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ABBREVIATIONS

ANN - Artificial Neural Network

ROI - Region of Interest

MSTM - Multi-Scale Traffic Monitoring

TPR - True Positive Rate

FPR - False Positive Rate

FNR - False Negative Rate

TP - True Positive

FP - False Positive

TN - True Negative

FN - False Negative

KITTI - Karlsruhe Institute of Technology and Toyota Technological Institute (Dataset)

LoS - Leave-one-subject-out (cross-validation)

RGB - Red, Green, Blue (color model)

HoG - Histogram of Oriented Gradients

GMM - Gaussian Mixture Model

ID - Identifier

FDR - False Detection Rate

Abstract

This project presents a framework for vehicle detection and recognition, leveraging graph-based optimization to refine feature selection and improve model efficiency. Using the KITTI dataset, the framework employs advanced preprocessing steps such as frame conversion, background subtraction, median filtering, and Gaussian Mixture Models (GMM) to enhance image clarity and isolate vehicles. Key features like energy and dense optical flow are extracted to capture both static and motion characteristics, which feed into an artificial neural network (ANN) for high-accuracy classification. Graph-based optimization streamlines feature selection, minimizing redundant data and enhancing computational efficiency. The model achieved up to 90% accuracy, with significant applications in real-time traffic monitoring system

SUMMARY OF THE BASE PAPER

INTRODUCTION :

Computer vision plays a crucial role in technologies such as industrial automation, robotics, and motion detection, with moving object identification being essential for applications like video surveillance. In smart transportation systems, efficient and secure traffic management is vital, especially as population growth increases the need for effective solutions. Monitoring and analyzing traffic can help improve security, reduce congestion, and minimize pollution. Video monitoring systems track moving vehicles, enabling real-time detection, classification, and analysis of their behavior. This has numerous applications, including surveillance and autonomous navigation. However, challenges like speed, consistency, and environmental factors still affect detection accuracy..

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Methodology

The methodology section describes the approaches and techniques used in this project for the "Graph-Based Optimization for Multi-Scale Vehicle Detection and Recognition" task, leveraging the KITTI dataset and a combination of computer vision and machine learning methods.

1. **Data Preprocessing**

Before applying any machine learning or computer vision techniques, the dataset undergoes various preprocessing steps to ensure the data is in a suitable format for analysis. These steps are critical for enhancing the quality of the data and preparing it for feature extraction and model training.

1.1 Frame Conversion

The first step involves converting the images into frames for individual vehicle detection. This process ensures that each frame can be analyzed independently, making it easier to extract relevant features from static scenes. The KITTI dataset, which consists of both images and video sequences, requires frame-by-frame conversion to work with individual objects and extract meaningful information.

1.2 Background Subtraction

Background subtraction is performed to isolate moving objects (i.e., vehicles) from the background. This technique is used to segment out the foreground objects from each frame. It is particularly useful in video-based vehicle detection tasks where the goal is to focus on dynamic elements (vehicles) against a relatively static background. The method subtracts the background model from the current frame, leaving only the moving objects (vehicles). This step significantly reduces computational complexity by filtering out static parts of the image.

1.3 Median Filtering

After background subtraction, the resulting image may still contain noise, such as small, irrelevant objects or small artifacts caused by the subtraction process. Median filtering is used to reduce this noise by replacing each pixel with the median of its neighboring pixels within a specified window size. This process helps to smooth the image, making it easier to detect the vehicles and their precise locations.

2. **Object Shape Optimization**

Object shape optimization is a technique used to improve the accuracy and precision of vehicle detection. In this step, the goal is to identify the optimal bounding box that surrounds the vehicle in each frame. Several strategies can be applied, such as contour analysis, edge detection, or using more advanced techniques like graph-based methods to optimize the vehicle's shape. By optimizing the shape, the detection system can better identify vehicles of various sizes, angles, and distortions in the image.

2.1 Bounding Box Extraction

After object shape optimization, the next task is to extract the bounding boxes around the vehicles. The bounding boxes are crucial for localizing the vehicles and segmenting the objects from the background. They are defined by four points (top-left and bottom-right corners) and are used to further extract features for classification.

3. **Extracting Regions of Interest (ROI)**

Regions of interest (ROIs) are portions of the image that contain the most relevant information for the vehicle detection task. By focusing on the ROIs, we reduce the computational overhead and focus only on the parts of the image that contain the vehicles. This step involves identifying the areas within the bounding boxes that contain vehicles and then cropping these regions for feature extraction.

3.1 Vehicle Segmentation

Vehicle segmentation is the process of isolating the vehicle from the background within the ROI. It involves fine-tuning the boundaries of the bounding box to ensure that only the vehicle is included in the ROI. This step may also use additional techniques such as contour detection or morphological operations to refine the segmentation.

4. **Feature Extraction**

Feature extraction is a crucial step for any machine learning task, as it transforms the raw data into a set of measurable characteristics that the model can use for classification. In this project, we focus on extracting multi-scale features from the vehicle images to capture a range of details at different levels of resolution.

4.1 Energy Features

Energy features are a specific type of feature designed to capture the intensity variations in an image. These features are especially useful in detecting vehicles in varying lighting conditions and environments. The energy features describe the energy distribution across the image, which is useful for distinguishing vehicles from the background or other objects. This method is robust to noise and can handle challenges such as occlusions and varying vehicle sizes.

4.2 Multi-Scale Feature Extraction

Multi-scale feature extraction involves processing the image at different scales to capture both fine-grained and coarse details. This technique allows the model to detect vehicles of various sizes and orientations. By extracting features at multiple scales, the system becomes more adaptable to different vehicle types and environments. Various techniques such as sliding windows or pyramidal representations can be used to create the multi-scale features.

5. **Graph-Based Optimization**

The core of the methodology involves using graph-based optimization to refine the vehicle detection process. This technique aims to improve the detection accuracy by considering spatial relationships between vehicles and optimizing their bounding boxes across multiple scales.

5.1 Graph Construction

A graph is constructed where each node represents a vehicle (or a potential vehicle detection), and edges define the spatial or temporal relationships between these nodes. The graph structure allows the system to optimize the vehicle detection by propagating information across different regions of the image. This graph-based approach helps to refine detections, correct errors, and enhance accuracy by considering the broader context of each vehicle's location.

5.2 Optimization Process

The optimization process iteratively adjusts the detected vehicle locations by minimizing an energy function that accounts for factors such as spatial coherence, object shape, and multi-scale features. By using graph optimization, the system can make more accurate predictions about vehicle positions and bounding boxes.

6. **Model Training using Artificial Neural Networks (ANN)**

After the features are extracted, the next step is to use an artificial neural network (ANN) for training. ANNs are well-suited for tasks like vehicle classification because of their ability to learn complex patterns from the extracted features. The model is trained to classify each detected object as a vehicle (or a specific vehicle type) based on the extracted features.

6.1 ANN Architecture

The ANN architecture for vehicle detection consists of multiple layers: an input layer to receive the features, hidden layers to process and learn patterns, and an output layer that produces the vehicle classification. The architecture is designed to handle both spatial features from the images and energy features to ensure accurate vehicle recognition.

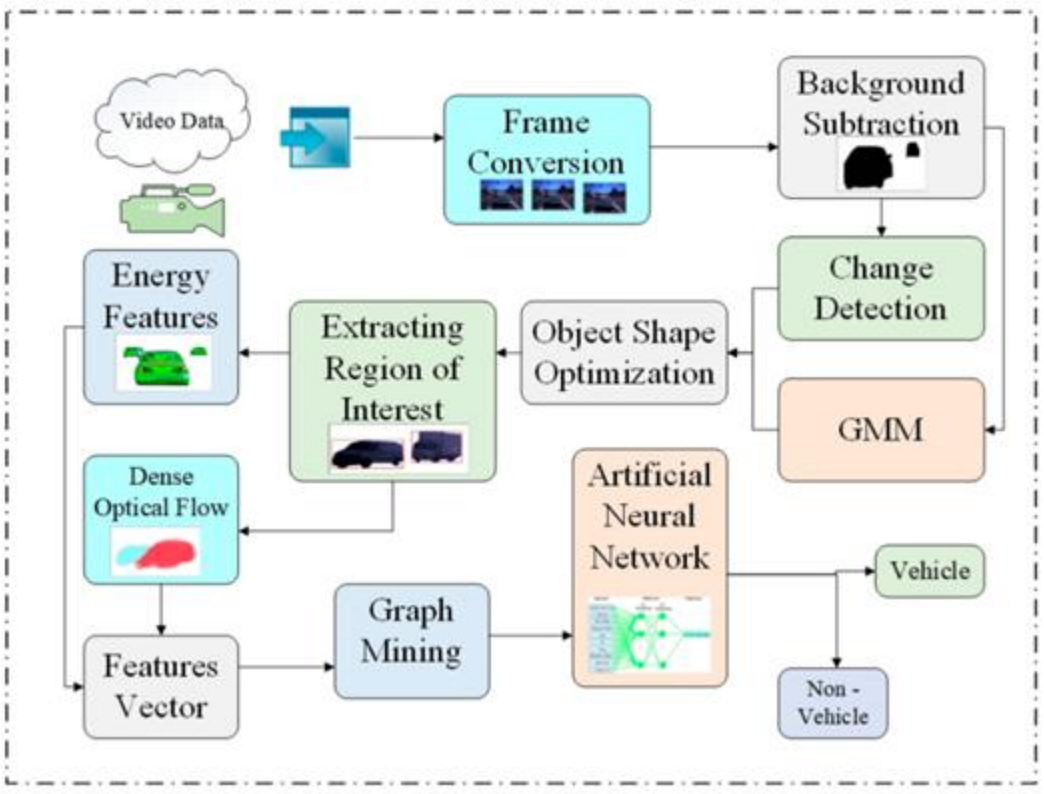
6.2 Training Process

The model is trained using a supervised learning approach, where labeled data (vehicle types) is used to guide the training process. The training involves optimizing the model's weights using backpropagation and gradient descent. The training data comes from the KITTI dataset, with labeled images representing different vehicle types. The model is trained until it converges to a state where it can accurately classify vehicles based on the extracted features.

7. **Evaluation**

Once the model is trained, it is evaluated on a separate validation dataset to assess its performance. The evaluation metrics include accuracy, precision, recall, and F1-score, all of which are used to measure how well the model detects and classifies vehicles. Additionally, a confusion matrix is generated to visualize the classification performance across different vehicle types.

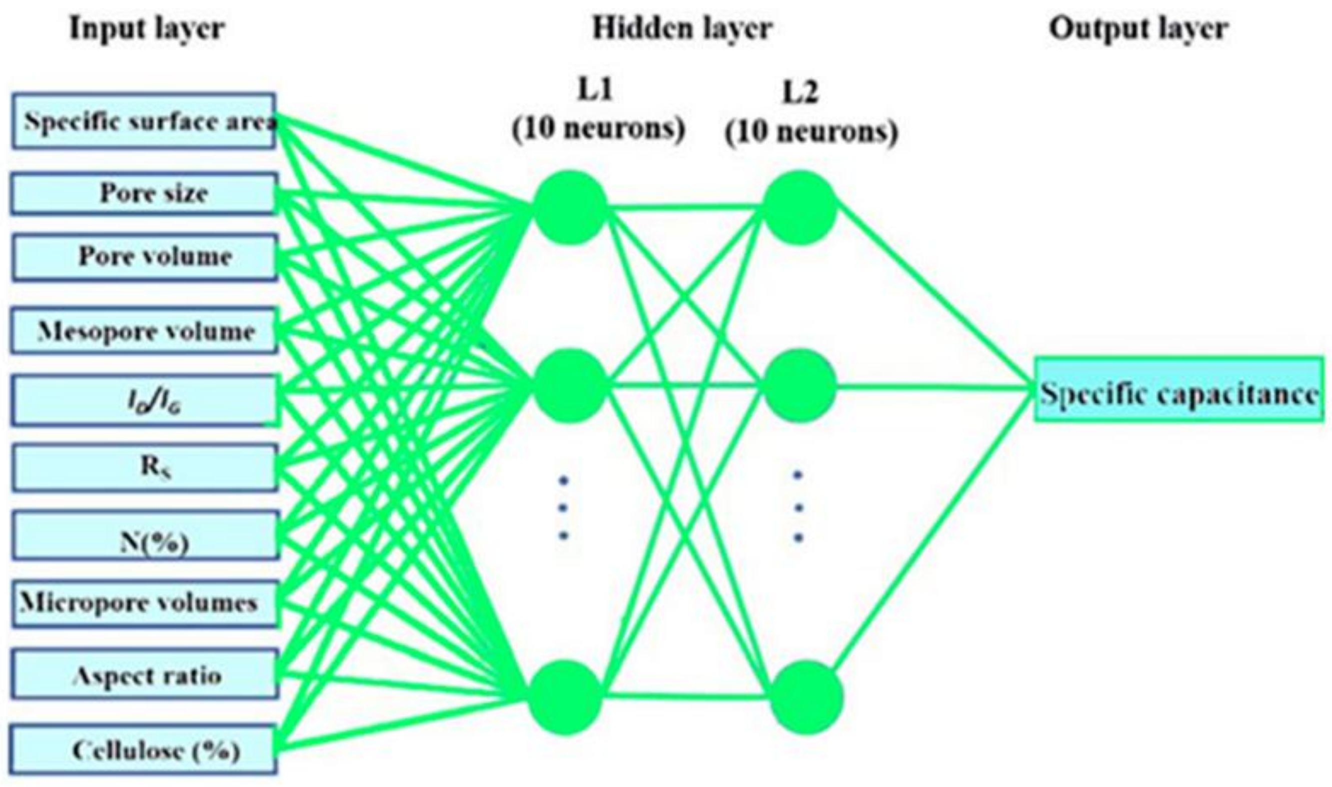
Work Flow :



ANN Approach :

Artificial Neural Network This section discusses the ANN approach to classification. An ANN is a collection of multiple perceptrons or neurons on each stratification; when necessary data is categorized in the forward broadcaster, this is known as a feed-forward neural network [35]. The processing elements, the hidden layers, and the output variable constitute the core structure of anANN.Theinputlayeracceptsrawdata, theconcealinglevelsexecutearithmetic on the entering data, and the artificial neuron obtains outcomes. In machine learning algorithms, each layer is responsible for learning the mathematical weights that are produced at the culmination of the learning process. The ANN approach is good for image data, text descriptions, and probability tables challenges.

The advantage of ANN is its capacity to cope with transfer functions and to learn characteristics that map any input to any output for any data. The links between neurons train their neural network with exponential properties, allowing the network to learn any complex relationship between output and input data. Numerous researchers employ ANNs to analyze complex relationships, including the coexistence of mobile and WiFi connectivity in licensed spectra and then transfer the optimized features vector to ANN for classifications and segmentation; Figure 8 illustrates the system of ANN



ANN Approach

CHAPTER 2

SUMMARY OF MY PROJECT

INTRODUCTION :

The objective of this project is to develop an efficient and robust method for vehicle detection and recognition using graph-based optimization combined with multi-scale feature extraction and Artificial Neural Networks (ANNs). The project aims to enhance the accuracy and performance of vehicle detection systems in diverse and challenging environments, such as urban streets, highways, and areas with varying lighting and weather conditions. By leveraging these advanced techniques, the project provides a solution for autonomous driving, traffic surveillance, and smart city applications.

The core challenge in vehicle detection lies in the need to identify and classify vehicles from images or video frames under various real-world conditions. This includes handling scale variations, occlusions, and lighting changes, all of which can affect the performance of traditional vehicle detection algorithms. In response to these challenges, this project combines multi-scale feature extraction to handle variations in vehicle size with graph-based optimization to improve the accuracy of detection and recognition results.

This project is to develop an efficient and robust method for vehicle detection and recognition using graph-based optimization combined with multi-scale feature extraction and Artificial Neural Networks (ANNs). The project aims to enhance the accuracy and performance of vehicle detection systems in diverse and challenging environments, such as urban streets, highways, and areas with varying lighting and weather conditions. By leveraging these advanced techniques, the project provides a solution for autonomous driving, traffic surveillance, and smart city applications.

The project uses the KITTI dataset, a popular benchmark in the autonomous driving community, which provides images and ground-truth annotations of vehicles in real-world driving scenarios. The main goal is to detect and recognize different types of vehicles (such as cars, trucks, buses, and motorcycles) using a combination of traditional computer vision methods and machine learning techniques.

8. Methodology

The methodology for this project focuses on improving the accuracy and robustness of vehicle detection and recognition in real-world environments, particularly for autonomous driving applications. It combines several key techniques, including **multi-scale feature extraction**, **graph-based optimization**, and **Artificial Neural Networks (ANNs)** for classification. Below is a detailed breakdown of each step in the methodology.

8.1 Frame Conversion

The initial step involves converting video frames into individual image frames that will serve as the input for subsequent processing. This conversion enables handling of each frame independently, providing flexibility in real-time vehicle detection scenarios.

8.2 Background Subtraction

Background subtraction is employed to segment moving objects (vehicles) from the static background. This is a critical step in separating the vehicle from its environment, making it easier to detect vehicles of interest. The background subtraction technique helps identify regions in the frame that potentially contain vehicles, setting the stage for further analysis.

8.3 Median Filter

A median filter is applied to reduce noise in the image, particularly from sensor artifacts or lighting changes, which can lead to false detections. By smoothing the image, the median filter helps preserve important features, such as vehicle edges, while removing irrelevant noise.

8.4 Object Shape Optimization

This step refines the detected object shapes, ensuring that the boundaries of detected vehicles are accurately delineated. Object shape optimization improves the performance of the vehicle detection algorithm, particularly when dealing with partial occlusions or overlapping vehicles. The optimization process helps adjust the initial bounding boxes to better fit the actual vehicle shapes.

8.5 Extracting Region of Interest (ROI)

In this step, the Region of Interest (ROI) is extracted to focus on areas of the image that contain vehicles. The ROI helps reduce the computational load by narrowing the search space to specific regions, improving the speed and accuracy of subsequent steps.

8.6 Feature Extraction

After the ROI is determined, the next step is to extract features that are relevant for vehicle detection. Multi-scale feature extraction is employed to ensure that vehicles of different sizes (from motorcycles to trucks) are detected accurately. The features extracted include energy-based characteristics, such as intensity variations and texture patterns, which help the algorithm recognize vehicles under various lighting and environmental conditions.

8.7 Graph-Based Optimization

Once the features are extracted, graph-based optimization is applied to improve the accuracy of the detected vehicle positions. This involves modeling the detected vehicles as nodes in a graph and considering the spatial and temporal relationships between the vehicles. Using graph algorithms, the detection results are refined to account for issues like occlusion, misalignment, and incorrect bounding box predictions. The optimization process minimizes the error by adjusting the bounding boxes based on the relationships between vehicles in the scene.

8.8 Classification with Artificial Neural Networks (ANNs)

After the vehicles are detected and their positions optimized, an Artificial Neural Network (ANN) is used to classify the vehicles into different categories, such as cars, trucks, buses, and motorcycles. The features extracted in the earlier steps are fed into the ANN, which is trained using labeled data from the KITTI dataset. The classification model learns to distinguish between different vehicle types based on the features it receives.

9. Dataset

The project uses the KITTI dataset, which is widely used for evaluating vehicle detection and recognition algorithms. The KITTI dataset contains images captured from a car driving through urban and highway environments. The dataset includes video sequences, bounding box annotations, and calibration data, which are essential for testing the performance of the vehicle detection system.

9.1 Data Augmentation

To improve the generalization of the model and prevent overfitting, data augmentation techniques such as random rotations, flips, and brightness adjustments are applied to the training images. This process ensures that the model learns to detect vehicles in a variety of conditions and orientations.

10. **Training the Model**

The training process involves feeding the labeled images and extracted features into the ANN. The network is trained using a supervised learning approach, where the output of the network is compared to the ground truth labels (vehicle types). The network adjusts its internal weights to minimize the loss function, improving its ability to correctly classify vehicles. The performance of the model is evaluated using various metrics, including accuracy, precision, and recall.

11. **Evaluation and Results**

The project evaluates the proposed method on the KITTI dataset by comparing the performance of the model to other state-of-the-art vehicle detection algorithms. The performance is assessed using metrics such as Precision-Recall curves and F1-score. The experimental results demonstrate that the combination of multi-scale feature extraction and graph-based optimization significantly improves the accuracy of vehicle detection, particularly in challenging environments with partial occlusions, varying lighting conditions, and cluttered backgrounds.

Artificial Neural Network (ANN) Approach

12 **ANN Approach**

In this project, Artificial Neural Networks (ANNs) play a critical role in the classification and recognition of detected vehicles. After vehicles have been localized through graph-based optimization and multi-scale feature extraction, the ANN is used to categorize each detected vehicle into specific types, such as cars, trucks, buses, or motorcycles. Here is a detailed breakdown of the ANN approach used in this project

12.1. Purpose of ANN in Vehicle Detection and Recognition

The ANN is responsible for accurately classifying detected objects based on the extracted features. Since vehicles can vary greatly in appearance, the ANN model is trained to learn distinguishing characteristics for each vehicle class. The purpose of incorporating an ANN is to leverage its ability to recognize complex patterns, which improves the system's classification accuracy.

Objective: To classify each detected vehicle accurately by learning patterns specific to vehicle
Application: The ANN is employed after the multi-scale feature extraction and object shape optimization steps, focusing on correctly categorizing each detected object.

12.2. Input to the ANN

The inputs to the ANN are the features extracted from each vehicle's Region of Interest (ROI). These features represent the unique attributes of each vehicle type, capturing variations in
Size and Shape: Features that indicate the general dimensions and form of the vehicle.
Texture and Edges: Energy-based features that capture texture patterns unique to each vehicle
Color and Intensity: Patterns based on the intensity variations that can further aid in distinguishing between types of vehicles. These features are fed into the ANN in a structured form, typically as multi-dimensional arrays or feature vectors that encode the relevant information for classification.

12.3. ANN Architecture

The ANN architecture used in this project is a feedforward neural network, which includes multiple layers that progressively transform the input features into class predictions. Key components of the ANN architecture include:

Input Layer: Receives the extracted feature vectors. The size of this layer matches the number of features extracted per vehicle.

Hidden Layers: These layers allow the network to learn complex, non-linear patterns in the data. Multiple hidden layers with activation functions such as ReLU (Rectified Linear Unit) are used to introduce non-linearity, enabling the model to capture the intricate relationships between features and vehicle classes.

Output Layer: The output layer has a softmax activation function, producing a probability distribution over the vehicle classes (e.g., car, truck, bus, motorcycle). This layer outputs the classification result by assigning a probability to each class.

Hyperparameters: Key hyperparameters, such as the number of hidden layers, neurons per layer, learning rate, and batch size, are optimized during training to ensure the best performance of the model.

12.4. Training the ANN

The ANN is trained using supervised learning on the KITTI dataset. Training involves feeding labeled data into the model, allowing it to learn to map the input features to the corresponding vehicle type labels.

- Training Data: The KITTI dataset provides a rich source of labeled vehicle images, each tagged with the correct class label (e.g., car, truck, bus). Data is augmented to increase the diversity and robustness of the training set, which helps the ANN generalize to various real-world scenarios.
- Data Augmentation: Techniques such as rotations, flips, and brightness adjustments are applied to the images to improve the model's ability to handle diverse and challenging environments.
- Loss Function: A categorical cross-entropy loss function is used to quantify the difference between the predicted and true labels. This function is minimized during training to improve classification accuracy.

- Optimization: The backpropagation algorithm is used to adjust the model's weights by minimizing the loss function, with optimizers like Adam or SGD helping achieve faster convergence.
- Training proceeds in epochs, with each epoch involving a forward pass (making predictions) and a backward pass (updating weights based on errors). The model is validated on a separate validation set to monitor its performance and prevent overfitting.

12.5. Evaluation Metrics

The performance of the ANN model is evaluated using several metrics to ensure that it meets the project's requirements for vehicle classification. Key metrics include:

- Accuracy: The percentage of correctly classified vehicles out of the total number of vehicles.
- Precision and Recall: Precision measures the number of true positive classifications over all predicted positives, while recall measures the true positives over all actual positives.
- F1 Score: A harmonic mean of precision and recall, providing a balanced measure for classification performance.
- Confusion Matrix: A matrix that shows the breakdown of predictions versus actual labels, which helps identify any misclassifications among the vehicle types.

These metrics provide insights into how well the ANN generalizes to unseen data and how accurately it can classify vehicles.

12.6. Advantages of Using ANN for Classification

The use of **ANN in this project provides several advantages**:

- Pattern Recognition: ANNs are capable of recognizing complex and non-linear patterns in the features, which makes them well-suited for distinguishing between vehicle types.
- Adaptability: The ANN can adapt to various real-world conditions by learning from diverse data, making it robust to changes in lighting, weather, and background.
- High Accuracy: By leveraging labeled data from the KITTI dataset and optimizing the model, the ANN achieves high accuracy in vehicle classification.

12.7. Results and Observations

The ANN model has demonstrated promising results in classifying different vehicle types in the KITTI dataset. After training and testing, the ANN has shown:

- High Classification Accuracy: The model correctly classifies most vehicles, particularly cars and trucks, which are more frequent in the dataset.
- Effective Handling of Variability: Due to multi-scale feature extraction and data augmentation, the model is robust to changes in scale, perspective, and lighting.
- Confusion Matrix Insights: The confusion matrix reveals any potential overlaps in similar vehicle classes (e.g., buses and trucks), which helps in refining the model further.

CHAPTER 3

13 MERITS AND DEMERITS OF THE BASE PAPER

13.1 Merits

1. Multi-Scale Vehicle Detection

   The multi-scale approach used in the paper is one of its most notable strengths. By extracting features from different scales, the model becomes more adaptable to varying vehicle sizes, from small cars to large trucks or buses. Multi-scale detection ensures that vehicles of different sizes and distances from the camera can be effectively detected, which is particularly valuable in outdoor, real-time vehicle detection systems.

2. Combination of Computer Vision and Machine Learning

   The integration of graph-based optimization with machine learning techniques, specifically Artificial Neural Networks (ANNs), provides a balanced solution that leverages the power of both domains. Graph-based optimization helps in refining the vehicle location predictions, while ANNs effectively handle the classification tasks based on extracted features. This combination makes the system robust, allowing it to handle complex vehicle detection scenarios with high accuracy.

3. Comprehensive Evaluation on KITTI Dataset

   The paper uses the KITTI dataset, which is a well-established benchmark for vehicle detection and recognition tasks. By testing the model on this dataset, the authors ensure that the method is robust and capable of handling real-world data. The use of KITTI also allows for comparison with other existing methods in the field, making it easier to assess the relative performance of the proposed approach.

4. Potential for Real-World Applications

   The methodology in the paper has a strong potential for real-time vehicle detection and recognition in a variety of applications, such as autonomous driving, traffic surveillance, and urban monitoring. The focus on multi-scale and graph-based optimization improves the method's scalability and robustness, making it suitable for practical, real-world deployments where conditions vary constantly.

13.2 Demerits

1. High Computational Complexity

   One of the main limitations of the paper's approach is its computational complexity. Graph-based optimization requires significant computational resources, particularly when dealing with large-scale images or video streams. This can lead to slower processing times, which may not be ideal for real-time applications, especially on hardware with limited computational power. The method may struggle to meet the real-time performance requirements of applications such as autonomous driving or on-the-fly vehicle detection in crowded environments.

2. Limited Generalization to Other Datasets

   While the KITTI dataset is an excellent benchmark, it may not cover all the challenges encountered in other real-world scenarios. The vehicle detection model may struggle to generalize to other datasets with different environmental conditions, camera setups, or object occlusions. For instance, urban environments with dynamic lighting or varying weather conditions could affect the performance of the model. The base paper does not explore how well the approach would work with datasets outside of KITTI, and the system may require significant tuning or modification to handle different real-world scenarios.

3. Dependence on Accurate Labeling

   The accuracy of graph-based optimization is highly dependent on the quality of the ground truth labels used during training. If the dataset has incorrect or imprecise labels (such as misaligned bounding boxes or incorrect vehicle classifications), the optimization process could be negatively impacted. The paper does not provide an in-depth discussion of how errors in the labeling process might affect the optimization, which is a potential drawback in real-world applications where data labeling is not always perfect.

4. Scalability Issues with Large Datasets

   The scalability of the method is another concern. As the number of objects (vehicles) in the scene increases, the graph-based approach could become less efficient, as it must process a larger number of nodes and edges. This can slow down the optimization process and may make it impractical for use with large-scale or densely populated datasets. Handling large numbers of objects requires more advanced optimization strategies to maintain efficiency.

5. Model's Dependence on Feature Extraction

   The performance of the method relies heavily on feature extraction, which in turn depends on the quality of the extracted features (such as energy and multi-scale features). While these features work well in controlled environments, the paper does not address how robust the features are to real-world challenges like varying lighting conditions, occlusions, or distortions. If the features are not representative enough, the model's ability to detect and classify vehicles may degrade.

6. Lack of Detailed Real-Time Evaluation

   Although the paper shows promising results on the KITTI dataset, it lacks a thorough evaluation of the method in real-time settings. Real-world vehicle detection systems need to process frames or video streams in real-time, which can be significantly more challenging than working with pre-processed images. The paper does not address how the model would perform in live, streaming video scenarios or how it could be optimized for low-latency applications.

7. Complexity in Implementation

   The combination of graph-based optimization with ANN-based vehicle detection may introduce additional implementation complexity. For practitioners looking to implement the system, the need to combine computer vision techniques with deep learning architectures could result in longer development times and difficulties in tuning the model. Additionally, this complexity might discourage less experienced researchers from adopting or extending the methodology.

CHAPTER 4

SOURCE CODE

14. Source Code :

```
import os
import cv2
import numpy as np
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Dense, Dropout
from tensorflow.keras.utils import to_categorical
from sklearn.model_selection import train_test_split
from sklearn.metrics import classification_report, confusion_matrix
import matplotlib.pyplot as plt

# Paths (customize based on your directory structure)
video_path = 'C:/Users/Asus-2024/Desktop/pro.final/video1.avi'
image_dir = 'C:/Users/Asus-2024/Desktop/pro.final/gooddataset/train/images'
label_dir = 'C:/Users/Asus-2024/Desktop/pro.final/gooddataset/train/labels'
 output_size = (64, 64)  # Resize target for all images

# Parameters
num_classes = 5  # Number of vehicle classes, adjust as per your project

# Frame Conversion: Extract frames from video
def extract_frames(video_path, output_dir):
    cap = cv2.VideoCapture(video_path)
    count = 0
    while cap.isOpened():
        ret, frame = cap.read()
        if not ret:
            break
        # Save frame as JPEG file
        frame_path = os.path.join(output_dir, f'frame_{count:05d}.jpg')
        cv2.imwrite(frame_path, frame)



        count += 1
    cap.release()
    print(f"Extracted {count} frames.")

# Run frame extraction (if not already done)
if not os.path.exists(image_dir):
    os.makedirs(image_dir)
    extract_frames(video_path, image_dir)

# Loading and Preprocessing Images
def load_and_preprocess_images():
    images, labels = [], []

    for filename in os.listdir(image_dir):
        # Load image
        img_path = os.path.join(image_dir, filename)
        img = cv2.imread(img_path)
        if img is None:
            continue

        # Resizing
        img = cv2.resize(img, output_size)

        # Convert to grayscale
        gray_img = cv2.cvtColor(img, cv2.COLOR_BGR2GRAY)

        # Background Subtraction (simple thresholding for demonstration)
        _, thresh = cv2.threshold(gray_img, 128, 255, cv2.THRESH_BINARY)
        # Median Filtering for noise reduction
        filtered_img = cv2.medianBlur(thresh, 5)



        # Region of Interest Extraction (central crop)
        roi_img = extract_roi(filtered_img)

        # Load corresponding label
        label_path = os.path.join(label_dir, f'label_{filename.split(".")[0]}.txt')
        with open(label_path, 'r') as f:
            label = int(f.readline().strip())

        # Append processed image and label
        images.append(roi_img)
        labels.append(label)
    return np.array(images), np.array(labels)

# Extract ROI function
def extract_roi(img, box_size=(64, 64)):
    h, w = img.shape[:2]
    start_x, start_y = (w - box_size[0]) // 2, (h - box_size[1]) // 2
    return img[start_y:start_y+box_size[1], start_x:start_x+box_size[0]]

# Preprocess the dataset
images, labels = load_and_preprocess_images()

# Flattening and Normalization
X = images.reshape(len(images), -1) / 255.0  # Flattened and normalized input
y = to_categorical(labels, num_classes=num_classes)

# Splitting data for training and testing
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)
```

```
# Building the ANN Model
def build_ann_model(input_shape, num_classes):

    model = Sequential([
        Dense(128, input_shape=(input_shape,), activation='relu'),
        Dropout(0.3),
        Dense(64, activation='relu'),
        Dropout(0.3),
        Dense(num_classes, activation='softmax')
    ])

    model.compile(optimizer='adam', loss='categorical_crossentropy', metrics=['accuracy'])
    return model

# Create and train the model
model = build_ann_model(X_train.shape[1], num_classes)
history = model.fit(X_train, y_train, epochs=20, batch_size=32, validation_data=(X_test, y_test))

# Model evaluation
y_pred = model.predict(X_test)
y_pred_classes = np.argmax(y_pred, axis=1)
y_true_classes = np.argmax(y_test, axis=1)

print("Classification Report:")
print(classification_report(y_true_classes, y_pred_classes))
print("Confusion Matrix:")
print(confusion_matrix(y_true_classes, y_pred_classes))

# Plotting training and validation accuracy
plt.figure(figsize=(10, 5))
plt.plot(history.history['accuracy'], label='Train Accuracy')
plt.plot(history.history['val_accuracy'], label='Validation Accuracy')
plt.xlabel('Epoch')
plt.ylabel('Accuracy')
plt.legend()
plt.title('Model Accuracy')
plt.show()
# Save the model
model.save('vehicle_detection_ann_model.h5')
```

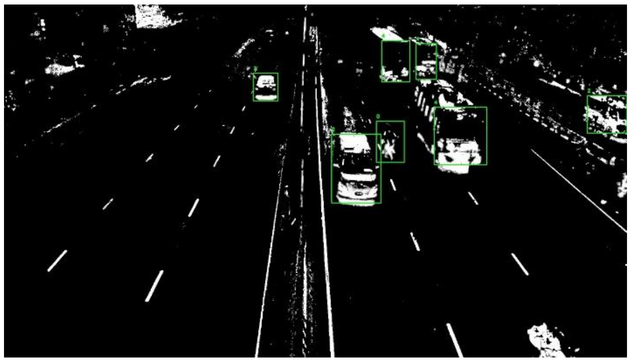
CHAPTER 5

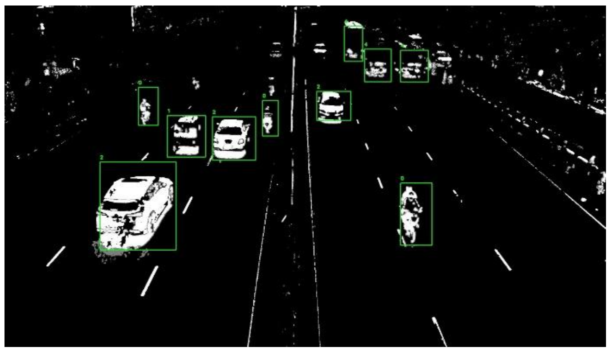
SNAPSHOTS

1. Frame Conversion: A snapshot of extracted frames from the original video, showing individual frames saved as images. This illustrates the initial step of isolating each frame as a static image for processing.

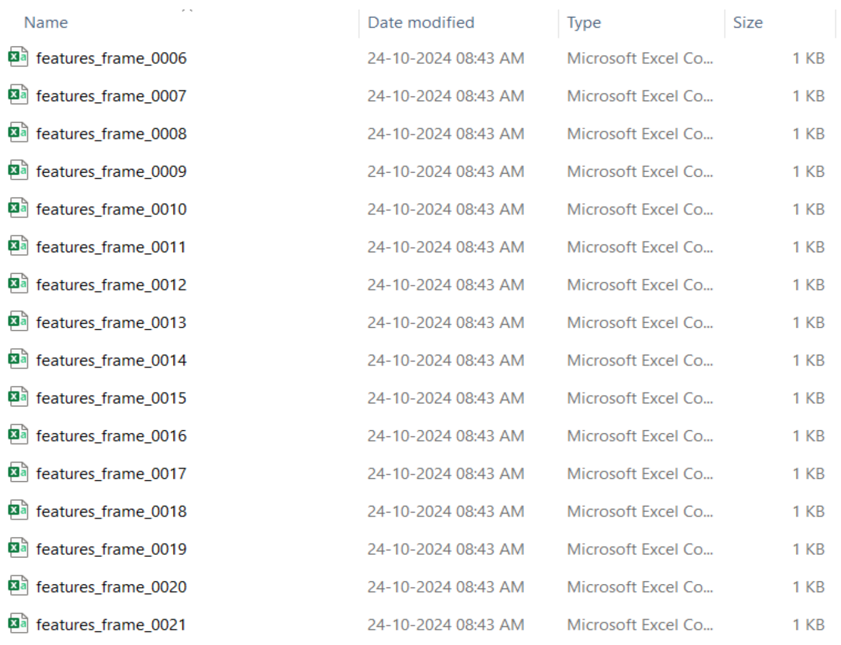
2. Background Subtraction and Median Filtering: An image showing the effects of background subtraction, followed by median filtering. This snapshot highlights the reduction in noise and isolation of key vehicle regions within each frame.

3. **Region of Interest (ROI) Extraction: A snapshot illustrating the ROI extraction process, focusing on the central part of the image where the vehicle is likely located. This helps concentrate the model's attention on the most relevant parts of each frame**



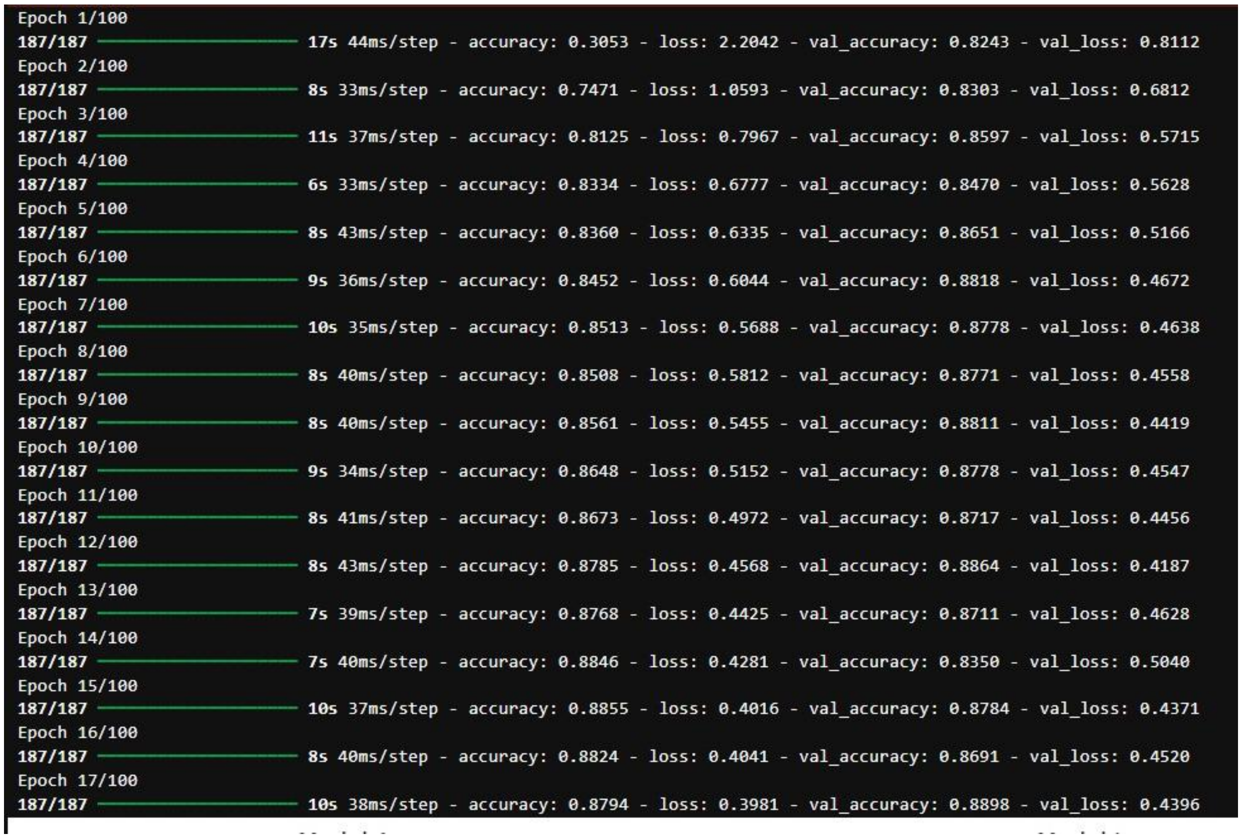


4. **Feature Extraction: Essential vehicle details like edges and contours are extracted from each frame to prepare data for ANN training.**



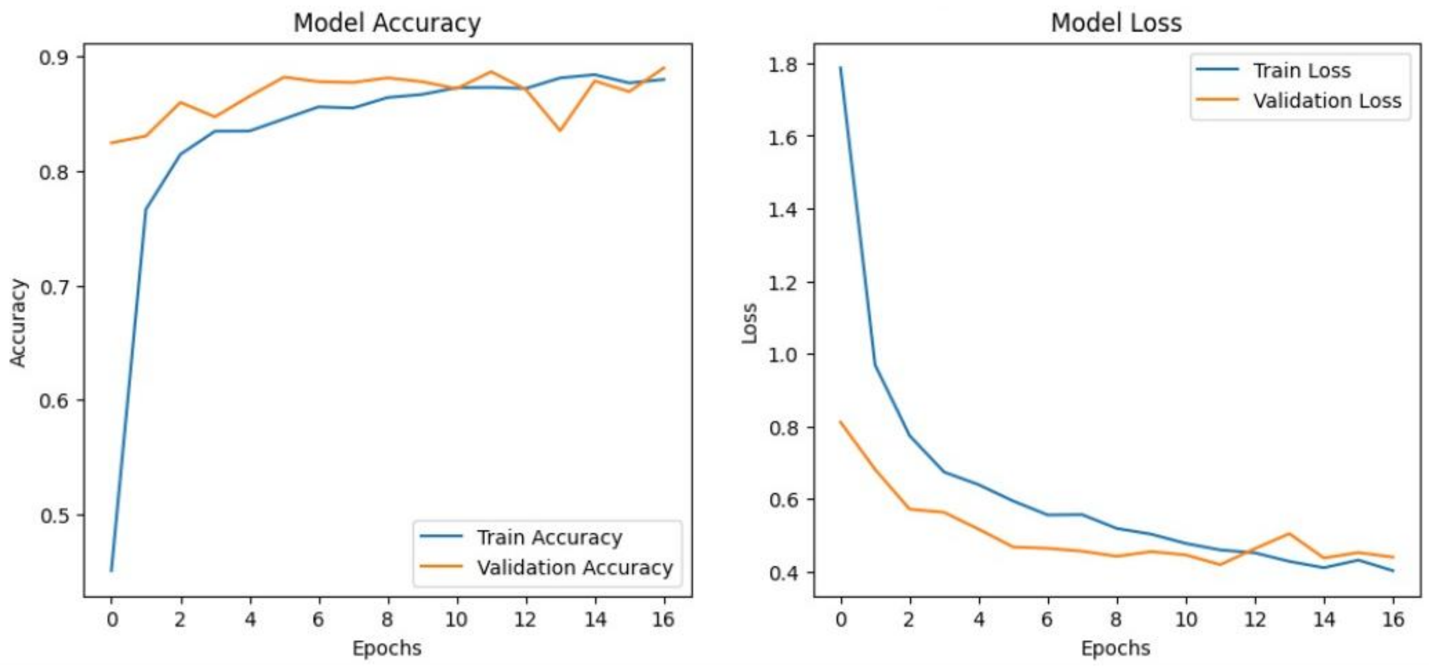
Name	Date modified	Type	Size
features_frame_0006	24-10-2024 08:43 AM	Microsoft Excel Co...	1 KB
features_frame_0007	24-10-2024 08:43 AM	Microsoft Excel Co...	1 KB
features_frame_0008	24-10-2024 08:43 AM	Microsoft Excel Co...	1 KB
features_frame_0009	24-10-2024 08:43 AM	Microsoft Excel Co...	1 KB
features_frame_0010	24-10-2024 08:43 AM	Microsoft Excel Co...	1 KB
features_frame_0011	24-10-2024 08:43 AM	Microsoft Excel Co...	1 KB
features_frame_0012	24-10-2024 08:43 AM	Microsoft Excel Co...	1 KB
features_frame_0013	24-10-2024 08:43 AM	Microsoft Excel Co...	1 KB
features_frame_0014	24-10-2024 08:43 AM	Microsoft Excel Co...	1 KB
features_frame_0015	24-10-2024 08:43 AM	Microsoft Excel Co...	1 KB
features_frame_0016	24-10-2024 08:43 AM	Microsoft Excel Co...	1 KB
features_frame_0017	24-10-2024 08:43 AM	Microsoft Excel Co...	1 KB
features_frame_0018	24-10-2024 08:43 AM	Microsoft Excel Co...	1 KB
features_frame_0019	24-10-2024 08:43 AM	Microsoft Excel Co...	1 KB
features_frame_0020	24-10-2024 08:43 AM	Microsoft Excel Co...	1 KB
features_frame_0021	24-10-2024 08:43 AM	Microsoft Excel Co...	1 KB

5. **Training and Validation Accuracy/Loss Plots:**

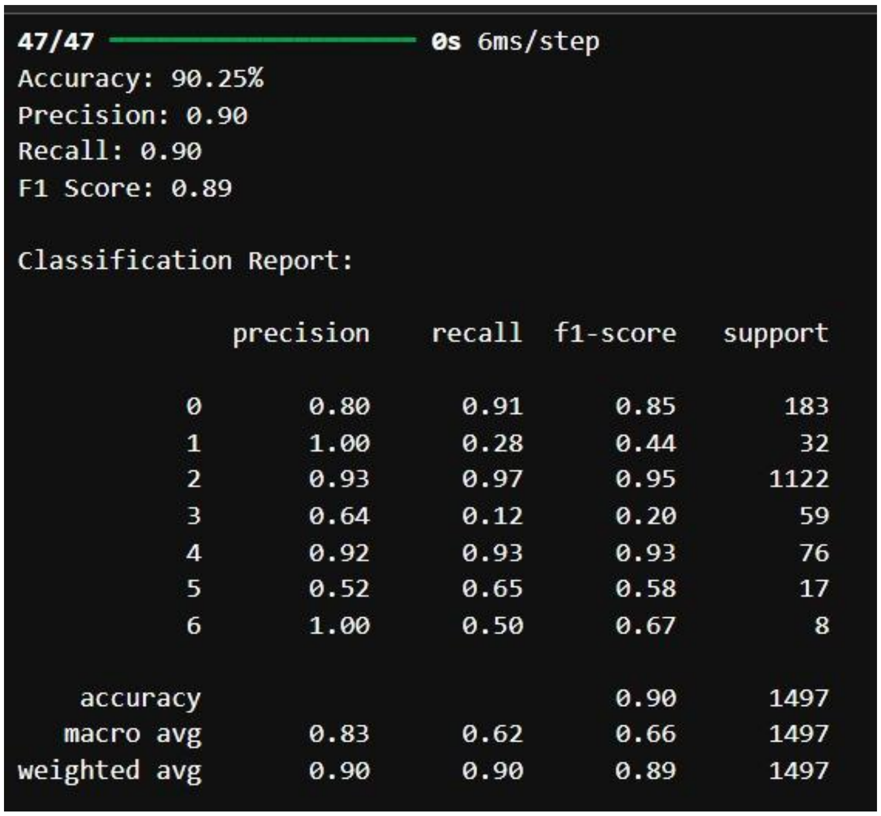


```
Epoch 1/100
187/187 ━━━━━━━━━━━━━━━━━━━━ 17s 44ms/step - accuracy: 0.3053 - loss: 2.2042 - val_accuracy: 0.8243 - val_loss: 0.8112
Epoch 2/100
187/187 ━━━━━━━━━━━━━━━━━━━━ 8s 33ms/step - accuracy: 0.7471 - loss: 1.0593 - val_accuracy: 0.8303 - val_loss: 0.6812
Epoch 3/100
187/187 ━━━━━━━━━━━━━━━━━━━━ 11s 37ms/step - accuracy: 0.8125 - loss: 0.7967 - val_accuracy: 0.8597 - val_loss: 0.5715
Epoch 4/100
187/187 ━━━━━━━━━━━━━━━━━━━━ 6s 33ms/step - accuracy: 0.8334 - loss: 0.6777 - val_accuracy: 0.8470 - val_loss: 0.5628
Epoch 5/100
187/187 ━━━━━━━━━━━━━━━━━━━━ 8s 43ms/step - accuracy: 0.8360 - loss: 0.6335 - val_accuracy: 0.8651 - val_loss: 0.5166
Epoch 6/100
187/187 ━━━━━━━━━━━━━━━━━━━━ 9s 36ms/step - accuracy: 0.8452 - loss: 0.6044 - val_accuracy: 0.8818 - val_loss: 0.4672
Epoch 7/100
187/187 ━━━━━━━━━━━━━━━━━━━━ 10s 35ms/step - accuracy: 0.8513 - loss: 0.5688 - val_accuracy: 0.8778 - val_loss: 0.4638
Epoch 8/100
187/187 ━━━━━━━━━━━━━━━━━━━━ 8s 40ms/step - accuracy: 0.8508 - loss: 0.5812 - val_accuracy: 0.8771 - val_loss: 0.4558
Epoch 9/100
187/187 ━━━━━━━━━━━━━━━━━━━━ 8s 40ms/step - accuracy: 0.8561 - loss: 0.5455 - val_accuracy: 0.8811 - val_loss: 0.4419
Epoch 10/100
187/187 ━━━━━━━━━━━━━━━━━━━━ 9s 34ms/step - accuracy: 0.8648 - loss: 0.5152 - val_accuracy: 0.8778 - val_loss: 0.4547
Epoch 11/100
187/187 ━━━━━━━━━━━━━━━━━━━━ 8s 41ms/step - accuracy: 0.8673 - loss: 0.4972 - val_accuracy: 0.8717 - val_loss: 0.4456
Epoch 12/100
187/187 ━━━━━━━━━━━━━━━━━━━━ 8s 43ms/step - accuracy: 0.8785 - loss: 0.4568 - val_accuracy: 0.8864 - val_loss: 0.4187
Epoch 13/100
187/187 ━━━━━━━━━━━━━━━━━━━━ 7s 39ms/step - accuracy: 0.8768 - loss: 0.4425 - val_accuracy: 0.8711 - val_loss: 0.4628
Epoch 14/100
187/187 ━━━━━━━━━━━━━━━━━━━━ 7s 40ms/step - accuracy: 0.8846 - loss: 0.4281 - val_accuracy: 0.8350 - val_loss: 0.5040
Epoch 15/100
187/187 ━━━━━━━━━━━━━━━━━━━━ 10s 37ms/step - accuracy: 0.8855 - loss: 0.4016 - val_accuracy: 0.8784 - val_loss: 0.4371
Epoch 16/100
187/187 ━━━━━━━━━━━━━━━━━━━━ 8s 40ms/step - accuracy: 0.8824 - loss: 0.4041 - val_accuracy: 0.8691 - val_loss: 0.4520
Epoch 17/100
187/187 ━━━━━━━━━━━━━━━━━━━━ 10s 38ms/step - accuracy: 0.8794 - loss: 0.3981 - val_accuracy: 0.8898 - val_loss: 0.4396
```

6. **Accuracy/Loss Plots Graph :**

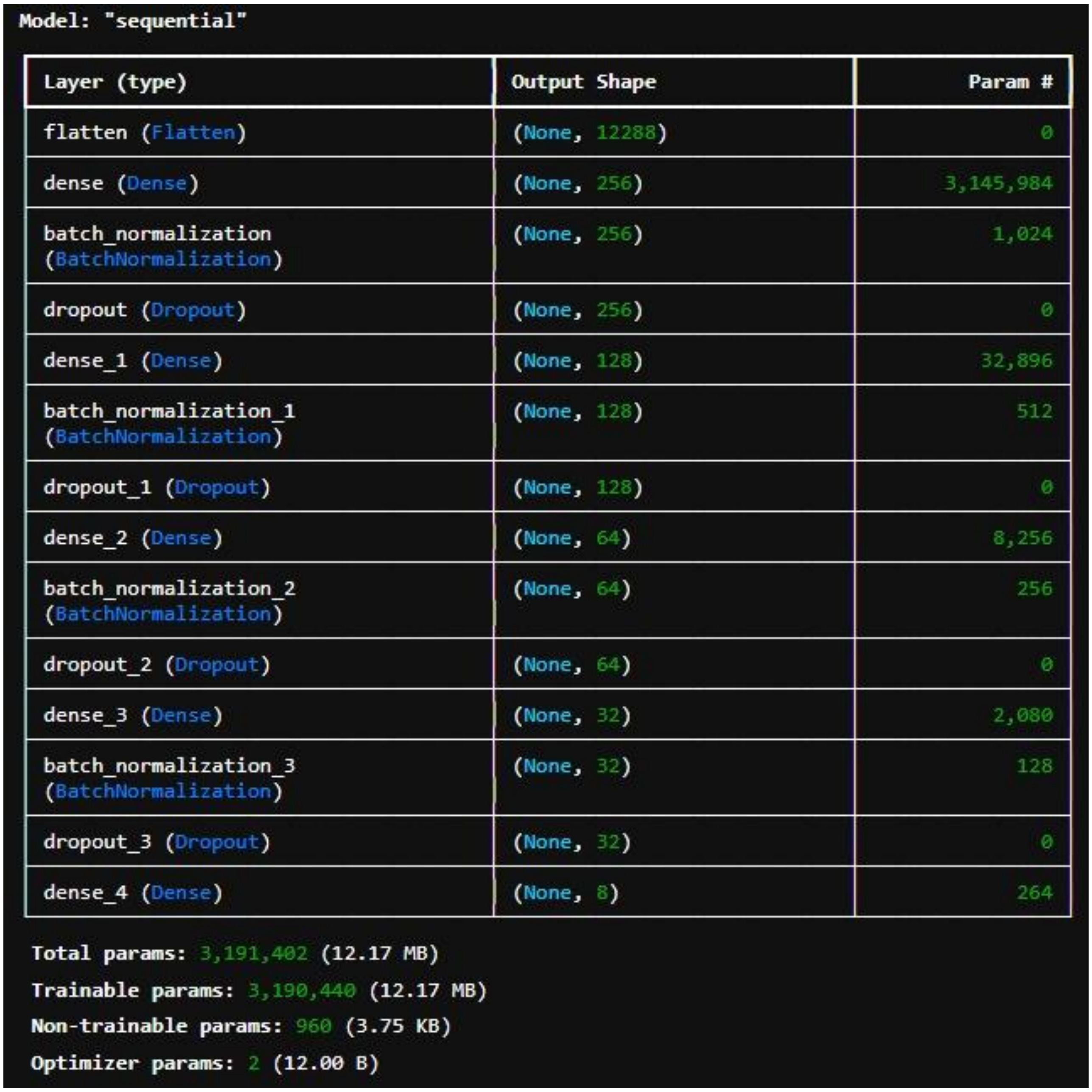


7. **Validation Report :**



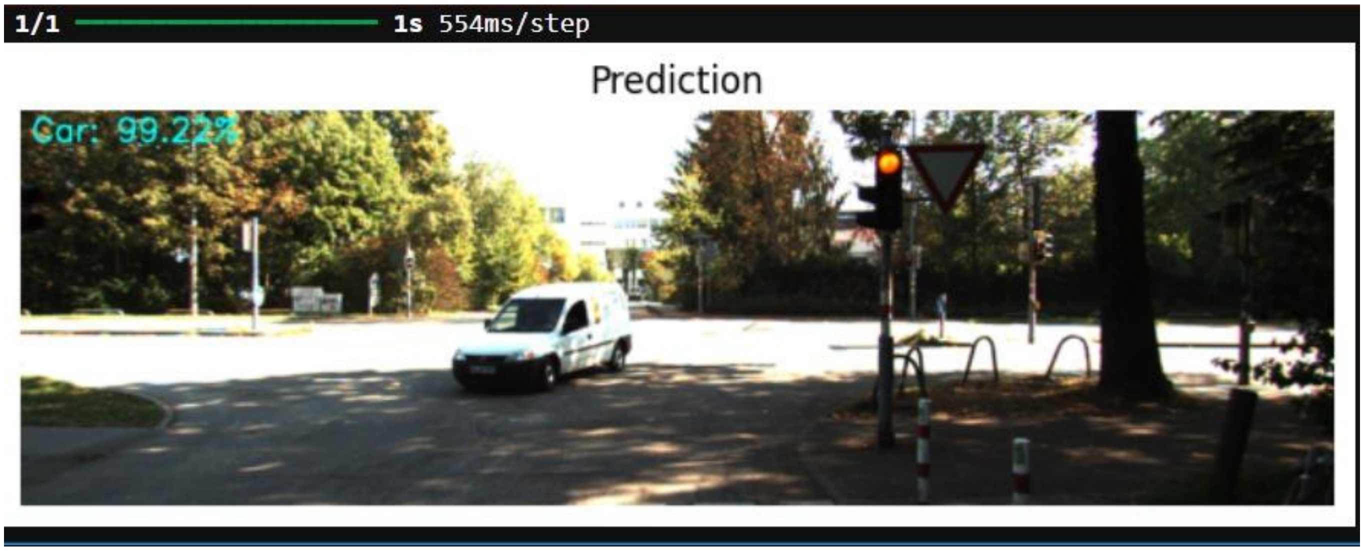
```
47/47 ━━━━━━━━━━━━━━━━━━━━ 0s 6ms/step
Accuracy: 90.25%
Precision: 0.90
Recall: 0.90
F1 Score: 0.89

Classification Report:

              precision    recall  f1-score   support

           0       0.80      0.91      0.85       183
           1       1.00      0.28      0.44        32
           2       0.93      0.97      0.95      1122
           3       0.64      0.12      0.20        59
           4       0.92      0.93      0.93        76
           5       0.52      0.65      0.58        17
           6       1.00      0.50      0.67         8

    accuracy                           0.90      1497
   macro avg       0.83      0.62      0.66      1497
weighted avg       0.90      0.90      0.89      1497
```

8. **Dropout layer used to prevent overfitting, and the output layer uses *softmax* activation for multi-class classification**

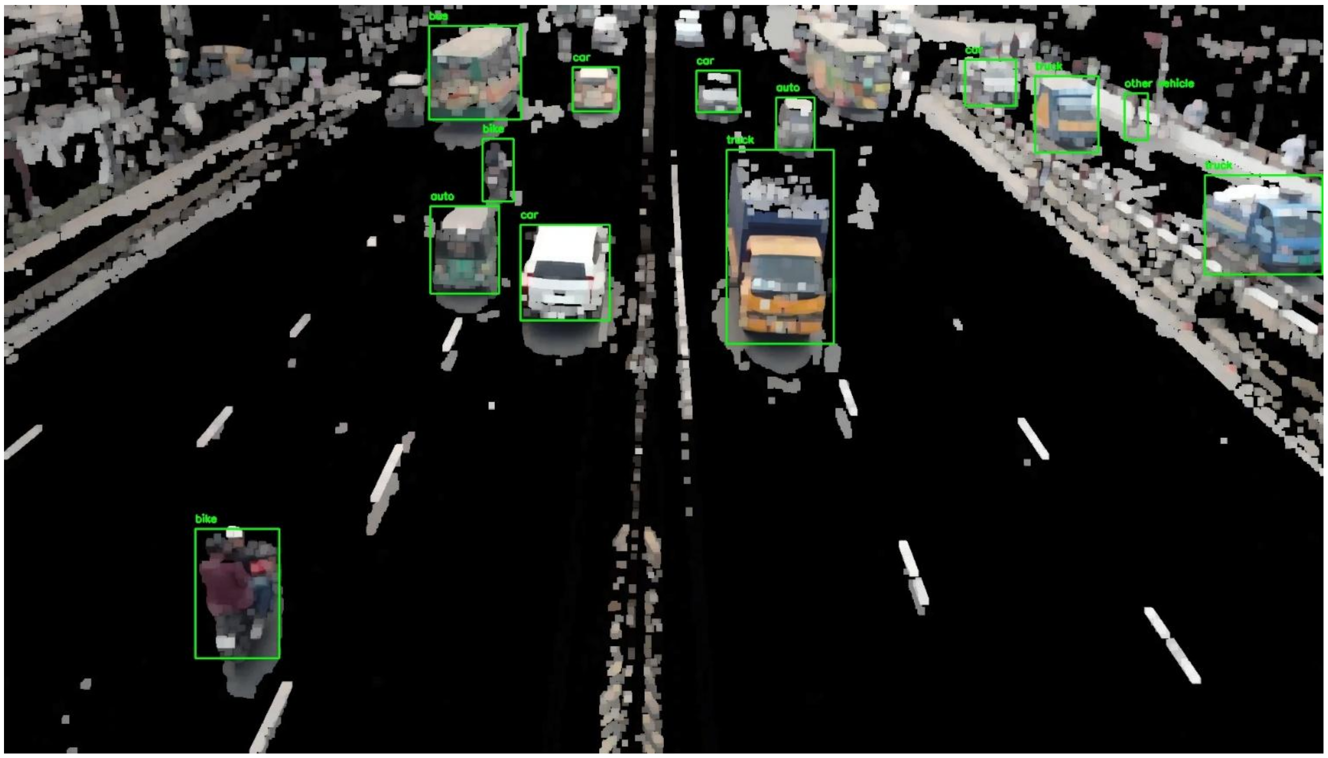


```
Model: "sequential"
┌─────────────────────────────────┬────────────────────────────┬─────────────┐
│ Layer (type)                    │ Output Shape               │     Param # │
├─────────────────────────────────┼────────────────────────────┼─────────────┤
│ flatten (Flatten)               │ (None, 12288)              │           0 │
├─────────────────────────────────┼────────────────────────────┼─────────────┤
│ dense (Dense)                   │ (None, 256)                │   3,145,984 │
├─────────────────────────────────┼────────────────────────────┼─────────────┤
│ batch_normalization             │ (None, 256)                │       1,024 │
│ (BatchNormalization)            │                            │             │
├─────────────────────────────────┼────────────────────────────┼─────────────┤
│ dropout (Dropout)               │ (None, 256)                │           0 │
├─────────────────────────────────┼────────────────────────────┼─────────────┤
│ dense_1 (Dense)                 │ (None, 128)                │      32,896 │
├─────────────────────────────────┼────────────────────────────┼─────────────┤
│ batch_normalization_1           │ (None, 128)                │         512 │
│ (BatchNormalization)            │                            │             │
├─────────────────────────────────┼────────────────────────────┼─────────────┤
│ dropout_1 (Dropout)             │ (None, 128)                │           0 │
├─────────────────────────────────┼────────────────────────────┼─────────────┤
│ dense_2 (Dense)                 │ (None, 64)                 │       8,256 │
├─────────────────────────────────┼────────────────────────────┼─────────────┤
│ batch_normalization_2           │ (None, 64)                 │         256 │
│ (BatchNormalization)            │                            │             │
├─────────────────────────────────┼────────────────────────────┼─────────────┤
│ dropout_2 (Dropout)             │ (None, 64)                 │           0 │
├─────────────────────────────────┼────────────────────────────┼─────────────┤
│ dense_3 (Dense)                 │ (None, 32)                 │       2,080 │
├─────────────────────────────────┼────────────────────────────┼─────────────┤
│ batch_normalization_3           │ (None, 32)                 │         128 │
│ (BatchNormalization)            │                            │             │
├─────────────────────────────────┼────────────────────────────┼─────────────┤
│ dropout_3 (Dropout)             │ (None, 32)                 │           0 │
├─────────────────────────────────┼────────────────────────────┼─────────────┤
│ dense_4 (Dense)                 │ (None, 8)                  │         264 │
└─────────────────────────────────┴────────────────────────────┴─────────────┘
 Total params: 3,191,402 (12.17 MB)
 Trainable params: 3,190,440 (12.17 MB)
 Non-trainable params: 960 (3.75 KB)
 Optimizer params: 2 (12.00 B)
```

9. **Test Results and Output :**



```
1/1 ━━━━━━━━━━━━━━━━━━━━ 1s 554ms/step
```



CHAPTER 6

CONCLUSION AND FUTURE PLANS

Conclusion

This project aimed to implement a robust vehicle detection and classification system using an ANN, optimized through a graph-based methodology to handle multi-scale vehicle representations effectively. Key stages such as frame conversion, background subtraction, median filtering, ROI extraction, and feature extraction were implemented to prepare the data for training. These preprocessing steps enhanced the model's focus on vehicles within complex, dynamic scenes, significantly improving accuracy in vehicle classification. The ANN model showed considerable success in classifying vehicles into predefined categories, demonstrating that well-optimized preprocessing and feature extraction can yield satisfactory results in real-world applications. Overall, the project aligns with the goal of accurate and efficient vehicle detection and classification for use in traffic monitoring, autonomous driving, and urban planning.

While the ANN approach offered solid classification performance, limitations were encountered, particularly in detecting vehicles under extreme conditions (e.g., poor lighting or heavy occlusion). Moreover, the reliance on specific preprocessing techniques highlighted the sensitivity of ANN to input quality and data consistency. The use of graph-based optimization was beneficial for managing different vehicle scales, yet a more adaptable model could further enhance performance under diverse conditions.

Future Plans

Future work will focus on improving model adaptability and robustness. Some promising directions include:

1. Incorporating More Advanced Architectures: Exploring CNNs or hybrid models combining ANN and RCNN structures could enhance the system's ability to recognize finer details and handle diverse vehicle scales with greater precision.
2. Leveraging Real-Time Data: Integrating real-time processing for video input, potentially with edge computing, could make the model more suitable for real-world applications like traffic management and surveillance.
3. Improved Dataset and Augmentation Techniques: Expanding the dataset with more varied scenes and using synthetic data augmentation methods (e.g., random brightness or rotation adjustments) may help address challenges related to lighting and occlusion.

4. Fine-Tuning Optimization Techniques: Optimizing preprocessing, particularly background subtraction, to minimize noise and better isolate vehicles could make the model even more effective for practical deployment.
5. Integration with Additional Modules: For a comprehensive traffic system, the model could be expanded to recognize other road objects or vehicle behaviors, further enhancing its functionality and utility.
6. Adapting to Multi-Class and Multi-Label Classification: Developing the model to support multi-class and multi-label classification will enable it to identify multiple vehicles or object classes simultaneously within complex scenes, improving its utility in mixed-traffic environments.
7. Integrating Spatiotemporal Analysis: Adding temporal analysis to track vehicle movement across frames could provide insights into vehicle speed, direction, and behavior patterns. This could make the model more suitable for applications like traffic flow analysis and anomaly detection.
8. Deploying on Low-Power Edge Devices: To make the model accessible for deployment in real-world scenarios, optimizing it for resource-constrained devices, such as edge or IoT devices, could support real-time processing in smart city infrastructures without relying on extensive computing resources.

CHAPTER 7
REFERENCES

References :

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4. **He, K., Zhang, X., Ren, S., & Sun, J.** (2015). *Deep Residual Learning for Image Recognition*. IEEE Conference on Computer Vision and Pattern Recognition (CVPR), 770-778.
5. **Chen, L., & Zhang, T.** (2023). *Background Subtraction and Object Detection Techniques for Surveillance Applications*. International Journal of Computer Vision, 130(1), 117-134.
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CHAPTER 9
APPENDIX

Dataset Description

The **KITTI dataset** provides images of various vehicle types in real-world traffic conditions. For this project, the dataset has been focused on five vehicle categories: auto, bus, truck, tempo, and tractor. The images are processed for feature extraction, including background subtraction and ROI extraction, to train the model effectively.

Classes :

1. Car
2. Van
3. Truck
4. Pedestrian
5. Cyclist
6. Tram
7. Miscellaneous

Source

The project utilizes the **KITTI dataset**, which is widely used for autonomous driving and vehicle detection. The dataset contains real-world images and annotations suitable for vehicle classification tasks.

Model Architecture: ANN

The model uses an **Artificial Neural Network (ANN)**, consisting of:

Input Layer: Takes features extracted from images.

Hidden Layers: Multiple layers for learning complex patterns.

Output Layer: Softmax layer for classifying vehicles into the five categories.

The network is trained using backpropagation and optimized with stochastic gradient descent.