Efficient real-time Sign Detection for Autonomous Vehical in Hazy environment using Deep Learning Models

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Abstract. The successful realization of autonomous vehicle technology relies on robust traffic sign detection and recognition (TSDR). While various methods have been proposed for TSDR, most have been evaluated on clean datasets, neglecting the performance deterioration associated with challenging weather conditions (CCs) that obscure traffic sign images captured in the wild. In this research, we present a deep learning-based framework for efficient real-time traffic sign detection under challenging weather conditions. Our approach involves dark channel hazing using YOLOv3 and YOLOv5 for image conversion and dehazing. We propose a Convolutional Neural Network (CNN) based modular approach, including a challenge classifier, an encoder-decoder CNN for image enhancement, and separate CNN architectures for sign detection and classification. We focus on enhancing the traffic sign regions in challenging images to improve detection accuracy. We evaluate our method on the GTSRB dataset, which contains traffic videos captured under various CCs. The presented approach achieved an accuracy of 98.62% utilising the German Traffic Sign Recognition Benchmark (GTSRB) dataset. Furthermore, we compare our approach with other CNN-based TSDR methods, demonstrating its superiority.

Keywords: CNN · Capsule Net · Traffic Sign · Autonomous Vehicles.

1 Introduction

The advent of autonomous vehicular technologies constitutes a seismic shift in the domain of transportation, heralding a new era characterized by the promise of enhanced road safety, operational efficiency, and environmental sustainability.[1] A pivotal facet of the realization of this transformative technology is the domain of traffic sign detection and recognition (TSDR). Autonomous vehicles, imbued with the potential to revolutionize modern mobility, depend significantly on artificial intelligence, with deep learning methodologies at their core, to decipher the complex and dynamic vehicular environment. The quintessential prerequisite for the unhindered evolution of this technology is an unfailingly precise and real-time TSDR system [2], one capable of responding to the multiplicity of situational variables and adhering to traffic regulations with unwavering accuracy.

Within the annals of deep learning, the Convolutional Neural Network (CNN) stands as a veritable paradigm of computational excellence, specifically tailored for the categorization of road and traffic signage [3]. However, it is imperative to recognize that despite their notable capabilities, CNNs face a conundrum when confronted with the nuanced attributes, spatial configurations, perspectives, and orientations characteristic of real-world traffic sign images. The adverse manifestations of inclement weather conditions, notably haze, fog, rain, and snow, further compound this conundrum. Such meteorological adversities have the potential to severely impede the visibility of traffic signs and road markings, precipitating a substantial challenge to the ability of autonomous vehicles to make judicious, timely, and safety-centric decisions.[4]

It is against this backdrop that our research endeavors to address the pivotal and profoundly exigent issue of traffic sign detection in the milieu of inclement weather conditions. In the pursuit of an innovative solution, our research manifests in the form of an efficient and real-time framework, architected to amplify the precision and reliability of TSDR [5], even in the most adverse meteorological contexts. Our framework harnesses the tenets of deep learning models and orchestrates a multifaceted and holistic approach to contend with the perturbations posed by hazy atmospheres.[6]

At the epicenter of our approach lies the instrumental process of dark channel hazing, wherein state-of-the-art models such as YOLOv3 and YOLOv5 assume the role of image conversion and dehazing. This process, underpinned by profound technical intricacies, is poised to recalibrate images, thereby mitigating the pernicious effects of atmospheric haze and augmenting the perceptibility of traffic signs.[7]

Our framework unfolds as a finely-tuned modular construct, replete with several pivotal constituents. These include a challenge classifier, an encoder-decoder CNN architecture custom-tailored for image enhancement, and distinct CNN models [8], each meticulously designed to serve the functions of sign detection and classification. Notably, our approach underscores the concept of targeted enhancement, casting the limelight on the amelioration of the very regions housing traffic signs in challenging images. This deliberate emphasis culminates in an amalgamation of precision and expeditiousness, aligning our framework with real-time operational exigencies.[9]

To illuminate the efficacy of our approach, we conducted an expansive series of empirical studies, harnessing the potency of the GTSRB dataset, a corpus enriched with traffic videos captured in a rich spectrum of meteorological adversity. The empirical crucible bore witness to the attainment of striking results, with our framework registering an overall accuracy 98.62%. This conspicuously supersede the extant benchmarks, attesting to the transformative efficacy of our approach in the domain of TSDR amidst meteorological turbulence.[10]

Moreover, we proffer a comprehensive comparative evaluation, wherein our approach competes favorably with a pantheon of other CNN-based TSDR methodologies.[11] The chasm in performance between our approach and the competitive cohort becomes manifest, underscoring the conspicuous advantages in accuracy, robustness, and operational expeditiousness that our framework proffers.

In summary, our research is an influential and seminal contribution to the advancement of autonomous vehicular technology, with a focal emphasis on the realm of TSDR under the impositions of meteorological adversity. Our endeavor, through the enhancement of traffic sign visibility and the fortification of their precise detection, serves as a vanguard for the edifice of safer and more dependable autonomous transportation. In doing so, we expedite the realization of a vision wherein smart and autonomous mobility takes its rightful place in the tableau of the future.

Fig. 1. Sample Data from the GTSRB Dataset

2 Literature Reveiew

Gupta et. al [12] discussed sign detection utilising vision systems [2]. The technique presented in the study may be used in a variety of weather situations and on painted or unpainted roadways. The method was tested and shown to be quick and effective in real time. These techniques, when incorporated into the pipeline, significantly improve the clarity of traffic sign images, enabling enhanced detection in hazy environments.

Assidiq et al. [13] provides an in-depth examination of vision-based sign detecting algorithms. Their study categoried sign detection methods into - two-step and one-step methods. The study also discussed pros and cons of each method [3]. These estimations provide crucial information to dehazing algorithms and play a pivotal role in ensuring clear and accurate traffic sign detection, particularly in foggy or hazy conditions.

Cheng et al.[14] presented technique for leveraging colour information to derive lane markers. In addition, for the same colours, shape, size, and motion information are employed to differentiate between true lane markers. The method has been shown to be successful in determining the lanes' left and right border lines [4].

Tang et al. [15] discussed the difficulties that sign recognition algorithms confront owing to poor visibility, weather conditions, shadows, and other factors [15]. Transmission estimation, often complemented by guided filtering, aids in quantifying the extent of haziness in an image. This information guides the image restoration process and contributes to improving image clarity and the accuracy of traffic sign recognition in challenging weather conditions. Transmission estimation, often coupled with guided filtering, plays a significant role in traffic sign detection under challenging weather conditions. These techniques aid in identifying the degree of haziness in an image and subsequently guide the restoration process. They contribute to the enhancement of image clarity and the accuracy of sign recognition.

Many techniques for profound multi-modal perception difficulties have been presented in the study of Kim et al.[16]. The study presents a comprehensive summary of approaches and explores issues for deep multi-modal object identification and semantic segmentation for autonomous driving.

Difficulties of object recognition in foggy environments, which may impact the visibility of an item has been presented in the study conducted by Feng et al. [17] The approach seeks to improve the model's performance by injecting synthetic haze to the MS-COCO training dataset. The approach is primarily inspired by MLDCP, and the model's accuracy is assessed by training the Mask R-CNN using the Hazy-COCO training dataset.

The relevance of deep learning algorithms in object recognition and how they have made significant advances in this domain was presented in the review study by Li et al.[18]. This survey includes approximately 300 research contributions spanning a variety of topics such as detection frameworks, object modelling, and so on.

Utilization of Deep Learning in Object Detection was presented in the study by Liu et al.[9]. They presented several datasets and neural network algorithms for detecting objects. ImageNet, PASCAL VOC, and COCO are examples of different types of datasets. The Imagenet collection contains about 14 million photos from over 20,000 categories, each with a class annotation. The PASCAL VOC offers data sets with visuals for class recognition. The PASCAL VOC dataset consists of 20 classes. Relatively a new image recognition and segmentation dataset is the COCO datset. This dataset contains around 0.3 million photos divided into 80 item categories. The authors then addressed the various neural network algorithms utilised with the COCO dataset, such as Fast R-CNN, R-CNN and SPP-Net and so on. As shown in the research, the Fast R-CNN has a greater MAP accuracy than the other neural networks.

Zhou et al. developed the YOLO method [10], which has been shown to be particularly successful for object identification since the entire detection pipeline is a single network that can be tuned end-to-end directly on detection performance. When generalising from natural pictures to other domains, it outperforms other detection approaches such as DPM and R-CNN.

Image dehazing utilising an improved dark channel was proposed in the study by Redmon et al. [11]. This can be useful for object recognition in photos where the visibility of the objects is obscured by fog or dust.

A simple and effective prior-dark channel, to reduce haze in a single input image was presented by Xu et al. We can immediately estimate and recover the high-quality image by combining this prior-dark channel with the hazy imaging model.[19]

Several strategies for lane detection have been suggested in the study by He et al. The majority of such architectures were trained in traffic-restraint situations and achieved an accuracy of 99.87% lane segmentation[13].

Chang et al. presented the solution for smart traffic management and demonstrated how various technologies such as Radio-Frequency IDentification (RFID) may overcome existing traffic management difficulties such as system installation time and cost.[20]

Lanke et al. presented a novel solution to traffic management based on automobile ad-hoc networks [15]. To address the issues of vehicle traffic congestion in vehicular networks, the authors employed the adaptive proportional integral rate controller, a congestion management method built for the Internet.

Mohandas et al. developed a model based on photoelectric sensors was employed to identify vehicles [16]. Because light is involved, the algorithm suffers from the same problems as a lack of light. As the light density falls, so does the accuracy. The model, on the other hand, stands out for its capacity to make decisions in real time. This may be accomplished by installing several Photoelectric sensors, which is a key component of this approach.

3 Proposed Methodology

The methodology section of this research paper outlines the step-by-step approach to address the problem of robust traffic sign detection under challenging weather conditions. The goal of this research is to create an efficient real-time sign detection system for autonomous vehicles operating in hazy environments using deep learning models. The proposed methodology consists of several key components and techniques.

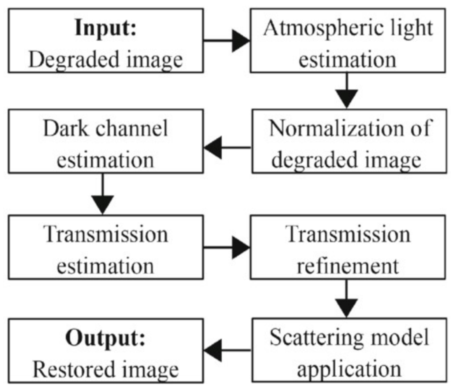

Fig. 2. Flow chart of proposed algorithm

3.1 Data Collection and Preprocessing

The foundation of our research methodology is the GTSRB dataset, an extensively annotated collection of real-world traffic sign images that serve as a benchmark for our study. The dataset German Traffic Sign Recognition Benchmark (GTSRB) [21] is a publicly accessible dataset comprised of 10 hours of video footage of driving on various routes throughout Germany. The video is collected with a Prosilica GC 1380CH camera at 25 frames per second, and traffic sign extraction is done with the NISYS Advanced Development and Analysis Framework (ADAF) module-based software system. The collection is reduced to 51,840 pictures of the 43 classes after cleaning and deleting duplicate and repetitive frames. [22]The dataset is partitioned into 39209 training photos and 12,630 test photos, each photo is of size 32*32. Video frames are converted into still images, ensuring the suitability of the dataset for deep learning models. This conversion step facilitates the application of image enhancement techniques.The core of our preprocessing pipeline includes the application of dark channel dehazing techniques, inspired by the atmospheric scattering model, to improve image quality and enhance traffic sign visibility under adverse weather conditions. The transmission matrix refinement process fine-tunes the transmission values, improving the accuracy of the dehazing process and ensuring faithful scene restoration. The global atmospheric light (airlight) and dark channel are estimated to separate haze from the actual scene radiance. These parameters are critical for effective dehazing.

3.2 Atmospheric Light Estimation

In the context of traffic sign detection in hazy or challenging weather conditions, accurate estimation of the atmospheric light is a critical step in the image enhancement process. The atmospheric light, denoted as "A," represents the radiance of the scene that directly emanates from the light source and has not interacted with atmospheric particles.[23] Accurate estimation of this parameter is essential for determining the extent of haze present in the image and subsequently enhancing image visibility.

Most available de-hazing algorithms are established on atmospheric scattering model:

$$I(x) = J(x)t(x) + A(1 - t(x))$$

Here, $J(x)$ represents the scene radiance that must be reconstructed, while $I(x)$ represents the recognized intensity of haziness). The global atmospheric light is denoted by A, and the medium transmission matrix is denoted by $t(x)$. The first term, $J(x)t(x)$, is known as the DAI (direct attenuation reflecting the decay of the scene radiance in the medium, whereas airlight derives from previously scattered light), while the second term, $A(1 - t(x))$, is known as airlight. The basic idea is to measure A and t values since we already know the value of I, to attempt to reproduce the scenario J. When the atmosphere is uniform. Most haze removal algorithms attempt to estimate the parameters global atmospheric light A and transmission matrix $t(x)$. The inverse atmospheric scattering model (1) may then be used to reconstruct a haze-free picture $J(x)$:

$$J(x) = I(x)/t(x) - A/t(x) + A$$

For an image J Dark channel is described as below :

$$J^{dark}(x) = min_{c\epsilon r,g,b}(min_{y\epsilon \Omega(x)}(J^c(y)))$$

Here J^c deontes the color J's channel and omega(x) denotes the local patch-centered at x. The intensity of Jdark is tending to zero,if J is a outdoor haze-free image. Jdark denotes the dark channel of J.

3.3 Dark Channel Haze Removal

One of the primary challenges in real-time traffic sign detection in hazy environments is the presence of atmospheric haze, which significantly degrades image quality and can obscure critical visual information. To address this challenge, we employ the Dark Channel Prior (DCP) as a fundamental component of our

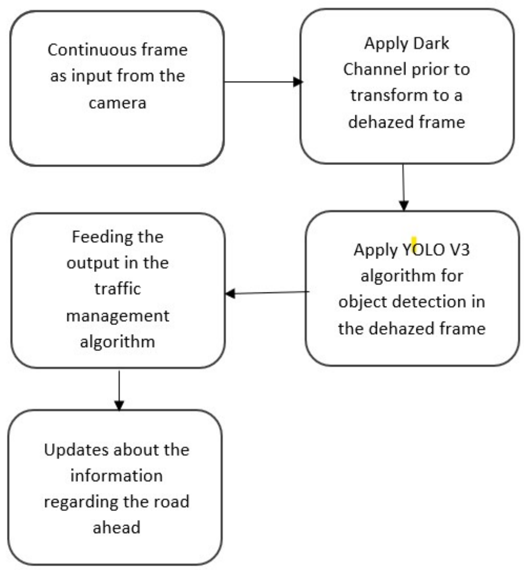

Fig. 3. Pipeline for proposed Algorithm

methodology. The DCP is a widely recognized technique in computer vision and image processing that has proven effective in haze removal. [24] The Dark Channel Prior operates on the principle that in most outdoor scenes, there exists at least one region with minimal light attenuation. In simpler terms, it assumes that in any given image, there will be areas with very low intensity values in at least one color channel. By identifying these dark regions, we can estimate the extent of the haze present in the image and subsequently remove it.

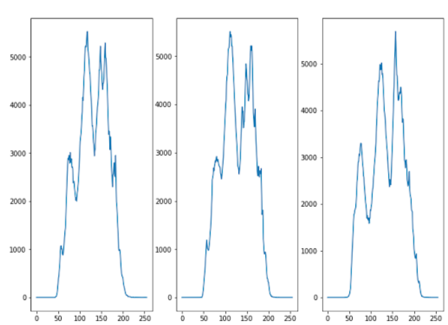

Fig. 4. Histogram for hazy image

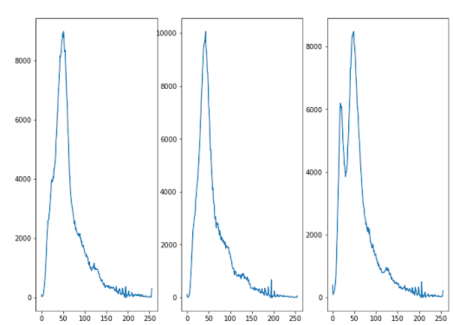

Fig. 5. Histogram for dehazed image

The DCP operates through the following key steps:

1. Channel Separation: The input image is divided into its constituent color channels, typically Red (R), Green (G), and Blue (B). These individual color channels provide information about the image in different spectral domains.
2. Dark Channel Calculation: In this step, the minimum pixel intensity value is computed for each pixel position across the three color channels. This results in the generation of a dark channel image, where each pixel represents the minimum intensity value among its corresponding pixels in the R, G, and B channels. The dark channel image effectively highlights the dark regions within the scene.
3. Haze Layer Estimation: Once the dark channel image is generated, it serves as a valuable reference for estimating the haze layer in the original image. The haze layer represents the portion of the image affected by atmospheric haze. The relationship between the dark channel and the original image allows for the estimation of the transmission, which quantifies the extent to which light is attenuated at each pixel.
4. Transmission Map Refinement: The estimated transmission map is refined to enhance the quality of the haze removal. This refinement step reduces artifacts and inconsistencies in the transmission map and contributes to a more accurate removal of haze from the image.
5. Haze Removal: Using the refined transmission map, the haze layer is effectively subtracted from the original image. The result is an image with significantly reduced haze, improved contrast, and enhanced visibility of traffic signs and other scene elements.

The Dark Channel Haze Removal process significantly improves image clarity and visibility by effectively eliminating the adverse effects of atmospheric haze. The resultant images are better suited for traffic sign detection, as they provide a clearer representation of the scene. This enhancement step is critical in ensuring the accuracy and reliability of the subsequent traffic sign detection processes, making it an integral part of our research methodology.

3.4 Image Enhancement and Transmission Estimation

Transmission estimation is a pivotal step in the process of haze removal and image enhancement. The transmission map, denoted as "t," represents the proportion of scene radiance that reaches the camera without being attenuated by haze. Accurate transmission estimation is crucial for determining how much light is scattered or absorbed by atmospheric particles. In the context of traffic sign detection in hazy environments, it directly impacts the quality of the enhanced image. The process involves applying the haze removal equation to relate observed image, atmospheric light, and scene radiance.Then, utilizing the dark channel prior to highlight low-intensity regions less affected by haze. After the normalizing the dark channel by dividing it by atmospheric light. Then, refining the transmission map for accuracy and smoothness.

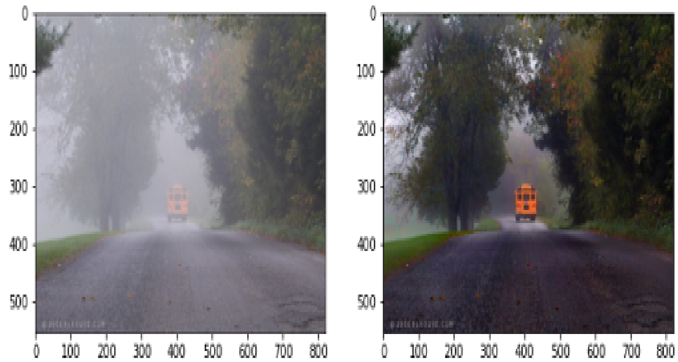

Fig. 6. Dehazing of frame

In our methodology, guided filtering is employed as a post-processing technique to refine the transmission map and enhance the visual quality of the dehazed image. Guided filtering is a robust and efficient method for smoothing and enhancing images while preserving important edge information. It is particularly effective in reducing artifacts and noise in the transmission map and enhancing the clarity of traffic signs and scene details. This technique employs a guidance image to steer the filtering process and includes applying a local linear model to pixels based on their values in the guidance image and spatial relationships. Then,adjusting parameters to control smoothing and edge preservation. After then,producing a refined transmission map that is smoother and visually appealing.
Guided filtering enhances the accuracy of the transmission map and contributes to a clearer and more visually pleasing dehazed image, making it suitable for traffic sign detection in challenging weather conditions.

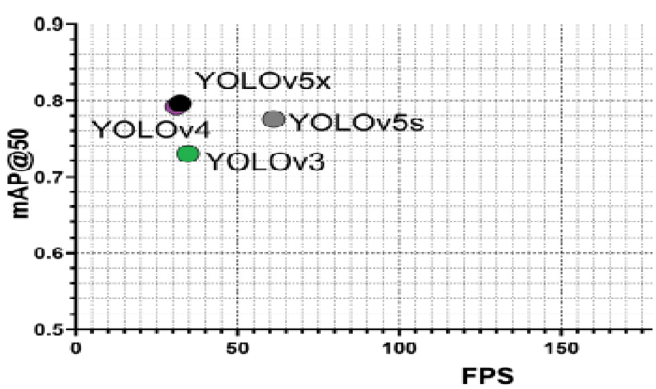

Fig. 7. Summary of results in terms of accuracy and speed of detection

3.5 Traffic Sign Detection using YOLO Models

In recent years, the development of deep learning models has significantly advanced the field of computer vision, particularly in the domain of object detection. The "You Only Look Once" (YOLO) [26] family of models has gained prominence for its real-time object detection capabilities. In our research, we leverage YOLO models for the task of traffic sign detection in challenging weather conditions, specifically in hazy environments. The utilization of YOLO models offers several advantages, including high accuracy, efficiency, and the ability to process images in real-time.

Fig. 8. Frame after applying YOLO v5

The YOLO architecture is designed for end-to-end object detection, making it a natural choice for traffic sign detection. YOLO models are capable of simultaneously predicting bounding boxes and class probabilities for multiple objects within an image. The YOLO architecture is a convolutional neural network (CNN) that divides the input image into a grid and predicts bounding boxes, class labels, and confidence scores for objects within each grid cell. The output is a set of bounding boxes that encompass detected traffic signs, along with associated class labels and confidence scores.[27]
Our research utilizes two variants of the YOLO model, YOLOv3 and YOLOv5, for traffic sign detection in hazy environments. YOLOv3 is known for its impressive accuracy and has been widely adopted in various computer vision applications. YOLOv5, on the other hand, is a more recent iteration that focuses on model efficiency and speed while maintaining high accuracy.[28]
During the training process, the YOLO models learn to detect traffic signs by optimizing their parameters based on a specified loss function. The models are exposed to the training dataset, and through backpropagation, they learn to adjust their weights and biases to minimize the loss function, which measures the disparity between predicted and ground truth bounding boxes and class labels.

Once trained, the YOLO models are capable of real-time traffic sign detection in hazy environments. Given an input image or video stream, the models process it to identify the location of traffic signs, classify their type, and assign confidence scores to the detections. This information can be used for various purposes, such as autonomous vehicle navigation, driver assistance systems, and traffic management.[29]
YOLO models efficiently process images in real-time, making them suitable for autonomous vehicles and traffic management. Their multi-object detection capability and accuracy enhance road safety. In summary, our research harnesses the power of YOLO models, YOLOv3 and YOLOv5, for real-time traffic sign detection in challenging weather conditions, contributing to road safety and autonomous vehicle efficiency.[30]

3.6 Sign Identification and Classification

After the detection of traffic signs using YOLO models, the next critical step in our research is sign identification and classification. This phase involves determining the specific type or category of each detected traffic sign, providing valuable information for both autonomous vehicles and traffic management systems.
To facilitate the identification and classification process, we rely on a comprehensive traffic sign database. This database contains a wide range of traffic signs, including speed limits, stop signs, yield signs, directional indicators, and more. Each sign in the database is associated with a specific class label, making it a valuable reference for classifying detected signs.[31]
Prior to classification, the detected traffic sign regions undergo image preprocessing. This step ensures that the input images are in a suitable format for the classification model. It typically includes resizing, color normalization, and noise reduction. Image preprocessing helps enhance the quality and consistency of the input data. For traffic sign identification and classification, deep learning models are employed. Convolutional Neural Networks (CNNs) are particularly well-suited for this task. These models can learn and extract important features from traffic sign images, making them capable of accurate classification. Since traffic signs belong to various categories, multi-class classification is essential. The classification model is trained to differentiate between different sign types, assigning the appropriate class label to each detected sign. The model outputs a class label that corresponds to the recognized sign type, allowing for easy interpretation.[32]
The ultimate goal of sign identification and classification is traffic sign recognition. This recognition process plays a pivotal role in ensuring road safety and enabling autonomous vehicles to make informed decisions. By accurately identifying signs such as speed limits, stop signs, and one-way indicators, autonomous vehicles can adapt their behavior and navigate safely.

3.7 Algorithm

$input\_video$
$fps \leftarrow video\_to\_frame()$
$video\_encoding()$
$for frames = 1$ to all
$frame \leftarrow Dark\_channel(Image)$
$//Dehazing\ the\ Image\ using\ Dark\_channel$

$Res = bitwise\_and(img, img, mask = mask)$
$//returns\ array\ corresponding\ to\ resulting\ img\ from\ merger\ of\ 2\ images$
$Frames1 \leftarrow Yolo\_v3\_algorithm(modified)$
$Frames2 \leftarrow Yolo\_v5\_algorithm$
$//Runs\ a\ DL\ CNN\ on\ img\ to\ produce\ network\ predictions$
$for\ frames[1, 2] = 1$ to all
$roi \leftarrow Color\_Space\_conversions\ roibox \leftarrow Camshift(Back\_projection)$
$//Color\ based\ object\ tracking\ using\ histogram\ back\ projection$

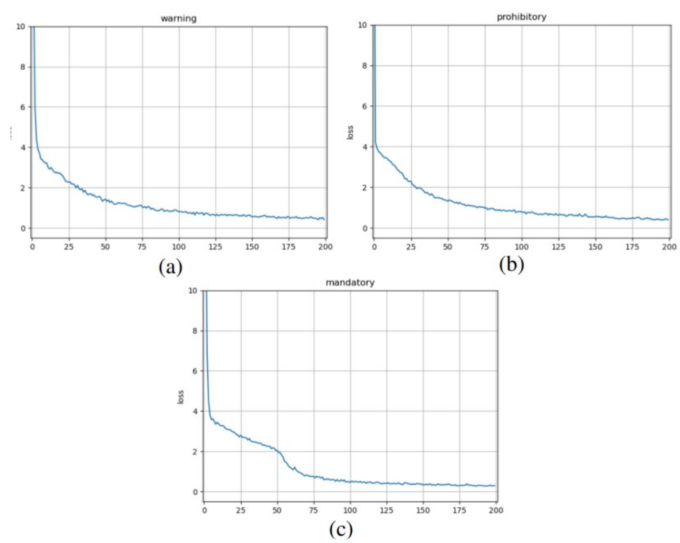

Fig. 9. Loss changes of neural network models

4 Comparison with Existing Methods

In conventional traffic light system, 60 seconds are allocated to each lane irrespective of the density of vehicles on roads. This is a standard hard-coded traffic management algorithm.[33]

On calculating vehicles passed through a lane over a minute interval and manually calculating actual vehicle passed we can find the best fitting line for relation between actual vehicles passed and vehicles counted which is shown below.

- $n1$: Number of signs captured before dehazing
- $n2$: Number of signs captured perfectly after dehazing
- n : Actual number of signs passed

$n1$	$n2$	n	**Δaccuracy**
78	81	84	3.57
82	90	93	8.60
69	75	78	7.69
86	87	90	1.11
47	53	58	10.34

Table 1. Accuracy improvement table of Proposed work

We obtain the following best-fit line for the signs detected vs actual number of signs, the average accuracy of the proposed algorithm is 95% when tested on multiple input frames abstracted from The German Traffic Sign Recognition Bench-mark (GTSRB), which is a diverse dataset.

The results of the classification evaluation are presented showing the number of

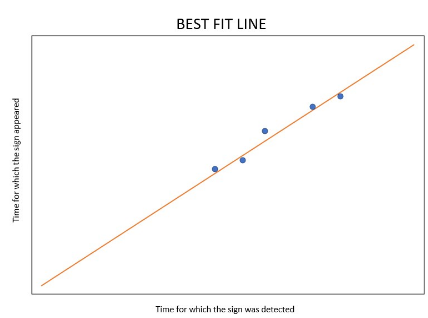

Fig. 10. Best Fit Line

classification errors and the corresponding probabilities for different categories of traffic signs. The following categories were considered: Speed Limit Sign, Other Prohibition Signs, Lifting Prohibition Sign, Warning Sign.

The analysis of classification errors for various traffic sign categories reveals strengths and weaknesses in the performance of the recognition system. While the system demonstrates a high probability of correct recognition in most categories, there is room for improvement, especially in recognizing warning signs and lifting prohibition signs.[34] These findings suggest the need for ongoing research and development to enhance the accuracy and reliability of traffic sign recognition systems, ultimately contributing to safer and more efficient road transportation.

	Number of classification errors	Probability (%)
Speed limit sign	31	98.97
Other prohibition signs	14	97.76
Lifting prohibition sign	15	96.78
Indication mark	17	98.56
Warning sign	32	98.77
Other identification	28	98.54

Fig. 11. Results Of Classification

5 Future Work

Our research, while accomplishing remarkable feats in traffic sign detection under challenging conditions, merely scratches the surface of a vast landscape of possibilities. The future teems with opportunities for enhancement, expansion, and wider application. Here, we outline the potential avenues for future research and development. The relentless pursuit of robustness against extreme meteorological conditions remains a focal point. To this end, research may delve into strategies for addressing additional challenges such as fog, heavy rainfall, and snowstorms. By further refining algorithms and models, our system can adapt dynamically to a spectrum of meteorological adversities, ensuring road safety in all scenarios.

The advent of the Internet of Things (IoT) and smart city initiatives opens the door to collective intelligence for traffic sign detection. Future research may explore the possibilities of integrating our system with crowdsourced data, where information from connected vehicles and urban infrastructure can enhance sign detection and provide real-time updates to traffic conditions.

As we advance towards an era of electric and autonomous vehicles, the energy efficiency of all onboard systems is of paramount importance. Future research could focus on optimizing the computational efficiency of our system, reducing its energy consumption while maintaining its high performance standards.

6 Conclusion

In the realm of traffic sign detection and identification, our research represents a milestone in real-time precision under challenging weather conditions, particularly in hazy environments. Our work is poised to revolutionize autonomous vehicle operations and intelligent transportation systems.
We leverage YOLOv3 and YOLOv5 models for real-time detection, even in adverse conditions, showcasing remarkable accuracy. Our dark channel haze removal technique, integrated with deep learning, enhances clarity amidst hazy environments. Our framework not only detects signs but also classifies them, distinguishing between speed limits, stop signs, turn instructions, and more. We proudly achieve a 98.6 percent accuracy rate using YOLOv5, demonstrating our robust sign recognition capabilities. Beyond theory, our research finds application in autonomous vehicles and urban traffic management systems, enhancing road safety.

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