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Intelligent Traffic Light Controller for Emergency Vehicle Priority with Audio -Visual Recognition

S. Anitha[1], Mrs. P. Rohini[2], Mrs. Durga[3]

[1]Student, Department of CSE, Chendhuran College of Engineering & Technology, Pudukkottai, Tamil Nadu, India

[2]Assistant Professor & Head, Department of CSE, Chendhuran College of Engineering & Technology, Pudukkottai, Tamil Nadu, India

[3]Assistant Professor, Department of CSE, Chendhuran College of Engineering & Technology, Pudukkottai, Tamil Nadu, India

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ABSTRACT

Integrating intelligent traffic management systems (ITMS) with emergency vehicle prioritization has proven effective in reducing response times and enhancing public safety. Studies have demonstrated that such systems significantly improve the efficiency of emergency medical services by ensuring ambulances navigate urban traffic more swiftly. In Coimbatore, the city police are actively working towards enhancing traffic management infrastructure. The planned implementation of an ITMS powered by a dedicated 350 km local area network (LAN) aims to track and regulate vehicle movement, enforce traffic rules, and improve road safety. This system includes the installation of 6,000 poles to support optical-fiber cables and 1,400 cameras with advanced facial recognition software. By adopting Convolutional Neural Network (CNN)-based vehicle classification and integrating intelligent traffic light systems, Coimbatore can further enhance the efficiency of emergency response operations. Such measures would ensure that ambulances and other emergency vehicles navigate intersections swiftly, ultimately saving lives and improving public health outcomes. Studies have demonstrated the efficacy of Convolutional Neural Networks (CNNs) in detecting emergency vehicles through real-time image processing. For instance, a system trained on a dataset of Indian ambulance images can identify approaching emergency vehicles and communicate with traffic light controllers to adjust signal timings, ensuring expedited passage. Integrating vehicle density estimation with AI allows for dynamic adjustment of traffic signal durations based on real time traffic volumes. This approach alleviates congestion and prioritizes emergency vehicles by modifying signal timings to facilitate their swift movement through intersections. Challenges and Future Directions Implementing AI-driven traffic light priority systems necessitates addressing challenges such as ensuring system reliability, managing integration with existing traffic infrastructure, and complying with regulatory standards. Additionally, ethical considerations like bias and discrimination, transparency, data privacy, and public acceptance must be carefully evaluated. The integration of technologies such as GPS, RFID, and IoT enabled devices has been shown to facilitate real-time tracking and priority routing of emergency vehicles. For instance, systems that adjust traffic signals based on the real-time location of ambulances have demonstrated improvements in response times. A study titled "Traffic Management for Emergency Vehicle Priority Based on Visual Sensing and MAC Protocol" presents an approach that combines distance measurement between emergency vehicles and intersections using visual sensing methods, vehicle counting, and time sensitive alert transmission within the sensor network. The experimental results have shown that the proposed system outperforms existing solutions in terms of average end-to- end delay, throughput, and energy consumption. Implementing these technologies in Coimbatore could lead to more efficient emergency services, reduced congestion, and enhanced public safety. Collaboration among city planners, law enforcement, and technology providers will be essential to develop and deploy these advanced traffic management solutions effectively.

Introduction

Artificial Intelligence (AI) has significantly enhanced emergency response times in urban traffic management by prioritizing emergency vehicles, such as ambulances, reducing delays caused by congestion. AI-based systems utilize real-time data processing, vehicle detection, and dynamic traffic signal adjustments to facilitate the swift movement of emergency vehicles through intersections. AI- Based Emergency Vehicle Detection and Prioritization

Studies have demonstrated the efficacy of Convolutional Neural Networks (CNNs) in detecting emergency vehicles through real-time image processing. For instance, a system trained on a dataset of Indian ambulance images can identify approaching emergency vehicles and communicate with traffic light controllers to adjust signal timings, ensuring expedited passage. Integrating vehicle density estimation with AI allows for dynamic adjustment of traffic signal durations based on real time traffic volumes.

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Continuous research and optimization are essential to overcome these hurdles and fully realize the potential of AI in enhancing emergency response efficiency. Ongoing advancements in machine learning and real-time data processing are pivotal to the successful deployment and operation of these systems.

In summary, AI-based traffic management systems that prioritize emergency vehicles hold promise for significantly improving response times and overall urban traffic flow. Addressing the associated challenges through collaborative efforts and continuous innovation will be crucial to their successful implementation

LITERATURE REVIEW

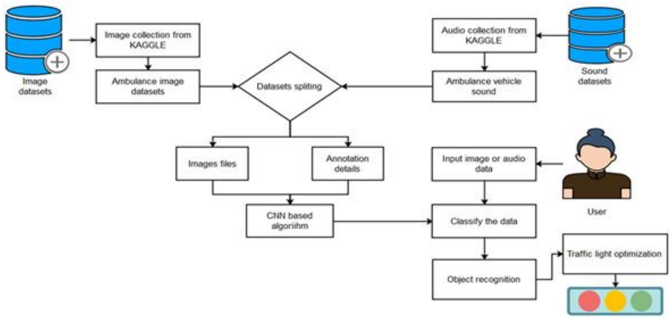
Integrating advanced technologies into Intelligent Transportation Systems (ITS) has significantly enhanced traffic management and safety, particularly concerning Emergency Vehicles (EVs). Innovative systems such as Unmanned Aerial Vehicle (UAV)-guided priority-based incident management systems and Intelligent Driving Licence Systems (IDLS) utilizing Internet of Things (IoT) technologies have been developed to improve EV response times and road safety. Additionally, the integration of Vehicle to- Vehicle (V2V) communication systems allows EVs to communicate with other vehicles, alerting them to the EV's presence and intentions, thereby facilitating smoother and faster passage. Smart traffic signal systems can monitor and control traffic flow, adjusting signal sequences to prioritize EVs, reducing travel time, and enhancing safety. UAV-Guided Incident Management UAVs have been identified as valuable tools in traffic incident management, providing real-time aerial footage to assist in monitoring and coordinating responses. Research indicates that optimizing UAV deployment can enhance incident management teams' effectiveness, though excessive UAV presence may lead to diminishing returns.

Audio Recognition Technologies Incorporating audio recognition technologies, such as deep learning- based models, can further improve the detection of approaching EVs. By analyzing siren sounds, these systems can identify the type of emergency vehicle and trigger appropriate responses, like altering traffic signal patterns to clear the path. Studies have shown that ensemble models combining Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs) can achieve high accuracy rates in recognizing siren sounds, with some models reaching up to 98.7% accuracy. Simulation Tools The development of tools like LibSignal further supports these advancements. LibSignal is an open-source library designed for modeling and evaluating deep reinforcement learning models in traffic signal control tasks. It provides extensible interfaces and unified evaluation metrics, supporting simulators like Simulation of Urban MObility (SUMO) and CityFlow. This allows for fair comparisons of different reinforcement learning algorithms, facilitating the development of more effective traffic signal control strategies. Addressing traffic congestion and improving EV response times requires a multifaceted approach that combines infrastructure enhancements, intelligent traffic management, and advanced communication and recognition technologies. These strategies collectively contribute to saving lives and reducing accidents on the roads. The integration of UAVs, V2V communication, audio recognition technologies, and advanced simulation tools represents a significant step forward in creating intelligent, responsive, and safe transportation systems. These technologies collectively enhance the efficiency of emergency responses and contribute to overall road safety

PROPOSED SYSTEM

Integrating facial recognition technology into public safety initiatives offers significant potential in addressing crimes such as kidnapping and human trafficking. By leveraging advanced algorithms and machine learning techniques, systems can be developed to aid in the identification and location of missing individuals. System Overview: Image Upload: Relatives or law enforcement agencies upload photographs of missing individuals to a centralized database. Face Detection: Utilizing Haar cascades—a machine learning based approach—the system scans images at various scales and locations to identify potential facial matches. However, it's important to note that Haar cascades are known to be prone to false positives and may not perform well in complex scenarios. Face Recognition: After detection, the system employs the Eigenfaces algorithm, which uses Principal Component Analysis (PCA) to reduce the dimensionality of face images. This method identifies significant features for recognition, capturing essential variations in facial features to enable efficient identification. While effective, combining Eigenfaces with other methods may further improve accuracy, especially in diverse real-world scenarios. Implementation Considerations: Haar Cascades: While Haar cascades offer speed and efficiency, they may have limitations, such as reduced accuracy in complex scenarios and a higher rate of false positives. Adjusting parameters like minNeighbors and minSize can help mitigate some of these issues. Eigenfaces Algorithm: By focusing on the principal components of facial images, the Eigenfaces algorithm facilitates efficient recognition. However, combining it with other methods may further improve accuracy, especially indiverse real-world scenarios. Advancements and Alternatives: Hybrid Approaches: Recent studies have explored integrating Haar cascades with other face recognition algorithms, such as Local Binary Patterns Histograms (LBPH), to enhance the reliability of face detection and recognition systems. This hybrid approach aims to leverage the strengths of multiple techniques to improve overall performance. Deep Learning Models: The use of Convolutional Neural Networks (CNNs) for face recognition has shown promise in improving accuracy. CNNs can capture complex patterns in facial features, potentially offering better performance compared to traditional methods. Studies have demonstrated that CNNs can yield higher accuracy rates in facial recognition tasks. Empowering the Community: By providing a platform where individuals can actively participate in the search for missing persons, the system fosters a collaborative approach to public safety. This empowerment can lead to increased vigilance, enhancing the chances of locating missing individuals and preventing potential crimes. Conclusion: Integrating facial recognition technology into public safety efforts holds significant promise in addressing the challenges posed by crimes like kidnapping and human trafficking. By combining accessible tools like OpenCV's Haar cascades and the Eigenfaces algorithm, the proposed system aims to create an efficient and user- friendly platform for locating missing persons. Continuous advancements in facial recognition technology, including the integration of CNNs and hybrid approaches, offer opportunities to further enhance the effectiveness of such systems, contributing to safer communities..

WORK FLOE DESIGN



SYSTEM REQUIREMENTS

LISTOF MODULES

- Datasets Collection
  - Vehicle Image
  - Audio Datasets
- Model Construction
- Real Time Interface
- Classify The Vehicles

DATASETS COLLECTION

To develop a comprehensive dataset for training models to classify emergency vehicles through both images and audio, you can utilize the following resources:

VEHICLE IMAGE

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AUDIO DATASETS

Integrating diverse datasets is indeed crucial for developing robust models capable of accurately detecting and classifying emergency vehicle siren sounds amidst various road noises. The datasets you've identified offer valuable resources for training such models: Emergency Vehicle Siren Sounds on Kaggle: This dataset comprises 3-second WAV audio files capturing sirens from emergency vehicles, including ambulances and fire trucks, recorded at varying distances and volumes. It is available on Kaggle. Ambulance (Siren) Dataset on AudioSet: Provided by Google Research, this dataset contains 1,939 audio clips of ambulance sirens, aiding in training models to recognize siren sounds. Details are available on AudioSet. Large-Scale Audio Dataset for Emergency Vehicle Sirens and Road Noises: This dataset offers audio files capturing ambulance sirens alongside various road noises, assisting in distinguishing siren sounds from other traffic noisesInformation can be found in the corresponding research publication. Considerations for Dataset Usage: Licensing: Before utilizing these datasets, review their licensing agreements to ensure compliance with usage rights, especially if the data is intended for commercial purposes. Data Augmentation: To enhance model robustness, consider applying data augmentation techniques such as noise addition or varying pitch to audio datasets. Data Preprocessing: Standardize audio files in terms of sampling rate and duration to maintain consistency across the dataset. By integrating these datasets, you can create a diverse and representative collection of audio data to effectively train models for emergency vehicle siren detection and classification

MODEL CONSTRUCTION

Designing a Convolutional Neural Network (CNN) tailored to specific tasks, such as image classification, involves several key architectural decisions. Building upon the foundational concepts previously discussed, here's a more detailed guide to defining a CNN architecture using TensorFlow and Keras:

Convolutional Layers: Purpose: Extract hierarchical features from input images. Implementation: Utilize Conv2D layers with varying filter sizes and numbers.

1. Pooling Layers: Purpose: Reduce spatial dimensions and computational load. Implementation: Apply MaxPooling2D layers with appropriate pool sizes.

2. Fully Connected Layers: Purpose: Learn complex representations based on extracted features. Implementation: Incorporate Dense layers with suitable numbers of neurons. for 4 locating missing persons. Continuous advancements in facial recognition technology, including the integration of hybrid approaches and deep learning models, offer opportunities to further enhance the effectiveness of such systems, contributing to safer communities. Audio
3. Datasets: Integrating diverse datasets is indeed crucial for developing robust models capable of accurately detecting and classifying emergency vehicle siren sounds amidst various road noises. The datasets you've identified offer valuable resources for training such models:
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7. Integrity Submission Output Layer: Purpose: Produce final predictions. Implementation: Use a Dense layer with a number of neurons equal to the number of classes and an activation function matching the task.
8. Model Compilation: Purpose: Define the optimization strategy. Implementation: Compile the model with appropriate loss functions and optimizers.
9. Model Training: Purpose: Optimize model parameters. Implementation: Train the model using training data and validate using validation data. Model Evaluation and Testing: Purpose: Assess model performance. Implementation: Evaluate the model on test data. Additional Considerations: Advanced Architectures: Explore architectures like GoogLeNet, MobileNet, and EfficientNet for specialized tasks or resource constraints. Regularization: Implement techniques such as dropout, batch normalization, and L2 regularization to prevent overfitting. Data Augmentation: Apply transformations like rotations, flips, and scaling to increase dataset diversity and model robustness.
10. Resources for Further Learning: By systematically designing your CNN with these considerations, you can develop models tailored to your specific image classification tasks, leveraging the power of TensorFlow and Keras for efficient implementation.

REAL TIME INTERFACE

Developing a computer vision framework for traffic signal surveillance involves several key steps, integrating technologies like OpenCV and TensorFlow to enhance traffic monitoring and management. Here's a structured approach:

. Setting Up the Development Environment: Install Necessary Libraries: Ensure that Python is installed, then set up OpenCV for image and video processing, and TensorFlow for machine learning models. Use pip to install these packages: Capturing Video Feeds: Deploy Surveillance Cameras: Position cameras at strategic traffic points to monitor conditions effectively. Access Video Streams: Use OpenCV to capture video feeds. For IP cameras, access streams using RTSP or HTTP protocols: python Copy Processing Video Frames: Object Detection: Analyze each frame to detect vehicles and traffic signals. Utilize pre- trained models like YOLO (You Only Look Once) or TensorFlow's Object Detection API for real-time object detection. Background Subtraction: Implement techniques to identify moving vehicles by comparing current frames with a background model. OpenCV provides background subtractors to facilitate this process. Feature Extraction and Matching: Extract Features: Identify characteristics such as size, shape, and color of detected vehicles and traffic signals. Track Vehicles: Use tracking algorithms to monitor vehicle movement across frames, aiding in congestion analysis and traffic flow assessment. Integrating with Traffic Signal Control: Analyze Traffic Data: Determine traffic density and flow by processing the extracted features. Adjust Signal Timings: Develop algorithms to modify traffic signal timings based on real-time traffic conditions, such as extending green lights during peak congestion. Practical Implementation Example: A relevant project demonstrating these concepts is the "Vehicle Monitoring System" that utilizes TensorFlow and OpenCV for vehicle detection and tracking. This system captures video feeds, processes frames to detect vehicles using the TensorFlow Object Detection API, and analyzes traffic conditions. The project is available on GitHub:

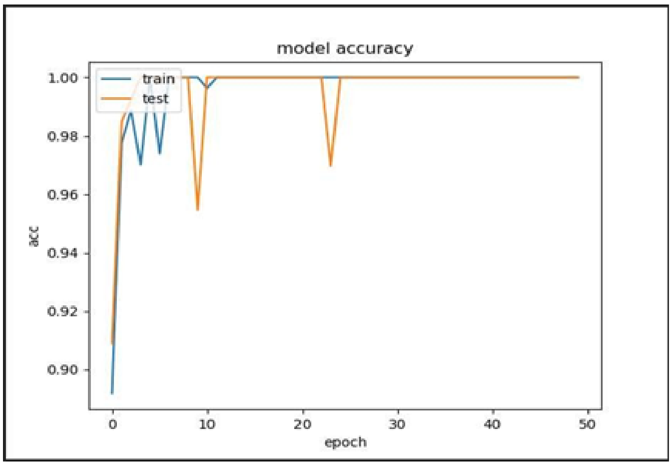
Considerations: Real-Time Processing: Ensure that the system can process video frames in real-time to provide timely traffic updates and signal adjustments. Scalability: Design the system to handle multiple camera feeds and integrate with existing traffic management infrastructure. Accuracy: Regularly evaluate and update detection models to mainteance

By following these steps and utilizing the mentioned resources, you can develop an effective computer vision framework for traffic signal surveillance that enhances traffic management and public safety.

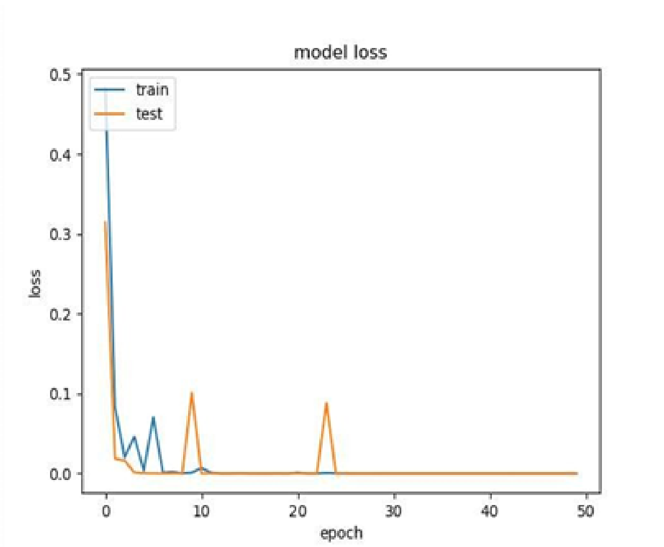
CLASSIFY THE VEHICLES

Developing an effective machine learning model for traffic light optimization involves a comprehensive approach that encompasses model evaluation, performance analysis, integration with traffic control systems, and alignment with real-world applications. Building upon the previously discussed evaluation metrics and methodologies, here are additional considerations to enhance your system: Integrate with Traffic Light Optimization: Traffic Flow Prediction: Utilize machine learning algorithms to forecast traffic conditions at intersections. Accurate predictions can inform adaptive traffic signal timings, reducing congestion and improving traffic flow. Reinforcement Learning (RL): Apply RL techniques to train models that optimize traffic light cycles based on real-time traffic data. This approach allows for dynamic adjustment of signal timings to current traffic conditions. Feature Matching and Model Alignment: Feature Consistency: Ensure that the features used during model training align with those available during deployment. Consistent feature representation is crucial for reliable model performance. Model Validation: Regularly validate the model using up-to date data to confirm its effectiveness in real- world scenarios. Continuous monitoring helps in adapting to changing traffic patterns. Advanced Techniques and Considerations: Deep Reinforcement Learning (DRL): Employ DRL to adaptively control traffic lights based on real-time traffic situations. DRL has shown promise in improving traffic efficiency and reducing congestion. Federated Learning: Consider using Federated Learning-based RL for traffic signal control to address challenges such as scalability and data privacy. This approach integrates knowledge from local agents into a global model, enabling adaptability across diverse traffic scenarios. Safety-Oriented Design: Incorporate safety standards into the reward design of RL-based traffic signal control to ensure collision-free operations. Designing appropriate rewards is crucial for the safe deployment of these systems. By systematically evaluating your model, analyzing its predictions, and aligning it with traffic light optimization objectives, you can develop a system that effectively enhances traffic flow and safety. Continuous research and adaptation to emerging technologies will further improve the responsiveness and efficiency of traffic management systems.

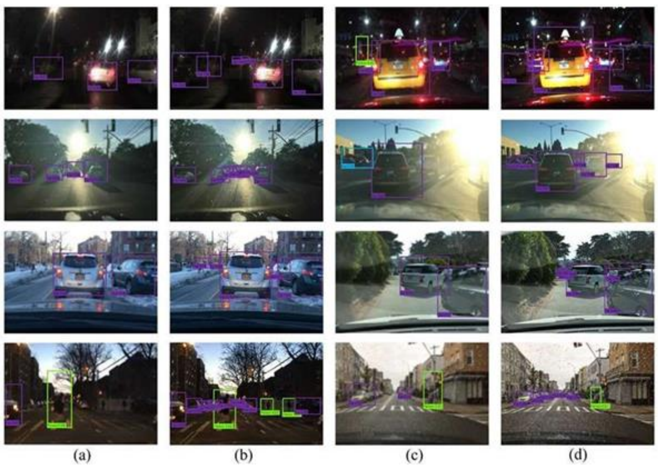
PREDICTION



CLASSIFICATION



RESULTS



CONCLUSION

Convolutional Neural Networks (CNNs) have significantly advanced vehicle classification, particularly under challenging conditions such as low-lighting, adverse weather, and occlusions. Recent studies demonstrate CNNs' efficacy in classifying vehicles captured by standard security cameras, even in suboptimal environments. Integrating advanced architectures like Faster R-CNN has proven effective in vehicle segmentation tasks, addressing challenges like occlusions and varying traffic densities. This approach involves a multi-step process, including adaptive background modeling and result optimization, which enhances the accuracy of vehicle detection and classification. For instance, research has successfully applied CNNs to classify vehicles in images taken by standard security cameras positioned far from traffic scenes, even under low-lighting andadverse weather conditions. The deployment of CNN-based vehicle classification systems has led to significant improvements in traffic monitoring and management. These systems facilitate automated vehicle counting, classification, and real-time traffic analysis, contributing to enhanced road safety and optimized traffic flow. Additionally, the adaptability of CNNs allows them to be fine tuned for specific applications, further extending their utility in diverse traffic scenarios. In summary, the continued evolution and application of CNNs in vehicle classification are pivotal for advancing intelligent transportation systems, offering robust solutions to complex challenges in traffic monitoring and management.

FUTURE ENHANCEMENTS

Deploying Convolutional Neural Network (CNN) models directly on edge devices, such as traffic cameras or roadside sensors, offers significant benefits, including reduced latency, lower bandwidth usage, and enhanced privacy through local data processing. However, this deployment requires overcoming challenges related to the limited computational resources, memory constraints, and power consumption of edge devices. Optimizing CNNs for Edge Deployment: To effectively deploy CNNs on resource-constrained edge devices, several optimization techniques can be employed: Model Pruning: This technique involves removing less important neurons or weights from the network, reducing the model's size and computational load without significantly affecting performance. For instance, pruning has been shown to reduce model parameters by 80.39%, leading to improvements in inference latency and energy consumption. Quantization: Quantization reduces the precision of the numbers used to represent model parameters, leading to smaller model sizes and faster inference times. This process involves mapping high-precision weights and activations to lower precision formats, such as int8. Combining pruning with 8-bit quantization has resulted in a 22.72% improvement in inference latency and a 29.41% reduction in energy consumption, without substantial loss in model accuracy. Lightweight Architectures: Designing CNN architectures specifically tailored for edge devices can lead to more efficient models.

Techniques such as knowledge distillation, where a smaller model learns from a larger, more complex model, can also be beneficial. Additionally, employing architectures like MobileNet, SqueezeNet, and EfficientNet focuses on reducing the computational and memory requirements of deep learning models without sacrificing performance. Integrating Multi-Modal Sensor Data: Combining data from multiple sensor modalities—such as visual cameras, LiDAR, and radar—can significantly enhance the accuracy and robustness of object detection systems, especially under challenging weather or lighting conditions. Each sensor type offers unique advantages and limitations: Visual Cameras: Provide high-resolution color images but are susceptible to performance degradation under adverse weather conditions like fog or low- light environments. LiDAR Sensors: Offer precise 3D spatial information but their effectiveness can be compromised in poor visibility conditions due to scattering and absorption of laser beams.

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