Journal of Theoretical and Applied Information Technology
30th June 2026. Vol.104. No.12

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

DEEP VEHICLE RE-IDENTIFICATION USING VGG 16 AND SIAMESE NEURAL NETWORK: A ROBUST APPROACH FOR VISUAL IDENTIFICATION OF VEHICLES

MARY SHAJI MATHEWS[1], P K NIZAR BANU[2]

[1]CHRIST (Deemed to be University), Department of Computer Science, India

[2]CHRIST (Deemed to be University), Department of Computer Science, India

E-mail: [1]mary.mathews@res.christuniversity.in, [2]nizar.banu@christuniversity.in

ABSTRACT

Vehicle re-identification is a challenging task in computer vision that aims to identify the same vehicle across images captured by different cameras in a surveillance system. Despite recent advancements, several challenges continue to hinder the performance of vehicle re-identification systems, including limited data availability, subtle intra-class and inter-class variations among vehicle instances, the need to handle diverse input modalities, and re-identification under extreme weather conditions. To address these issues, this paper proposes a vehicle re-identification framework based on VGG-16 and a Siamese Neural Network. The VGG-16 model is utilized to extract discriminative features from vehicle images by focusing on key regions such as the vehicle body and license plate. These extracted features are subsequently fed into a Siamese Neural Network, which learns a similarity metric between pairs of vehicle images while effectively accounting for variations in viewpoint, illumination, and occlusion. In addition, a triplet loss function is incorporated to improve feature discrimination and effectively handle difficult image pairs. The proposed network is trained on a large-scale vehicle image dataset with similarity labels, enabling accurate similarity measurement between vehicles captured under diverse conditions. Experimental evaluation on the VeRi-776 dataset achieves a mean average precision (mAP) of 0.8853, demonstrating the effectiveness and robustness of the proposed approach for vehicle re-identification tasks.

Keywords: *Vehicle Re-Identification, Image Classification, VGG16 Neural Network, Siamese Neural Network*

1. INTRODUCTION

Vehicle re-identification (Re-ID) is a prominent research domain within computer vision that aims to identify and match the same vehicle across multiple non-overlapping surveillance cameras. The process primarily relies on visual attributes such as vehicle color, shape, texture, and license plate information. Despite significant progress, accurate vehicle re-identification remains a challenging task due to factors such as varying camera viewpoints, illumination changes, occlusions, and complex backgrounds. Furthermore, vehicles from different identities may exhibit highly similar appearances, while the appearance of the same vehicle can vary considerably under different environmental and imaging conditions. These factors result in inter-class similarity and intra-class variation, which adversely affect identification performance. Vehicle Re-ID has become an essential component of intelligent transportation systems, enabling applications including vehicle trajectory analysis, traffic monitoring, urban surveillance, and forensic investigations [32].

Vehicle re-identification, also known as vehicle tracking or vehicle matching, is the process of identifying and tracking vehicles across different cameras or video frames. It involves associating a vehicle's identity or track from one camera to another, enabling its continuous monitoring and analysis. This technology has gained significant importance in various applications due to its potential benefits. Here is an overview of vehicle re-identification and its importance in different fields:

Vehicle re-identification plays a crucial role in traffic monitoring and management systems. It enables the tracking of individual vehicles across multiple cameras, allowing the analysis of traffic flow, congestion patterns, and route optimization. This information can help authorities make

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

informed decisions regarding traffic management, signal control, and infrastructure planning. It is valuable for law enforcement agencies and security purposes. It aids in tracking and identifying vehicles involved in criminal activities, such as hit-and-runs, robberies, or terrorism incidents. Linking vehicles across different locations and timeframes provides valuable evidence for investigations and can contribute to the prevention and detection of crimes. The logo is the clearest identity factor in vehicle re-identification because every vehicle manufacturer has different logos [1].

Vehicle re-identification enhances the capabilities of surveillance systems. Tracking vehicles across multiple cameras, it enables the creation of comprehensive situational awareness. It helps security personnel monitor high-security areas, identify suspicious or unauthorized vehicles, and improving response times in emergency situations. Vehicle re-identification is an essential component of Intelligent Transportation Systems. It enables the implementation of services such as automatic tolling, parking management, and access control. By accurately identifying vehicles, these systems can streamline operations, enhance security, and improve the overall efficiency of transportation networks. By analysing vehicle movement patterns, traffic densities, and origin-destination information, urban planners can make informed decisions about road network expansions, public transportation enhancements, and optimizing transportation infrastructure to meet the needs of growing cities.

In retail environments, vehicle re-identification can be used for marketing and customer analytics. Retailers can gain insights into customer behaviour, footfall analysis, and targeted marketing campaigns by tracking vehicles entering parking lots or specific areas. This information can be used to optimize store layouts, improve customer experiences, and tailor promotional activities. By integrating it with other technologies like video analytics, IoT sensors, and data analytics, cities can develop intelligent transportation systems, optimize traffic management, improve safety and security, and enhance the overall quality of urban life. Vehicle re-identification plays a significant role in various applications, enabling improved traffic management, enhanced security, efficient transportation systems, and informed decision-making. It contributes to the development of smarter cities and safer environments by harnessing the power of computer vision and data analytics. Figure 1 depicts the scenario of a smart city where all the components of the city are interconnected with each other through wifi. Automatic parking, computerized toll collection, border control, and in-car navigation systems. As a result, an ITS is required to analyze recorded video, regulate, maintain, and interact with ground transportation in order to improve mobility and efficiently manage difficulties.

This paper proposes a novel approach for vehicle re-identification using VGG 16 and Siamese Neural Network. Our method involves extracting features such as color of the vehicle, model of the vehicle, and number plate of the vehicle from a pre-trained VGG 16 model and then using a Siamese Neural Network to learn the similarity between different vehicle images to identify that two different images belong to the same car or to different cars.

Figure. 1 Conceptual Illustration of An Intelligent Transportation System Integrating Surveillance Cameras, Automated Tolling, Parking Management, and Vehicle Re-Identification Modules.

The VGG16 networks are relatively simple in structure compared to other CNN architectures. They consist of a series of convolutional layers, followed by max pooling layers, and finally fully connected layers. VGG networks can be used for transfer learning. A pre-trained VGG network can be fine-tuned on a new task by adding a few layers on top of it and training the new layers on the new dataset. The pre-trained VGG 16 model to extract features from the vehicle images. The extracted features (color, model and number plate) are then fed into a Siamese Neural Network that learns the similarity between different vehicle images.

2. LITERATURE REVIEW

Recent studies in vehicle re-identification have increasingly focused on deep learning-based approaches to improve feature extraction and matching accuracy under challenging surveillance

Journal of Theoretical and Applied Information Technology
30th June 2026. Vol.104. No.12

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

conditions. Convolutional Neural Networks (CNNs), Siamese Neural Networks, attention mechanisms, and Transformer-based architectures are widely used to learn discriminative vehicle features from large-scale datasets such as VeRi-776 and Vehicle [35]. Earlier methods mainly relied on handcrafted features, whereas recent approaches employ deep feature learning to address issues such as viewpoint variation, illumination changes, occlusion, and inter-class similarity. Researchers have also incorporated metric learning techniques such as triplet loss and contrastive loss to enhance feature discrimination and similarity matching between vehicle pairs. In addition, Transformer-based models and multi-scale feature fusion networks have shown improved performance by capturing both global and local vehicle characteristics more effectively. These advancements have significantly improved the accuracy and robustness of modern vehicle Re-ID systems in intelligent transportation and surveillance applications [36].

Several deep learning-based methods have been proposed for vehicle re-identification. Li et al. (2017) proposed a deep metric learning approach that uses a triplet loss function to learn a discriminative feature space. Zhao et al. (2019) proposed a multi-scale feature fusion method that fuses features from different scales to capture global and local features. The features are fused for end-to-end learning [3] Zhang et al. (2020) proposed a two-stream network that learns both appearance and motion features from vehicle images. Learning deep neural networks for vehicle re-id with a visual-spatio-temporal [4] path proposes a spatial-temporal transforming network for vehicle re-identification. The proposed method utilizes both spatial and temporal information to learn discriminative features. Extensive experiments on large-scale vehicle re-identification datasets demonstrate the effectiveness of the approach [5].

A dual-path model with adaptive attention for vehicle re-identification presents a dual-graph attention network for vehicle re-identification. The method leverages both local and global graph attention mechanisms to capture fine-grained spatial relationships between vehicle parts. Experimental results on benchmark datasets demonstrate the superior performance of the approach [6].

Transformer-based attention network for vehicle re-id introduces a prospective transformer network for vehicle re-identification. The proposed method learns a transformation matrix to adjust the perspective distortion caused by different camera viewpoints. Extensive experiments on public vehicle re-identification datasets demonstrate the effectiveness of the approach in handling viewpoint variations [7]. A structured graph attention network for vehicle re-identification proposes a joint learning framework for vehicle re-identification, combining graph attention and convolutional embedding. The method leverages spatial and semantic relationships between vehicles to learn discriminative representations. Experimental results on benchmark datasets demonstrate the superiority of the approach over state-of-the-art methods [8].

Figure. 2 Examples of Appearance Variation Among Vehicles Caused by Changes in Illumination, Viewpoint, and Environmental Conditions.

Previous approaches used in vehicle re-identification have made significant advancements but still face certain limitations. Previous approaches struggle with handling significant variations in vehicle appearance due to changes in lighting conditions, viewpoints, occlusions, and environmental factors. Matching vehicles accurately across different cameras or frames becomes challenging when there are substantial appearance differences.

Many existing methods face difficulties in scaling up to handle large-scale surveillance systems with numerous cameras and high volumes of video data.

The computational complexity increases as the number of vehicles and cameras increases, leading to slower processing times and limited real-time performance. Extracting discriminative features from low-resolution images or poor-quality video footage can be challenging. Insufficient and noisy features can result in decreased accuracy and higher

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

misidentification rates. Global feature extraction can be used, where the entire vehicle's appearance is considered [11].

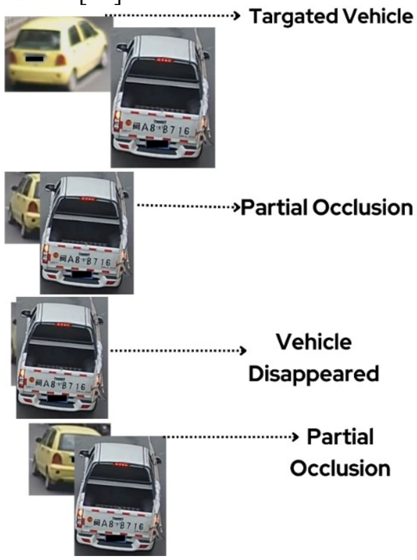

Figure. 3 Illustration of Partial Vehicle Occlusion Scenarios Commonly Encountered in Real-World Surveillance Footage

Figure. 4 Sample Low-Resolution Vehicle Images Highlighting Challenges in Feature Extraction for Re-Identification.

Vehicles of the same make and model can exhibit significant variations due to customization, modifications, or aging. Previous approaches struggle to handle these intra-class variations, leading to incorrect matches or false negatives. The use of surveillance cameras for vehicle re-identification raises privacy concerns. Previous approaches may not adequately address privacy protection, potentially leading to violations of individuals' privacy rights. Some existing methods lack generalization capabilities, meaning they may perform well on specific datasets or scenarios but struggle to adapt to new environments or unseen variations. This limits the practical applicability of these approaches in real-world settings.

To overcome these limitations and achieve a more effective solution for vehicle re-identification, several advancements and improvements are necessary:

Developing advanced feature extraction techniques that can handle appearance variations (refer Figure 2), partial occlusions (refer Figure 3), and low-resolution (refer Figure 4) images is crucial. These features should be more discriminative and noise-resilient, improving vehicle matching accuracy. The development of efficient algorithms that can handle large-scale surveillance systems with real-time or near-real-time performance is essential. These algorithms should be capable of processing high volumes of data and be computationally efficient. Addressing the challenge of intra-class variation requires more sophisticated modelling techniques. Approaches that can accurately capture and represent variations within vehicle classes will improve re-identification accuracy.

Designing privacy-preserving methods that ensure the protection of an individual's privacy rights is crucial. Techniques such as data anonymization, encryption, and secure protocols can be explored to address privacy concerns effectively. Developing models that can generalize well across different datasets, camera setups, and environmental conditions is essential. This allows for broader applicability and robust performance in real-world scenarios.

Overall, the need for a more effective vehicle re-identification solution arises from limitations of previous approaches by addressing these limitations through advancements in feature extraction, algorithmic efficiency, handling intra-class variation, privacy protection, and generalization capabilities.

3. METHODOLOGY

Robust VGG16 involves two stages: feature extraction and similarity learning. This research uses a pre-trained VGG 16 model in the feature extraction stage to extract features from the vehicle images. The VGG 16 model has 13 convolutional layers and three fully connected layers. The last fully connected layer was removed and the output of the second last fully connected layer was used as the feature vector. The feature vector has a dimension of 4096.In the similarity learning stage, this paper uses a Siamese Neural Network to learn the similarity between different vehicle images. A Siamese Neural Network consists of two identical sub-networks that share the same weights. The two sub-networks take two input images and extract their respective feature vectors. The feature vectors are then concatenated and fed into a fully connected layer that outputs the similarity score.

The Siamese Neural Network was trained using a contrastive loss function. The contrastive loss function encourages similar images to have a small distance in the feature space and dissimilar images to have a significant distance. The Adam optimizer with a learning rate 0.001 and a batch size of 128 was used. The network was trained for 100 epochs. Image 2 represents the vehicle re-id process.

Vehicle re-identification (Re-ID) datasets are crucial for developing and evaluating algorithms aimed at recognizing and tracking vehicles across multiple cameras or time periods. While a general overview of the typical characteristics of such datasets based on existing research and common practices, can be provided by us, it should be noted that specific details may vary depending on the dataset in question.

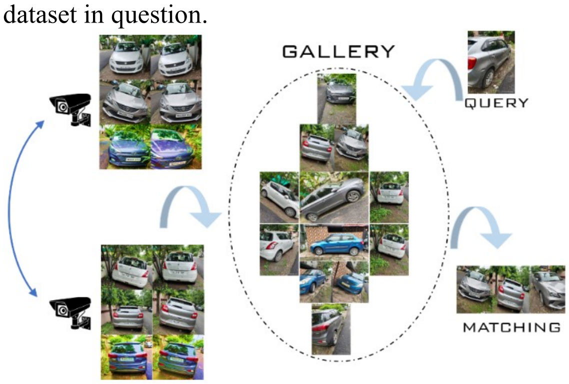

Figure. 5 Overview of the Vehicle Re-Identification Pipeline, Including Feature Extraction and Similarity Matching.

Data Sources: Vehicle Re-ID datasets are often compiled from various sources, including public surveillance cameras, proprietary datasets, and online resources. These sources may encompass traffic cameras, security footage, vehicle databases, or other publicly available data. In some cases, datasets are specifically collected for research purposes through dedicated data collection efforts. The dataset consists of 776 car images and each car consist a set of 20 images from different angles and view point.

3.1 VGG16 ARCHITECTURE

The VGG-16 architecture is a deep convolutional neural network (CNN) model that was introduced by the Visual Geometry Group (VGG) at the University of Oxford. It has achieved significant success in various computer vision tasks, including image classification [4], object detection, and feature extraction. VGG-16 is a convolutional neural network (CNN) architecture that has been widely used for image classification tasks. It consists of 16 layers, including 13 convolutional layers and three fully connected layers. VGG-16 has been shown to achieve high accuracy on various image classification benchmarks, including the ImageNet dataset. Vehicle re-identification using the VGG-16 algorithm involves training the model on a large dataset of vehicle images and using the learned features to identify vehicles from new images or videos. The VGG-16 architecture offers several advantages in image classification tasks. Few of the advantages are Strong Performance

The pre-trained weights of VGG 16 on large-scale image datasets such as ImageNet are widely available. These pre-trained weights can be used as initializations for transfer learning, allowing the model to leverage the learned features from a large dataset and adapt them to a specific image classification task with a smaller labelled dataset. Transfer learning with VGG-16 has been shown to be effective in achieving good performance even with limited training data. The stacked convolutional layers with small filter sizes (3x3) in VGG-16 enable the model to capture fine-grained spatial information and learn complex feature representations. This helps in generalizing well to images from different domains, viewpoints, and variations, making it suitable for a wide range of image classification tasks.

3.2 SIAMESE NEURAL NETWORK

A Siamese neural network is a type of neural network architecture that is designed to measure the similarity or dissimilarity between two inputs [12]. It gets its name from the famous conjoined twins Chang and Eng Bunker, who were from Siam (now Thailand). The Siamese neural network consists of two identical subnetworks (often referred to as twin networks) that share the same architecture and weights. Each subnetwork takes one input and processes it independently. The outputs of the twin networks are then fed into a similarity metric or a distance function, which compares the two representations and calculates a similarity score. The main idea behind Siamese networks is that they learn to encode inputs into fixed-length feature vectors that capture the important information necessary for similarity comparison. These feature vectors are often referred to as embeddings. By sharing weights between the twin networks, the network is encouraged to learn similar representations for similar inputs and dissimilar representations for dissimilar inputs. Siamese networks are also used for tracking objects in combination with re-id features and graph convolutional networks [13]. To make the system more efficient, two Siamese networks are used, performing two different tasks [14].

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

To train a Siamese network, a dataset is required where pairs of inputs are labeled with their similarity or dissimilarity. The network learns to optimize the similarity metric or distance function based on the provided labels, enabling it to generalize to unseen pairs of inputs and accurately measure their similarity. Overall, Siamese neural networks are powerful tools for similarity-based tasks, allowing for the comparison of inputs in various domains and enabling applications that require measuring similarity or dissimilarity between data points. Figure 6 shows the combined architecture of VGG 16 and Siamese Neural Network.

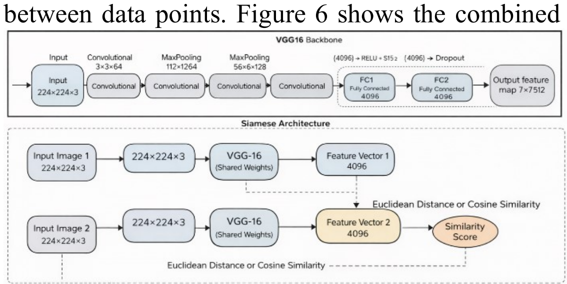

Figure. 6 Architecture of the Proposed VGG16-Based Siamese Neural Network for Vehicle Re-Identification

3.3 THE ARCHITECTURE OF SIAMESE NEURAL NETWORK IN VEHICLE RE-IDENTIFICATION

Vehicle re-identification is a task in computer vision that aims to identify and track vehicles across multiple cameras or frames, and Figure 6 shows the implementation of vehicle re-id. Siamese networks have been successfully used in vehicle re-identification due to their ability to compare the similarity between two vehicle images. Siamese neural network was proposed by Bromley et al. in the first instance; it was used to verify handwritten signatures [15]. The architecture of a Siamese network used in vehicle re-identification typically consists of the following components:

3.3.1 Input Layers: The network takes a pair of vehicle images as input. Each image is passed through separate branches of the network.

3.3.2 Convolutional Neural Network (CNN): Each branch of the network typically starts with a CNN, which extracts visual features from the input images. The CNN consists of multiple convolutional layers, followed by activation functions (such as ReLU (Rectified Linear Unit)) and pooling layers. The purpose of the CNN is to capture and encode the visual characteristics of the vehicle images. It is also used for an important factor i.e. the recognition of make and model. [16]

3.3.3 Shared Weights: The twin branches of the network share the same weights, which means that the CNN layers of both branches have identical parameters. This weight sharing encourages the network to learn similar representations for similar vehicles.

3.3.4 Feature Extraction: After passing through the CNN layers, the input images are transformed into feature vectors, also known as embeddings. This is typically achieved by flattening the output of the CNN and passing it through one or more fully connected layers. The output of this stage is a fixed-length feature vector that encodes the visual information of the vehicle image. Character recognition is one of the feature extraction types used in automatic number plate recognition systems [17]. It is characterized as OCR [18] (Optical character recognition).

3.3.5 Distance Calculation: The feature vectors of the two input images are fed into a distance metric or similarity measure. Commonly used distance metrics include Euclidean distance, cosine similarity, or contrastive loss. The distance metric calculates the similarity or dissimilarity between the feature vectors and produces a similarity score.

3.3.6 Training and Loss: During the training process, the Siamese network is trained using pairs of vehicle images labelled with their similarity or dissimilarity. The network learns to minimize a loss function, such as contrastive loss or triplet loss, which encourages similar images to have small distances and dissimilar images to have large distances. In a research paper titled Point Aware Re-identification, the authors have replaced that it is based on triplet loss where intra-view and inter-view triplet loss is used [19].

3.3.7 Output: The final output of the Siamese network is the similarity score between the two input vehicle images. This score can be used for tasks like vehicle matching or ranking.

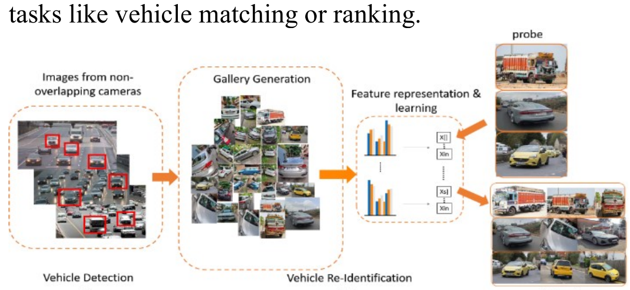

Figure. 7 Visualization of Vehicle Detection and Re-Identification Using Bounding Boxes and Learned Feature Embeddings.

4. RESULTS AND ANALYSIS

4.1 Accuracy: Accuracy is a straightforward metric that measures the percentage of correctly matched vehicle pairs in the evaluation dataset. It is

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

calculated as the ratio of the number of correctly matched pairs to the total number of pairs.

4.2 Mean Average Precision (mAP): mAP is a commonly used metric in information retrieval tasks and measures the average precision across different recall levels. In vehicle re-identification, it considers the ranking of the identified similar vehicles and measures the average precision at different recall points. Higher mAP indicates better performance. Figure 8 Depicts the evaluation of accuracy and mAP value of other CNN with Robust VGG model.

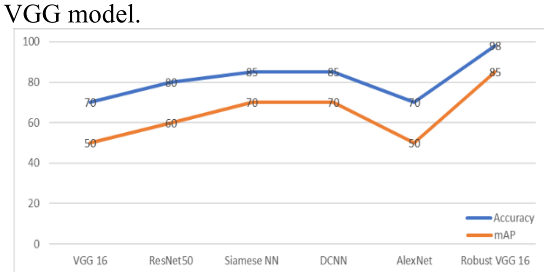

Figure. 8 Comparative Performance Analysis Showing Accuracy and Mean Average Precision (Map) Across Different CNN-Based Models.

4.3 Advantages of Combining VGG 16 and Siamese Neural Network

The combination of VGG16 and Siamese Neural Network allows for the extraction of discriminative features from vehicle images, enhancing the network's ability to distinguish between different vehicles during re-identification. VGG16, known for its effectiveness in image recognition, provides a multi-modal approach for vehicle re-identification when combined with Siamese networks. This enables the model to leverage both spatial and contextual information for better accuracy.

The combination enhances the latent space representation, allowing for better vehicle representation and similarity calculations. This is crucial for accurate matching during the re-identification process. Using VGG16 in combination with Siamese networks supports novel approaches for vehicle pose estimation, combining deep learning with traditional pose estimation methods. Although not directly related to vehicle re-identification, VGG16's effectiveness in fingerprint recognition can enhance the combined network's overall robustness.

4.4 Dataset and Evaluation Metric

The last update was in September 2021. The "Veri-776" dataset is a popular benchmark dataset used for vehicle re-identification research. It is designed for evaluating the performance of vehicle re-identification algorithms under real-world scenarios, particularly in urban traffic surveillance scenarios. In the present re-identification papers, Veri 776 has been marked as a benchmark dataset and is being used for many re-id problems, and has provided better results when compared to other datasets [25]. Training and validation accuracy and loss are specified in Figure 9.

The dataset contains a total of 50,000 images [26] of vehicles captured by non-overlapping cameras [27] in real traffic scenes. It includes 776 unique vehicle identities (or classes) that appear across the dataset. The images exhibit various variations, such as different viewpoints, lighting conditions, occlusions, and partial visibility of vehicles, making it challenging for re-identification algorithms. Each image in the dataset is manually annotated with bounding boxes around the vehicles and corresponding identity labels. 3D bounding boxes [28] are the new standards that are used for vehicle detection problems [29]. The dataset is typically divided into a training set and a testing set. The training set includes a subset of vehicle identities, while the testing set contains the remaining identities for evaluation. The dataset follows a standard evaluation protocol for vehicle re-identification tasks, where the goal is to match vehicles across different camera views correctly. Researchers often use the Veri-776 dataset to evaluate the performance of their vehicle re-identification algorithms and compare their results with state-of-the-art methods. It has been instrumental in advancing research in this area, helping to develop more robust and accurate techniques for vehicle tracking and identification in real-world surveillance scenarios. Veri-Wild is an advanced version of the Veri dataset [30] The images are captured via a large closed-circuit television system, also called CCTV. It is a challenging dataset as it contains images from different illumination and poses consisting of 416,314 images [31].

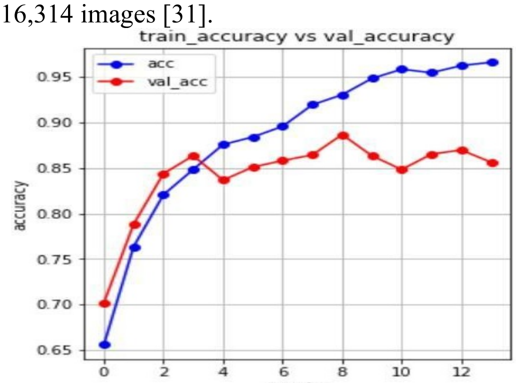

Figure. 9 Training and Validation Accuracy Curves Illustrating Convergence Behaviour of the Proposed Model.

4.5 Implications and Potential Areas of the Application

The proposed method of using a Siamese neural network with the VGG 16 model for vehicle re-identification has several implications and potential applications. Here are some key implications and potential areas of application:

4.5.1 Surveillance and Security: Vehicle re-identification plays a crucial role in surveillance and security systems. The proposed method can be applied in scenarios such as traffic monitoring, parking lot management, and access control. It can help identify and track vehicles of interest, detect suspicious activities, and enhance overall security measures.

4.5.2 Law Enforcement and Forensics: Law enforcement agencies can benefit from accurate vehicle re-identification for various purposes. It can aid in investigations, identifying suspects involved in criminal activities captured by surveillance cameras, and tracking the movement of vehicles linked to specific incidents.

4.5.3 Smart Transportation: Vehicle re-identification can be integrated into smart transportation systems to improve traffic management and for traffic analysis [32]. By accurately tracking vehicles across different cameras or checkpoints, it can enable applications like congestion analysis, traffic pattern recognition, and adaptive traffic signal control.

4.5.4 Parking Management: Efficient parking management can be achieved through vehicle re-identification. The proposed method can help monitor parking spaces, detect unauthorized parking, manage occupancy, and facilitate seamless entry and exit in parking lots or garages.

4.5.5 Toll Collection and Electronic Road Pricing: Vehicle re-identification can be utilized for automated toll collection and electronic road pricing systems. By accurately identifying vehicles, tolls can be automatically collected without the need for physical toll booths, reducing congestion and improving overall efficiency.

4.5.6 Vehicle Sharing and Fleet Management: Car sharing services and fleet management can benefit from accurate vehicle re-identification. It can aid in monitoring vehicle usage, ensuring proper allocation, and tracking vehicles' whereabouts for maintenance and logistics purposes.

4.5.7 Border Security and Customs: Vehicle re-identification can play a crucial role in border security and customs operations. It can help identify and track vehicles crossing borders, detect smuggling attempts, and enhance border control measures.

4.5.8 Smart Cities and Infrastructure: In the context of smart cities, vehicle re-identification can contribute to overall infrastructure optimization. It can support intelligent transportation systems, parking management, traffic control, and contribute to creating more efficient and sustainable urban environments.

These applications demonstrate the potential impact of the proposed method in various domains, ranging from security and surveillance to transportation and urban planning. As technology advances and more sophisticated models and datasets become available, the accuracy and capabilities of vehicle re-identification systems are expected to improve, further expanding the range of practical applications.

5. EVIDENCE OF THE RESEARCH

Table 1. Description Of Key Architectural Modules in the Proposed Vehicle Re-Identification System

Aspect	Description
Discriminative Feature Learning	VGG-16 combined with a Siamese learning framework enables effective extraction of discriminative vehicle features by reducing intra-class variation and enhancing inter-class separation, improving re-identification accuracy under varying viewpoints and lighting conditions.
Two-Stream Siamese Neural Network	A two-stream Siamese architecture processes image pairs with shared weights to learn similarity-aware feature representations, leading to improved vehicle matching performance across different camera views.
Baseline Model Using VGG-16	VGG-16 is commonly used as a baseline in vehicle re-identification due to its stable architecture and strong hierarchical feature extraction capability, making it suitable for comparative evaluation.
Similarity Metric Learning	Distance-based loss functions within Siamese networks enable effective similarity measurement between vehicle feature embeddings, improving retrieval precision in large-scale datasets.
Relevance of Siamese Networks	Prior studies highlight the effectiveness of Siamese networks in learning similarity-driven representations, supporting their applicability to vehicle re-identification and related visual recognition tasks.

6. FUTURE WORK

Future research in vehicle re-identification should focus on improving the robustness, scalability, and real-world applicability of existing models. Several promising directions can be explored:

- Integrating Transformer-based architectures and attention mechanisms to more effectively capture both fine-grained local details and global vehicle characteristics, thereby enhancing feature representation and matching accuracy.

- Investigating federated learning approaches to facilitate collaborative vehicle Re-ID across different organizations, regions, or cities while ensuring the privacy and security of sensitive surveillance data.
- Developing advanced techniques to address challenging conditions such as occlusion, motion blur, adverse weather, and complex backgrounds that are commonly encountered in real-world traffic surveillance scenarios.

Pursuing these research directions can contribute to the development of more accurate, reliable, and adaptable vehicle re-identification systems for intelligent transportation and surveillance applications.

7. CONCLUSION

The study demonstrates that the combination of VGG-16 and Siamese neural network architectures leads to significant improvements in the accuracy of vehicle re-identification compared to traditional methods. The proposed approach shows robustness in handling variations in lighting conditions, viewpoints, and occlusions, making it suitable for real-world scenarios where such challenges are prevalent. The research investigates the effectiveness of VGG-16 as a feature extractor for vehicle images and demonstrates its ability to learn discriminative representations. The study highlights the importance of the Siamese neural network in learning a suitable distance metric that aids in measuring similarity between vehicle images effectively. It explores the applicability of transfer learning with VGG-16 for vehicle re-identification tasks and showcases its ability to generalize well on unseen datasets. The findings compare the proposed VGG-16 and Siamese network-based method with existing state-of-the-art techniques, demonstrating its superiority in terms of accuracy and efficiency. The research discusses the scalability of the proposed approach and evaluates its performance in real-time settings, making it feasible for practical deployment. The study highlights the potential applications of the proposed method in enhancing surveillance systems and traffic management by accurately tracking vehicles across multiple cameras. The research can include ablation studies to analyze the contribution of individual components of the proposed method, such as the importance of using VGG-16 features or the impact of the Siamese network in future studies. The findings could also include an analysis of the dataset used for training and evaluation, discussing any biases, limitations, or potential challenges in the data.

Overall, these key findings would demonstrate the effectiveness and potential of the VGG-16 and Siamese neural network-based approach in addressing vehicle re-identification tasks, emphasizing its relevance and contributions to the field of computer vision and intelligent transportation systems

This research works on our method on the VeRi-776 dataset, a large-scale vehicle re-identification dataset. The dataset contains 49,357 images of 776 vehicles captured by 20 cameras. This research has used the standard train/test split provided by the dataset, which contains 576 vehicles for training and 200 for testing.

REFERENCES:

[1] Y. Huang, R. Wu, Y. Sun, W. Wang, and X. Ding, "Vehicle logo recognition system based on convolutional neural networks with a pretraining strategy, " *IEEE Transactions on Intelligent Transportation Systems*, vol. 16, no. 4, pp. 1951–1960, Aug. 2015, doi: 10.1109/TITS.2014.2387069.

[2] Zakria, Deng, J., Hao, Y., Khokhar, M. S., Kumar, R., Cai, J., ... & Aftab, M. U. Trends in vehicle re-identification past, present, and future: A comprehensive review. *Mathematics*, *9*(24), 3162, Dec 2021

[3] H. Guo, K. Zhu, M. Tang, and J. Wang, "Two-Level Attention Network with Multi-Grain Ranking Loss for Vehicle Re-Identification, " *IEEE Transactions on Image Processing*, vol. 28, no. 9, pp. 4328–4338, Sep. 2019, doi: 10.1109/TIP.2019.2910408.

[4] Shen, Y., Xiao, T., Li, H., Yi, S., & Wang, X. Learning deep neural networks for vehicle re-id with visual-spatio-temporal path proposals. In *Proceedings of the IEEE international conference on computer vision* (pp. 1900-1909). 2017

[5] Shen, Y., Xiao, T., Li, H., Yi, S., & Wang, X. Learning deep neural networks for vehicle re-id with visual-spatio-temporal path proposals. In *Proceedings of the IEEE international conference on computer vision* (pp. 1900-1909). 2017

[6] P. Khorramshahi, A. Kumar, N. Peri, S. Saketh Rambhatla, J.-C. Chen, and R. Chellappa, "A Dual-Path Model With Adaptive Attention For Vehicle Re-Identification." [Online]. Available: https://github.com/Pirazh/Vehicle_Key_

[7] J. Lian, D. Wang, S. Zhu, Y. Wu, and C. Li, "Transformer-Based Attention Network for Vehicle Re-Identification, " *Electronics*

(Switzerland), vol. 11, no. 7, Apr. 2022, doi: 10.3390/electronics11071016.

[8] Y. Zhu, Z. J. Zha, T. Zhang, J. Liu, and J. Luo, "A Structured Graph Attention Network for Vehicle Re-Identification, " in *MM 2020 - Proceedings of the 28th ACM International Conference on Multimedia*, Association for Computing Machinery, Inc, Oct. 2020, pp. 646–654. doi: 10.1145/3394171.3413607.

[9] Wu, C. W., Liu, C. T., Chiang, C. E., Tu, W. C., & Chien, S. Y. (2018). Vehicle re-identification with the space-time prior. In *Proceedings of the IEEE conference on computer vision and pattern recognition workshops* (pp. 121-128). 2018

[10] H. Wang, J. Peng, G. Jiang, F. Xu, and X. Fu, "Discriminative Feature and Dictionary Learning with Part-aware Model for Vehicle Re-identification, " Mar. 2020, [Online]. Available: http://arxiv.org/abs/2003.07139

[11] W. Sun, G. Dai, X. Zhang, X. He, and X. Chen, "TBE-Net: A Three-Branch Embedding Network With Part-Aware Ability and Feature Complementary Learning for Vehicle Re-Identification, " *IEEE Transactions on Intelligent Transportation Systems*, vol. 23, no. 9, pp. 14557–14569, Sep. 2022, doi: 10.1109/TITS.2021.3130403.

[12] Chung, D., Tahboub, K., & Delp, E. J. A two stream siamese convolutional neural network for person re-identification. In *Proceedings of the IEEE international conference on computer vision* (pp. 1983-1991). 2017

[13] Lusardi, C., Taufique, A. M. N., & Savakis, A. Robust multi-object tracking using re-identification features and graph convolutional networks. In *Proceedings of the IEEE/CVF International Conference on Computer Vision* (pp. 3868-3877). 2021

[14] I. O. de Oliveira, K. V. O. Fonseca, and R. Minetto, "A Two-Stream Siamese Neural Network for Vehicle Re-Identification by Using Non-Overlapping Cameras", Feb. 2019, [Online]. Available: http://arxiv.org/abs/1902.01496

[15] X. Liu, W. Liu, T. Mei, and H. Ma, "PROVID: Progressive and Multimodal Vehicle Reidentification for Large-Scale Urban Surveillance, " *IEEE Trans Multimedia*, vol. 20, no. 3, pp. 645–658, Mar. 2018, doi: 10.1109/TMM.2017.2751966.

[16] Sochor, J., Herout, A., & Havel, J. Boxcars: 3d boxes as cnn input for improved fine-grained vehicle recognition. In *Proceedings of the IEEE conference on computer vision and pattern recognition* (pp. 3006-3015). 2016

[17] Lubna, N. Mufti, and S. A. A. Shah, "Automatic number plate recognition:A detailed survey of relevant algorithms, " *Sensors*, vol. 21, no. 9. MDPI AG, May 01, 2021. doi: 10.3390/s21093028.

[18] M. Samantaray, A. K. Biswal, D. Singh, D. Samanta, M. Karuppiah, and N. P. Joseph, "Optical Character Recognition (OCR) based Vehicle's License Plate Recognition System Using Python and OpenCV, " in *Proceedings of the 5th International Conference on Electronics, Communication and Aerospace Technology, ICECA 2021*, Institute of Electrical and Electronics Engineers Inc., 2021, pp. 849–853. doi: 10.1109/ICECA52323.2021.9676015.

[19] Y. Li, K. Liu, Y. Jin, T. Wang, and W. Lin, "VARID: Viewpoint-Aware Re-IDentification of Vehicle Based on Triplet Loss, " *IEEE Transactions on Intelligent Transportation Systems*, vol. 23, no. 2, pp. 1381–1390, Feb. 2022, doi: 10.1109/TITS.2020.3025387.

[20] Albera, S. (2016). Vehicle Logo Recognition Using Image Processing Methods. *Atilim University*.

[21] Nguyen, K. T., Hoang, T. H., Tran, M. T., Le, T. N., Bui, N. M., Do, T. L., ... & Do, M. N. Vehicle re-identification with learned representation and spatial verification and abnormality detection with multi-adaptive vehicle detectors for traffic video analysis. In *CVPR Workshops* (pp. 363-372). June 2019

[22] L. Rong, Y. Xu, X. Zhou, L. Han, L. Li, and X. Pan, "A vehicle re-identification framework based on the improved multi-branch feature fusion network, " *Sci Rep*, vol. 11, no. 1, Dec. 2021, doi: 10.1038/s41598-021-99646-6.

[23] Shen, F., Zhu, J., Zhu, X., Huang, J., Zeng, H., Lei, Z., & Cai, C. An efficient multiresolution network for vehicle reidentification. *IEEE Internet of Things Journal*, *9*(11), 9049-9059. 202 1

[24] Shen, F., Zhu, J., Zhu, X., Huang, J., Zeng, H., Lei, Z., & Cai, C. An efficient multiresolution network for vehicle reidentification. *IEEE Internet of Things Journal*, *9*(11), 9049-9059.2021.

[25] Y. Bai, Y. Lou, F. Gao, S. Wang, Y. Wu, and L. Y. Duan, "Group-sensitive triplet embedding for vehicle reidentification, " *IEEE Trans Multimedia*, vol. 20, no. 9, pp. 2385–2399, Sep. 2018, doi: 10.1109/TMM.2018.2796240.

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

[26] P. Khorramshahi, A. Kumar, N. Peri, S. Saketh Rambhatla, J.-C. Chen, and R. Chellappa, "A Dual-Path Model With Adaptive Attention For Vehicle Re-Identification." [Online]. Available: https://github.com/Pirazh/Vehicle_Key_

[27] J. Sochor, J. Spanhel, and A. Herout, "BoxCars: Improving Fine-Grained Recognition of Vehicles Using 3-D Bounding Boxes in Traffic Surveillance, " *IEEE Transactions on Intelligent Transportation Systems*, vol. 20, no. 1, pp. 97–108, Jan. 2019, doi: 10.1109/TITS.2018.2799228.

[28] Shen, F., Zhu, J., Zhu, X., Huang, J., Zeng, H., Lei, Z., & Cai, C. An efficient multiresolution network for vehicle reidentification. *IEEE Internet of Things Journal*, *9*(11), 9049-9059. 2021

[29] H. Wang, J. Hou, and N. Chen, "A Survey of Vehicle Re-Identification Based on Deep Learning, " *IEEE Access*, vol. 7. Institute of Electrical and Electronics Engineers Inc., pp. 172443–172469, 2019. doi: 10.1109/ACCESS.2019.2956172.

[30] Y. Lou, Y. Bai, J. Liu, S. Wang, and L.-Y. Duan, "VERI-Wild: A Large Dataset and a New Method for Vehicle Re-Identification in the Wild." [Online]. Available: https://github.com/PKU-IMRE/

[31] Z. Zheng, T. Ruan, Y. Wei, Y. Yang, and T. Mei, "VehicleNet: Learning Robust Visual Representation for Vehicle Re-Identification, " *IEEE Trans Multimedia*, vol. 23, pp. 2683–2693, 2021, doi: 10.1109/TMM.2020.3014488.

[32] Holla, A., Pai, M. M., Verma, U., & Pai, R. M. (2025). Vehicle re-identification and tracking: Algorithmic approach, challenges and future directions. *IEEE Open Journal of Intelligent Transportation Systems*, *6*, 155-183.

[33] Bagavathyraj, H., Joseph, R., & Madathil, S. C. Vehicle Detection, Classification, and Re-identification using AI: A Systematic Review. *Classification, and Re-identification using AI: A Systematic Review*.

[34] Siyoufi, H., Ismail, K., & Badran, A. (2026, February). Heavy Vehicle Re-Identification Using Multi-Attribute Recognition Across Multiple Locations. In *2026 International Conference on Artificial Intelligence, Computer, Data Sciences and Applications (ACDSA)* (pp. 1-10). IEEE.

[35] Yi, X., Wang, Q., Liu, Q., Rui, Y., & Ran, B. (2025). Advances in vehicle re-identification techniques: A survey. *Neurocomputing*, *614*, 128745.

[36] Zhu, M., & Feng, Q. (2025). Transformer-based vehicle re-identification with view information. *Scientific Reports*, *15*(1), 40576.