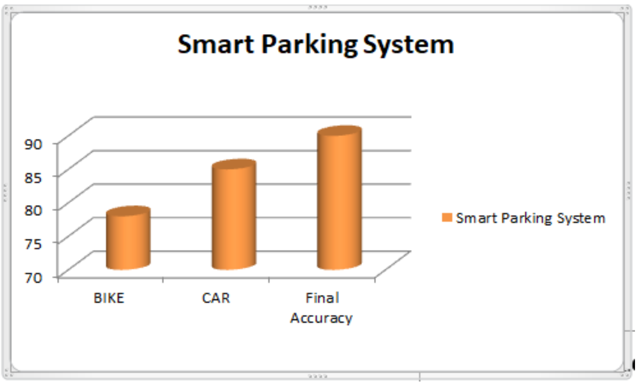
VII RESULTS

From above data, as shown in graph, the numbers of vehicle frames goes through test module some of found correct vehicle detected, some of found wrong vehicle detection.



Graph 1: Classification of vehicle videos

In our experimental setup, as shown in graph , the total numbers of frames were 414. These frames were then divided into three subcategories; among which 4,567 found correct vehicle detected and 433 found wrong vehicle detection respectively We classified video data into vehicle categories based on accuracy factor which is our main motive.

VIII CONCLUSION

We are invented smart parking system over machine learning and CNN techniques which overcome illegal parking problem. And give best result over post-event recognition by our pre-event recognition and alert generation work. We are developed wrong vehicle parking and alert generation system.

For future work, we can implement this technique real time CCTV based application.

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