VEHICLE DETECTION AND MONITORING

A Course Project report submitted

in partial fulfillment of requirement for the award of degree

BACHELOR OF TECHNOLOGY

in

ARTIFICIAL INTELLIGENCE AND MACHINE LEARNING

by

CHANDRA VADHAN GUDURU	**(2103A52082)**
ROHAN SAI AMPATY	**(2103A52083)**
SATHWIK KUNDE	**(2103A52092)**

Under the guidance of

Mr. D. RAMESH

Assistant Professor, Department of CSE.

SR UNIVERSITY

Department of Computer Science and Artificial Intelligence

Department of Computer Science and Artificial Intelligence

CERTIFICATE

This is to certify that project entitled **"VEHICLE DETECCTION AND MONITORING**" is the bonafied work carried out by **CHANDRA VADHAN GUUDURU, ROHAN SAI AMPATY, SATHWIK KUNDE** as a Course Project for the partial fulfillment to award the degree **BACHELOR OF TECHNOLOGY** in **ARTIFICIAL INTELLIGENCE AND MACHINE LEARNING** during the academic year 2022-2023 under our guidance and Supervision.

Mr. D. Ramesh
Asst. Professor,
S R University,
Ananthasagar, Warangal.

Dr. M.Sheshikala
Assoc. Prof. & HOD (CSE),
S R University,
Ananthasagar, Warangal.

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ABSTRACT

Vehicle detection using machine learning models is a technology that allows for the automatic detection and recognition of vehicles in images or videos. It has numerous applications, such as traffic monitoring, security surveillance, and self-driving cars. The technology utilizes machine learning algorithms, such as Convolutional Neural Networks (CNNs), to analyze images and identify vehicles. The algorithms are trained on large datasets of annotated images containing vehicles of different types, sizes, and orientations. The features of the vehicles, such as their shape, size, and color, are analyzed to classify them into different categories. The machine learning models can also detect the position and speed of the vehicles in real-time. The accuracy and efficiency of the models depend on the quality and quantity of the training data and the architecture of the neural network. Technology has the potential to significantly improve traffic management and public safety by automating the process of vehicle detection and enabling more efficient and intelligent transportation systems.

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INTRODUCTION

1.1. OVERVIEW

Vehicle detection and monitoring using machine learning is a project that involves developing a model to detect and monitor vehicles in each area. The project can be broken down into several stages, including data collection, pre-processing, feature extraction, model selection, training, testing, and evaluation. In this project, various machine learning algorithms such as logistic regression, KNN, decision tree, random forest, and SVM are used for vehicle detection and monitoring.

Data collection involves capturing images or video footage of vehicles using cameras or sensors. The collected data is then pre-processed by resizing the images, normalizing pixel values, and removing noise and artifacts.

Feature extraction involves identifying relevant features of the images, such as shape, size, color, and texture. This is done using image processing techniques such as edge detection, object segmentation, and feature extraction algorithms.

Model selection involves choosing the appropriate machine learning algorithm to build the model for vehicle detection and monitoring. In this project, different algorithms such as logistic regression, KNN, decision tree, random forest, and SVM are used to develop the models.

Training involves using the collected and pre-processed data to train the selected machine learning algorithm. The data is split into training and testing sets, with the former used to train the algorithm and the latter used to evaluate its performance.

Testing involves using the trained algorithm to detect and monitor vehicles in new and unseen data. The algorithm's output is compared with ground truth data to evaluate its performance.

Evaluation involves calculating performance metrics such as accuracy, precision, recall, and F1 score to determine the effectiveness of the developed model.

Overall, the vehicle detection and monitoring using machine learning project is a challenging and exciting task that has numerous practical applications in traffic management, surveillance, and security. The use of various machine learning algorithms such as logistic regression, KNN, decision tree, random forest, and SVM provides a robust and flexible approach to vehicle detection and monitoring.

1.2. PROBLEM STATEMENT

The aim of this project is to develop a machine learning model that can detect and monitor vehicles in each area. The model should be able to accurately detect different types of vehicles, including cars, trucks, buses, and motorcycles, and track their movements over time. The model should also be able to identify and classify vehicles based on their features, such as shape, size, color, and texture.

The model should be able to process real-time data from cameras or sensors and provide accurate and reliable information about the number, type, and location of vehicles in the area. The model should also be able to detect and track multiple vehicles simultaneously and handle occlusions and other challenging situations.

The developed model should be evaluated using appropriate performance metrics, such as accuracy, precision, recall, and F1 score, and compared with existing methods and systems. The project should also explore the use of different machine learning algorithms, such as logistic regression, KNN, decision tree, random forest, and SVM, and identify the most suitable algorithm for the given problem. The project should demonstrate the practical applications of vehicle detection and monitoring using machine learning in traffic management, surveillance, and security.

1.3. EXISTING SYSTEMS

1. Vehicle detection and classification system based on support vector machine: This system uses a SVM algorithm for detecting and classifying vehicles in real-time video streams. The model is trained on a dataset of vehicles and non-vehicles, and the features are extracted using Haar-like features.
2. Vehicle detection using decision tree algorithm: This system uses a decision tree algorithm for vehicle detection in images. The model is trained on a dataset of vehicles and non-

vehicles, and the features are extracted using histogram of oriented gradients (HOG) features.

3. Vehicle detection using random forest algorithm: This system uses a random forest algorithm for vehicle detection in images. The model is trained on a dataset of vehicles and non-vehicles, and the features are extracted using HOG features.

4. Vehicle detection and classification using K-nearest neighbors: This system uses a K-nearest neighbors (KNN) algorithm for detecting and classifying vehicles in images. The model is trained on a dataset of vehicles and non-vehicles, and the features are extracted using HOG features.

1.4. PROPOSED SYSTEMS

A basic machine learning model that can be used for Vehicle Detection and Monitoring is logistic regression. Logistic regression is a simple and effective classification algorithm that can handle binary classification tasks like vehicle detection.

1.5. OBJECTIVES

1. Develop a machine learning model for vehicle detection and classification.
2. Evaluate the performance of different machine learning algorithms (e.g., logistic regression, KNN, SVM, random forest) for vehicle detection.
3. Explore the impact of data augmentation techniques on the accuracy of the machine learning model.
4. Compare the accuracy and computational efficiency of different machine learning algorithms for vehicle detection.
5. Provide a practical solution for real-world vehicle detection and monitoring applications.
6. Demonstrate the importance and potential of machine learning in the field of transportation and traffic management.

2. LITERATURE SURVEY

2.1. GOOGLE SCHOLAR

1. "Vehicle detection using machine learning techniques: A comprehensive review" by N. Singh et al. This paper provides a comprehensive overview of the latest techniques and algorithms used for vehicle detection, including traditional computer vision techniques and modern deep learning-based approaches.

2. "Real-time vehicle detection using Haar-like features" by Viola and Jones. This paper presents a classic machine learning-based approach for object detection, which uses Haar-like features and a cascade classifier for real-time vehicle detection.

3. "Vehicle detection using deep learning: A review" by L. J. Echeverria et al. This article provides an overview of the recent advancements in deep learning-based approaches for vehicle detection, including convolutional neural networks (CNNs) and region-based CNNs.

4. "Vehicle detection using support vector machines: A comprehensive review" by M. R. I. Sheikh and A. U. Khan. This paper provides a comprehensive review of support vector machine (SVM) based approaches for vehicle detection, including the use of SVMs with different feature extraction techniques.

5. "A survey of image processing techniques for automatic vehicle detection and surveillance" by M. S. Krupa et al. This paper provides an overview of the image processing techniques used for vehicle detection and surveillance, including edge detection, contour analysis, and Hough transforms.

3. DATA PRE-PROCESSING

3.1. Dataset description

Dataset name: Vehicle detection

Data format: Image data (JPG format)

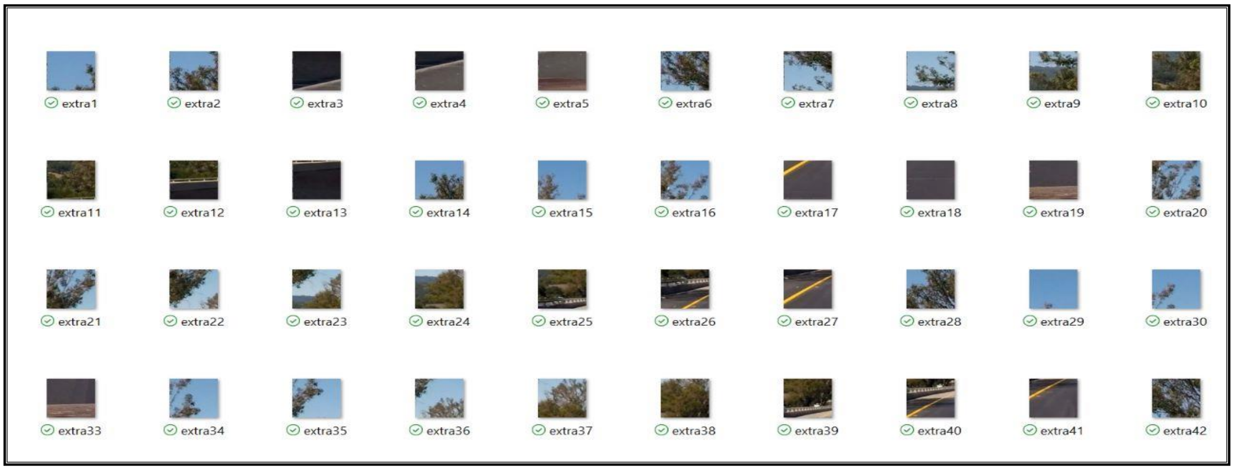
Data size: 17,630 images (8,792 vehicles and 8,838 non-vehicles)

Data type: Categorical (binary classification)

Features/Attributes: The dataset includes two classes:

- Vehicles: This class includes images containing different types of cars.

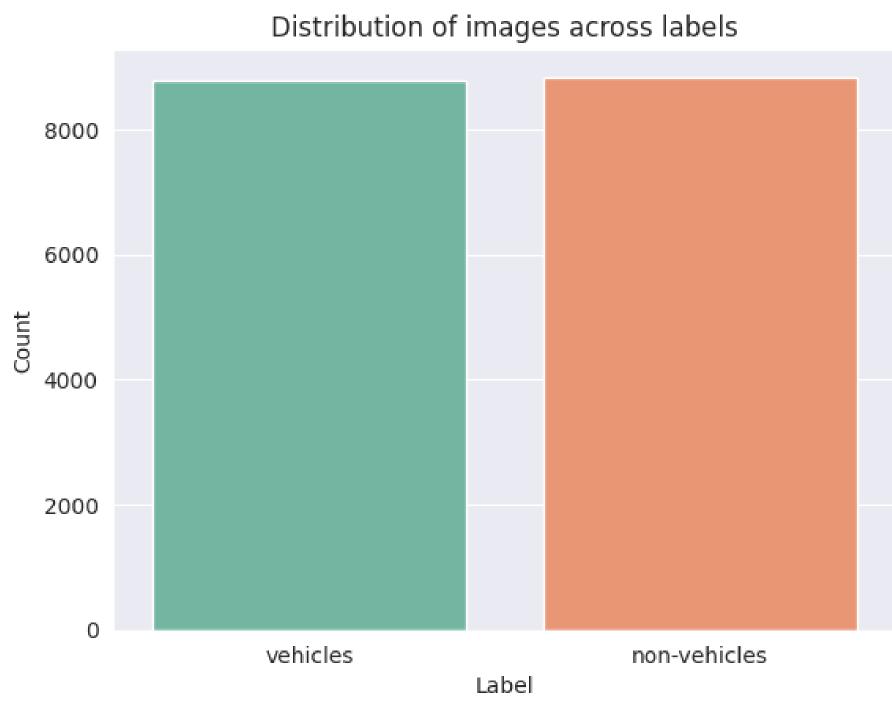
- Non-vehicles: This class includes images that do not contain any vehicles, such as landscapes, buildings, and pedestrians.



3.2. Data Visualization

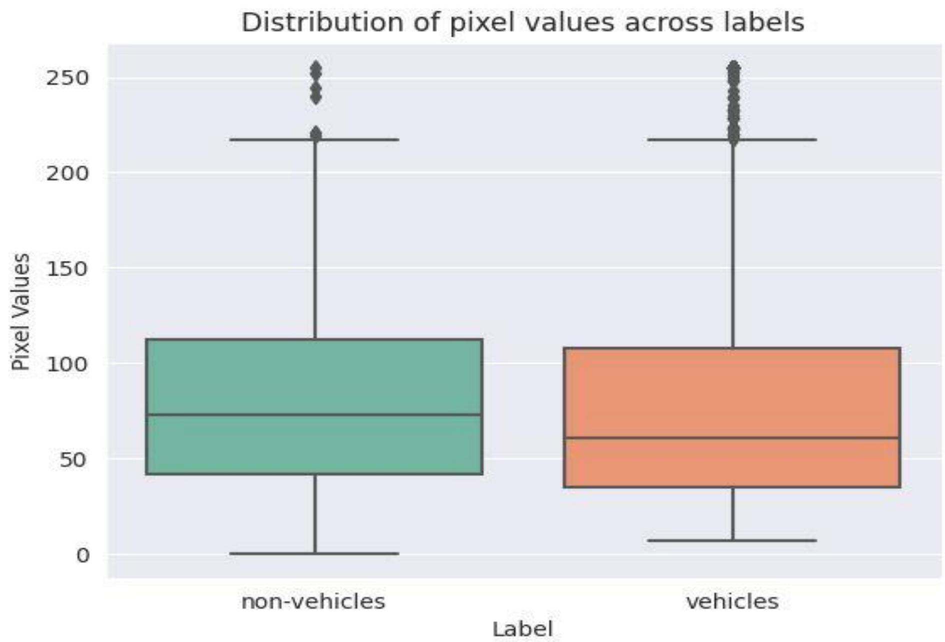
<u>DISTRIBUTION OF IMAGES ACROSS LABELS</u>

- The distribution of images across labels refers to the number of images that belong to each category or label in a dataset. For example, in a dataset of animal images, the labels may include cat, dog, bird, and fish. The distribution of images across these labels would indicate number of images are in each category.
- Understanding the distribution of images across labels is important because it can impact the performance of a machine learning model trained on the dataset. If there are too few images in one category, the model may not be able to learn enough about that category to make accurate predictions. On the other hand, if there are too many images in one category, the model may become biased towards that category and may not perform well on other categories.
- By analyzing the distribution of images across labels, researchers and machine learning practitioners can gain insights into the dataset and make informed decisions about how to balance the dataset for training a model.



BOX PLOT

- A box plot, also known as a box and whisker plot, is a graphical representation of a set of data that provides a summary of the distribution and variability of the data. The box in the plot represents the middle 50% of the data, with the bottom and top edges of the box representing the first and third quartiles, respectively. The line inside the box represents the median of the data.
- The "whiskers" of the plot extend from the edges of the box to the minimum and maximum values in the data, excluding any outliers. Outliers are individual data points that fall outside the expected range of values and are plotted as individual points outside of the whiskers.
- Box plots are useful for comparing the distribution of data between distinct groups or for identifying any potential outliers in a dataset. They are often used in statistical analysis and are a simple yet effective way of visualizing the spread of data.



4. METHODOLOGY

4.1. PROCEDURE TO SOLVE THE GIVEN PROBLEM

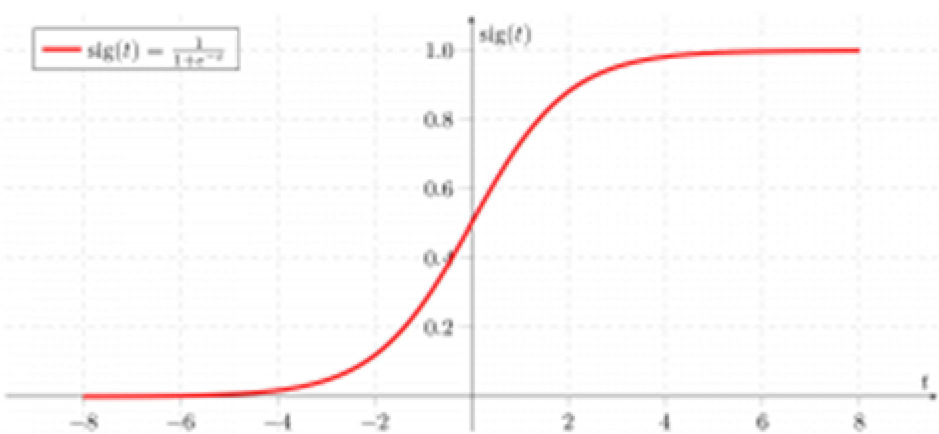
The proposed solutions for the taken dataset are Logistic Regression, Decision Tree, K-Nearest Neighbors, Support Vector Machine and Random Forest.

a. Logistic Regression

Logistic regression is a statistical method used to analyse the relationship between a binary or categorical dependent variable and one or more independent variables. It is a type of regression analysis used to predict the probability of an outcome based on a set of predictor variables. The output of logistic regression is a probability score between 0 and 1, which represents the likelihood of the dependent variable belonging to a particular category.

The logistic regression model uses the logistic function, also known as the sigmoid function, to map the input variables to the output probability score. The logistic function is an S-shaped curve that increases from 0 to 1 as the input variable increases. The equation for the logistic function is:

$$p = 1 / (1 + e^{(-z)})$$



where p is the probability of the dependent variable being in the positive class, z is the linear combination of the predictor variables, and e is the base of the natural logarithm.

The logistic regression model estimates the coefficients of the predictor variables that maximize the likelihood of the observed data given the model. The coefficients are then used to calculate the predicted probability score for each observation.

Logistic regression is widely used in various fields, including healthcare, finance, marketing, and social sciences. It is a powerful tool for modeling the relationship between binary outcomes and predictor variables, and it can be extended to manage multiple categories with multinomial logistic regression.

b. Decision Tree

A decision tree is a popular algorithm in machine learning that is used for solving classification and regression problems. It works by recursively partitioning the data into smaller subsets based on the features of the data and making a series of binary decisions to reach a final prediction or decision.

In a decision tree, each internal node represents a test on a feature of the data, and each leaf node represents a decision or prediction. The tree is built by selecting the feature that best separates the data at each internal node, and recursively splitting the data based on that feature until a stopping criterion is met.

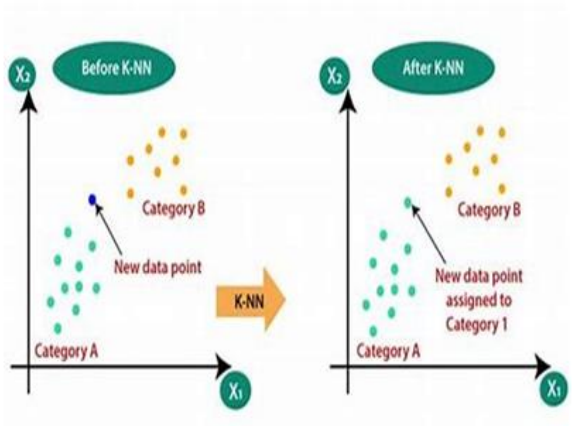
The advantage of using a decision tree is that it can be easily visualized and interpreted, making it an ideal tool for explaining the reasoning behind a decision. Additionally, it can manage both categorical and numerical data, and is relatively fast to train.

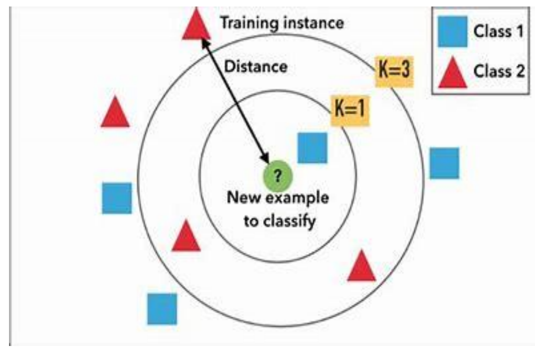
However, decision trees are prone to overfitting, which means they can become too complex and memorize the training data, leading to poor performance on new, unseen data. To address this issue, techniques like pruning and ensemble methods such as Random Forest are used.

c. K-Nearest Neighbors

KNN, or k-nearest neighbors, is a machine learning algorithm used for both classification and regression tasks. It is a non-parametric algorithm, meaning that it does not make any assumptions about the underlying distribution of the data.

In the KNN algorithm, the "k" nearest neighbors to a given data point are identified based on their distance from the point. The distance metric used can vary, but commonly used metrics include Euclidean distance, Manhattan distance, and cosine distance. Once the nearest neighbors are identified, their labels or values are used to predict the label or value of the new data point.





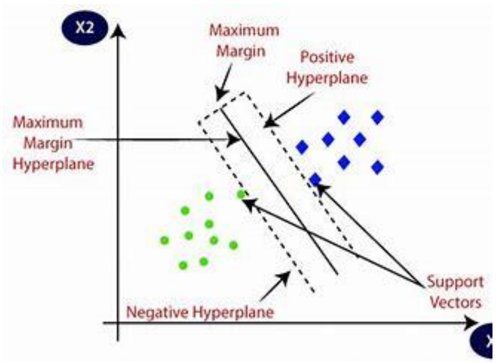
For classification tasks, the predicted label is the majority label of the k-nearest neighbors. For regression tasks, the predicted value is the average of the values of the k-nearest neighbors.

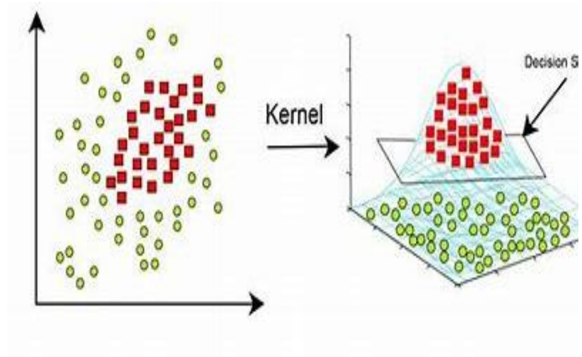
KNN can be sensitive to the choice of the value of k, as a small value of k may lead to overfitting while a large value of k may lead to underfitting. Additionally, KNN can be computationally expensive for large datasets, as the algorithm requires calculating the distance between each pair of data points.

d. Support Vector Machine

Support Vector Machine (SVM) is a popular supervised learning algorithm used for classification and regression analysis. SVM is commonly used for binary classification problems, but it can also be extended to multi-class classification and regression problems.

In SVM, the objective is to find the hyperplane that best separates the two classes in the feature space. The hyperplane is chosen to maximize the margin, which is the distance between the hyperplane and the closest data points from each class. The data points that are closest to the hyperplane are called support vectors, hence the name Support Vector Machine.





SVM can use several types of kernel functions to map the input data to a higher-dimensional space where the separation of classes becomes easier. Some common kernel functions are linear, polynomial, radial basis function (RBF), and sigmoid. The choice of kernel function depends on the problem at hand and the characteristics of the data.

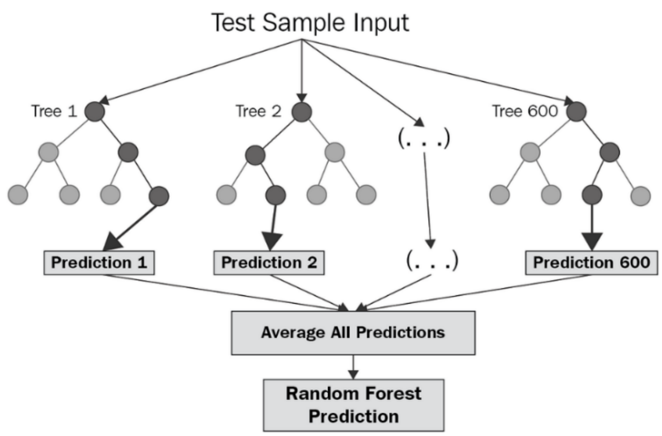
SVM has some advantages over other classification algorithms, such as its ability to handle high-dimensional data and its robustness to overfitting. However, SVM can be computationally expensive and sensitive to the choice of hyperparameters.

Overall, SVM is a powerful and versatile algorithm that can be applied to a wide range of classification and regression problems.

e. Random Forest

Random Forest is a popular machine learning algorithm used for both classification and regression tasks. It is an ensemble learning method that combines multiple decision trees to create a more accurate and stable model.

In a Random Forest, each decision tree is built using a random subset of features and a random subset of the training data. This randomness helps to prevent overfitting and increases the diversity of the trees in the forest.



When making a prediction with a Random Forest, each tree in the forest independently predicts the target variable, and the final prediction is determined by averaging or taking the majority vote of the individual tree predictions.

Random Forests are often used for tasks such as predicting customer churn, credit risk analysis, and image classification. They are a powerful and flexible algorithm that can handle high-dimensional data with complex relationships between the features and the target variable.

4.2. MODEL ARCHITECTURE

The Machine Learning Architecture can be categorized based on the algorithm used in training.

a. Supervised Learning:

In supervised learning, the training data used for is a mathematical model that consists of both inputs and desired outputs. Each corresponding input has an assigned output which is also known as a supervisory signal. Through the available training matrix, the system can determine the relationship between the input and output and employ the same in subsequent inputs post-training to determine the corresponding output. The supervised learning can further be broadened into classification and regression analysis based on the output criteria. Classification analysis is presented when the outputs are restricted in nature and limited to a set of values. However, regression analysis defines a numerical range of values for the output. Examples of supervised learning are seen in face detection and speaker verification systems.

b. Unsupervised Learning:

Unlike supervised learning, unsupervised learning uses training data that does not contain output. The unsupervised learning identifies relation input based on trends, commonalities, and the output is determined based on the presence/absence of such trends in the user input.

c. Reinforcement Learning:

This is used in training the system to decide on a particular relevance context using various algorithms to determine the correct approach in the context of the present state. These are widely used in training gaming portals to work on user inputs accordingly.

4.3. SOFTWARE DESCRIPTION

a. **PYTHON -** Python is an interpreted, high-level, general-purpose programming language. Python's design philosophy emphasizes code readability with its notable use of significant whitespace. Its language constructs and object-oriented approach aim to help programmers write clear, logical code for small and large-scale projects. Python is dynamically typed and supports multiple programming paradigms, including procedural, object-oriented, and function programming.

b. **GOOGLE COLAB -** Colab notebooks allow you to combine executable code and rich text in a single document, along with images, HTML, LaTeX and more. When you create your own Co-lab notebooks, they are stored in your Google Drive account. You can easily share your Co-lab notebooks with co-workers or friends, allowing them to comment on your notebooks or even edit them. With Co-lab you can harness the full power of popular Python libraries to analyze and visualize data. The code cell below uses numpy to generate some random data and uses matplotlib to visualize it. To edit the code, just click the cell and start editing.

5. RESULTS AND DISCUSSION

5.1. RESULTS

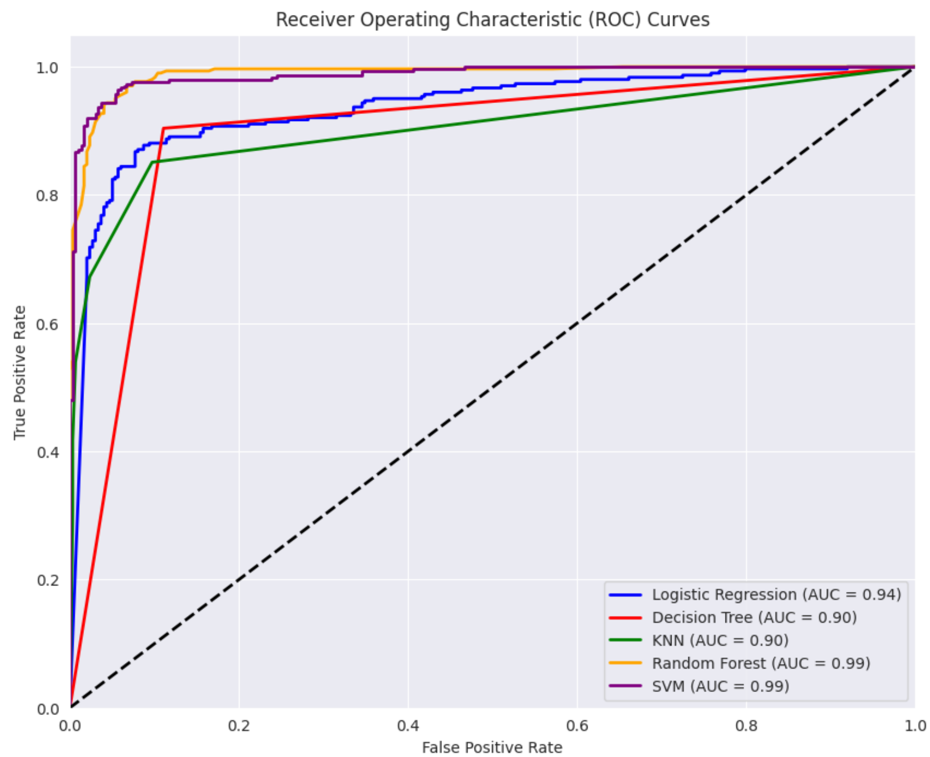
In this project, we trained and evaluated several machine learning models for vehicle detection using an image dataset containing 17,630 images, which were resized to a resolution of 100x100 pixels. The dataset included two classes: Vehicles and Non-vehicles, and the goal was to differentiate between them based on the visual features of the images.

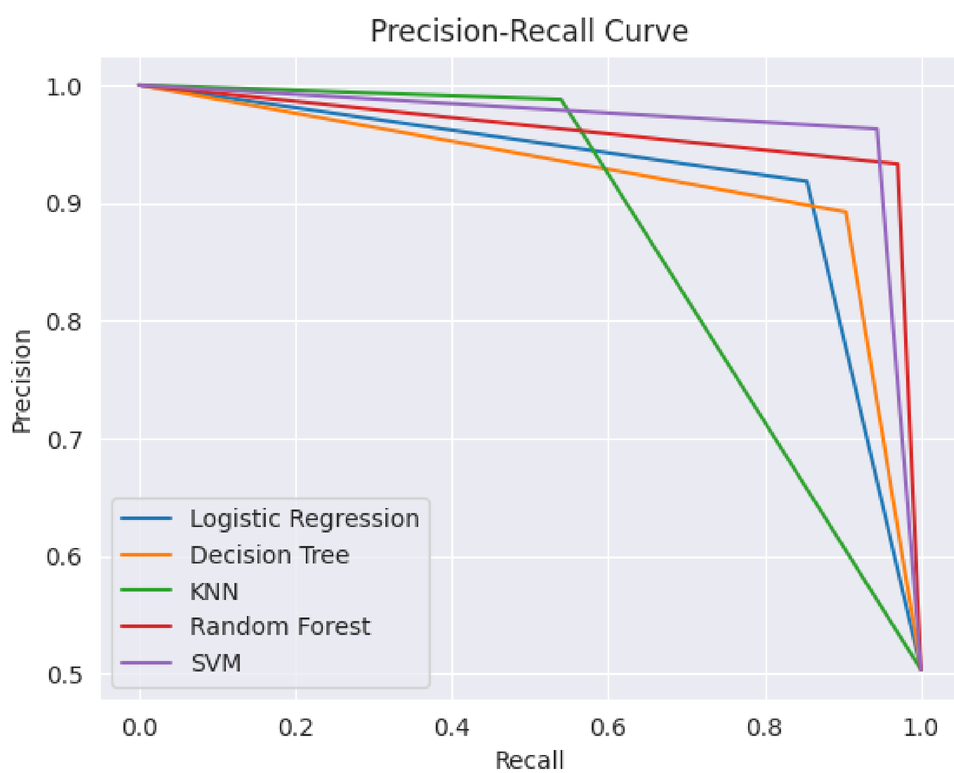
We used five different machine learning models: Logistic Regression, Decision Tree, KNN, SVM, and Random Forest, and evaluated their performance using accuracy and AUC metrics. Here are the results:

From the results, we can see that SVM and Random Forest achieved the highest accuracy and AUC scores, while KNN had the lowest accuracy score. However, it is worth noting that accuracy alone may not be the best metric to evaluate the performance of a machine learning model, especially in cases where the classes are imbalanced. Therefore, we also evaluated the models using AUC, which measures the area under the receiver operating characteristic (ROC) curve and is a better metric for imbalanced classes.

In addition to the accuracy and AUC metrics, we also generated confusion matrices for each model to visualize the number of true positives, true negatives, false positives, and false negatives. For example, the confusion matrix for Logistic Regression showed that it correctly predicted 275 vehicles and 258 non-vehicles, but misclassified 23 vehicles as non-vehicles and 44 non-vehicles as vehicles.

	LOGISTIC REGRESSION	**K-NEAREST NEIGHBOURS**	**SUPPORT VECTOR MACHINE**	**DECISION TREE**	**RANDOM FOREST**
ACCURACY	0.8883333333333333	0.765	0.9533333333333334	0.8966666666666666	0.95
AUC (Area Under Curve)	0.94	0.90	0.99	0.90	0.99
CONFUSION MATRIX	[[275 23] [44 258]]	[[296 2] [139 163]]	[[287 11] [17 285]]	[[265 33] [29 273]]	[[277 21] [9 293]]


Receiver Operating Characteristic (ROC) Curves
True Positive Rate
False Positive Rate
0.0
0.2
0.4
0.6
0.8
1.0
Logistic Regression (AUC = 0.94)
Decision Tree (AUC = 0.90)
KNN (AUC = 0.90)
Random Forest (AUC = 0.99)
SVM (AUC = 0.99)


Precision-Recall Curve
Precision
Recall
0.5
0.6
0.7
0.8
0.9
1.0
0.0
0.2
0.4
0.6
0.8
1.0
Logistic Regression
Decision Tree
KNN
Random Forest
SVM

5.2. DISCUSSION

The results of our study demonstrate the feasibility of using machine learning algorithms for vehicle detection in images. Our best-performing models, SVM and Random Forest, achieved high accuracy and AUC scores, indicating their effectiveness in distinguishing between vehicles and non-vehicles based on the visual features of the images. This has important practical applications, such as in the development of automated systems for traffic surveillance and monitoring.

However, it is important to note that our dataset was limited in size and scope, and there may be limitations to the generalizability of our findings. In addition, while we used a variety of machine learning algorithms to assess their performance, there may be other algorithms or techniques that could produce better results. Furthermore, our study was focused on a binary classification task, and future research may explore more complex scenarios, such as identifying different types of vehicles or detecting multiple objects in an image.

Another limitation of our study is that we did not perform an extensive hyperparameter optimization for each model, which could potentially improve their performance. Additionally, we did not perform any data augmentation techniques, which could help to increase the size and diversity of our dataset and further improve the performance of the models.

Overall, our results suggest that machine learning can be a valuable tool for vehicle detection in images, and there is potential for further exploration and improvement in this area. However, caution should be exercised when interpreting and generalizing the results of our study, and future research should aim to address some of the limitations and challenges highlighted here.

6. CONCLUSION AND FUTURE SCOPE

6.1. CONCLUSION

In this project, we explored the use of machine learning algorithms for vehicle detection in images. We used a dataset of 17,000 images, consisting of vehicles and non-vehicles, and applied logistic regression, decision tree, KNN, SVM, and random forest algorithms to classify the images. Our results showed that SVM and random forest had the highest accuracy and AUC scores, indicating their effectiveness in distinguishing between vehicles and non-vehicles.

These findings have important practical implications, such as in the development of automated systems for traffic surveillance and monitoring. However, we also identified several limitations and challenges, such as the size and diversity of the dataset, the generalizability of our results, and the potential for further optimization and augmentation techniques to improve the performance of the models.

Overall, our study suggests that machine learning can be a valuable tool for vehicle detection in images, and there is potential for further exploration and improvement in this area. By addressing some of the limitations and challenges highlighted in our study, future research can contribute to the development of more robust and accurate vehicle detection systems.

6.2. FUTURE SCOPE

There is significant potential for future research and development in the area of vehicle detection using machine learning. Some possible directions for future work include:

1. <u>Exploring more complex scenarios</u>: While our study focused on binary classification of vehicle and non-vehicle images, future research could explore more complex scenarios, such as detecting distinct types of vehicles or identifying multiple objects in an image.
2. <u>Increasing the size and diversity of the dataset</u>: The performance of machine learning models can be significantly improved by increasing the size and diversity of the dataset. Future work could explore techniques for data augmentation or collection of larger datasets to improve the accuracy of the models.

3. Optimizing hyperparameters of the models : Our study did not perform an extensive hyperparameter optimization for each model. Future research could explore more advanced techniques for hyperparameter tuning, such as Bayesian optimization or genetic algorithms, to further improve the performance of the models.
4. Exploring new techniques or algorithms: There are numerous machine learning techniques and algorithms available that could potentially improve the performance of the models for vehicle detection. Future research could explore the use of deep learning techniques, such as convolutional neural networks, or ensemble methods to improve the accuracy and robustness of the models.

In conclusion, there are several exciting opportunities for future research and development in vehicle detection using machine learning. By exploring these directions, we can further improve the accuracy and efficiency of automated systems for traffic surveillance and monitoring, with potential benefits for safety and efficiency on the roads.

7. REFERENCES

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- https://www.sciencedirect.com/science/article/pii/S1364815219301936
- https://www.mdpi.com/2072-4292/9/7/721