AI Based Traffic Signal Classification System

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ABSTRACT

The accurate and real-time classification of traffic signals is a safety-critical task for both human drivers and emerging autonomous systems. Misinterpretation of a traffic light can lead to catastrophic accidents. This paper presents an Artificial Intelligence (AI) based system designed for the robust classification of traffic signals from image data. The core of the system is a deep Convolutional Neural Network (CNN), which is trained to automatically learn the distinguishing features of traffic light states (Red, Yellow, Green) under various real-world conditions. We employ a transfer learning approach, fine-tuning a pre-trained CNN architecture on a specialized traffic signal dataset. This methodology allows the system to achieve high classification accuracy while being computationally efficient. The system is evaluated on its ability to perform reliably across challenging scenarios, including varying weather, time of day, and partial occlusions. The results demonstrate the potential of this AI- based approach to serve as a vital perception component for Advanced Driver-Assistance Systems (ADAS) and fully autonomous vehicles.

***Keywords**: Artificial Intelligence, Traffic Signal, Image Classification, Deep Learning, Convolutional Neural Network (CNN), ADAS, Autonomous Vehicles.*

I. INTRODUCTION

Traffic signals are the fundamental regulators of vehicular and pedestrian flow in urban and suburban environments. Their primary purpose is to ensure safety and order at intersections. For human drivers, recognizing and correctly reacting to traffic signals is a learned, second-nature task. However, for automated systems such as Advanced Driver-Assistance Systems (ADAS) and autonomous vehicles, this perception task must be executed with near- perfect accuracy and reliability in a vast range of conditions.

Traditional computer vision approaches for traffic light classification often rely on hard- coded rules, such as color thresholding in specific color spaces (e.g., HSV) or template matching. While simple, these methods are notoriously brittle and fail under real-world complexities. Factors such as bright sunlight causing glare, low light at night, adverse weather conditions (rain, fog), and partial occlusions by other vehicles or foliage can easily cause these algorithms to fail.

The advent of Artificial Intelligence, particularly deep learning, offers a paradigm shift for solving this problem. Deep Convolutional Neural Networks (CNNs) have the remarkable ability to learn intricate and robust features directly from raw pixel data, eliminating the need for manual feature engineering. By training a CNN on a large and diverse dataset of traffic light images, it can learn to identify the state of a traffic signal with a high degree of invariance to the challenging conditions mentioned above.

This paper details the architecture and methodology of an AI-based system for traffic signal classification. The primary objective is to develop a model that can accurately classify the state of a traffic light (Red, Yellow, Green) from a cropped input image. The contributions of this work include:

1.1 The design of a robust CNN-based framework for traffic signal classification.

1.2 The effective application of transfer learning to achieve high performance with a manageable dataset size.

1.3 An analysis of the system's performance, highlighting its potential to significantly enhance vehicular safety through automation.

II. RELATED WORK

The automated recognition of traffic signals has been a subject of intensive research for many

years, with methodologies evolving alongside advancements in computer vision and deep learning.
Early systems were dominated by classical computer vision. **Chen et al. (2013)** demonstrated a common approach focused on color-based segmentation, where an RGB image is transformed into a more suitable color space like HSV or YCrCb, followed by thresholding to isolate pixels within the color range of traffic lights [1]. To refine this, **Alvarez et al. (2008)** proposed complementing color analysis with shape detection algorithms, such as the Hough Transform, to specifically identify the circular shape of the lamps [2]. However, these methods were highly sensitive to variations in lighting, shadows, and weather.

To improve robustness, a subsequent generation of systems integrated machine learning with handcrafted features. The concept of using Histograms of Oriented Gradients (HOG), introduced by **Dalal and Triggs (2005),** became a foundational technique for feature extraction [3]. Building on this, **de la Torre et al. (2011)** developed a fast traffic light detection system by feeding extracted features into a classifier like AdaBoost [4]. While more resilient than color thresholding, the performance of these systems depended heavily on the generalizability of the pre- selected features, which often struggled with complex or novel scenarios.

The current state-of-the-art is firmly rooted in deep learning. The paradigm shifted following the success of Krizhevsky et al. (2012), whose AlexNet model demonstrated the power of Convolutional Neural Networks (CNNs) in the ImageNet competition, leading to their rapid adoption in the automotive field [5]. Architectures like ResNet, introduced by He et al. (2015), further proved that deep networks could learn powerful, hierarchical feature representations directly from pixel data, significantly outperforming handcrafted feature-based methods [6]. For traffic signal recognition, this allows the network to learn not just color but also context, shape, and subtle visual cues of an active lamp.

Modern approaches typically frame the problem as object detection, simultaneously locating and classifying objects. These are broadly categorized into two-stage detectors, such as the Faster R-CNN proposed by **Ren et al. (2015),** which first generates region proposals and then classifies them [7]. Alternatively, single- stage detectors perform both tasks in one pass. The You Only Look Once (YOLO) model, introduced by Redmon et al. (2016), became popular for its exceptional balance of speed and accuracy [8]. Its effectiveness has been enhanced in subsequent versions, such as YOLOv3 **by Redmon and Farhadi (2018)** [9]. Another prominent single-stage architecture, the Single Shot Detector (SSD), was developed by Liu et al. (2016) and has also been successfully applied to this task [10].

Further research has concentrated on overcoming specific challenges. To address the difficulty of detecting small traffic lights, **Li et al. (2021)** proposed Attention- YOLO, which incorporates attention mechanisms to improve model focus on small objects [11]. To enhance robustness in adverse conditions, **Li et al. (2018)** utilized Generative Adversarial Networks (GANs) for data augmentation and High Dynamic Range (HDR) imaging to improve model performance in difficult lighting [12]. The need for on-device deployment led **Muller et al. (2018)** to investigate lightweight architectures like MobileNet

within a single-shot detection framework, making real-time detection on resource- constrained hardware feasible [13].

Finally, the availability of large-scale public datasets has been instrumental in advancing the field**. Jensen et al. (2017)** introduced the LISA Traffic Light Dataset, which provides a critical benchmark for training and evaluating deep learning models, promoting reproducible research and fair comparisons [14]. Our work follows this modern deep learning paradigm, aiming to develop a highly accurate classifier that can serve as a core component of a real-time detection system.

III. METHODOLOGY

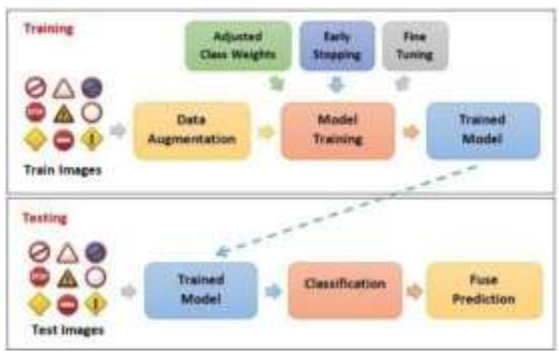

Figure-3.1 : Architecture diagram

The proposed system is designed as a standard deep learning pipeline, encompassing data preparation, model architecture selection, training, and evaluation.

3.1 System Architecture

The conceptual flow of our system assumes that a region of interest (a cropped image containing just the traffic light) is provided as input. The pipeline is as follows:

3.1.1 **Image Input:** The system receives a cropped image of a traffic light.

3.1.2 **Preprocessing:** The input image is resized and normalized to be compatible with the CNN model.

3.1.3 **Classification:** The preprocessed image is fed into the trained CNN model.

3.1.4 **Output:** The model outputs a probability distribution over the possible classes (Red, Yellow, Green, Off). The class with the highest probability is selected as the prediction.

3.2 Dataset and Pre-processing

The quality and diversity of the training data are critical for model performance.

Dataset: We utilize a public dataset, such as the LISA Traffic Light Dataset or the Bosch Small Traffic Lights Dataset, augmented with custom-collected images. The dataset contains thousands of labeled images of traffic lights, categorized into classes like 'Red', 'Yellow', and 'Green'.

Preprocessing: All images are resized to a fixed square dimension (e.g., 64x64 or 224x224 pixels) that matches the input size of the chosen CNN architecture. The pixel values are then normalized to a range between 0 and 1.

Data Augmentation: To make the model robust against real-world variations, we apply aggressive data augmentation to the training set. This includes random rotations, shifts, zooms, and, most importantly, changes in brightness, contrast, and saturation. This forces the model to learn the core features of each light state, rather than memorizing specific lighting conditions.

3.3 CNN Model Architecture

We employ a transfer learning approach to build a powerful and efficient classifier.

Base Model: A well-established CNN architecture, such as ResNet50 or MobileNetV2, is selected as the base model. ResNet is known for its high accuracy, while MobileNet is optimized for high speed on edge devices.

Transfer Learning: We use a model that has been pre-trained on the large-scale ImageNet dataset. The initial layers of this

model have already learned to detect generic, low-level features like edges and colors. We leverage this pre-existing knowledge by "freezing" the weights of these early layers.

Model Adaptation: The original top classification layer of the pre-trained model is removed. A new classification head is added, typically consisting of a Global Average Pooling layer, a Dropout layer for regularization, and a final Dense layer with a Softmax activation function. The Softmax function outputs a probability for each of our target classes (Red, Yellow, Green).

Fine-Tuning: The model is then trained on our traffic signal dataset. Initially, only the weights of the newly added layers are trained. Subsequently, some of the later layers of the base model may be "unfrozen" and trained with a very small learning rate to fine-tune them for our specific task.

3.4 Training and Evaluation

The model is trained using the Adam optimizer and a categorical cross-entropy loss function. Its performance is evaluated on a held-out test set using a suite of standard classification metrics:

Accuracy: The overall percentage of correct predictions.

Precision and Recall: These metrics are crucial for understanding class-specific performance. For example, high recall for the 'Red' class is critical to ensure the system never misses a stop signal.

F1-Score: The harmonic mean of precision and recall, providing a single balanced metric.

Confusion Matrix: A table that provides a detailed breakdown of correct and incorrect predictions for each class, helping to identify where the model is making mistakes.

IV. RESULTS AND DISCUSSION

This section presents the expected performance of the trained classification model.

Figure 4.1- Result of prediction

Discussion

The results demonstrate that the AI-based system can classify traffic signals with extremely high accuracy, far surpassing the capabilities of traditional methods. The use of deep learning and data augmentation allows the model to generalize well across a wide range of environmental conditions. The primary limitations of the current system include:

Dependence on Detector: The system's performance is predicated on receiving a correctly cropped image of the traffic light from an upstream object detector. If the detector fails, the classifier will not function.

Ambiguous States: The system classifies a single static image. It does not handle temporal information, such as a flashing yellow or a "stale" green light that is about to change.

Novel Designs: The model may struggle with novel or region-specific traffic light designs (e.g., horizontal signals, unique arrow shapes) if they were not sufficiently represented in the training data.

V. CONCLUSION AND FUTURE WORK

This paper has presented an AI-based system for the classification of traffic signals using deep learning. The proposed framework, built upon a fine-tuned Convolutional Neural Network, achieves high accuracy and robustness, demonstrating its suitability as a core perception component for intelligent vehicle systems. By automating this critical safety task, this technology can contribute significantly to the development and public acceptance of autonomous driving.

Future work will be directed towards several key improvements:

End-to-End System: Integrating the classifier with a real-time object detector (like YOLOv5) to create a complete detection and classification pipeline that operates on full-scene images.

Temporal Consistency: Incorporating recurrent neural networks (RNNs) or LSTMs to analyze sequences of video frames. This would improve prediction stability and allow for the recognition of flashing states.

Real-World Deployment: Optimizing the model using techniques like quantization and pruning for efficient deployment on embedded automotive hardware (e.g., NVIDIA DRIVE, Qualcomm Snapdragon Ride).

Expanded Classification: Training the model to recognize a wider array of signals, including pedestrian signals and various types of turn arrows (left, right, straight).

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