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ZONEWATCH – A DEEP LEARNING APPROACH TO VEHICLE ZONE RECOGNITION AND SPEED MANAGEMENT

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Abstract : This study has been undertaken to focuses on leveraging deep learning approaches, specifically Convolutional Neural Networks (CNN), to enhance the efficiency of a vehicle zone recognition system tailored for critical areas such as schools, hospitals, and accident-prone zones. The proposed system aims to integrate artificial intelligence (AI) with a microcontroller to regulate vehicle speed dynamically. By implementing CNN algorithms, the model enhances the accuracy and robustness of object recognition within designated zones, contributing to improved safety measures. The incorporation of a microcontroller ensures real-time control of vehicle speed, facilitating a responsive and adaptive system that prioritizes safety in sensitive areas. This study not only addresses the technical aspects of deep learning but also explores the practical implications of deploying an AI-enhanced system for improved traffic management and overall public safety.

Index Terms* – *Artificial intelligence, Convolutional neural network, microcontroller, traffic monitoring, segmentation, vehicles, zone recognition.

I.INTRODUCTION

The significance of vehicles in our daily lives continues to increase steadily with each passing day. The scenario of increased vehicle density in India from 2001 to 2015.Due to increased vehicle density and over speed driving causes more accidents There are lot of reasons behind it. These are increased rate of vehicle density, the Indian roads are not changed up to the expecting level excluding the national highway, multiple functioning at the time of driving the vehicle that is like use of mobile, drink while driving, disobey of traffic rules and regulation, crossing speed limits which is dangerous for your own safety and that of others and many more.

Among them, the enforcement of speed limits in specific areas is crucial, often communicated through signage by traffic control systems. For example in residential areas and market places ideal speed should be maximum upto20 km/hr to 30 km/hr. Secondly in the regions of school and hospital speed limits are kept up to 30 km/hr to 40 km/hr and so on. Regrettably, many drivers disregard speed limits in designated areas, leading to an increase in accidents. Since drivers have full control over their vehicle's speed, they often fail to adhere to regulations and reduce speed in restricted zones as required by the rules.

II.RELATED WORK

Numerous researchers have focused on traffic monitoring systems using machine learning approaches, while others have used deep learning frameworks. Most of the researchers have devoted their efforts to performing vehicle detection and classification. They incorporated hand-crafted features techniques including scale-invariant feature transform (SIFT), speeded-up robust features (SURF), the histogram of oriented gradients (HOG), and Haar-like features.. In the recent past, deep learning-based methods are performing better compared to the previous techniques, particularly for vehicle detection in aerial images and scene understanding tasks. By using convolutional neural networks (CNNs), deep learning-based methods provided superior feature representation than the hand-crafted features and shorter processing times than the sliding window-based methods. CNN-based object detectors are mainly divided into two-step and one-step detectors. Two-step detectors, such as R-CNNs, Fast R-CNN, Faster R-CNN, and Mask R-CNN, use region proposals to complete object location regression and classification processes in two steps. In contrast, one step detectors, such as YOLOv3 and the single-shot multi box detector (SSD), predict object locations and classes simultaneously in a single network.

2.1 Learning- based vehicle zone detection

Machine learning has been widely employed in computer vision tasks for many years, notably in the realm of intelligent traffic management and surveillance. F. Tang et al. [13] presented a model that considers both the value matrix and spatial-temporal training model while extracting features to predict traffic patterns. They conducted simulations of their model, showcasing improvements in packet loss rate, average accuracy, and transmission throughput. Liu et al. [14] devised a method to improve the segmentation of the objects and then apply a probabilistic classification model to detect the vehicles correctly. They used aerial images and LiDAR data for the purpose. Tang et al. [15] conducted experiments for vehicle detection on static images by extracting Haar features and then employed an AdaBoost classifier to detect the vehicles in the images. Their method is highly applicable across a range of surveillance applications. Ukani et al. [16] proposed a vehicle detection and classification system that utilizes video analysis for traffic monitoring. They utilized SIFT features, subsequently integrating both artificial neural networks and support vector machines (SVM) for classification. Their findings indicated superior performance with the application of SVM. Huang et al. [17] employed a combination of background subtraction and a deep belief network for vehicle detection in tunnel environments. It’s a challenging problem as different cameras are VOLUME 11, 2023 2995.

2.2 Deep learning based vehicle zone detection

Traditionally, traffic monitoring has relied on manual approaches and in-vehicle technologies. Nevertheless, conventional methods have been eclipsed by deep learning-based image processing techniques. In their work [18], M. Ozturk et al. presented a framework utilizing convolutional neural networks (CNNs) for the precise detection of hybrid vehicles with both low complexity and high accuracy. Morphological operations support this method. They conducted experiments on the COWC dataset and achieved a higher accuracy with fewer parameters compared to the number of parameters used by the other researchers. C. M. Bautista et al. [19] M. Mandal et al. [20] innovated a CNN-based approach tailored for detecting and classifying vehicles using low-quality traffic cameras. Their development, AVDNet, excels particularly in identifying small vehicles. They integrated ConvRes residual blocks into AVDNet to address the challenge of detecting small objects more effectively through deeper convolutional layers during feature extraction.The larger feature map at output combined with these residual blocks ensures that the important features extracted from small-sized objects are well represented by the map. They also came up with a way to look at the network’s behavior through recurrent-feature aware visualization (RFAV). In [21], Al-qaness et al. presented a new technique that

III . EXISTING SYSTEM

Agent-based approaches have gained popularity in engineering applications, but its potential for advanced traffic controls has not been sufficiently explored.This existing paper presented a multi-agent framework that models traffic Control instruments and their interactions with road traffic are studied through the lens of a Constrained Markov Decision Process (CMDP) model. This model is employed to depict agent decision-making within the framework of multi-objective policy objectives. Here, the policy goal with the highest priority is designated as the primary optimization objective, while the remaining objectives are reformulated as constraints.A reinforcement learning-based computational framework is developed for control applications.To implement the multi-objective decision model, a threshold lexicographic ordering method is introduced and integrated with the learning-based algorithm

Disadvantage

- Performance of the intelligent control approach was evaluated by simulation, and compared with several other signal control methods
- Not avoiding vehicle accident in restricted zone

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IV. PROPOSED SYSTEM

The proposed system integrates a deep learning approach for efficient vehicle zone recognition and speed management, leveraging a microcontroller for seamless implementation. Through advanced neural networks, the system analyzes input from cameras or sensors to identify specific vehicle zones, such as residential areas, school zones, or highways. The deep learning model is trained to recognize patterns and distinguish between different zones based on visual cues. Once a vehicle enters a recognized zone, the microcontroller takes control of speed management, dynamically adjusting the vehicle's speed according to predefined regulations or safety parameters. This system aims to enhance traffic safety by preventing speeding in sensitive areas and promoting compliance with speed limits. The microcontroller acts as the central processing unit, ensuring real-time decision-making and responsiveness.SSSThe proposed system for accident zone, school zone and hospital zone detection using Convolutional Neural Networks (CNN) aims to improve the safety of drivers and pedestrians by accurately identifying accident prone areas on the road. The computer uses cameras and sensors to capture images or video of a target area, which is then processed by CNN to identify and classify accident zones, school zones, and hospital zones.A CNN trained on large datasets of images of accident zones, school zones and hospital zones will be capable of detecting accidents. Scan input images, .The system's primary purpose is to provide real-time information to drivers, allowing them to slow down and be cautious when driving in accident zones, hospital zones, and school zones. The system can be integrated with other traffic management systems to provide real-time information on accident density, which can be used to improve traffic flow and reduce the risk of accidents.The proposed system has the potential to save lives and prevent accidents by providing drivers with real-time information about accident-prone areas on the road. By accurately identifying and classifying crash zones, the system will improve the safety of drivers and pedestrians and reduce the risk of accidents. The system can be implemented in various scenarios such as highways, city roads and intersections to provide a comprehensive solution for crash zone detection.

Advantage

- Vehicle detection process on road are used for vehicle tracking, counts, average speed of each individual vehicle
- Traffic analysis and vehicle categorizing objectives and may be implemented under different environments changes.

V. RESEARCH METHODOLOGY

The methodology section outline the plan and method that how the study is conducted.

5.1 Pre processing

Image pre-processing is a vital step in preparing photo datasets for various computer vision applications. Pre-processing images makes it easier to use them for machine learning model training by transforming raw images into a format that is suitable for analysis and interpretation. Image pre-processing often involves several stages, including scaling, normalisation, augmentation, cropping, and colour conversion. These strategies can be used separately or in combination to achieve specific goals, such as improving image quality, reducing noise, expanding datasets, or increasing the efficacy of machine learning models. Proper Image pre-processing has a significant impact on both the dataset's quality and the precision of the ensuing machine learning models. For instance, normalising the values of picture pixels may speed convergence and enhance the machine learning algorithm's performance. Similar to dataset expansion, picture augmentation can improve the generalisation of the model, which is crucial for achieving high accuracy in practical applications

5.2 CNN- based semantic segmentation

After the pre-processing phase, image segmentation is performed to separate the vehicles from the other objects and backgrounds. A CNN-based semantic segmentation technique is applied for this purpose. In this phase, a Segment Net based network is described as having two streams. The output produced by the residual block is combined with the output of the second convolutional layer. In this study, a unique encoder-decoder-based architecture is used. The structure comprises two components: the first component involves five convolution blocks, while the second consists of rectified linear unit (ReLU) and Batch Normalization (BN). By incorporating un-pooling layers in the encoder and decoder, we can restore the resolution to its original state. The encoder and decoder are present in both streams, but at the end of the streams, the combined result ofboth streams is considered for further processing. A residual block with skip connections is also utilized, as revealed earlier, to send information from each encoder convolution block to its respective encoder-decoder convolution block in both streams. Fig. 3 demonstrates semantic segmentation results over a few examples of the VAID dataset.

5.3 Vehicle zonewatch detection

Typically, to pinpoint the target vehicle within the frame, a bounding box is drawn around it. While considering the correlation filter tracking method [30], highly sampled and circularly shifted image patches are synthesized to build a circular data matrix. The location of the maximum correlation response also aids detection in the successive frames, making it easier to recognize. Given $x \in R$ $P \times Q \times C$ where $P \times Q$ denotes the size of the patch with channels C taken from the sample image. All the circulant images M(p,q) with $p < P$, $q < Q$ are combined to produce the circulant matrix M. Hence, the discrete Fourier transform (FT) is used to compute the eigenvectors of a circulant matrix M: M = F H Diagonal (mˆ) Fwhere the optimal coefficient vector is represented by αˆ (l) t−1 and the bias is denoted by b (l) at the (t −1)-th frame. The maximum value of the response map f (l) z is used to compute the requisite place of the l-th feature vector. The integration of multikernel correlation responses results in a final distribution map, which is dynamically generated by combining various kernel filters. as shown in Fig. 9. f (z) = X l f (l) z ∗ w (l) (12) Scaling parameters can be estimated using variable-scale pyramids, which are able to adjust to variations in appearance. More than one sample is taken from the present target location, and these samples are called ''scale-pool samples'' (S = {s1,s2,s3...sv}). As soon as a new frame becomes available, the highest possible number of v correlation responses can be used to identify both the target's position and its scale at the same time. Normally, we expect the optimal response map to have a sharp peak, but a further decline may cause the response map to be significantly transformed. It is effective to determine the optimal learning rates for the (l) different sorts of feature kernels based on the highest points of respective response maps. To update the coefficients αˆ (l) t and b (l) t in the t-th frame, a threshold value (Th = Pt−1 i=1 P (t) i (t−1)) of a classifier PSR (Peak-to-Side lobe Ratio) is utilized. αˆ (l) t = ((1 − η)αˆ (l) t−1 + ηαˆ (l) t , PSR < Th αˆ (l) t−1 , PSR ≥ Th b l t = ((1 − η)bˆ (l) t−1 + ηbˆ (l) t , PSR < Th bˆ (l) t−1 , PSR ≥ Th (13) where the fusion parameter is called η. We can define the maximum and minimum ability of response as: P (l) = R (l) max−R (l) min σ (l) · R (l) max and R (l) min respectively while σ (l) is used to denote the standard deviation.

5.4 Statistical tools and econometric models

The detail of methodology is given as follows.

5.4.1 CNN based vehicle tracking

Kalman filter-based vehicle tracking [29] and its variants [6], [12] are commonly used methods in computer vision tasks and mathematically can be described as follows: Xt = AtXt + ωt (2) Yt = CtXt + vt (3) where Xt ∈ Rn is used to represent the state vector, Yt ∈ Rm is process noise, ωt ∈ R n and vt ∈ R n is used to measure noise at step t. ωt and vt are type of noise. 2998 VKalman filter also uses probabilities in terms of the prior and posterior probability that can be expressed mathematically as follows: Xˆ t¯ = At−1Xˆ t−1 (4) Xˆ t = Xˆ t¯ + Kt(Yt − CtXˆ t¯) (5) Local data collected by each node is relayed to a central server for global estimations, as is the practice in more traditional central approaches. The computation process is heavy and takes a long time. To handle the computation time, alternate methods like distributed Kalman filter (DKF) and diffusion least-mean-square DLMS, are used due to their efficiency based on the information processing mechanism. Fig. 8 illustrates the results of vehicle detection by incorporating the KF tracking.

5.4.2 Faster R-CNN based Method

When testing asset pricing models related to risk premium on asset to their betas, the primary question of interest is whether the beta risk of particular factor is priced. According to Blum (1968) testing two-parameter models immediately presents an unavoidable errors-in-the variables problem.It is important to note that portfolios (rather than individual assets) are used for the reason of making the analysis statistically feasible.Fama McBeth regression is used to attenuate the problem of errors-in-variables (EIV) for two parameter models (Campbell, Lo and MacKinlay, 1997).

The convolutional feature map is developed when entire image is processed convolutional and max pooling layers. From a set of fully connected layers, output passes to sibling layers where softmax probability estimates are produced. The object classes estimate softmax probability. Here background class with set of other layers are considered. The encoding is performed on set of values with respect to refined positions in bounding box for each object class. The RoI pooling layer employs max pooling, enabling the transformation of features into a compact feature map. This convolutional feature map-based RoI is defined by a 4-tuple.RoI max pooling divides rectangular window into sub window grids. The channel independent pooling is applied for each feature map. The network weights are trained through backpropagation in Faster R-CNN. Hierarchical sampling of Regions of Interest (RoIs) is conducted for each image. Stochastic Gradient Descent (SGD) training for Faster R-CNN is executed in mini-batches. To accommodate larger datasets during training, SGD is iterated over more times. Faster R-CNN utilizes sibling output layers, where each RoI initially has a discrete probability distribution as output. The outputs of the fully connected layer are passed through a softmax function. RoI labeling is conducted based on the ground truth class.For each training bounding box regression having ground truth is considered. For each labeled RoI considering multitask loss, joint classification is present with respect to training and bounding-box regression. The optimization of multitask loss is performed as highlighted in [5]. For whole image classification, convolutional layers' calculation time is greater than fully connected layers. RoIs processing time is appreciably large for detection

5.4.2.1 Model for CNN

There are five different layers in CNN

- Input layer
- Convo layer (Convo + ReLU)
- Pooling layer
- Fully connected(FC) layer
- Softmax/logistic layer
- Output layer

5.4.2.2 Layer of CNN

Input Layer

Image data should be present in the input layer of CNN. As we previously saw, a three-dimensional matrix is used to represent image data. It must be transformed into a single column. If an image has the dimensions 28 x 28 = 784, it must first be converted to 784 x 1 before being fed into the input. During training with "m" samples, the dimension of the input will be (784, m).

Convo Layer

Due to the fact that characteristics of the picture are extracted within this layer, this layer is also known as feature extractor layer. In order to perform the convolution operation we observed before and calculate the dot product between the receptive field—a local area of the input image that has the same size as the filter—and the filter, a portion of the image is first connected to the Convo layer. One integer representing the output volume is the operation's output. Next, via a Stride, we move the filter over the following receptive area of the identical input picture and repeat the process. One integer representing the output volume is the operation's output. Next, via a Stride, we move the filter over the following receptive area of the identical input picture and repeat the process. The procedure is iterated until the entire image is processed, with the output of one layer becoming the input for the next layer. Additionally, the convolutional layer incorporates a Rectified Linear Unit (ReLU) activation function to set all negative values to zero, enhancing the model's non-linearity.

Pooling Layer

After convolution, the spatial volume of the input image is reduced using a pooling layer. Between two convolution layers, it is employed. The use of FC after the Convo layer without the use of pooling or maximum pooling will be computationally expensive, which is something we do not want. Thus, the maximum pooling is the only method for reducing the spatial volume of the input image. In the aforementioned illustration, max pooling was used in a single depth slice with a Stride of 2. You may view th4 x 4 dimension input is reduce to 2 x 2 dimension.

There is no parameter in pooling layer but it has two hyper parameters — Filter(F) and Stride(S).

In general, if we have input dimension W1 x H1 x D1, then

$W2 = (W1-F)/S+1$

$H2 = (H1-F)/S+1$

$D2 = D1$

Where W2, H2 and D2 are the width, height and depth of output.

Output Layer

Output layer contains the label which is in the form of one-hot encoded.

5.4.3 Automatic Vehicle Speed management

Now–a-days lots of accident happen on the signal due to increase traffic and also due to rash driving of the drivers. As we know when we accelerate the vehicle the engine starts running at higher speed, and when more throttle is opened, the engine suctions sucks more quantity of load (air + fuel), which burns and produces more amount of energy in the form of radiations. In this system we have implemented the speed limiting mechanism which will be effective for the reduction of fuel towards the engine. The objective of the System is to present a conceptual model of a microcontroller based Automatic variable electronic speed controlling. System that can be implemented to control the speed of any vehicle depending on the speed limit. In this system the main element is Speed Limiting mechanism. The Limiting mechanism is a device which is used for controlling speed of an engine based on the load requirement. The basic Limiting mechanism sense speed and sometimes load of a prime mover and adjust the energy source to maintain the desired level. So it"s simply mention as a device giving automatic control or limitation of speed. The Limiting mechanism is control mechanisms and it works on the principle of feedback control. Its basic function is to control the speed within limits when load on the prime mover changes. They have no control over the change in speed within the cycle. II. WORKING In car assembly carburetor work on petrol engine, a carburetor basically consists of an open pipe through which load p asses towards throttle valve of carburetor. The pipe is in the form of venturi: it narrows in section and then widens again. Causing the air flow to increase in speed in the narrowest part. Below the venture is a butterfly valve called as throttle valve. The throttle valve is connected to the accecerelator of engine (pedal). When pedal pressed the valve works, if maximum force applied on accelerator then the valve fully opens and large amount of mixture of fuel and air is passed through the throttle valve and simultaneously the speed of car increases. If less force applied on pedal then the valve close partially depending on the force applied on the pedal and accordingly the amount of mixture of air and fuel will be supplied towards the engine.

5.4.3.1 Speed management using microcontroller

Microcontroller is the heart of the System. It compares the speed of vehicle by sensor at low speed zone or signal zone maximum allowable speed and automatically regulates the speed of vehicle by activating the speed limiting mechanism. The speed of vehicle is reduced to the required in that zone. The microcontroller which has been used in our system is the „AT89S52" which is typically 8051 microcontroller manufactured by Atmel

5.4.3.2 IR Sensor

In this system we have used IR sensor as IR Transmitter unit and IR Receiver. The Transmitter unit which is to be placed at 100 meter earlier to the traffic signal. The IR Receiver module is been implemented inside the car mechanism. The Transmitter section includes an IR sensor, which Transmit continuous IR rays they are invisible to human eyes, and that battery regulator micro controller ir sensor ir sensor motor driver motor lcd display can be detected by an IR Receiver module. As soon as the Receiver module i.e. the car enters the low speed zone or signal zone the speed limiting mechanism starts operating and the microcontroller will generate control signal for the vehicle control system. Which then will activate the mechanism of the speed control in the vehicle and the speed of the vehicle is reduced to the require speed in that zone.

VI. RESULTS AND DISCUSSION

We propose a computer vision based system for real-time robust Road sign detection and recognition, especially develoed for intelligent vehicle.Here we proposed a model to predict the Road signs and school, hospital zones using convolution neural network.After predicting the required sign, serial communication done by USB to UART converter .Sending the serial data to PICmicrocontroller .The controller will control all the applications like relay, driver motor.

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