COLOUR CORRECTION

A PROJECT REPORT

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BONAFIDE CERTIFICATE

Certified that this project report titled **"COLOUR CORRECTION"** is the Bonafide work of "**Gitika Jain (19BAI10108), Mansi Shrivastav (19BAI10175), Mandavi Pandey (19BAI10133), Hrudayangam Mehta (19BAI10158)**" who carried out the project work under my supervision. Certified further that to the best of my knowledge the work reported here does not form part of any other project / research work on the basis of which a degree or award was conferred on an earlier occasion on this or any other candidate.

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LIST OF ABBREVIATIONS

ReLU	Rectified Linear Unit/ Rectifier Neural network
CNN	Convolutional Neural Network
RNN	Recurrent Neural Network
RGB	Red Green Blue

LIST OF FIGURES

ABSTRACT

With the aim of extending the visualization ability of the different electronic systems, in recent years the machine vision has been developed, increasing the autonomy of these devices and in the same way the amount of data that can be obtained. It is for this reason that this paper seeks a method to recognize color in different real images. From the above in this work is developed a recognition method of colors, using filtering by HSV and image processing through a camera and a data acquisition system with the aim of identifying different colors without taking into account environmental effects (luminosity, Intensity, Angle, Deepness) or electronic issues (Noise, Overcurrent, etc.). That is why was used a raspberry pi connected to a servomotor, in order to select the color through the angle of the motor. From the work was established that digital signal processing is very important at present increasing the autonomy of the system and the possibilities with a trained robot and a complete source of data. Taking into account that this work was performed with a camera that just gave the basic information of the image taken, and replacing it with a most sophisticated one, would give access to additional data that would increase the reach of this work. The last is due to

allows the system to have a better identification of the environment, in addition to, the vision for machines, in the report performed was evidenced that digital processing of images allows the identification of the primary colors.

There are a few unique kinds of traffic signs like speed restricts, no access, traffic lights, turn left or right, youngsters crossing, no going of substantial vehicles, and so forth. Traffic signs order is the way toward recognizing which class a traffic sign has a place with. You more likely than not found out about oneself driving vehicles in which the traveller can completely rely upon the vehicle for voyaging. Yet, to accomplish level 5 self-sufficient, it is vital for vehicles to comprehend and adhere to all traffic rules. In the realm of Artificial Intelligence and progression in advancements, numerous specialists and huge organizations like Tesla, Uber, Google, Mercedes-Benz, Toyota, Ford, Audi, and so on are taking a shot at self-governing vehicles and self-driving vehicles. Along these lines, for accomplishing precision in this innovation, the vehicles ought to have the option to decipher traffic signs and settle on choices likewise. The exact acknowledgment rate and normal preparing time are particularly improved. This improvement is critical to diminish the mishap rate and upgrade the street traffic wellbeing circumstance, giving a solid specialized assurance to the consistent advancement of astute vehicle driving help.

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INTRODUCTION

With rapid increase in Science & Technology in future Autonomous cars will be widely used and developed which employee sensors and computer vision software's for better safety and control Ramler, R. and Ziebermayr, T. (2017). Innovation is helping to minimize human efforts and enhance use of sophisticated machines for interaction with a clear motive of Automation and achieve better Accuracy of work, Safe precious time and most important safety of human lives. I choose this futuristic topic to work on an approach and area of interest of solving a problem case using computer vision technology for classification of traffic sign with introducing some challenges in the dataset which will aim to be highly productive and a godsend better result. Applications of this project can be directly used in the industry for making better computer vision models for automation.

In the development of quality processes in the industry different types of sensors are used, as is for quality control of the external part or a cover of any product, where a color sensor is used, which allows a quick and effective way to determine if a product has the requirements necessary for its use. Initially, in a color contrast enhancement algorithm is designed that its dependences on decomposing the interrelated color component of the color images based on RGB color model. Similarly, in a color image edge detection algorithm is proposed in this paper. Average maximum color difference value is used to predict the optimum threshold value for a color image and thinning technique is applied to extract proper edges. The proposed method is applied over large database of color images both synthetic and real-life images and performance of the algorithm is evident from the results and is comparable with other edge detection algorithms. On the other hand, proposes new real time color recognition features, i.e., extracting primary colors for the purpose of vision-based human–computer interaction. Vision-based human–computer interaction could be achieved by analyzing segmented primary color regions. And deals with the implementation of various MATLAB functions present in image processing toolbox of MATLAB and using the same to create a basic image processor having different features like, viewing the red, green and blue components of a color image separately. The photoelectric sensor works through a stream that crosses by the phototransistor, which varies with according to the infrared light produced by an LED, this change depending on the surface in which the light hits. The schedule that requires consists in identifying the voltage with respect to a reference color. With the CMOS sensor (complementary metal oxide semiconductor by its acronym in English). The area of work can be increased and have a greater control of quality of the object, the operating principle for these two circuits is the photoelectric effect, which produces current depending on the intensity of the light that the sensor is receiving. When using the sensor of active pixels, it is important to take into account that it I necessary to perform a program in a specialized software, in this case was used python with the tools that provides OpenCV, due to that is compatible with the operating systems GNU-Linux ARM. With the Python Software and OpenCV the image produced by the sensor is obtained which is in RGB color model (Red Green Blue by its acronym in Spanish), which is a representation by the mixture the three primary colors. With the purpose of making a correct identification of the color it is necessary to perform an additional treatment applying the HSV model (High Saturation value)

which unlike the RGB color model, this one will not depend on factors such as the light, shade and lighting, allowing to obtain a measure of the sample more accurate in its processing.

Each individual, regardless of whether a Traveller, driver, walker would have seen along the side of the road different sign board that fill significant needs. These significant street gear help us as course aides, admonitions and traffic controllers.

As control gadgets for traffic, signs need complete consideration, regard and suitable driver's reaction. With the approach of mechanized traffic and its expanding pressure on street, many have received pictorial signs and normalized their signs to encourage global travel, where language contrasts would make hindrances. In unfavorable rush hour gridlock conditions, the driver may not see traffic signs, which may cause mishaps. In such situations, programmed street sign recognition becomes effective. The fundamental goal of proposed framework is to recognize the street sign naturally while driving and controls the speed or makes the go as indicated by that Road sign. Street sign acknowledgment is utilized to caution the occupied driver, and forestall his/her activities that can lead a mishap. The objective is to maintain a strategic distance from mishaps by both manual and robotization measure in which all the activities will be performed dependent on the identified Road signs. A continuous programmed speed sign discovery and acknowledgment can support the driver, essentially expanding his/her wellbeing. To evade mishaps and gridlock street signs are commonly positioned close to bended zones, emergency clinic zones, school zones and so forth. Driver needs to see the street signs and control the speed or makes the go as per it. Because of different issues, drivers are less mindful to street signs which lead to mishaps.

In Existing System, a thought is proposed to dodge mishaps in which street signs are perceived consequently by web camera utilizing Image handling strategies and Raspberry Pi3. In our cutting-edge age, around 1.3M individuals kick the bucket on streets every year. This number would be a lot higher without our street signs. Normally, self-ruling vehicles should likewise maintain street enactment and in this way perceive and comprehend traffic signs. Traffic sign grouping is the cycle of consequently perceiving traffic signs along the street, including speed limit signs, caution signs, blend signs, and so on. Having the option to consequently perceive traffic signs empowers us to fabricate "more brilliant cars". Self-driving vehicles need traffic sign acknowledgment so as to appropriately parse and comprehend the street. Additionally, "driver alert" frameworks inside vehicles need to comprehend the street around them to help and secure drivers. Traffic sign acknowledgment is only one of the issues that PC vision and profound learning can comprehend. The Road Signs we were around us date long back ever. The most punctual street signs were achievements, provide separation or guidance. In the medieval times, multidirectional signs at crossing points got normal, offering bearings to urban areas and towns. With the approach of mechanized traffic and its expanding pressure on street, many have embraced pictorial signs and normalized their signs to encourage worldwide travel, where language contrasts would make hindrances.

All in all, it is utilized to assist improve with dealing security through proper alert, guideline and informatory signs. The greater parts of them use images instead of words and have universal acknowledgment and acknowledgment.

With the rapid development of economy and technology in the modern society, automobiles have become an indispensable means of transportation in the daily travel of people. Although the popularity of automobiles has introduced considerable convenience to people, it has also caused a numerous traffic safety problem that cannot be ignored, such as traffic congestion and frequent road accidents. Traffic safety issues are largely caused by subjective reasons related to the driver, such as inattention, improper driving operation and non-compliance with traffic rules, and smart cars have become an effective means to eliminate these human factors. Self-driving technology can assist, or even independently complete the driving operation, which is of remarkable importance to liberate the human body and considerably reduce the incidence of accidents. Traffic sign detection and recognition are crucial in the development of intelligent vehicles, which directly affects the implementation of driving behaviors. Smart cars use a vehicle-mounted camera to obtain real and effective road traffic information;

they can also recognize and understand traffic signs in real time in the actual road scenes to provide correct command output and good motion control for intelligent vehicles, which can remarkably improve the efficiency and safety of automatic driving. Therefore, conducting an in-depth study on it is necessary. The traffic sign recognition process generally includes two stages: traffic sign detection and recognition. However, in the daily natural conditions, the changes of light, the complex backgrounds and the aging of signs have caused many difficulties in accurately identifying traffic signs. With the rapid increase in computer running speed, many experts and scholars have focused on the traffic sign recognition process, which is mainly divided into traffic sign detection and recognition technologies. Traffic sign detection technology is mainly based on inherent information, such as color, shape and texture features of traffic signs, and accurately extracts traffic sign candidate areas from the actual road scenes. Wang et al. proposed a red bitmap method to detect traffic signs. Firstly, color segmentation of the detected images is performed, and then shape detection of the region of interest (ROI) based on edge information is conducted. This method achieved good detection results but was only applicable to red circular traffic signs, which had some limitations. Hachi et al used the template matching method to match the traffic signs. By setting the sliding window of the same size as the traffic signs, the useless parts of non-traffic signs in the current road scenes were removed. However, some signs had different shapes and sizes, and the road traffic environment was complex and changeable; thus, the real-time performance of this method was poor. Lillo-Castellano et al. adopted the color segmentation method that combines HIS and LAB color spaces to enable detection of black, white and colorful traffic signs. Xiao et al. proposed a traffic sign detection method combining HOG features and Boolean convolutional neural networks. This method can eliminate the error detection areas of candidate regions and achieve good detection results by connecting cascaded classifiers. Guan et al. proposed a method for detecting traffic signs from mobile LiDAR point clouds and digital images. Traffic signs were detected from mobile LiDAR point clouds based on valid road information and traffic-sign size, and segmented by digital image projection, and the given images can be classified automatically after normalization. Traffic sign recognition technology is mainly used to analyze and classify the detected traffic signs and accurately obtain their actual meaning. Sun et al. proposed a traffic sign classification method based on extreme learning machine (ELM), which is a supervised learning algorithm related to feedforward neural network. Only one hidden layer is observed; therefore, the parameters were few and the training time was short. The algorithm classified traffic signs according to the calculation results by selecting a certain proportion of features and obtained high recognition accuracy. Qian et al. trained the traffic sign data by using the regional depth convolutional neural network (CNN) and the collected Chinese traffic sign dataset for identification test, which achieved a high accurate recognition rate. He et al. proposed ResNet network based on the concept of residuals. By continuously learning the residuals, the network performance was considerably raised, and the recognition accuracy was further improved. Yuan et al. adopted the traffic sign recognition combining Adaboost algorithm and support vector machine. The candidate recognition images were screened by the Adaboost and then classified by the SVM. The recognition accuracy was high, but the detection time was long. Kumar et al. proposed a traffic sign detection method based on capsule network. The multi-parameter deep learning network structure can realize automatic feature extraction, which had good robustness and stability. The experimental results showed that the method had a conspicuous detection effect. Yuan et al. proposed an end-to-end traffic sign detection method. The multi-feature fusion network structure can extract effective features for different size images, and then establishing a vertical space sequence attention module to obtain background information around the detected image, which also had prominent detection performance in complex road traffic environments.

The research results show that many methods have improved the accurate recognition rate of traffic signs, but advantages and disadvantages still exist between the algorithms, which will be limited by various conditions. In the study of traffic sign detection technology, disturbances, such as bad weather conditions, changes in lighting conditions and fading of signage, will lead to an evident decline in the accuracy of traffic sign detection and poor environmental adaptability. Moreover, recognition algorithms based on deep learning-based methodologies have a high accurate recognition rate, but some problems, such as high complexity of the algorithms and long processing time, exist. Meanwhile, the algorithms have high requirements on system hardware, and the structures of training models are complicated, thereby indicating the presence of some limitations. Therefore, further improvement of the traffic sign detection and recognition algorithm is urgent. In this study, an improved traffic sign detection and recognition algorithm for intelligent vehicles is proposed. Firstly, the HSV color space is used for spatial threshold segmentation, and traffic signs are effectively detected based on the shape features. Secondly, the model is considerably improved on the basis of the classical LeNet-5 convolutional neural network model by using Gabor kernel as the initial convolutional kernel, adding the batch normalization processing after the pooling layer and selecting the Adam method as the optimizer algorithm. Finally, the traffic sign classification and recognition experiments are conducted based on the German Traffic Sign Recognition Benchmark. The favorable prediction and accurate recognition of traffic signs are achieved through the continuous training and testing of the network model. According to the analysis of experimental results and performance comparison with other algorithms, the comprehensive performance of the algorithm is evaluated. The rest of this paper is organized as follows: In Section 2, the HSV color space is used for spatial threshold segmentation, and traffic signs are effectively detected based on the shape features. In Section 3, the classic LeNet-5 CNN model is further improved. In Section 4, the experiments on traffic sign classification and recognition based on the GTSRB are conducted and analyzed, and the performance of algorithms are compared. In Section 5, conclusions and suggestions for possible future work are outlined.

LITERATURE SURVEY

[1] Deep Correct: Deep Learning color correction for color blindness.

Color vision deficiency affects 8% men and one in every 200 women. There are many different types of color blindness with the red-green as the most common. Most models for color correction are based on physiological models of how people with color vision deficiency perceive the world, with the goal of reducing errors derived from the color blindness simulation formula.

In this paper Deep Correct, a novel Deep Learning based method for color correcting images in order to improve accessibility for people with color vision deficiency. The key elements of this work with regard to color blindness are two-fold: 1) we propose a data-driven Deep Learning approach for color correction and 2) we create an objective, quantitative metric for determining the distinguishability of images.

Results:

The Referee is trained on the Pascal dataset, with the goal of predicting the correct image label from 20 defined categories. We have created this network by using VGG16 (one of the popular winning ImageNet models), removing the top fully connected layers (which are not useful for Pascal) and adding and training new fully connected layers to predict image categories for Pascal. VGG itself is trained on the much larger ImageNet dataset, and learns to produce one of the original 1000 categories, with relatively high accuracies (70% on Top1 and 90% on Top5).

[2] Optimizing colormaps with consideration for color vision deficiency to enable accurate interpretation of scientific data

Color vision deficiency (CVD) affects more than 4% of the population and leads to a different visual perception of colors. Until the creation of the module presented here, there were no colormaps mathematically optimized for CVD using modern color appearance models. An example CVD-optimized colormap created with this module that is optimized for viewing by those without a CVD as well as those with red-green colorblindness.

The CVD simulation model used in *color spacious* is from Machado et al. and requires as input the CVD type as well as severity, both of which are easily controlled through this module. Specifically, CIECAM02-UCS was used for the color space for altering the colormap. Deuteranomaly was chosen as the CVD type because deuteranomaly, also referred to as a red-green color deficiency (protanomaly being another form of red-green color deficiency), is by far the most common form of CVD. Severity can also be controlled by adjusting it along a scale of 0–100, with 0 representing no colorblindness and 100 representing complete dichromacy.

Result:

Therefore, the ability to linearize J′ in two different ways:

(i) fit to the original J′ line as closely as possible without considering how these values will map back to RGB color space or

(ii) maximize the range of J′ based on valid (J′, a′, b′) to (R, G, B) mappings. It uses *cmaputil* to create several example colormaps. It identifies one colormap in particular to be optimal for viewing by those with or without CVD, which we name cividis , generated by optimizing the viridis colormap and selecting the J' linearization that maximizes the range of J'.

[3] Development of Color Vision Deficiency Assistive System.

With the help of OpenCV library, color detection, filtering and processing can be carried out easily. Benchmark shape and color of has been designed for experimental purposes to test for the performance and functionality of the system. The result of the distance test shows that the hue (H) element is almost consistent whereas the saturation (S) varies by roughly 49.3% and value (V) by 30.5%. As for the range of detection, the minimum range is 12 cm where the maximum range is up to 15 meters.

There are two different types of photoreceptors in our eyeballs that allow us to see everything. They are called rods and cones. The rods receptors are very sensitive to low light level but not to color [5-10] while cones are sensitive to colors. There are three types of cones that responsible for color vision: long, medium, short wavelength cones. Each of these cones corresponds to a specific light wavelength, which is red (long wavelength), green (medium) and blue (short). Hence, each of these cones had its own specific color absorption curve that peaked at different points in the color spectrum.

Results:

The characteristics and type of color blind has been studied and identified as well as the problem faced by individual that is color blind. A real-time color recognizing system using image processing technique is successfully developed and tested In conclusion, this prototype is able to recognize up to four colors such as red, blue, green and yellow as well as their respective variations such as light blue or dark blue. The region with similar HSV value to the designated region is also highlighted. The visual results which is text indicating the object color as well as the boundary line is successfully shown on the LCD monitor. The result of the distance test shows that the hue (H) element is almost consistent whereas the saturation (S) varies by roughly 49.3% and value (V) by 30.5%.

SYSTEM ANALYSIS

The first stage of any image processing task is to have an image for detecting colors in it. One can capture it from the camera or load a previously clicked image from the memory. Read the input image in RGB format which is the most commonly used format to represent colored images, if the resolution of the image is MxN, then the RGB format of the image will be a three-dimensional matrix of size MxNx3 where each dimension of the matrix represents the red, green and blue color components of the image.

Extract out the red, green and blue colour bands from the input image into three separate two dimensional matrices, one for each colour component. First, second and third slice of three-dimensional matrices of RGB image contains the red, green and blue colour components respectively.

In photography and image processing, histogram is the distribution of colors in an image. Compute and plot red, green and blue color band histogram using imhist() function of MATLAB.

The RGB image is converted into grayscale image, the grayscale format of the image will be a two-dimensional image containing the intensity value of each of the pixel of the image. Usually a grayscale image increases the speed of processing, ease of visualization, and reduces complexity of code by converting a three-dimensional image into twodimensional image resulting in reduction in number of bits used to represent each pixel of an image legitimately influences the usage of driving practices. Brilliant vehicles utilize a vehicle-mounted camera to get genuine and compelling street traffic data; they can likewise perceive and comprehend traffic signs continuously in the real street scenes to give right order yield and great movement control for shrewd vehicles, which can surprisingly improve the productivity and security of programmed driving. Thusly, leading a top to bottom examination on it is important. The traffic sign acknowledgment measure by and large incorporates two phases: traffic sign discovery and acknowledgment. Notwithstanding, in the day-by-day common conditions, the progressions of light, the mind-boggling foundations and the maturing of signs have caused numerous troubles in precisely recognizing rush hour gridlock signs. With the fast increment in PC running pace, numerous specialists and researchers have concentrated on the traffic sign acknowledgment measure, which is basically separated into traffic sign discovery and acknowledgment innovations. Traffic sign identification innovation is mostly founded on characteristic data, for example, shading, shape and surface highlights of traffic signs, and precisely removes traffic sign competitor territories from the genuine street scenes. Wang et al. proposed a red bitmap strategy to identify traffic signs. Initially, shading division of the distinguished pictures is performed, and afterward shape location of the area of intrigue (ROI) in view of edge data is directed. This strategy accomplished great discovery results yet was just appropriate to red round traffic signs, which had a few constraints. Hechri et al. utilized the layout coordinating strategy to coordinate the traffic signs. By setting the sliding window of a similar size as the traffic signs, the pointless pieces of non-traffic signs in the current street scenes were eliminated. Be that as it may, a few signs had various shapes and estimates, and the street traffic condition was perplexing and alterable; accordingly, the on-going presentation of this strategy was poor.

PROPOSED SYSTEM

The street traffic pictures are caught by vehicle-mounted cameras introduced on the keen vehicles, and the traffic sign recognition means to remove the intrigued traffic sign areas from the current street traffic pictures adequately. Nonetheless, in various outer conditions, the characteristics of the obtained pictures are lopsided, and these characteristics must be successfully recognized after the inalienable qualities of traffic signs, for example, shading and shape. In this segment, it fundamentally incorporates two sections: traffic sign division dependent on the shading space and traffic sign location dependent on shape highlights.

Shading is a significant element of traffic sign, and traffic sign can be immediately situated by shading division. Contrasted and RGB shading space and YCbCr shading space, the YCbCr shading space has a quicker recognition speed, less influenced by brightening, and has a best division advantage. Figure 1 shows the HSV shading space changed over from the RGB shading space. It speaks to the focuses in the RGB shading space by a reversed cone, where Y is the luminance, CbCr is the chrominance esteem. During the time spent limit division, the pixels inside the set edge go are set to white, else they are set to dark, and the picture is totally binarized. Since the traffic sign in the first picture is red, the acquired limit coarse division picture just shows red. Right off the bat, the paired picture is handled by picture consumption and extension. Some disconnected futile pixels regularly exist on the edge of the picture, and these pixels can be adequately eliminated by erosion. Then, extension means to amplify the territory of the ROI. The blend of them can sift through some unobtrusive obstruction, along these lines delivering conspicuous shape attributes of traffic signs. The filling cycle is then directed. The traffic signs might be stained, harmed and hindered by certain snags in the genuine street scenes, and the ROI can't be totally shown. The filling cycle can help finish and picture the shapes of traffic signs. At last, the successful identification of traffic signs is figured it out. Some huge sporadic impedance territories despite everything exist in the divided picture after the filling cycle and consequently should be sifted. Shape separating is directed by the form examination of associated territory. This are in the picture is a set with in no way different pixel focuses. The circuit and territory of the forms of all associated territories are determined and afterward contrasted and the standard round imprint. The shapes that meet the necessities are held; else, they are disposed of. Likewise, this technique is similarly relevant to the traffic sign discovery of triangle, square shape and different shapes. The rest of the aspect of the divided picture after shape sifting compares to the distinguished traffic sign.

IMPROVED MODEL

Traffic sign acknowledgment depends on existing dataset assets and utilizations powerful characterization calculation to perceive recognized traffic signs and criticism to shrewd vehicles precisely progressively. CNN removes includes legitimately from the information identification picture and yields the characterization results through the prepared classifier dependent on picture highlights. This condition shows that CNN has great realistic acknowledgment execution. Besides, CNN doesn't have to extricate includes physically. The tangible psychological cycle of human minds can be very much reenacted through forward learning and criticism system, in this way progressively improving the capacity of traffic sign arrangement and acknowledgment. In this area, the inadequacies of the old style organize model are dissected, and the model is significantly improved to additionally extend the exceptional focal points of CNN in designs acknowledgment.

We will build a deep neural network model that can classify traffic signs present in the image into different categories. With this model, we are able to read and understand traffic signs which are a very important task for all autonomous vehicles. For achieving accuracy in this technology, the vehicles should be able to interpret traffic signs and make decisions accordingly. ` There are several different types of traffic signs like speed limits, no entry, traffic signals, turn left or right, children crossing, no passing of heavy vehicles, etc. Traffic signs classification is the process of identifying which class a traffic sign belongs to. Three main traffic signs categories, i.e., warning signs, prohibition signs and mandatory signs are covered for experiments. Specifically, in our video-based CNN- SVM recognition framework, by introducing the YCbCr color space, we firstly divide the color channels, secondly employ CNN deep network for deep feature extraction and then adopt SVM for classification. The experiments are conducted on a real-world data set, based on which, a synthetically comparison illustrates the superiority of our model

Image Preprocessing

The ROI in the traffic sign training image is not 100% in the center of the image, and some edge background information is included around the traffic sign. With the change of illumination conditions, these useless interference areas will increase the influence on traffic sign recognition, thereby undoubtedly raising the computational complexity of the training network and the misrecognition rate of traffic signs. Therefore, image preprocessing is necessary. Image preprocessing mainly includes the following three stages:

(1) Edge clipping. Edge cropping is a particularly important step in the image preprocessing. Some background parts in the edge are not related to traffic signs, and these parts can account for approximately 10% of the entire image. The bounding box coordinates are used for proportional cropping to obtain the ROI. The removal of the interference region helps to reduce redundant information and speed up the network training.

(2) Image enhancement. The recognition effects of the same type of traffic signs in the training network under different illumination conditions are significantly different. Therefore, reducing or removing the noise interference caused by the light change via image enhancement is necessary. Direct grey-scale conversion method is used to adjust the grey value of the original image using the transformation function, which presents clear details of the ROI and demonstrates a blurred interference area. Thus, this method effectively improves the image quality and reduces the computational load of the training network.

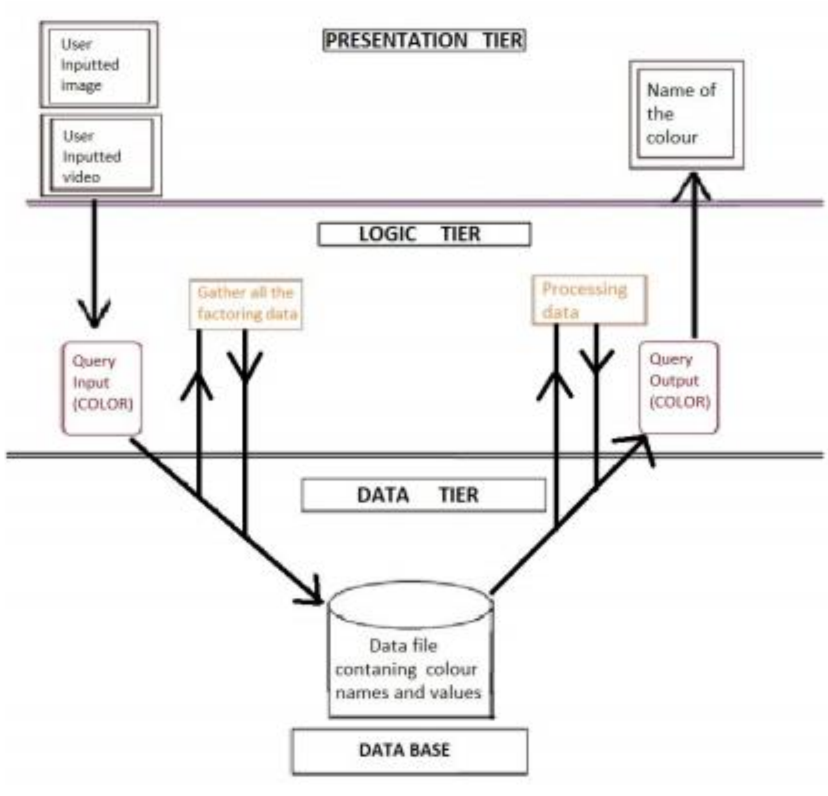
(3) Size normalization. The same type of traffic signs may have different sizes. The different sizes of training images may have different feature dimensions during the CNN training process, which leads to difficulties in the subsequent classification and recognition. In this paper, the image is uniformly normalized in size, and the normalized image size is 32×32.

From the perspective of traffic sign acknowledgment exactness and calculation tedious, the proposed traffic sign identification and acknowledgment calculation has astounding points of interest. Extensively upgrading the driving security of wise vehicles in the genuine driving conditions and viably meeting the on-going objective necessities of keen vehicles are helpful. Moreover, a solid specialized assurance is accommodated the consistent improvement of smart vehicle driving help. Later on, the comprehensiveness and against mistake acknowledgment of the traffic sign acknowledgment calculation can be additionally enhanced and improved to abuse the general presentation of the calculation.

SYSTEM DESIGN AND IPLEMENTATION

Architecture

1) Challenge Detection: Challenge Detection consists of four blocks, each with 2 convolution layers, a ReLU Activation Layer and a Max-Pooling layer. The output after these 4 blocks is then flattened, and, a fully connected layer is used to map this flattened feature vector to 12 classes. These 12 classes represent the 12 types of challenge that are to be detected.



2) Selective Preprocessing: Before passing the image on to the corresponding localizer for detecting traffic-signs, it is first preprocessed. The preprocessing method that we choose to use is a variant of Histogram-Equalization, called, Contrast Limited Adaptive Histogram Equalization (CLAHE). This version of histogram equalization works on a local neighborhood of the image and limits contrast to prevent enhancement of noise. To do this, we first convert the image from RGB to HSV (Hue, Saturation, Value) space, and then, equalize the histogram of the proper HSV channel. The equalizing operations that are performed for the different challenge types are given in Table III. The table states the number of applications of

CLAHE to the Saturation or Value channel, and, the Contrast Clip-Limit used. The result of our preprocessing method, performed on level 4 noisy images.

For images affected with Rain, we use a CNN of ResNet type architecture to remove the rain. The architecture of this network is shown in figure. It consists of consecutive Convolution blocks, each with a Convolution layer, a Batch Normalization layer and a ReLU layer. Skip connections are used which help to directly propagate lossless information throughout the entire network. This is useful for estimating the de-rained image. Finally, the Residual image generated by the model is added to the original image to output the de-rained image. Here, all pooling operations are removed to preserve spatial information.

3) Traffic-Sign Localization: This stage of the model is implemented by using a Fully Convolutional Neural Network inspired by the U-Net Architecture. The detailed network architecture is illustrated in figure. The network consists of 2 stages: a down sampling stage and an up-sampling stage, which are connected by using a Residual Learning strategy.

a) Down-sampling: This stage consists of several convolution blocks, each with 2 convolution layers, a Batch Normalization layer and a ReLU Activation layer. After each block, a Max-Pooling operation is performed for down-sampling. The number of feature channels is doubled at each down-sampling step.

b) Up-sampling: During up-sampling of the feature map, at each step, it is concatenated with a corresponding cropped feature map from the down sampling stage. Here, cropping is necessary for the loss of border pixels in every convolution. Finally, two more convolution layers are added, which map each component feature vector from the previous layer to 2 classes (traffic sign and background). The motivation for using the U-Net architecture is its robustness against low-resolution features of the image during training. In the up-sampling layers employed within it, there are a large number of feature channels which allow the network to propagate context information to higher resolution layers. This is quite an attractive feature for localizing objects in noisy conditions where the target object may not be dominantly visible in the image. The U-Net architecture produces the location of the object by performing a pixel-wise image-segmentation. It predicts a probability for each pixel based on its likelihood of being present in a region corresponding to one of 2 classes (Traffic Sign and Background). So, the traffic signs are detected as islands of high-probability regions in the image. The bounding box of these regions are the predicted traffic signs in this image.

4) Classification: The architecture of the CNN used for classifying the traffic sign proposals is shown in Fig. 5. It has 2 Convolution Blocks, each with two consecutive Convolution layers, a ReLU activation layer, and a Max-Pooling layer. A dropout layer is added after each block. Finally, there are 2 fully connected layers - the first

one has a hidden size of 1024 with ReLU activation, and, the latter has a hidden size of 14 with SoftMax activation. The output of this layer are the class probabilities for each of the 14 sign-classes.

Common traffic signs mainly include red, yellow and blue colors. In order to meet the target requirements of real-time color segmentation, it is necessary to determine the corresponding threshold range. Through multiple test experiments, the three-channel threshold segmentation ranges of three colors are obtained on the premise of ensuring good segmentation effects.

In the process of threshold segmentation, the pixels within the set threshold range are set to white, otherwise they are set to black, and the image is completely binarized. Since the traffic sign in the original picture is red, the obtained threshold coarse segmentation image only displays red. Traffic Sign Detection Based on the Shape Features In the actual road scenes, traffic signs do not exist independently. Colorful clothes of pedestrians and colored billboards are likely to be consistent with the color of traffic signs, thereby resulting in some useless interference to the binary image with threshold coarse segmentation. Therefore, filtering these interferences is necessary to achieve effective detection of the ROI.

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Firstly, the binary image is processed by image corrosion and expansion. Some isolated useless pixels often exist on the edge of the image, and these pixels can be effectively removed by corrosion. Meanwhile, expansion aims to enlarge the area of the ROI. The combination of them can filter out some subtle interference, thereby producing prominent shape characteristics of traffic signs. The filling process is then conducted. The traffic signs may be discolored, damaged and blocked by some obstacles in the actual road scenes, and the ROI cannot be completely displayed. The filling process can help complete and visualize the contours of traffic signs. Finally, the effective detection of traffic signs is realized. Some large irregular interference areas still exist in the segmented image after the filling process and thus need to be filtered. Contour filtering is conducted by the contour analysis of connected area. This are in the image is a set with all the same pixel points. The circumference and area of the contours of all connected areas are calculated and then compared with the standard circular mark. The contours that meet the requirements are retained; otherwise, they are discarded. Similarly, this method is equally applicable to the traffic sign detection of triangle, rectangle and other shapes. The remaining part of the segmented image after contour filtering corresponds to the detected traffic sign.

Models Implemented

In this section, we discuss the different models implemented and the proposed novel implementation as well. As said earlier, we began by taking a simple CNN architecture VGG-19. We then went on to selecting deeper neural networks with skip connections like ResNet and Dense Net. Additionally, we explored the performance of Inception Module in Google Net. We also implemented RNN to see if the image pixels have any sequential relation which can be exploited to boost the performance. Seeing the results, we proposed a novel architecture. VGG-19 We started off with a simpler highway architecture VGG-19 that was trained from scratch to classify traffic signs. It uses only 19 layers and has a relatively simpler architecture as it does not use inter-layer connections. ResNet50 and DenseNet121 Next, we performed transfer learning on a popular image classification architecture ResNet50 pretrained on ImageNet. The actual motivation to use ResNet50 which consist of 50 layers was to strengthen feature propagation across different layers and encourage feature reuse. It uses skip connections to add outputs of previous layers to the current layer which helps it reduce the residual error between the preceding and the current layer. Secondly, we tuned DenseNet121 (total 121 layers) architecture pretrained on ImageNet dataset for traffic sign detection. Dense Net is the logical extension of the concept used in building ResNet architecture. The feature maps of all preceding layers are used as input to the current layer and its output feature maps are used as input to the subsequent layers. It connects all layers in a feed forward manner to enhance feature learning and help the model converge faster.

Inception-V1 architecture uses inception modules which has convolution filters of different kernel sizes at a single layer and concatenate all of the output feature maps before passing it to the next layer. This architecture helps the classifier to simultaneously capture global and local feature details of the input image making it robust to size variations of the object of interest in the image. Traffic signs in the images of training data have large variations in their size. For instance, images of the traffic signs might be at different distances from the sign board making it appear larger or smaller than the actual image. Considering this fact, we trained Inception-V1 architecture from scratch for German traffic sign detection benchmark.

Recurrent Neural Network Another important neural network architecture is Recurrent Neural Network which uses hidden states of previous layers as inputs which makes it a suitable choice for sequential inputs. This architecture was implemented to explore if there exist any sequential relationship in the pixels which can be utilized to boost accuracy.

Proposed CNN architecture Finally, we implemented a convolution neural network architecture that has two stacks made up of three convolutions layers followed by one average pooling layer and two fully connected layers. We used batch normalization after every convolution layer to avoid exploding and vanishing of gradients while back propagating across different layers. Dropout layer was applied after each stack to avoid overfitting. The figure of the developed architecture. The first two convolution layers have 32 convolution filters with kernel size = 3. Grid Search over different kernel dimensions: 3, 5, 7, 9, 11, 19 and 31 for convolution layers was performed. The highest accuracy was achieved with kernel size = 3. ReLU activation function was used as a nonlinearity after each convolution layer which set negative input to zero. We did not use MaxPooling layer after every convolution layer to avoid losing spatial information of feature maps at early stages. Subsequent three convolution layers have 64 convolution filters each to increase the receptive field. Moreover, the last convolution layer has 128 convolution filters. This is followed by an average pooling layer to gather essence of all received feature maps. Its output is given to a fully connected hidden layer consisting of 512 neurons. Final output layer has 43 neurons with SoftMax as activation function to calculate the probability corresponding to 43 classes of ITSDB dataset. Most of this architecture was designed using Random Search for various parameters.

The first stage of any image processing task is to have an image for detecting colors in it. One can capture it from the camera or load a previously clicked image from the memory. Read the input image in RGB format which is the most commonly used format to represent colored images, if the resolution of the image is MxN, then the RGB format of the image will be a three-dimensional matrix of size MxNx3 where each dimension of the matrix represents the red, green and blue color components of the image. Extract out the red, green and blue colour bands from the input image into three separate two dimensional matrices, one for each colour component. First, second and third slice of three-dimensional matrices of RGB image contains the red, green and blue colour components respectively.

In photography and image processing, histogram is the distribution of colors in an image. Compute and plot red, green and blue color band histogram using imhist() function of MATLAB.

Color is an important feature of traffic sign, and traffic sign can be quickly located by color segmentation. Compared with RGB color space and HSI color space, the HSV color space has a faster detection speed, less affected by illumination, and has a preferable segmentation advantage. H indicates the color change of the image. The position of the spectral color is represented by the angle, and different color values correspond to different angles. Red, green and blue are 120◦ apart, that is, 0◦, 120◦ and 240◦, respectively. S denotes the proportion of the current color purity to the maximum purity with the maximum value of 1 and the minimum value of 0. V represents the brightness change of the image. The maximum value is 1 in white and the minimum value is 0 in black. In the HSV color space, given that V is a fixed value set and H and S are highly unrelated, the HSV color space has good illumination adaptability when the illumination conditions change, and its computational complexity is small, which are conducive to the color space threshold segmentation.

PERFORMANCE ANALYSIS

The internal traffic signs are collected from the real road traffic environment in India, and it has become a common traffic sign dataset used by experts and scholars in computer vision, self-driving and other fields. The ITSRB comprises 51,839 images, which are divided into training and testing sets. A total of 39,209 and 12,630 images are provided in the training and testing sets, accounting for approximately 75% and 25% of the whole, respectively. Each image contains only one traffic sign, which is not necessarily located in the center of the image. The image size is unequal; the maximum and smallest images are 250 × 250 and

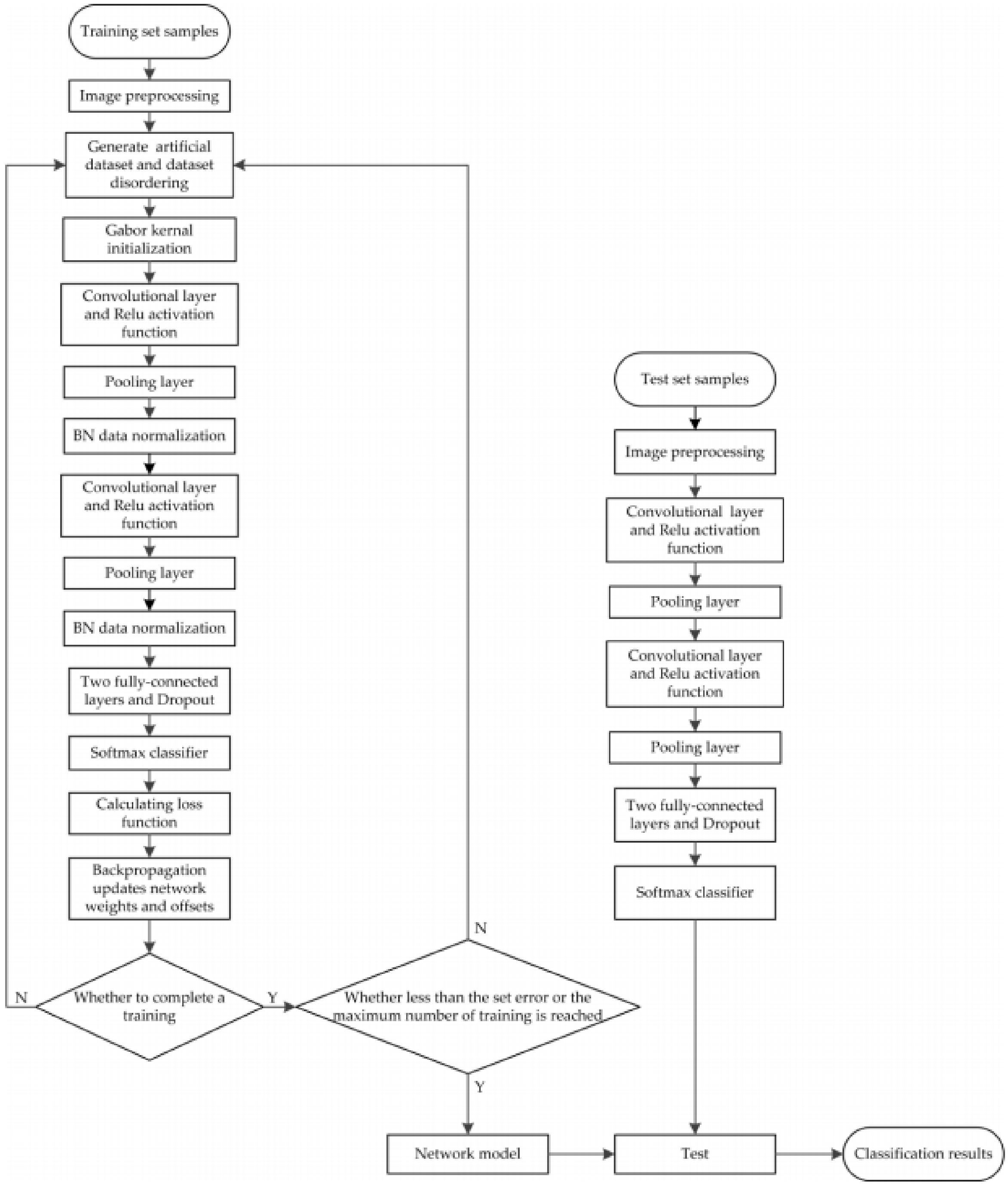
15 × 15 pixels, respectively [37,38].

The traffic sign images in ITSRB are taken from the video captured by the vehicle-mounted camera. ITSRB includes 43 classes of traffic signs, and the number of different types of traffic signs varies. Each type of traffic sign corresponds to a catalogue, which contains a CSV file annotated with a class label and a single image of multiple tracks (each track includes 30 images). In accordance with the different instruction contents, ITSRB can also be divided into six categories: speed limit, danger, mandatory, prohibitory, derestriction and unique traffic signs.

The same type of traffic signs includes different resolutions, illumination conditions, weather conditions, occlusion degree, tilt levels and other images, making the dataset more in line with the actual road scenes**.**

After image preprocessing, an artificial dataset must be generated for ITSRB. Given that the number of different types of traffic signs in ITSRB varies, this condition easily causes the imbalance of sample data. Different types of traffic signs have evident differences during classification and recognition, which affect the generalization of the entire network model. Generating an artificial dataset aims to construct a new artificial sample by randomly sampling from the value space of each attribute feature of the same sample type. The number of 43 classes of traffic signs. Sensors 2019, 19, 11 of 21 The traffic sign images in ITSRB are taken from the video captured by the vehicle-mounted camera. ITSRB includes 43 classes of traffic signs, and the number of different types of traffic signs varies. Each type of traffic sign corresponds to a catalogue, which contains a CSV file annotated with a class label and a single image of multiple tracks (each track includes 30 images). In accordance with the different instruction contents, ITSRB can also be divided into six categories: speed limit, danger, mandatory, prohibitory, derestriction and unique traffic signs. The same type of traffic signs includes different resolutions, illumination conditions, weather conditions, occlusion degree, tilt levels and other images, making the dataset more in line with the actual road scenes. The number of 43 classes of traffic signs. Six categories of traffic signs sample images. After image preprocessing, an artificial dataset must be generated for ITSRB. Given that the number of different types of traffic signs in ITSRB varies, this condition easily causes the imbalance of sample data. Different types of traffic signs have evident differences during classification and recognition, which affect the generalization of the entire network model. Generating an artificial dataset aims to construct a new artificial sample by randomly sampling from the value space of each attribute feature of the same sample type. Therefore, the Six categories of traffic signs sample images. After image preprocessing, an artificial dataset must be generated for ITSRB. Given that the number of different types of traffic signs in ITSRB varies, this condition easily causes the imbalance of sample data. Different types of traffic signs have evident differences during classification and recognition, which affect the generalization of the entire network model. Generating an artificial dataset aims to construct a new artificial sample by randomly sampling from the value space of each attribute feature of the same sample type. Therefore, the number of different kinds of traffic signs is as equal as possible to solve the problem of sample data imbalance. After generating the artificial dataset, the 43 classes of traffic signs

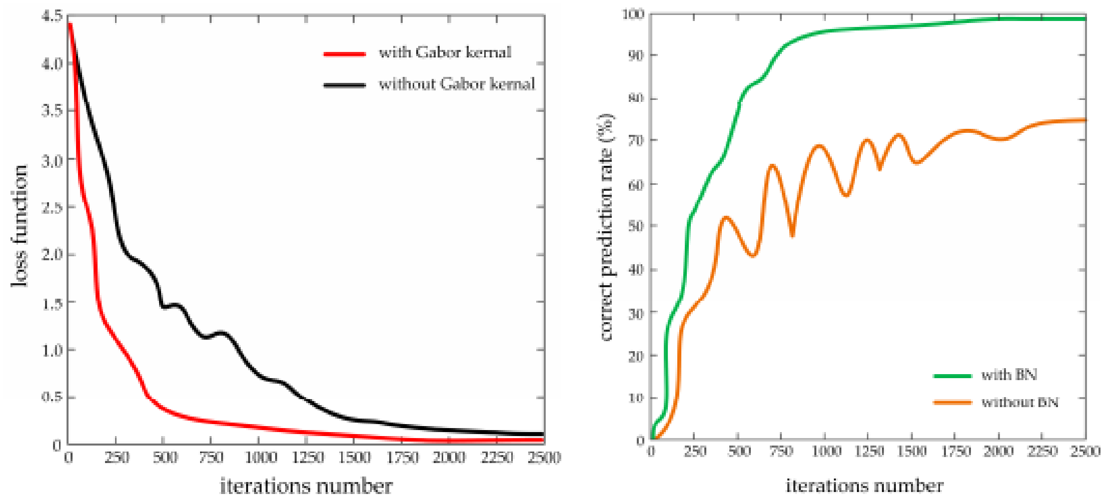
Traffic sign classification and recognition experiment can be divided into two stages, namely, the network training and testing stages. In the network training stage, the training set samples of ITSRB are taken as input. By performing thousands of network iterations, parameters, such as network weights and offsets, are continuously updated on the basis of forward learning and back propagation mechanisms until the loss function is reduced to the minimum, thereby classifying and predicting traffic signs. In the network testing stage, the testing set samples of ITSRB are inputted into the trained network model to test the accurate recognition rate of the training network



The graph presents the dynamic change curve of relevant parameters in the network training stage, in which,

(a) indicates the dynamic contrast curve of loss function with iteration number in the case of Gabor and non-Gabor kernels,

(b) shows the dynamic contrast curve of correct prediction rate with iteration number in the case of BN data normalization and non-BN data normalization. In the improved Lenet-5 network model, with the deepening of the network iterations, the loss function corresponding to the Gabor kernel initialization is much falling faster than that without the Gabor kernel initialization, and drops smoothly to 0. The reason is that the Gabor filter can extract effective target contour information and remove useless image noise, thereby effectively avoiding over-fitting of the training data and reducing the computational complexity, and further enhance the robustness and adaptability of the network model. Without the Gabor filter, the training network can easily fall into the local optimal solution, which makes the updating of network parameters such as weights and offsets become slower. It can be seen that a good sample image classification prediction effect is achieved in the network training stage, and the correct prediction rate using BN data normalization increases with iteration number and the highest value can reach about 99.82%. When BN data normalization is not used, the correct prediction rate has a large fluctuation and the highest value is only about 75%. The reason is that after adding BN data normalization processing, not only can the gradient dispersion phenomenon be effectively avoided, but also the convergence speed of the training model can be accelerated, the training model is more stable, and the generalization ability can be considerably enhanced.



(a) The loss function **(b)** The correct prediction rate

The traffic sign test images are inputted into the trained improved LeNet-5 network model for classification and recognition. For each test image, the traffic sign indicated by the first five probabilities are outputted, and the maximum probability is selected as the recognition result. The auto-numbered traffic sign test images. The traffic sign test images are inputted into the trained improved LeNet-5 network model for classification and recognition. For each test image, the traffic sign indicated by the first five probabilities are outputted, and the maximum probability is selected as the recognition result and compared with the actual reference meaning. The recognition results of traffic sign test images in the network testing stage. It can be seen that the maximum probability recognition results of the eight traffic sign test images are completely consistent with their true meaning, and all of them have achieved effective recognition with an absolute probability close to 100%. The recognition results in the network testing stage show that the trained improved LeNet-5 CNN model has excellent classification and recognition ability, strong anti-jamming ability and high accuracy recognition rate for traffic sign dataset with different backgrounds and interferences, thereby reflecting admirable robustness and accuracy.

Compared with other algorithms, although the average processing time of this algorithm was relatively short, the accurate recognition rate was the lowest. Therefore, this algorithm is more likely to cause false or missed recognition in the actual road scenes than other algorithms. In reference, iterative nearest neighbors-based linear projection was combined with iterative nearest-neighbor classifier. Multiple HOG features were used for detection, and sparse representations were adopted for classification, thereby achieving good recognition performance. Compared with literature, although the accurate recognition rate was considerably improved, the average processing time was excessively long, and real-time performance was poor when applied to actual road scenes. In reference, a traffic sign recognition method based on the histogram of oriented gradients was utilized. In reference, the weighted multi-CNN was trained by a new training method, and good recognition accuracy was obtained. Although the running environment of the algorithm included GPU and CPU, the average processing time was still relatively long. Deep learning-based methodologies can still be further improved because of the complex structure of the training model, the large amount of calculation, the long training time and the poor real-time performance. Compared with the aforementioned literature, the proposed algorithm has the best overall performance when using the same dataset. The accurate recognition rate reaches 99.75%, and the average processing time per frame is 5.4ms. The generalization ability and recognition efficiency of the network model are also remarkably improved. In terms of performance improvement, evident advantages are observed. The fully improved traffic sign recognition accuracy is conducive to considerably enhancing the driving safety of intelligent vehicles in the actual driving environments. Meanwhile, the fully shortened average processing time is conducive to meeting the real-time target requirements of intelligent vehicles in the actual driving environments effectively. Thus, this study contributes to further improving the technical level of intelligent vehicle driving assistance.

FUTURE ENHANCEMENT AND CONCLUSION

We examine the task of integrating color, which forms the base of object detection algorithms. Supreme modern object detectors depend on the shape while overlooking color. Current tactics to augmenting intensity centered detectors with color frequently deliver inferior outcomes for object categories with fluctuating significance of color as well as shape. Our approach uses the color attributes as an unambiguous color representation for object recognition tasks. While, color attributes are dense, computationally efficient, and holds some degree of photometric invariance while keeping discriminative power. Detection of regular polygons is one of the most significant tasks with multi-applications in computer vision and robotics. Planar shapes in sketches can be detected using this algorithm. It has been instigated as a working model for shape retrieval and architectural representation from sketches. This algorithm detects all minimal polygons that can be created from a set of line segments in polynomial time and space complexity. Using the latest, complex and efficient algorithms, there is a chance for improvement in the described algorithm. Many different data mining algorithms have to be used so as to make the proposed project more efficient. Additional work can be performed regarding the detection and correction of rounding errors resulting from finite precision calculations.

RESULT

A set of 100 images of different resolution and clarity were used for testing of this algorithm and the results were mostly accurate. Red, green, blue, magenta, cyan, yellow and white colors were successfully detected on these images. The result of this detection depends on the threshold value that have been set for the images. The major problem with thresholding is that it considers only intensity values of the pixels and does not take into consideration any relationship between them. Sometimes extra pixels are detected which are not the part of the desired region, and with increase in noise these errors increase. In the method of labeling of connected components for image segmentation there is one problem, that if overlapping objects are present in an image, then it will consider it as only one object.

After executing the experiments for different models, best results for each model were noted depicts validation accuracy achieved for each model over 100 epochs. First thing to be observed is that all models give an accuracy above 80% in the final training stage. VGG-19 gives the best performance amongst all the models and the new implementation gives comparable accuracy as well. Another critical observation is that RNN gives worst performance on validation data. This might be because the image pixels do not show good sequential relationship. Further, it can be noticed that models using skip connections, i.e., ResNet and Dense Net and Inception Module, i.e., Google Net give decent accuracy as well. A key observation in this plot is the accuracy in initial training stages. Although VGG-19 gives slightly higher accuracy, its initial accuracy is quite low. On the other hand, our proposed model gives decent initial accuracy. Next, we observed the trends in all training, validation and testing accuracy at respective best hyperparameters settings represented. Training accuracy goes to around 100% for all models. The highest test accuracy is given by VGG-19 (98.12%) and our proposed model gives an accuracy of (97.71%). As expected, RNN gives the worst performance (89%) and ResNet (94.8%), Dense Net (95.59%).

In this project, various deep learning models were compared not just in terms of their classification accuracy, but also in terms of their prediction speed. Recurrent Neural Networks do not perform well as compared to Convolutional Neural Networks in terms of both accuracy and evaluation time for image classification purpose. One thing to be noted is that even simpler architectures namely, our proposed implementation and the VGG-19 outperform much more complicated, deep neural networks. Thus, performance of a particular model totally depends on the problem and data at hand and it is not necessary for deeper neural networks to always surpass the rest. Additionally, our proposed model gives the best response time while providing reasonable accuracy.

FUTURE SCOPE

1. Computer vision- Color detection is the basic and important step for proceeding in computer vision. Some special type of spectacles can be made which will make

use of computer vision (image processing) along with neural networks to provide an artificial vision to blind people.

2. Spy robots- The spy robots are made to identify objects in the place where they are launched. Object's shape, size, color, orientation is of importance to robot.

3. Object Segregation- An object can be segregated (separated) on the basis of its color.

4. Object Tracking- A moving object can be tracked on the basis of its color.

In this Python venture with source code, we have effectively arranged the traffic signs classifier with 95% precision and furthermore envisioned how our exactness and misfortune changes with time, which is truly acceptable from a straightforward CNN model. In the preparation cycle, the profound picture highlights are separated by CNN in the YCbCr shading space. SVM is associated with the last layer of CNN for additional order, which adds to better preparing outcomes. Then again, a few pictures preprocessing techniques are led in the testing cycle, so as to dispose of those negative effects, e.g., deficient light, halfway impediment and genuine disfigurement. The proposed calculation has more honorable exactness, better on-going execution, more grounded speculation capacity and higher preparing productivity than different calculations. The precise acknowledgment rate and normal handling time are altogether improved. From the perspective of traffic sign acknowledgment exactness and calculation tedious, the proposed traffic sign identification and acknowledgment calculation has astounding points of interest. Extensively upgrading the driving security of wise vehicles in the genuine driving conditions and viably meeting the on-going objective necessities of keen vehicles are helpful. Moreover, a solid specialized assurance is accommodated the consistent improvement of smart vehicle driving help. Later on, the comprehensiveness and against mistake acknowledgment of the traffic sign acknowledgment calculation can be additionally enhanced and improved to abuse the general presentation of the calculation.

CONCLUSION

With the help of image processing toolbox in the MATLAB, the program had been made which can detect red, blue, green, magenta, yellow, cyan colors. Also, the colored object is being enclosed inside a bounded region along with the centroid of that region.

The goal of this research is to develop an efficient TSDR system based on Malaysian traffic sign dataset. In the image acquisition stage, the images were captured by an on-board camera under different weather conditions and the image preprocessing was done by using RGB colour segmentation. The recognition process is done by

SVM with bagged kernel which is used for the first time for traffic sign classification. The developed system has shown promising results with respect to the accuracy of 95.71%, false positive rate (0.009), and processing time (0.43 s). The recognition performance is evaluated by using ROC curve analysis. The simulation results are compared with the existing methods showing the correctness of the implementation.

We proposed a CNN-based model for detecting and classifying traffic signs from images which were captured in challenging conditions. We used CLAHE for preprocessing images, and, also used a CNN-based denoiser for images affected with Rain. The challenge-detector and classifier were built using VGG-16 type architecture, whereas, the localizers used a deep U-Net architecture. The model was tested and trained on the IEEE VIP Cup 2017 video dataset. The proposed model shows an overall precision and recall of 32% and 19% for real data, and, 65% and 43% for synthesized data. The reason for this bias is that there were much more frames with bounding boxes in the synthesized videos than there were in real videos. Besides, there were also some traffic-signs in the real video sequences which were not classified in the dataset. This resulted in erroneous training of the localizing models. Our training procedure ensures a low training time for the model. The model is also suitable for real-time application due to its low computational cost at each stage. As such, it can be implemented in a standard PC configuration by using a low-power GPU.

An improved traffic sign detection and recognition algorithm is proposed for intelligent vehicles. Firstly, the HSV color space is used for spatial threshold segmentation, and traffic signs are effectively detected based on the shape features. Secondly, this model is considerably improved on the basis of the classical LeNet-5 CNN model by using Gabor kernel as the initial convolutional kernel, adding the BN processing after the pooling layer, selecting Adam method as the optimizer algorithm. Finally, the traffic sign classification and recognition experiments are conducted based on the GTSRB. The favorable prediction and accurate recognition of traffic signs are achieved through the continuous training and testing of the network model. The experimental results show that the accurate recognition rate of traffic signs reaches 99.75%, and the average processing time per frame is 5.4 ms. The proposed algorithm has more admirable accuracy, better real-time performance, stronger generalization ability and higher training efficiency than other algorithms. The accurate recognition rate and average processing time are significantly improved. From the viewpoint of traffic sign recognition accuracy and algorithm time-consuming, the proposed traffic sign detection and recognition algorithm has remarkable advantages. Considerably enhancing the driving safety of intelligent vehicles in the actual driving environments and effectively meeting the real-time target requirements of smart cars are conducive. Furthermore, a strong technical guarantee is provided for the steady development of intelligent vehicle driving assistance. In the future, the inclusiveness and anti-error recognition of the traffic sign recognition algorithm can be further optimized and improved to exploit the overall performance of the algorithm.

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