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RESEARCH ARTICLE

Real Time Car Model and Plate Detection System by Using Deep Learning Architectures

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ABSTRACT The advent of deep learning has revolutionized computer vision, enabling real-time analysis crucial for traffic management and vehicle identification. This research introduces a system combining vehicle make and model detection with Automatic Number Plate Recognition (ANPR), achieving a ground-breaking 97.5% accuracy rate. Unlike traditional methods, which focus on either make and model detection or ANPR independently, this study integrates both aspects into a single, cohesive system, providing a more holistic and efficient solution for vehicle identification, ensuring robust performance even in adverse weather conditions. The paper explores the use of deep learning techniques, including OpenCV, in combination with Python programming language. Leveraging MobileNet-V2 and YOLOx (You Only Look Once) for vehicle identification, and YOLOv4-tiny, Paddle OCR (optical character recognition), and SVTR-tiny for ANPR, the system was rigorously tested at Firat University's entrance with a thousand images captured under various conditions such as fog, rain, and low light. The system's exceptional success rate in these tests highlights its robustness and practical applicability. Additionally, experiments evaluate the system's accuracy and effectiveness, using Gradient-weighted Class Activation Mapping (GradCam) technology to gain insights into neural networks' decision-making processes and identify areas for improvement, particularly in misclassifications. The implications of this research for computer vision are significant, paving the way for advanced applications in autonomous driving, traffic management, stolen vehicles, and security surveillance. Achieving real-time, high-accuracy vehicle identification, the integrated Vehicle Make and Model Recognition (VMM R) and ANPR system sets a new standard for future research in the field.

INDEX TERMS Car model, plate detection, deep learning, computer vision, OpenCV, MobileNet-V2, YOLOv4, GradCam, Firat University.

I. INTRODUCTION

Nowadays, with technology doubling in every phase of life, the services are obviously getting better using such technologies [1]. Technology is also playing an important factor in the vehicle transport system. The automobile transportation system plays a primary task in the monitoring of traffic [2], crime detection system, tracking stolen vehicles, and protection applications.

The quantity of active vehicles has drastically increased, leading to more illegal activities. The rapid proliferation of vehicles makes it difficult to track them, highlighting the importance for relevant authorities to do so. As the flow of vehicles grows daily, there is a heightened need for automatic number plate detection and vehicle make and model identification. This tool is also valuable for monitoring vehicle speeds, especially in light of the serious accidents that occur each year. The UK police first recognized the Automatic Number Plate Recognition (ANPR) system in 1976, and its prevalence has significantly increased in the last decade [1].

Along the highway, thousands of surveillance cameras are installed, primarily for traffic management and law enforcement. Continuous manual inspection would not be feasible, as such an approach would require colossal efforts, involving significant costs. Automatic visual interpretation offers the capability to detect, track, and classify all traffic. A particularly important concept in this context is make and model recognition (MMR). The make and model information of vehicles can be utilized to identify vehicles with stolen license plates by comparing the observed vehicle model with

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the registered information associated with the license plate. Another application is identifying specific vehicles after a crime when only a vehicle description is available without the license plate number. In such instances, the make and model of the vehicle need to be obtained visually [3]. These challenges are the focal points of this paper.

the Vehicle Make and Model Recognition (VMMR) or vehicle identification addresses the challenge of determining the make and model of a vehicle, that is, identifying the vehicle manufacturer's name and the specific product, when provided with an input image or video featuring the vehicle. In recent times, VMMR has increasingly become a crucial component of Intelligent Transportation Systems (ITS) and has attracted significant attention from the research community [4], [5].

Make and model recognition provides important information in many applications such as traffic management, intelligent surveillance, traffic behavior analysis, and traffic monitoring [6]. For example, the VMMR technology is employed in the traffic cameras installed in toll stations for the automatic detection and recognition of passing vehicles. In traffic monitoring, the vehicle model recognition is used by ITS to build the vehicle flow statistics used for the analysing of real-time traffic conditions. In traffic security [2], the make and model recognition can help locate stolen vehicles [7], [8].

The objective of this paper is therefore to solve the security and find the stolen car also mismatch and missing license plates cases with an accurate visual analysis system. To this end, we present an MMR system developed for the Turkey National Police, in which vehicles are observed from a camera mounted in an overhead sign structure on the highway, with the purpose to extract accurate make and model information. The extracted information may be combined with existing ANPR information [8]. The system implementation has a focus on observing a single lane (see Fig. 1). This existing camera is used to feed the training process of our recognition system. The recognition model is trained to recognize vehicles from a large training set of vehicle images and make and model labels. Due to bandwidth restrictions between the camera (online) and our training and testing facilities (offline), we have to optimize the gathering of training and testing samples. Another challenge is the automated handling of new and rare vehicle models as registered in the vehicle registration database, for which it is hard to collect training and testing images. For these reasons, we propose using dataset for vehicle and ANPR such as coco dataset and stanford dataset. The sampling and their annotation in this system are automated, while the updated training still needs manual control. This approach enables the construction of an initial dataset and allows to incrementally collect new vehicle samples over time, so that the best system performance is ensured at all moments [9], [10].

Specifically, the VMMR system is formulated with a detection and classification stage in order to localize vehicles into bounding boxes in a full-front frontal view. The aim of this work refers towards searching for vehicle's make and model information that could be done without depending on an ANPR system. Our two-stage approaches that allowed detecting vehicles for every video frame and performed their classification once a vehicle was found. This paper extends our initial previews work by extensive insight in our MMR classification performance and the discussion of the evaluation of MMR system in high detail. First, a comparison among different convolutional neural networks for vehicle model classification is reported. Second, we give more insight into the classification performance by finding most informative region for VMMR classification and measure robustness against occlusions. Third, we further explore false classifications within an VMMR classify system to find shortcomings in a system and information handling [10], [11].

Deep Learning – now evolved as an efficacious technique of handling big data – uses intricate algorithms and artificial neural networks to train machines/computers in such a manner that they may learn from experience, classify and recognize data/images just the way human brain does. For Deep Learning, in particular, a Convolutional Neural Network or CNN is an artificial neural network, used extensively for image/object recognition and classification. Thus, in the context of Deep Learning, objects within an image are essentially recognized using a CNN. CNNs have found broad applications in several tasks such as image processing problems, localization, and segmentation in computer vision tasks, video analysis to recognize obstacles in self-driving vehicles, speech recognition in natural language processing. As CNNs play a prominent role in such fast-growing and emerging areas, they are often used in Deep Learning [12].

Computer vision is an interdisciplinary scientific field dealing with how computers can acquire high-level understanding from digital images or videos. Therefore, the computer vision tasks contain methods of acquiring and processing digital images, analyzing and understanding the different formats they have, such as single pictures and video sequences, or extraction of data from high-dimensional information out of the real world in order to produce numerical or symbolic descriptions that are useful for decision making. ANPR has been a technology that uses optical character recognition on images to read vehicle registration plates. Modern advanced computer vision technology together with the falling prices of devices related to it in recent years makes it fairly possible to visually recognize vehicles automatically, irrespective of whether online or offline through video/CCTV. This research therefore aims to the development of an integrated system that combines vehicle make and model detection with ANPR, achieving a significant improvement in accuracy and efficiency with a remarkable 97.5% accuracy rate. The system demonstrates exceptional robustness in various environmental conditions such as fog, rain, and low light. It was rigorously tested at Firat University's entrance with a thousand images, showcasing its practical applicability. Additionally, the use of GradCam technology provides valuable insights into the decision-making processes of neural networks, identifying areas for improvement, particularly in cases of misclassification. These contributions pave the way for advanced applications in autonomous driving, traffic management, stolen vehicle tracking, and security surveillance, setting a new standard for future research in the field. as shown in Fig 1. The work then involves investigations on real-time automatic number-plate recognition and the possible extension of the above to other aspects of road traffic monitoring and control [13], [14].

The implications of this research for computer vision are substantial, laying the groundwork for sophisticated applications in various fields. In autonomous driving, it can enhance vehicle navigation and safety. For traffic management, car tracking, it offers the potential to optimize flow and reduce congestion. In the realm of stolen vehicle and security use cases among others, it improves tracking and identification capabilities. Additionally, in security surveillance, it bolsters the effectiveness of monitoring and threat detection systems.

Grad-CAM was a key factor of both diagnosing and sense-making the models' misclassifications. In that sense, when Grad-CAM highlighted the region of the image in which focal point the model gave predictions, it became possible to diagnose the patterns in misclassifications. For example, sometimes reflections or occlusions were the reason for which the model failed to classify a vehicle or its license plate correctly. Grad-CAM visualizations helped in tempering the model's behavior to be much robust towards such peculiarities [15].

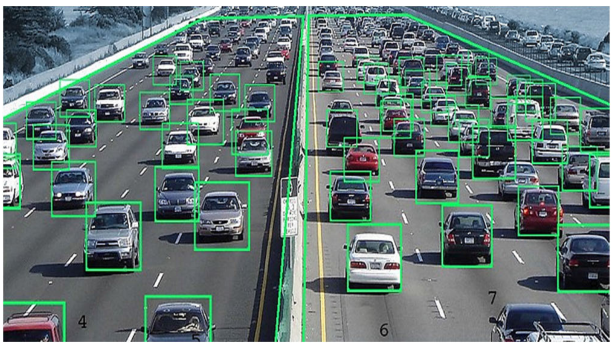

FIGURE 1. OCR technology used for object recognition [2].

Automatic License Plate Recognition (ALPR) is a technology that identifies the license plate numbers of vehicles from images captured by cameras, which may be in color, black and white, or infrared formats. This technology employs a mix of methodologies such as object detection, image processing, and pattern recognition. ALPR is referred to by various other terms including automatic vehicle identification (AVI), car plate recognition (CPR), ANPR, and optical character recognition (OCR) for vehicles. [16], [17].

Developing ANPR systems presents a complex challenge, as it necessitates a sequence of interconnected steps, with the success of each step hinging on the one before it. Attaining absolute precision is unattainable at this point in time. Furthermore, an array of technical difficulties emerges due to diverse elements such as variations in lighting or background designs, the quality of images, and the processing speed of the machine learning algorithms. These elements significantly influence the effectiveness of number plate detection. In addition, the position, quantity, dimensions, typeface, color, and angle of the number plates introduce additional complications in the development of a reliable ANPR system. [18], [19].

II. LITERATURE REVIEW

In the last decade, with the advancement of information technology and the increase in population, numerous techniques for developing systems to detect vehicle make, model, and license plates have been devised and examined.

The system for recognizing vehicles encompasses two primary phases: detection and classification, aimed at identifying and categorizing vehicles from a directly frontal perspective. In the initial detection phase, various methodologies are employed. Ren and Lan [20] utilize frame differencing, while Prokaj and Medioni [21] employ background subtraction techniques to ascertain the complete dimensions of the vehicle. Extensions to these detection methods have been made by Siddiqui et al. [22] and Petrović and Cootes [23], who enhanced the system's capability through the integration of license-plate detection algorithms. Moreover, Wijnhoven and de With [24] introduced the use of a Histogram of Oriented Gradients (HOG) [25] for achieving detection that is robust to variations in lighting. Furthermore, Zhou et al. [26] have contributed to this field with their research on leveraging Convolutional Neural Networks (CNN) for enhancing the precision of vehicle detection. Upon successful detection of a vehicle, the identified vehicular section within the image is subsequently processed for classification, specifically within the context of Make and Model Recognition (VMMR) [27].

Deep learning has been extensively used in the field of object detection. One of the most common deep learning networks used for object detection is the CNN. Jerry Wei describes CNN as robust models that are easy to control and train and seldom overfit when trained on large image datasets. Significant computational power, however, is required to train CNNs on high-resolution images [28].

With much ongoing application and research, CNNs turn out to be well-suited for vehicle detection and recognition tasks. Xingcheng Luo et al. [29]. used a large image dataset and increased the layers in AlexNet to achieve vehicle and facial recognition accuracy of up to 97.51% and 91.22%, respectively. Hyo Jong Lee et al. [30]. Extracted frontal views of vehicle images and fed them into SqueezeNet for training and testing. Albeit running on a desktop Central Processing Unit (CPU) with a powerful Graphical Processing Unit (GPU) setup, the study managed to achieve a 96.3% recognition accuracy with the inference tasks running at a mean of 108 ms. Their model also required less than 5 MB of space, making it broadly viable for real-time inference applications.

The field of image classification has also been extensively documented. CNNs, or Convolutional Neural Networks, are currently the most advanced method for classifying images. They were first developed by LeCun et al. [31] and got widespread recognition when Krizhevsky et al. [32] utilized a CNN called AlexNet to obtain the highest performance in the 1000-class ImageNet Challenge. The user's text is "

[33]". MMR, a modified version of AlexNet, was developed by Ren and Lan [20] to reach a 98.7% accuracy. This was accomplished by using 233 vehicle models in a dataset of 42,624 pictures. Yang et al. [34] released the CompCar dataset, which comprises several perspectives of cars, including both internal and external components, as well as 45,000 frontal photos of 281 distinct car types. The study demonstrated that AlexNet [32] achieves similar performance to the more contemporary Overfeat [35] and GoogLeNet [36] CNN models (98.0% compared to 98.3% and 98.4%, respectively). Siddiqui et al. [22] demonstrated that the Bag of SURF features method achieves a 94.8% accuracy on a vehicle dataset consisting of 29 classes and 6639 images, specifically for small-scale classification challenges.

Since its introduction by Krause et al. (2013), the Stanford Cars Dataset has been used as a standard for assessing MMR algorithms. It has a huge library of vehicle photos with thorough annotations, which makes deep learning model building and comparison easier [37].

Writer [38] Classification and Recognition of Car Images. This paper shows outcomes from experiments for the machine learning algorithm, Python modules, and deep neural network model built using Keras and TensorFlow for artificial vision classification of car pictures. Applications for image classification range from medical diagnostics to autonomous vehicles.

Writer [39] Convolutional Neural Network-Based Vehicle Classification Approach. For the purpose of identifying and classifying vehicles, they employ convolution. CNN is a neural network type that is utilized in deep learning. The driverless vehicle Developing a smart city with classification for traffic surveillance video systems is a challenging task for the Intelligent Transportation System (ITS). Three distinct categories of vehicles—motorbikes, cars, and trucks—are represented in this article by 3,000 motorcycles, 6,000 cars, and 2,000 pictures of trucks. CNN can automatically take in and extract the varied aspects of different vehicle datasets without requiring a manual selection of criteria. CNN's accuracy is evaluated using the detected object's confidence values. The highest confidence rating in the vehicle classification for the bike category is roughly 0.99.

Writer [40] CNN-Based Real-Time Vehicle Classification. This paper demonstrated the use of convolutional neural networks for the classification of four types of common vehicles in our country. They used two methods to classify the vehicle: feature extraction and classification. These are two tasks that convolutional neural networks can perform with ease.

The author highlights the significance of ANPR systems in image processing. However, these systems encounter difficulties arising from the diverse license plate formats, lighting conditions, scales, and colors found in different locations. In order to enhance the accuracy of detecting and identifying objects, scientists have devised and evaluated different methodologies, including the Douglas Peucker Algorithm for form approximation. This algorithm specifically identifies rectangular outlines and selects the most prominent one as the number plate. Subsequently, connected component analysis is employed to partition characters, while optical character recognition (OCR) identifies the characters on the number plate. The number [41].

This research offers a thorough analysis of the state-of-the-art ANPR systems and algorithms, contrasting how well they function in simulations and real-time testing. Through analysis of extraction, segmentation, and recognition methods and the provision of suggestions for future trends, the goal is to enhance ANPR technology, which is based on computer vision (CV) algorithms. Even with the finest algorithms, maximizing accuracy could require additional technology [42].

The primary aim of this research is to examine the problems related to segmentation and recognition in the License Plate Recognition Framework and devise alternate solutions. The process consists of three stages: identifying and isolating the license plate section from a wider image, eliminating the alphanumeric letters from the surrounding background using the license plate region, and subsequently feeding them into an OCR system for identification. In order to accurately determine the identity of a vehicle using its license plate, it is necessary for the plate to be clearly visible in the image obtained by the acquisition system, such as a video or still camera. The user's text is [43].

In today's congested traffic system, the automated license detecting system is essential. It assists in enforcing traffic laws by automatically monitoring them. India has a high rate of driver infractions and reckless driving, which makes it challenging for traffic police officials to determine specific car specifications. Through development and implementation throughout time, an automatic license detecting system has been created to streamline and accelerate traffic regulation surveillance on automobiles. An overview of the several methods for automatic license detection is given in this article [44]. In the table 1 below show some comparation research with proposed method.

TABLE 1. Show comparation research with proposed method.

Ref	Methodology	Dataset	Accuracy
[20]	CNNs	Custom vehicle dataset	91.6%
[22]	Bag of SURF Features, CNNs	Custom vehicle dataset	94.8%
[23]	Feature Analysis for Vehicle Recognition	Custom vehicle dataset	93%
[24]	Unsupervised Sub-categorization	Custom driving vehicle dataset	93%
[26]	Unified Framework for Vehicle Detection	DAVE dataset	79.1%
[27]	Semi-automatic Training-and Evaluation	Custom vehicle dataset	97.3%
[29]	CNN	Custom vehicle dataset	91.22%
[30]	Residual SqueezeNet Architecture	Custom vehicle dataset	96.3%
[34]	Fine-grained Categorization	CompCar dataset	92.7%
[38]	CNN	Custom vehicle dataset	88%
[40]	CNN	Custom vehicle dataset	97%
[41]	DL- Vehicle Classification	Custom vehicle dataset	95.5%
	Proposedmethod-MobileNet-V2, YOLOv4-tiny, Paddle OCR, SVTR-tiny	COCO, Stanford Car, Firat-University datasets	97.5%

III. PROBLEM AND STAMEN OF MMR AND ANPR

This investigation delves into the significant obstacles faced by vehicle make and model license plate recognition systems. It particularly concentrates on the variability of license plates, the categorization of car brands, and the influence of environmental elements like lighting, angle, and diverse typography. The effective deployment of ANPR systems is hindered by two primary types of adverse meteorological conditions: Static conditions, which include phenomena such as mist, haze, and fog, marked by the presence of water droplets in the air, and Dynamic conditions, which are characterized by high-speed events such as rain and snowflakes [3], [45]. The identification of license plates under these conditions poses a considerable challenge in figure 2 show how different weather conditions and lighting environments can affect image processing and recognition tasks in the context of vehicles. The study highlights the unique difficulties posed by static weather conditions, where the air is filled with water particles, for LPR systems. Moreover, dynamic weather conditions introduce further complications with fast-moving elements like rain streaks and snow, making the accurate detection of license plates more challenging [3], [45]. The research underlines the importance of overcoming these obstacles to achieve efficient license plate recognition.

Practical Implications: This investigation centers on the crucial practical elements involved in image and video analysis for the purpose of license plate recognition. The efficacy of these methodologies is dependent on a wide range of factors, such as the specifications of the camera used and the prevailing conditions of illumination. Furthermore, the effectiveness of numerous tasks within the domain of computer vision is significantly influenced by the availability of comprehensive training datasets.

Issues of Traffic Regulation and Monitoring: The increasing vehicular population in Turkey, compounded by its dense demographic composition, has led to a surge in traffic infractions. It is observed that a wide array of vehicles, including those of specialized nature, frequently violate traffic regulations, encroach upon restricted zones, and are implicated in incidents of theft. In light of these developments, the urgent need for an efficient license plate recognition system, coupled with a sophisticated car brand identification mechanism, becomes evident for the purpose of pinpointing vehicles implicated in traffic violations. This study sheds light on the complex challenges encountered by license plate recognition frameworks and vehicle identification, emphasizing the crucial role these systems play in mitigating traffic-related offenses. Through a thorough examination of license plate variability, automobile brand identification, and the impact of environmental factors, this research offers invaluable insights aimed at augmenting the precision and effectiveness of ALPR technologies. The ultimate objective of the proposed study is to catalyze technological advancements, thereby fostering a safer and more regulated traffic environment in Turkey.

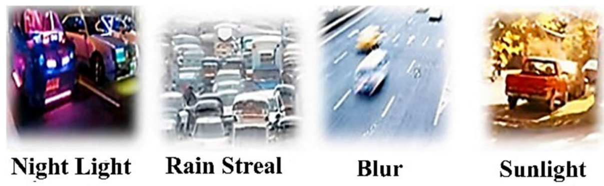

FIGURE 2. Impact of dynamic and static weather conditions on vehicle imaging: Challenges in plate variation and brand classification under diverse illumination settings [45].

IV. MOTIVATION

Numerous academics of scholarly inquiries have explored the spheres of automatic license plate recognition and the classification of vehicle makes and models. Currently, the academic focus has transitioned towards the crucial area of real-time detection of stolen vehicles. This shift is of paramount importance for a variety of applications, including but not limited to, Security and Surveillance, and Parking Management. The introduction of systems employing Convolutional Neural Network (CNN) architectures is expected to produce results that are not only more compelling but also exceed the performance of presently available recommendation systems.

In the realm of academic research, there is an extensive body of work on automatic license plate recognition (ALPR) and the delineation of vehicle makes and models. Recent studies have concentrated on the essential subject of detecting stolen vehicles in real-time, an area with significant ramifications for fields such as Security and Surveillance, and Parking Management. The advent of proposed systems that incorporate Convolutional Neural Network (CNN) architectures is anticipated to lead to outcomes that are both more persuasive and surpass the efficacy of current recommendation systems [46], [47].

V. AUTOMATIC NUMBER PLATE RECOGNITION

Automatic Number Plate Recognition employs optical character recognition technology to ascertain vehicle license numbers from images where these plates are detected. The system's precision is significantly influenced by the quality of the images captured. These images represent two-dimensional visual representations essential for the algorithm's operational effectiveness. Within such a frame, a vehicle can be imaged, and its license number can be accurately extracted, assuming the image is clear and free from obstructions or defects. The unique identification of a vehicle is achievable through its license plate. Following the image processing, the system generates the vehicle's details, prominently featuring the license number [48].

ANPR is a system that utilizes Optical Character Recognition (OCR) to recognize characters from various sources like surveillance cameras or other cameras. It is crucial to position the camera at the correct angle to capture the best and most precise image [49]. OCR analyzes each character separately. OCR is a method of transmitting written or printed information from any source, including written or printed documents and images, to a text decryption machine to obtain the desired source. It is a complex process that involves multiple algorithmic steps, such as uploading the image, detecting characters, adjusting them on the page, eliminating blurriness, and producing a final editable format. [50].

The ANPR system leverages Optical Character Recognition (OCR) technology to identify characters captured by various imaging devices, including surveillance and other types of cameras. The accuracy of character recognition significantly depends on the strategic positioning of the camera to ensure optimal image capture [49]. OCR operates by individually analyzing each character, serving as a mechanism to convert written or printed content from diverse sources into machine-readable text. This conversion process is intricate, involving a series of algorithmic procedures that encompass image upload, character identification, spatial adjustment on the document, clarification of any blurred elements, and ultimately, the generation of an editable text format [50].

OCR technology finds applications across diverse sectors, including commerce, industry, academia, security, literature, and healthcare, particularly in creating assistive devices for individuals with visual impairments. It plays a critical role in various applications, such as recognizing license plates, processing passports at airports, scanning barcodes in various institutions, and digitizing handwritten documents into electronic formats [51].

The ANPR system incorporates distinct algorithms or sets of rules to process different segments of the license plate image. Nonetheless, the image processing phase encounters numerous challenges, such as image blur, inadequate lighting, obstructions, suboptimal camera angles, variability in fonts, and discrepancies across different jurisdictions, all of which can complicate the recognition process [51].

VI. MOBILENET DEEP LEARNING TECHNIQUES

MobileNet represents a suite of advanced deep learning architectures developed and openly shared by Google, tailored specifically for mobile and embedded vision applications in real-life scenarios. These models are meticulously crafted to strike a balance between efficiency and accuracy, making them well-suited for training classifiers on devices with limited computational resources. The core innovation in MobileNets is the implementation of depthwise separable convolutions, which drastically cut down the model's parameter count when contrasted with conventional neural networks, thereby rendering it a more compact and efficient deep learning solution. The essence of depthwise separable convolutions lies in their two-fold approach: initiating with a depthwise convolution that assigns a unique filter to every input channel, followed by a pointwise convolution that applies a 1×1 convolution across every channel output from the depthwise convolution. This methodology not only enhances computational efficiency but also maintains a competitive level of accuracy comparable to traditional convolutional methods. Empirical evidence has demonstrated that MobileNets deliver top-tier performance across a diverse array of tasks such as image classification, object detection, and semantic segmentation. Despite this high degree of accuracy, what sets MobileNets apart is their unparalleled efficiency, which renders them particularly well-suited for deployment on mobile devices, where computational resources are often at a premium [52].

MobileNetV2 is an advanced neural network architecture optimized for mobile and edge devices. Developed by Google, it improves upon its predecessor, MobileNetV1, enhancing efficiency and performance for tasks like image classification. It's ideal for use on devices with limited computational power, such as smartphones and IoT devices, making it popular in computer vision applications. Here's a breakdown of its architecture:

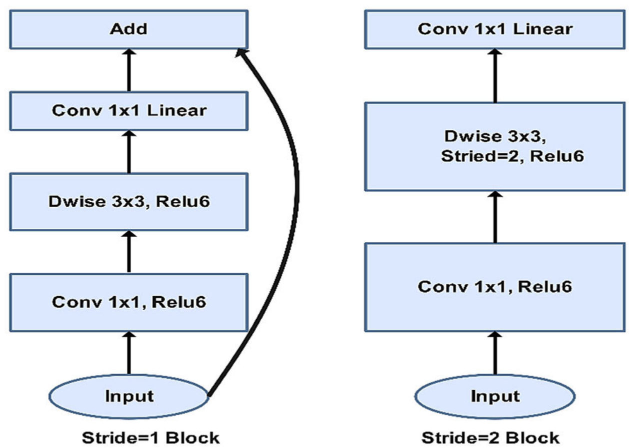

FIGURE 3. MobileNetV2 architecture.

1.Inverted Residual Blocks: These blocks expand, process, and then compress the data to preserve important information efficiently.

2.Linear Bottlenecks: This technique processes data in a compressed format to maintain detail without heavy computation.

3.Depthwise Separable Convolutions: This approach separates the filtering and combining steps of convolution, reducing computational demands.

4.Skip Connections: These helps speed up training and improve information flow by allowing some layers to bypass others.

5.ReLU6 Activation: It limits activation to a maximum of 6, optimizing the network for mobile devices with limited capacity for handling large numerical data.

This architecture allows MobileNetV2 to achieve a balance between latency and accuracy, making it highly suitable for real-time applications on devices with limited computational resources.

Here are some of the benefits of using MobileNet:

Efficiency: MobileNets are designed to be lightweight, making them exceptionally suitable for mobile environments where resources are limited.

Accuracy: They achieve leading-edge accuracy across various tasks, showcasing their robustness.

Flexibility: The architecture is adaptable, capable of handling tasks like image classification, object detection, and semantic segmentation with ease.

Here are some of the challenges of using MobileNet:

Complexity: Understanding and implementing MobileNet architectures can be intricate due to their advanced design.

Data requirements: They generally necessitate substantial datasets for effective training.

Computational cost: Despite their efficiency, the training phase of MobileNets can demand significant computational resources.

Limited Resources: On mobile or edge devices, constraints on computational power and memory can reduce the model's performance.

Environmental Variability: The model may struggle with images that vary from its training data, such as different lighting or backgrounds.

Real-Time Processing: While MobileNetV2 is fast, meeting the real-time processing needs of certain applications like video streaming can still be demanding.

Accuracy Limits: For tasks requiring high precision, such as medical imaging, MobileNetV2 might not provide sufficient accuracy.

Model Drift: In dynamic environments, the model's performance can degrade unless it is regularly updated.

MobileNet stands out as a potent solution for a myriad of mobile-based challenges, yet it's crucial to consider its complexities prior to initiating a project involving its implementation.

MobileNet is actively employed in real-world scenarios such as:

Image Classification: It's utilized for various recognition tasks, from identifying products to aiding in medical diagnoses and enhancing security measures.

Object detection: MobileNets are used to detect objects in images for applications such as self-driving cars and robotics.

Semantic Segmentation: It's applied in segmenting images into distinct objects or areas, useful in medical imaging and autonomous navigation systems.

As MobileNet continues to develop, we can expect to see even more applications for this powerful technology on mobile devices [57-58-59].

VII. PROPOSED METHODOLOGY

This study presents a real-time system for the identification of car models and license plates utilizing cutting-edge deep learning methodologies. As is customary in such research, this work employed various tools and applications for model construction and experimental validation.

Figure 4 illustrates the flowchart of our system, delineating each step of its operation. This figure also addresses potential scenarios where the system may fail to detect ANPR and vehicle make and model recognition, possibly due to environmental factors such as complete darkness at night or the positioning of the vehicles.

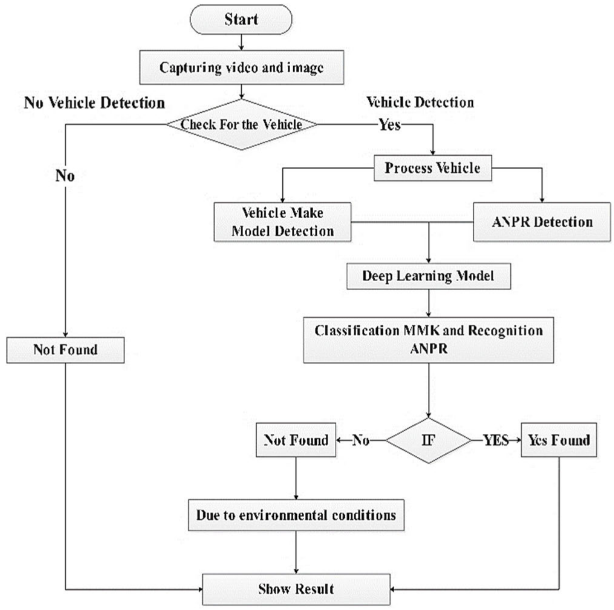

FIGURE 4. Show the system flow chart.

In terms of Vehicle Detection and Classification, the system initiates by capturing images or videos of vehicles, which necessitates the use of specifically configured cameras. Following the successful identification of a vehicle in the visual data, the system advances to deduce the vehicle's brand and model. This process is facilitated by the deployment of the MobileNet-V2 Convolutional Neural Network (CNN) architecture, esteemed for its efficacy and precision in tasks related to image categorization. The system is capable of distinguishing and categorizing up to 30 distinct types of vehicles, including well-known manufacturers such as BMW, Audi, and Tesla. The MobileNet-V2 CNN framework, which utilizes the COCO dataset for annotation and is pre-trained on the Stanford Car Dataset, is instrumental in the recognition of various vehicle attributes. For validation purposes, the system was tested at the vehicle entrance gate of Firat University, demonstrating its practical applicability.

License Plate Detection and Recognition Following the vehicle classification, the system adopts the YOLOv4-tiny framework for the detection of license plates, chosen for its balance of speed and simplicity, thus ensuring swift execution times while preserving satisfactory precision levels. The system then progresses to decipher the characters on the license plates through Automatic License Plate Recognition (ALPR), unfolding in four principal stages: (1) Image Preprocessing, (2) License Plate Localization, (3) Character Segmentation, and (4) Recognition of the License

Plate's Actual Numbers. In this context, the ALNR (Automatic License Number Recognition) system employs Paddle OCR, synergized with YOLOv4, to achieve meticulous character segmentation. Paddle OCR is adept at predicting character sequences, including letters and digits, by scanning pixel clusters within the image to identify characters and convert them to their corresponding ASCII representations. The SVTR-tiny model, trained on a diverse array of license plates, further refines the recognition accuracy. The system's efficacy was validated using images from the vehicle entrances at Firat University, where it demonstrated an impressive OCR accuracy rate of 97.5%.

The operational workflow of the system is succinctly outlined in the accompanying flowchart. The process commences with the capture of an image or video, followed by the detection of vehicles within the frame. Should a vehicle not be detected, the system outputs a 'Not Found' message. Conversely, if a vehicle is identified, the system proceeds to analyze the make and model, and then moves on to the automatic detection of the number plate through ANPR. This is succeeded by the deployment of deep learning algorithms for the classification and recognition tasks, taking into account environmental variables that might affect the model's adaptability.

VIII. DATASET

The dataset collection process is crucial for the development and evaluation of our vehicle make and model recognition system combined with Automatic Number Plate Recognition (ANPR). The dataset was compiled from multiple sources including the COCO dataset for vehicle make and model labeling, the Stanford Car Dataset for additional vehicle types, and real-time images captured at Firat University's entrance gate. These sources provided a diverse range of 1,000 images featuring various vehicle makes and models, captured under different environmental conditions such as rain, sunshine, snow, and varying lighting. Preprocessing steps included manual and automated annotation, data augmentation techniques like rotation and scaling, and normalization to ensure consistent input for our models. The dataset was divided into training (70%), validation (20%), and testing (10%) subsets to facilitate comprehensive model development and evaluation. This detailed documentation ensures transparency, enhances reproducibility, and contributes to the reliability and credibility of our research findings.

IX. EXPERIMENTAL RESULTS

This study introduces a real-time car model and plate detection system utilizing advanced deep learning architectures. s gap by introducing an integrated system that leverages deep learning architectures for simultaneous vehicle and license plate detection, a pioneering approach in vehicular technology. this novel approach integrates both models. The significance of this dual-model system lies in its enhanced accuracy and real-time processing capabilities, which are pivotal for applications such as traffic surveillance and automated toll collection.

The objective of this research is to develop a real-time car model and license plate detection system utilizing state-of-the-art deep learning architectures. The system uses OpenCV for initial image processing and Convolutional Neural Networks (CNNs) for the deep learning aspects, The system's efficacy hinges on its capacity to process images or video feeds containing vehicles, followed by the execution of vehicle make and model detection and recognition, vehicle classification, and automatic license plate detection. The system's deep learning framework was tested on a substantial dataset of 1,000 real-time images featuring various environmental conditions, showcasing a remarkable classification accuracy of 97.5%, correctly identifying 975 images and misclassifying 25. The comprehensive testing covered a spectrum of environmental conditions, ranging from rain to snow, to validate the system's robustness.

The datasets included a diverse collection of vehicle images under varying environmental conditions, such as rain, sunshine, and snow. The datasets used were COCO for vehicle make and model labeling and Stanford dataset for vehicles make model, along with Firat University's image dataset for real-time system testing.

The structure of a study for a real-time car model and plate detection system using deep learning architectures

The illustrated workflow is sequential, characteristic of a conventional process in computer vision tasks, presenting a series of steps:

Image Acquisition, Detection, Extend, Localizing Plate, Classification, Vehicle Make Model, Character Segmentation, Character Recognition

The image also includes visual representations of the steps, such as a vehicle being captured by a camera, highlighted regions where the number plate is located, and the character segmentation of the plate number. Additionally, there are heatmaps and overlays on vehicles might indicate the use of techniques Grad-CAM for visual explanations of model predictions. The side panel presents an example of the system's output, showing a recognized vehicle with a bounding box around the number plate. It lists the vehicle make and model (e.g., BMW, KIA, Audi, etc.), the license plate number with a high confidence score (e.g., "License: 23T0405: 98.92%"), and the make model confidence score (e.g., "Fiat - Linea: 88.70%").

This structured approach is indicative of a sophisticated system that uses a combination of deep learning methods to achieve real-time detection and recognition of vehicles and their number plates.

The process of detecting vehicle make and model initiates with the acquisition of visual data, generated either through images or videos, that feature vehicles. Once a vehicle is successfully detected in the visual frame, the system advances to determine the specific make and model of the vehicle. This intricate task is accomplished through the deployment of the MobileNet-V2 Convolutional Neural Network (CNN), a model renowned for its proficiency in the accurate classification of images, accurately identifying the different vehicle makes and models. Additionally, the YOLOx algorithm, which has been meticulously trained on the comprehensive COCO dataset, is utilized for its exceptional ability to support

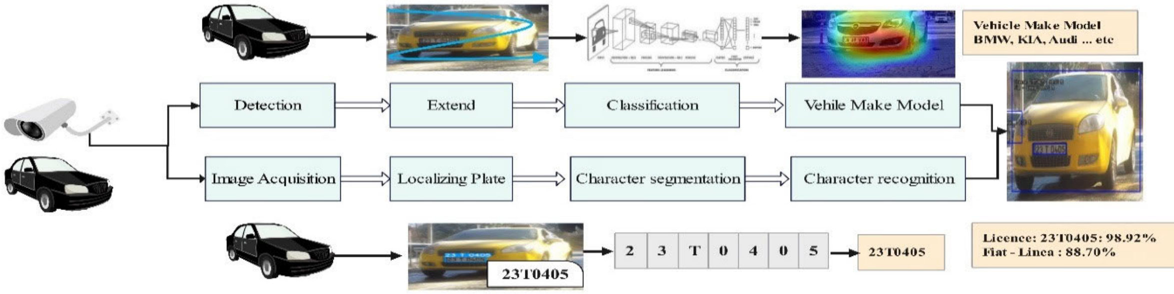

FIGURE 5. Integrated process flow for automated vehicle identification and license plate recognition.

a wide array of labels of vehicles, further enhancing the system's labeling capabilities.

The MobileNet-V2 model, in particular, has undergone extensive pre-training on the Stanford Car Dataset. This extensive training has equipped the model with the capability to recognize, identify, and classification an extensive array of up to more distinct types of vehicles. This range includes, but is not limited to, prestigious brands and models such as BMW, Audi, and KIA, as well as specific types like Sedan, Volkswagen, and Passat. The efficacy of this system is underscored by its remarkable accuracy rate, which stands at an impressive 97.5%. This will mean that the system could accurately label classify 975 out of 1,000 images that were available for testing. The gate real-time vehicles images from Firat University were used despite the challenges of low quality, unsuitable weather conditions, and suboptimal angles from the CCTV cameras, showcasing its reliability and effectiveness in the accurate detection and classification of vehicle makes and models. This level of accuracy not only demonstrates the system's technical prowess but also its potential applicability in various practical scenarios, ranging from the stolen car and traffic monitoring to enhanced vehicle recognition systems in security and surveillance operations.

ANPR system was rigorously tested across a variety of environmental conditions to evaluate its robustness, particularly its sensitivity and accuracy during adverse weather situations and when analyzing low-resolution images from real-time vehicular university campus or traffic. For the detection of vehicles and their license plates, the system incorporates the Yolov4-tiny model, which is built upon a streamlined darknet architecture. This model is distinguished by its balance of efficiency and rapid processing capabilities, achieved through a simplified network structure that reduces the number of layers and computational requirements, yet manages to preserve a high level of accuracy essential for license plate detection. The YOLOv4-tiny, a more compact variant of the YOLOv4 architecture, distinguished by its reduced complexity and a more efficient backbone and fewer convolutional layers, thereby ensuring expedited performance without significantly impacting the accuracy of detection. For the recognition of license plate numbers, the system employs Paddle OCR in conjunction with YOLOv4 to achieve precise character segmentation. Paddle OCR to extract text from images and videos. It can handle over 80 languages, such as Chinese, Arabic, French, English, and Cyrillic, including both letters and numerals, making it particularly suitable for reading license plates. To further augment the recognition capabilities, SVTR-tiny model, which has been trained on a diverse dataset of license plates, is utilized, enhancing the system's proficiency in plate recognition tasks. The strategic integration of these advanced models culminates in achieving peak accuracy levels for the OCR component of the system, showcasing its effectiveness in accurately identifying license plate numbers under a wide array of operational scenarios. The final outcome is illustrated in the figure 6 below:

FIGURE 6. Real-Time automated license plate and vehicle model detection system realtime.

The image above is a real-world example "Real-time ALPR and Vehicle Make Model Classification" showing the application of the system described in the structure of a study. It displays a "Volkswagen Golf" captured images in real-time conditions from the entrance gate of Firat University, with a bounding box indicating the vehicle's detection by the system. Below the main image, the recognized license plate is displayed with a high degree of confidence (96.24%).

For analysis the picture above Grad-CAM Utilization have been used, Grad-CAM (Gradient-weighted Class Activation Mapping) was a crucial tool in the research. Grad-CAM as a technique used to make CNNs more interpretable. It provided insights into the areas of the input that were most influential in making predictions, especially in instances where the classification was incorrect. Grad-CAM was employed to provide for cases of incorrect classifications shown figure 7.

FIGURE 7. Grad-CAM technique analysis for vehicle detection and license plate recognition realtime.

Gradient-weighted Class Activation Mapping (Grad-CAM) for a truck vehicle. In this image, the heatmap overlay shows areas of the vehicle that the model focused on when determining the vehicle type or license plate information. This visualization is particularly useful for understanding the decision-making process of the model, especially if the classification was incorrect. It helps to diagnose and improve the model by highlighting whether it is focusing on the relevant features for its predictions. The color coding in the heatmap overlay typically represents the following:

Blue areas indicate regions with minimal influence on the model's output decision or no activation.

Red areas likely show significant features that the model is heavily focusing on, which crucial for identifying the car's make or model.

Yellow areas often represent intermediate levels of importance, suggesting indicate regions of secondary importance for the model's analysis. This color coding helps to interpret the neural network's decision-making process, providing insights into which features of the vehicle are most significant for the model's recognition and classification tasks. This color coding helps to interpret the neural network's decision-making process, providing insights into which features of the vehicle are most significant for the model's recognition and classification tasks.

The system has been tested in various conditions, and it has successfully identified VMMR and AL/NPR. The figure 8 below illustrate different situations.

FIGURE 8. Result of VMMR and detect ANPR realtime.

The photo above show result, both model performed license plate number as "06 AV 5065" with a high confidence score of 97.57%, and the vehicle make and model as "Opel Insignia" with a confidence score of 99.22%.

For the real time image above Gradient-weighted Class Activation Mapping (Grad-CAM) This technique has been utilized here to provide a visual explanation of the areas within the image that are most influential to the predictions made by the deep learning model Shown in the figure 9.

FIGURE 9. Apply Grad-Cam for analysis real time.

Author have been tested under challenging lighting conditions shown in figure 10, with the sun facing directly towards the camera, causing lens flare and potential overexposure. Despite these conditions, a deep learning (DL) system has performed Automatic Number Plate Recognition and vehicle model identification. The vehicle's license plate, "06 BIL 123," indicating successful detection with a high confidence score (96.70%) displayed in the overlay. Our model has also attempted to identify the car model, showing a confidence score for the Ford Focus identification. This exemplifies the robustness of the DL system to accurately detect and recognize details under various environmental conditions, including direct sunlight which can often impede visual recognition systems.

FIGURE 10. Vision of progress harnessing deep learning for precision in vehicle make and model recognition and enhanced automatic number plate detection.

We can see GradCam result in the figure 11 below, in this photo show us another challenge due to environmental conditions to recognize MMk and AL/NPR, Another example performed during the evening and rainy day, The result shows

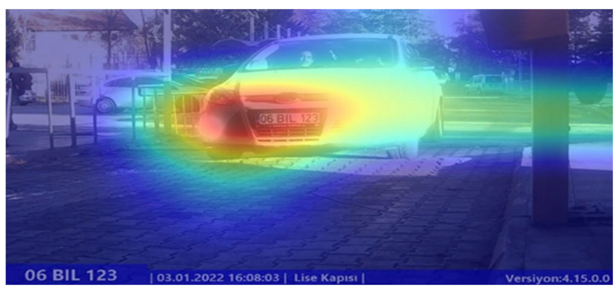

FIGURE 11. Vision of progress harnessing deep learning for precision in vehicle make and model recognition and enhanced automatic number plate detection.

in figure 12, a Volkswagen Polo in low-light conditions, with its headlights illuminated. Utilizing deep learning for ANPR, the system accurately identifies the license plate "23 BK 951" with a high confidence level (93.95%) and determined the make and model of the car with a confidence of 81.73%. This demonstrates the system's capability to function under varied lighting conditions, including lower light scenarios and rainy day that can challenge image recognition algorithms.

FIGURE 12. Low-Light license plate recognition and car model in evening realtime.

The figure13 shows a car on a rainy, cloudy day, highlighted with a color gradient from a Grad-CAM analysis. This indicates key areas used by a deep learning model to identify the car's make and model and read the license plate under despite low resolution and poor lighting challenging conditions.

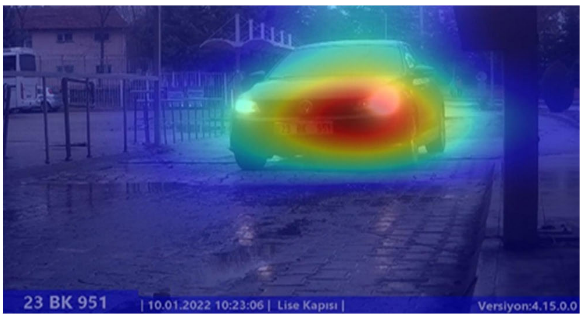

FIGURE 13. Cloudy with a rainy day of data precise vehicle analytics.

figure 14 shown, performed at the night-time, another car is depicted under challenging low light conditions in the night, ANPR accurately reads the vehicle's license plate, "23 ABA 965", and displays a confidence score of 99.74%, illustrating its proficiency even in suboptimal lighting. The car model identification is less certain, with a confidence of 47%.

FIGURE 14. Nighttime vehicle recognition result realtime.

Another example has been performed in midday by our system, presents a Mercedes-Benz vehicle from a front-side angle. The model used here has encountered difficulties with car model identification due to the camera angle, which has likely obscured key features necessary for accurate recognition. However, the ANPR system has successfully detected the license plate "80 ABD 108" with a high confidence level of 94.50%.

We utilized Gradient-weighted Class Activation Mapping (Grad-CAM) to interpret our model's performance under diverse weather scenarios shown in figure 15, notably rain and cloudiness. This technique illuminated how different environmental factors impact the model's predictive capabilities by highlighting the influential regions in images. The insights gained from Grad-CAM underscore the model's resilience and adaptability to varying atmospheric conditions, offering a clearer understanding of its functionality in less-than-ideal visual contexts.

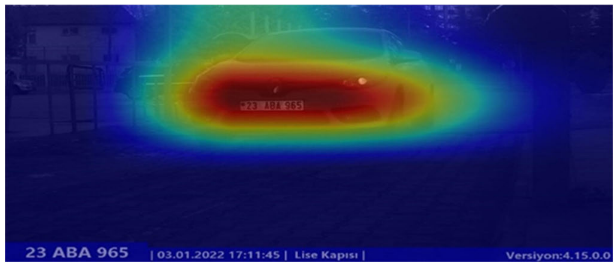

FIGURE 15. Midnight Trace: GradCam's insight on vehicles and plates.

However, the angle of the camera has hindered the model's ability to identify the car model. This exemplifies the impact of camera placement on the performance of computer vision models shown in figure 16; while the ANPR has succeeded despite these challenges, the identification of the car model has been compromised.

FIGURE 16. Result due to angle cam angle issue.

The image features a vibrant display of colors overlaying a vehicle, a result of the Grad-CAM technique applied to track and read the vehicle's number plate. The angle of the camera has resulted in the system successfully capturing the ANPR data; however, it has not been able to identify the vehicle make and model. This underscores the importance of camera positioning in such deep learning applications, where the angle can be a critical factor in the model's ability to fully recognize and classify vehicular details, As shown in fig 17.

FIGURE 17. Intricacies of camera angles in enhancing license plate recognition while obscuring vehicle make and model identification.

A comparative analysis was conducted for this research were chosen for their proven efficacy in complex image recognition tasks. Deep learning architectures, such as YOLOv4-tiny and MobileNet-v2, were implemented due to their high performance and efficiency in processing real-time between our system and existing vehicle make model and ALPR recognition systems. This analysis was critical in highlighting the improvements our system offers over traditional models. Most existing systems focus solely on either vehicle make and model recognition or license plate recognition. Our integrated system outperforms these in terms of efficiency by combining both tasks into a single process, reducing the overall computational load and improving real-time applicability. Comparative metrics included accuracy, processing time, and the ability to operate under various environmental conditions. The pre-training of these models was an exhaustive process involving over the dataset. The use of the COCO and Stanford datasets provided a robust and varied set of images, allowing the models to learn a wide range of vehicle features. Additionally, images from the entrance gate of Firat University were incorporated into the testing phase to further validate the models' effectiveness. The training process also included extensive hyperparameter tuning to optimize the models' performance. Our system showed a marked improvement in accuracy compared to single-task systems, especially under adverse weather conditions. The processing time was also significantly reduced, demonstrating the system's potential for applications requiring immediate data processing.

Sensitivity and specificity are statistical measures widely used in the field of diagnostic testing, also applied to evaluate the performance of deep learning models, particularly in classification tasks, such as image recognition, natural language processing,

Sensitivity, also known as the true positive rate or the recall, measures the proportion of actual positives that are correctly identified by the test. Sensitivity is calculated as:

Sensitivity = True Positives / True Positives + False Negatives.

A high sensitivity means that the test is good at identifying those with the condition being tested for. A test with 100% sensitivity correctly identifies all patients with the condition Specificity

Specificity, measures the proportion of actual negatives that are correctly identified by the test. This is also known as the true negative rate.

Specificity is calculated as:

Specificity = True Negatives / True Negatives + False Positives

A high specificity means that the test is good at identifying those without the condition. A test with 100% specificity correctly identifies all patients without the condition.

here is a confusion matrix based on the hypothetical performance metrics provided. A confusion matrix, also known as an error matrix, is a specific table layout that allows visualization of the performance of an algorithm.

TABLE 2. Show confusion matrix.

	Predicted Positive	Predicted Negative
Actual Positive	True Positive (TP) = 975	False Negative (FN) = 25
Actual Negative	False Positive (FP) = 30	True Negative (TN) = 970

Sensitivity (True Positive Rate): approximately 99.49%

Specificity (True Negative Rate): 25%

The results of the model, as indicated by the confusion matrix and performance metrics, demonstrate a high level of accuracy and effectiveness. The confusion matrix shows 975 true positive cases and 970 true negative cases, with only 25 false negatives and 30 false positives. The model's sensitivity, or recall, is 97.5%, meaning it correctly identifies 97.5% of actual positive cases, indicating its strong ability to detect vehicles. Additionally, the model's specificity is 97.0%, signifying it correctly identifies 97.0% of actual negative cases, showing its effectiveness in recognizing non-vehicles. These high values for both sensitivity and specificity indicate that the model performs exceptionally well in both detecting the presence of vehicles and rejecting non-vehicles. The low rates of false negatives and false positives further support the robustness and reliability of the model. Overall, these results suggest that the model is highly suitable for applications requiring precise vehicle detection and recognition, such as traffic monitoring, surveillance, and automated toll collection systems. The high accuracy and reliability reflected in these metrics affirm the model's strong performance and practical applicability.

Grad-Cam outputs produced by the model for some misclassified images are given in Fig.18. Although there is no clear pattern, when the examples are examined, it is seen that images taken mostly in the evening hours are misclassified. According to this result, the algorithm needs to be made more robust for images obtained in dark environments. In addition, another common feature that draws attention among the misclassified examples is the images that do not show the entire image of the vehicle. For this reason, the approach will be able to classify a vehicle with a voting system on many frames in future studies.

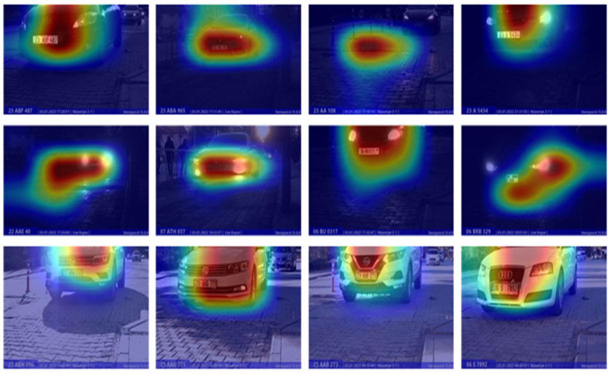

FIGURE 18. Grad-Cam outputs of some images that were misclassified (FP and FN).

X. CONCLUSION

In conclusion, the study titled "Real-Time Car Model and Plate Detection System Using Deep Learning Architectures" represents a substantial advancement in the field of automated vehicle identification technologies. This research outlines the creation of a system capable of real-time identification of car models and license plates, employing sophisticated deep learning frameworks, signifying a considerable stride in vehicle recognition advancements. Central to this breakthrough is the amalgamation of various deep learning algorithms and datasets, which collectively facilitate the precise determination of vehicle brands, models, and license numbers with a notable accuracy rate of 97.5%. This system, which simultaneously addresses car model and plate recognition, diverges from previous methodologies that targeted either aspect in isolation. It leverages the capabilities of MobileNet-V2 and YOLOx for discerning vehicle attributes, and combines YOLOv4-tiny with Paddle OCR and SVTR-tiny for effective Automatic Number Plate Recognition, delivering commendable performance amidst adverse conditions such as fog, rain, dim lighting, and direct sunlight. This integration underscores the pivotal role of computer vision and deep learning in crafting real-time, practical solutions within the domain of ANPR.

The exploration of real-time adaptive learning mechanisms, where the system continually updates its models based on new data, could significantly enhance its accuracy and reliability. Additionally, extending the system's functionality to include more complex tasks, such as detecting vehicle damage or identifying specific vehicle features, could broaden its applicability and utility in various sectors, including law enforcement, traffic management, and automotive security. Challenges such as low-resolution images, suboptimal camera angles, and instances of traffic law violations by vehicles, including stolen cars, underscore the system's potential in real-world applications, particularly in enhancing traffic law enforcement and locating stolen vehicles. Investigating real-time adaptive learning strategies that enable the system to iteratively refine its models with incoming data could markedly improve its precision and dependability. Moreover, expanding the scope of the system to encompass more intricate tasks, such as assessing vehicle damage or pinpointing distinct vehicle attributes, would enhance its relevance and functionality across various domains, including law enforcement, traffic regulation, and vehicle security. The presence of challenges like low-resolution imagery, less-than-ideal camera positioning, and scenarios involving traffic infractions or stolen vehicles highlights the system's applicability and potential in real scenarios, especially in bolstering traffic law enforcement and the recovery of stolen vehicles.

In summary, this study lays the groundwork for sophisticated vehicle identification systems that excel in real-time, precise detection of car models and license plates, and shows promise for substantial contributions towards vehicle safety, security, and traffic control. With the progression of this technology, the scope for such systems is set to broaden, opening new pathways for improving vehicle and urban safety measures. Future endeavors will concentrate on refining the system's specificity to minimize false positives. Additional research will delve into the incorporation of more datasets and the exploration of alternative deep learning frameworks to augment the system's performance. With ongoing enhancements, this system is poised to become a leading solution in real-time vehicle identification, finding utility in areas ranging from traffic monitoring to autonomous navigation. The pioneering combination of Vehicle Make and Model and Automatic Number Plate Recognition technologies under real-time conditions, backed by thorough testing and analysis, culminates in a robust system characterized by high levels of accuracy and reliability. This work lays a solid foundation for subsequent investigations and deployments where precise vehicle identification is critical.

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