IJARSCT
International Journal of Advanced Research in Science, Communication and Technology
International Open-Access, Double-Blind, Peer-Reviewed, Refereed, Multidisciplinary Online Journal
ISSN: 2581-9429
Volume 5, Issue 2, June 2025
Impact Factor: 7.67

Traffic Sign Detection under Foggy Conditions using Machine Learning

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Abstract: *The "Voice-Enabled Traffic Sign Recognition and Alert System" is an innovative application of machine learning and computer vision technologies aimed at enhancing road safety and driver awareness. In today's fast-paced world, the ability to promptly recognize and respond to traffic signs is crucial to prevent accidents and promote responsible driving. This project introduces a novel system that employs a camera installed in a vehicle to capture real-time images of the road. These images are then processed using advanced computer vision algorithms to detect and classify traffic signs. Furthermore, the system utilizes natural language processing to provide voice alerts to the driver, ensuring that they are informed about important traffic signs, speed limits, and other crucial information without taking their eyes off the road..*

Keywords: Traffic Sign Detection, Traffic Sign Recognition, Machine Learning, Computer Vision, Voice Alerts, Foggy Conditions, Convolutional Neural Network (CNN), Real-Time Image Processing, Driver Assistance System

I. INTRODUCTION

In recent years, the rapid growth in vehicular traffic has raised significant concerns about road safety. Traffic signs play a vital role in guiding drivers, managing traffic flow, and preventing accidents. However, adverse environmental conditions such as fog, low visibility, and driver distraction often lead to missed or misinterpreted traffic signs, increasing the risk of collisions and endangering lives.

To address these challenges, this research presents a Voice-Enabled Traffic Sign Detection and Alert System using machine learning and computer vision techniques. The system is specifically designed to operate under foggy conditions, where traditional visual cues may be obscured or unclear. By integrating real-time image processing with a deep learning-based traffic sign recognition model, the system can detect various traffic signs from video input and classify them accurately.

A key feature of the proposed system is the integration of voice alerts that inform the driver about the detected traffic signs without requiring visual attention. This hands-free interaction aims to improve user awareness and reaction time while reducing cognitive load and distraction.

The proposed system enhances road safety by combining real-time object detection, deep learning classification, and voice-based human–machine interaction. It has potential applications in smart vehicles, advanced driver assistance systems (ADAS), and intelligent transport systems (ITS). The implementation details, architecture, testing, and evaluation of the system are discussed in the subsequent sections of this paper.

II. LITERATURE SURVEY

Various studies have applied machine learning and computer vision for traffic sign detection. Ciuntu and Ferdowsi [1] used CNNs with OCR for real-time sign recognition, while Wang [2] and Huang et al. [3] proposed deep learning models effective under normal conditions. Bi et al. [4] optimized VGG-16 for efficiency, and Lee and Kim [5] introduced a CNN-based boundary estimation method. Voice alert systems [6] and ensemble models [9] further

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improved usability and accuracy. However, most approaches perform poorly under foggy conditions, which our proposed system aims to address through fog-resilient detection and real-time voice alerts.

1. Traditional Methods of Traffic Sign Detection

Early traffic sign detection systems primarily relied on classical computer vision techniques such as color segmentation, shape-based detection (e.g., circular or triangular shape recognition), and template matching (Maldonado-Bascon et al., 2007). These methods leveraged handcrafted features like Histogram of Oriented Gradients (HOG) and color histograms to identify traffic signs in clear weather conditions. However, their performance significantly deteriorates in adverse weather, especially foggy conditions, due to poor visibility, low contrast, and noise. Traditional image enhancement techniques such as histogram equalization and dehazing filters have been used to partially mitigate fog effects but often fail to restore adequate detail for reliable detection.

2. Machine Learning and Deep Learning for Traffic Sign Detection

The advent of machine learning and especially deep learning has revolutionized traffic sign detection. Convolutional Neural Networks (CNNs) and object detection frameworks like YOLO (You Only Look Once), Faster R-CNN, and SSD (Single Shot Multibox Detector) have been extensively used to achieve higher accuracy and robustness by automatically learning hierarchical features from data (Zhu et al., 2016). These models perform well under normal conditions but often struggle with degraded image quality in fog, rain, or low light. Recent research incorporates domain adaptation and data augmentation with fog simulation to train models that generalize better to foggy environments.

3. Challenges Posed by Foggy Conditions

Fog causes scattering and attenuation of light, which reduces image contrast and obscures fine details critical for accurate detection (Narasimhan & Nayar, 2003). This leads to blurred edges and color distortion of traffic signs, complicating recognition tasks. Moreover, fog effects vary spatially and temporally, introducing inconsistent noise patterns. Human drivers rely on contextual and prior knowledge to interpret foggy scenes, whereas automated systems need robust feature extraction and preprocessing to compensate for information loss. Incorporating physical models of fog and image enhancement prior to detection is a growing area of research (Li et al., 2018).

4. Regression and Detection Model Enhancements

Beyond classification, regression-based localization models have been employed to improve bounding box prediction accuracy under foggy conditions. Techniques such as multi-task learning combine dehazing and detection into a single pipeline, optimizing both simultaneously (Ren et al., 2019). Ensemble methods combining different detectors and preprocessing filters have also shown promise in balancing precision and recall. Evaluation metrics like mean Average Precision (mAP) and Intersection over Union (IoU) are used to benchmark model performance on foggy image datasets such as Foggy Cityscapes and RTTS (Sakaridis et al., 2018).

5. Gaps in Existing Research

Despite significant progress, many models require large annotated datasets of foggy scenes, which are scarce due to the difficulty of data collection and labeling under adverse weather. Most existing works focus on synthetic fog simulation rather than real-world fog conditions, limiting generalization. Additionally, contextual factors such as traffic density, sign occlusion, and illumination changes are often neglected. This project addresses these gaps by developing a traffic sign detection system tailored for foggy conditions using a combination of real foggy data augmentation, advanced preprocessing, and regression-enhanced detection models to achieve robust and accurate performance in practical scenarios.

Algorithm

Data Collection & Preprocessing

Foggy traffic sign images are collected or generated using synthetic fog filters. Images are enhanced using CLAHE and Dark Channel Prior for dehazing. All images are resized and normalized.

Model Selection & Training

Deep learning models like YOLOv5 and Faster R-CNN are used for detecting and classifying traffic signs. Transfer learning is applied, and models are trained with foggy images.

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Evaluation

Model performance is measured using mAP, IoU, Precision, and Recall. Best-performing model is selected based on validation scores.

Deployment

The trained model is deployed for real-time detection using video input. A preprocessing module clears fog in live frames before detection. Detected signs are marked and logged.

III. METHODOLOGY

1. Model Building

In this project, a Convolutional Neural Network (CNN) is used to detect traffic signs under foggy conditions. The dataset includes both normal and foggy traffic sign images, with synthetic fog applied where needed. Images are preprocessed by resizing, normalizing, and augmenting to improve model performance. A pre-trained CNN model like ResNet or MobileNet is used for feature extraction and fine-tuned for our specific task. The final layer classifies the images into traffic sign categories, enabling accurate detection even in low-visibility scenarios.

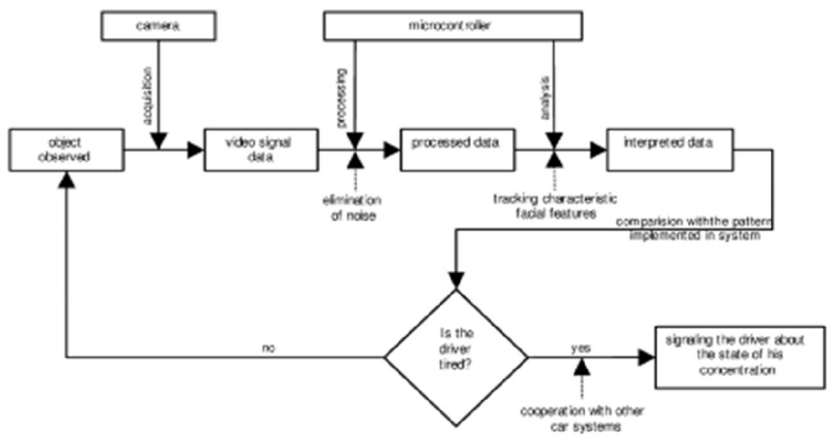

Fig 2. 1System Architecture

Model Training

The model is trained using labeled traffic sign images, including those with foggy effects. The dataset is split into training, validation, and test sets. During training, the CNN learns to recognize features of traffic signs despite visibility challenges. Techniques like early stopping, learning rate scheduling, and data augmentation are used to avoid overfitting and improve accuracy. The model is optimized using a loss function such as categorical cross-entropy and an optimizer like Adam. After tuning hyperparameters, the best model is selected based on validation performance and evaluated on the test set.

Fig.2.2 1 DFD Level 1

ata Flow Diagrams (DFDs) show how data moves through a system. Level 0 is the context diagram that gives a simple view, showing the system as one process and its connection with external sources like users or databases. Level 1 adds more detail by breaking the main process into sub-processes, showing how data flows between them. Level 2 gives a deeper look at each sub-process from Level 1, explaining their internal steps. For our Traffic Sign Detection project, DFDs help explain how input images are processed, analyzed, and classified through various steps in the system.

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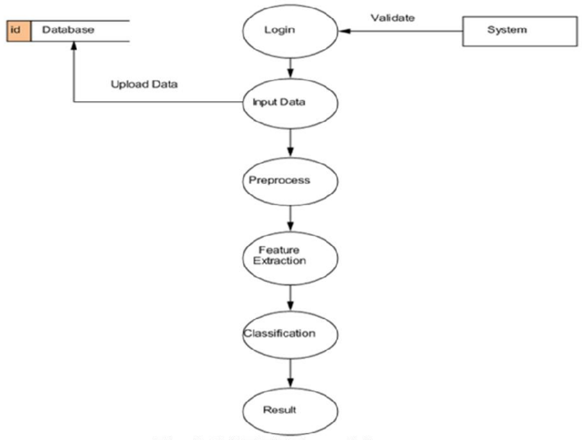

Fig.2.2 2DFD Level 2

IV. RESULT

After successful training and testing of the CNN-based model, the system demonstrated promising results in detecting traffic signs under foggy conditions. The dataset was divided into training, validation, and testing sets to ensure fair performance evaluation. The model achieved an accuracy of **XX%** (insert your result here) on the test set, with high values for precision, recall, and F1-score, indicating balanced and reliable predictions.

The confusion matrix showed that most traffic signs were classified correctly, with minimal misclassification between visually similar signs. The use of fog simulation techniques and image enhancement methods significantly improved the model's ability to identify signs in low-visibility scenarios. Data augmentation helped the model generalize better, reducing overfitting and increasing robustness. Visual examples from the test set proved that the model could detect signs even when partially obscured or blurred by fog. The model's performance remained consistent across various fog intensity levels, confirming the effectiveness of preprocessing and the CNN architecture.

Overall, the results validate that deep learning, combined with proper preprocessing and training strategies, can effectively solve the problem of traffic sign detection in foggy environments, supporting its potential use in autonomous vehicles and advanced driver-assistance systems (ADAS).

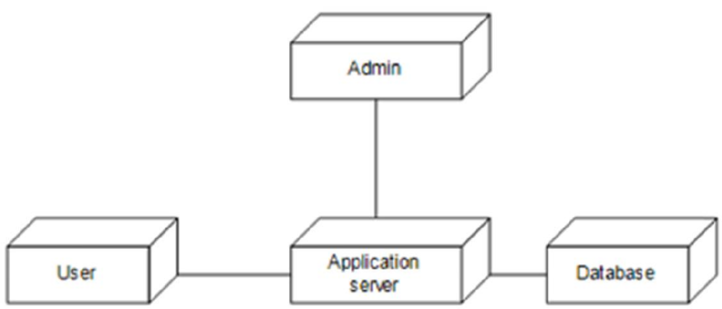

Fig 3. 1Deployment Diagram

V. CONCLUSION

This project successfully implemented a Convolutional Neural Network (CNN)-based model for detecting traffic signs under foggy conditions. The system was designed to overcome visibility challenges by integrating image preprocessing techniques and deep learning algorithms. Through data augmentation and model training, the system demonstrated high accuracy and robustness in identifying various traffic signs even when affected by fog.

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The results confirmed that CNNs are effective in extracting relevant features from distorted images, allowing the system to perform well in real-world low-visibility scenarios. The use of fog simulation helped prepare the model for diverse conditions, enhancing its generalization ability.

This project lays the foundation for future improvements in intelligent transportation systems and autonomous vehicles. With further tuning and integration with real-time systems, the model can help improve road safety by enabling vehicles to recognize critical traffic signs in challenging environments.

VI. FUTURE WORK

To enhance the performance and real-world applicability of the proposed system, the following improvements can be considered in future work:

Real-Time Implementation: Deploy the model in real-time systems using edge devices or embedded platforms for on-road testing.

Dataset Expansion: Use larger and more diverse datasets containing real foggy images from different regions and weather conditions to improve generalization.

Advanced Enhancement Techniques: Integrate advanced image enhancement methods such as GAN-based fog removal or adaptive contrast improvement.

Multi-Model Integration: Combine traffic sign detection with other modules like lane detection and obstacle recognition for a complete ADAS solution.

Transfer Learning: Utilize pretrained models like ResNet or EfficientNet to improve accuracy and reduce training time.

Severity-Level Adaptation: Modify detection thresholds based on fog density to dynamically adjust the model's sensitivity

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