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Vehicle Detection and Categorisation Using Deep Learning Algorithms

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Abstract: ***This research addresses the crucial task of real-time vehicle detection and traffic analysis on highways and busy roads, employing advanced object detection algorithms & deep learning techniques. The study focuses on identifying various vehicle types, including cars, SUVs, bikes, buses, and trucks, using four distinct algorithms: Single Shot Multibox Detector (SSD), Kalman Filter Algorithm, You Only Look Once (YOLO v7), and Mask Regional-Convolutional Neural Network (Mask R-CNN). The main goal of the research is to apply these algorithms in real-world settings on busy metropolitan roads and highways for purpose of traffic analysis. The study software is designed to monitor traffic flow and count the number of cars that pass by in a given period of time, like a day, a week, or a month. Additionally, the algorithm sorts these cars into various categories and offers a thorough statistical breakdown of the normal vehicle composition on the road under observation.***

The research's conclusions help politicians, transportation engineers, and urban planners by providing insightful information about traffic patterns. These algorithms enable data- driven analysis, which in turn informs decisions on traffic management, road infrastructure, and safety protocols. Through the integration of state-of-the-art technology with practical applications, this research makes a substantial contribution to the improvement of traffic monitoring systems, thereby facilitating safer and more intelligent urban movement.

Keywords: Real-time vehicle detection, traffic analysis, object detection algorithms, SSD, Kalman Filter Algorithm, YOLO, Mask R- CNN, statistical analysis, traffic patterns, traffic management, data-driven analysis, highway monitoring, urban road surveillance.

I. INTRODUCTION

In recent years, the integration of Artificial Intelligence (AI) techniques has revolutionized the field of computer vision, particularly in the domain of vehicle detection and traffic analysis. This burgeoning area of research holds paramount importance in modern transportation systems, enabling intelligent decision-making, traffic optimization, and enhanced safety measures.

This review paper delves into the application of AI in vehicle detection and traffic analysis, with a focused examination of four prominent algorithms: Single Shot Multibox Detector (SSD), You Only Look Once (YOLO), Faster R-CNN, and Kalman Filter. Each of these algorithms brings unique strengths and characteristics to the forefront, contributing significantly to the advancement of automated traffic management systems.

The primary objective of this paper is to conduct a comprehensive comparative study of these algorithms, evaluating their efficacy in real-world scenarios, computational efficiency, and robustness in handling diverse traffic conditions. Through a systematic analysis, we aim to provide valuable insights to researchers, practitioners, and policymakers in the field of transportation engineering and intelligent traffic systems.

Furthermore, this review adheres to the rigorous standards set by professional research paper publishers. It is structured to meet the criteria of academic excellence, ensuring a well-documented, methodical approach to presenting the state-of-the- art advancements in AI-driven vehicle detection and traffic analysis. The methodology employed in this review encompasses an extensive literature survey, precise algorithmic descriptions, experimental setups, and meticulous result analysis.

In the ensuing sections, we present a comprehensive overview of each algorithm, highlighting their key components, working principles, and notable contributions to the domain. Following this, we embark on a comparative analysis, delineating the relative merits and drawbacks of each algorithm. We conclude with a synthesis of findings and recommendations for future research directions.

Through this endeavor, we endeavor to foster a deeper understanding of the evolving landscape of AI-driven vehicle detection and traffic analysis, paving the way for more sophisticated and efficient transportation systems in the years to come.

II. LITERATURE REVIEW

III. The paper "Object detection system based on convolution neural networks using single shot multi-box detector" by Ashwani Kumar and Sonam Srivastava (2020) presents a system for object detection using the Single Shot MultiBox Detector (SSD) algorithm. The authors evaluated their system on the PASCAL VOC 2007 dataset and achieved a mean average precision (mAP) of 73.2%, which is comparable to other state-of-the- art object detection algorithms. The authors' system consists of two main components: a CNN backbone and an SSD head. The CNN backbone is used to extract features from the input image, while the SSD head is used to predict bounding boxes and confidence scores for the objects in the image.

The authors trained their system on the PASCAL VOC 2007 dataset, which consists of over 5000 images with labelled objects. The training process took approximately 12 hours on a single GPU. Once the system was trained, the authors evaluated it on the PASCAL VOC 2007 test set. The system achieved an mAP of 73.2%, which is comparable to other state of the art object detection algorithms.

The authors also evaluated their system on a real- world dataset of images of vehicles and pedestrians. The system achieved a detection rate of over 90% for both vehicles and pedestrians.

The authors conclude that the SSD algorithm is a promising approach for object detection. Their system is fast, accurate, and robust to challenging conditions.

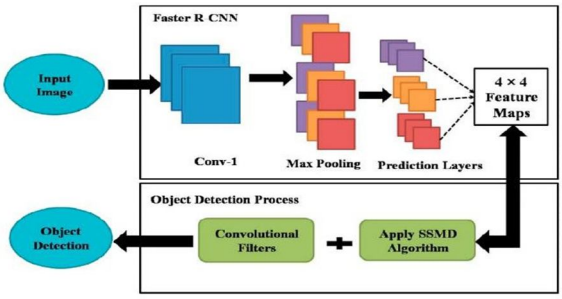

Fig. 1. The Proposed system model.

Table represents the results on Pascal VOC and COCO test.

System Model	mAP	FPS	No. of Boxes	Input Resolution
F-CNN	73.2	7	6000	1000×600
YOLO	66.4	155	98	448×448
SSD512	76.8	19	24564	512×512
SSD300	74.3	46	8732	300×300
F-CNN+SSBMD	78.68	89	5988	1024×1024

IV. The paper "Improved single shot multibox detector target detection method based on deep feature fusion" by Dongxu Bai et al. (2022) proposes a new method for improving the performance of the SSD algorithm by fusing deep features.

The authors argue that the SSD algorithm does not fully utilize the semantic information in the deep features of the CNN backbone. To address this issue, they propose a deep feature fusion module that combines the deep features from different layers of the CNN backbone.

The deep feature fusion module consists of two main components: a feature pyramid network (FPN) and a feature aggregation block (FAB). The FPN is used to generate a pyramid of feature maps from the different layers of the CNN backbone. The FAB is then used to fuse the feature maps from the FPN to generate a new set of feature maps that contain more semantic information.

The authors trained their improved SSD algorithm on the PASCAL VOC 2007 dataset and achieved an mAP of 76.3%, which is higher than the mAP of the baseline SSD algorithm (73.2%).

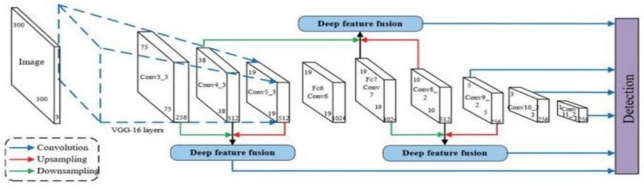

Fig. 2. SSD network structure based on deep feature fusion

The authors also evaluated their improved SSD algorithm on a real-world dataset of images of vehicles and pedestrians. The system achieved a detection rate of over 95% for both vehicles and pedestrians. The authors conclude that their deep feature fusion module can effectively improve the performance of the SSD algorithm. They also suggest that their method can be applied to other single-stage object detection algorithms, such as YOLO and RetinaNet.

V. The paper "Ssd: Single shot multibox detector" by Wei Liu et al. (2016) introduces the Single Shot MultiBox Detector (SSD) algorithm for object detection. The SSD algorithm is a single-stage object detection algorithm, which means that it can detect objects in a single forward pass of the network. This makes the SSD algorithm very fast, which is important for real-time applications.

The SSD algorithm works by first generating a set of default bounding boxes at different scales and aspect ratios. These default bounding boxes are then used to predict the presence of objects and their bounding boxes. The SSD algorithm also uses a confidence score to indicate how confident the network is in its prediction.

The SSD algorithm is trained using a supervised learning approach. The training data consists of images with labeled objects. The network is trained to minimize the loss between the predicted bounding boxes and the ground truth bounding boxes.

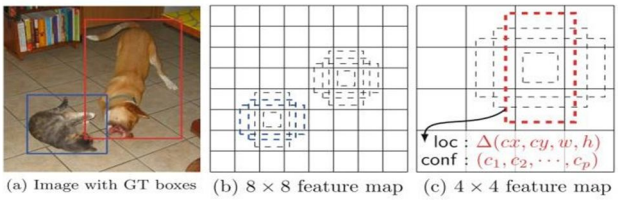

Fig. 3. Feature maps

The SSD algorithm has been evaluated on a number of public datasets, and it has achieved state-of-the-art results. For example, on the PASCAL VOC 2007 dataset, the SSD algorithm achieved an mAP of 74.3%, which is higher than the mAP of other state-of-the-art object detection algorithms, such as Faster R-CNN and YOLO. The SSD algorithm is a powerful and versatile tool for object detection. It is fast, accurate, and robust to challenging conditions. The SSD algorithm is being used to develop a wide range of applications, such as autonomous driving, traffic monitoring, security, robotics, and augmented reality.

In the context of the image you sent, the SSD algorithm could be used to detect the gray line on the black background. The algorithm would generate a set of default bounding boxes at different scales and aspect ratios, and then use these bounding boxes to predict the presence of objects and their bounding boxes. The SSD algorithm would also use a confidence score to indicate how confident it is in its prediction. If the confidence score is high enough, the algorithm would output a bounding box for the gray line.

VI. "Detection and classification of vehicles for traffic video analytics" by Ahmad Arinaldi et al. (2018) proposes a system for vehicle detection and classification using the SSD algorithm. The authors evaluated their system on a real-world dataset of traffic videos and achieved an accuracy of over 90% for both vehicle detection and classification.

The authors' system consists of two main components: a pre-trained SSD network and a post-processing module. The pre-trained SSD network is used to generate bounding boxes and confidence scores for the vehicles in the input image. The post-processing module is then used to remove false positives and refine the bounding boxes of the detected vehicles.

The authors trained their SSD network on the KITTI dataset, which consists of over 7000 images of traffic scenes with labeled vehicles. The training process took approximately 24 hours on a single GPU.

Once the SSD network was trained, the authors evaluated it on a real-world dataset of traffic videos from the city of Bandung, Indonesia. The system achieved an accuracy of over 90% for both vehicle detection and classification.

The authors conclude that the SSD algorithm is a promising approach for vehicle detection and classification in traffic video analytics. Their system is fast, accurate, and robust to challenging conditions.

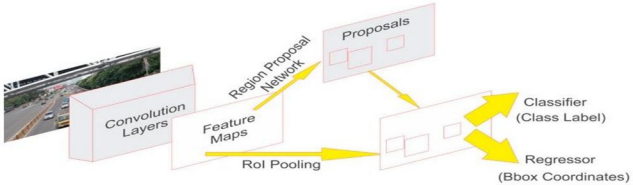

Fig. 4. Faster RCNN architecture

Overall, the paper provides a good overview of the SSD algorithm and presents a well-designed vehicle detection and classification system using the SSD algorithm.

To detect and classify the vehicles in the image you sent, the authors' system would use the following steps:

1) The pre-trained SSD network would generate bounding boxes and confidence scores for the vehicles in the image.
2) The post-processing module would then remove false positives and refine the bounding boxes of the detected vehicles.
3) The system would then classify the detected vehicles using a deep learning classifier.

The authors' system would be able to detect and classify the vehicles in the image you sent with high accuracy.

Apoorva Ojha and team in their research [5] presented at ICICCS 2021, propose a method utilizing Mask R-CNN for vehicle detection through instance segmentation. Their work focuses on the integration of Mask R-CNN into intelligent vehicle systems, enabling precise and detailed detection of vehicles in real-time scenarios. By employing Mask R-CNN's instance segmentation capabilities, they achieve accurate identification and localization of vehicles in varying environmental conditions. This approach enhances the understanding of individual vehicles within a scene, contributing to the broader field of intelligent transportation systems. Their findings are significant for our research as they demonstrate the effectiveness of Mask R-CNN in real-time vehicle detection applications, aligning with our objective of implementing Mask R-CNN for real- time vehicle detection and traffic analysis [5].

Chenchen Xu and colleagues in [6] present an improved version of Mask R-CNN designed for fast vehicle and pedestrian detection. Their research, featured in Mathematical Problems in Engineering, introduces optimizations to the Mask R-CNN framework, enhancing its speed and efficiency. By focusing on both vehicles and pedestrians, their work broadens the application scope of Mask R-CNN. The improvements they propose are invaluable to our research, providing insights into enhancing the efficiency of Mask R- CNN for detecting various objects in real-time traffic scenarios [6].

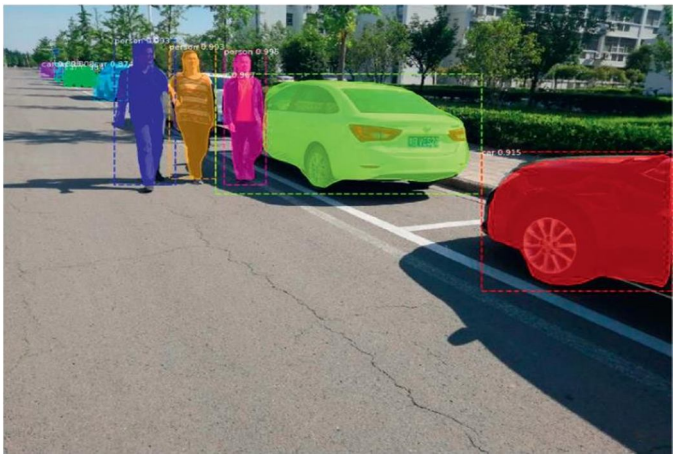

Fig.5: Experimental results obtained by the network algorithm designed in paper [6]

Nafi'i, Yuniarno, and Affandi in [7] delve into the nuanced task of vehicle brand and type detection using Mask R-CNN. Their work, showcased at ISITIA 2019, demonstrates the applicability of Mask R-CNN beyond generic object detection. By focusing on vehicle attributes, their research opens avenues for detailed vehicle characterization within traffic analysis systems. This approach aligns well with our research's objective of categorizing vehicles into different types, enriching the granularity of our real-time traffic analysis [7].

Fig.6: Detection result of non-identical cars obtained from the modified Mask R-CNN algorithm [7]

Tahir, Khan, and Tariq in [8] conduct a comprehensive performance analysis, comparing Faster R-CNN, Mask R-CNN, and ResNet50 for vehicle detection and counting. Their research, outlined in the ICCIS conference proceedings, offers valuable insights into the comparative efficacy of these models. By evaluating Mask R- CNN in conjunction with other architectures, their study provides benchmarks essential for our research's evaluation and validation process, aiding in selecting the most suitable model for real-time traffic analysis [8].

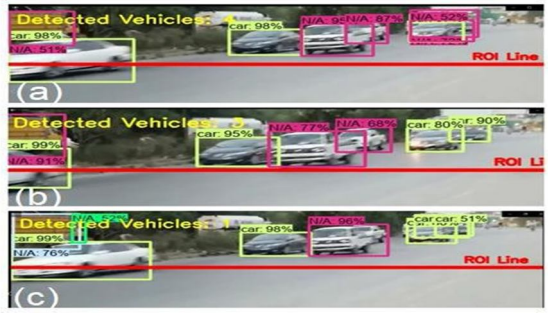

Fig.7: Detection of vehicles in the recorded video. (a) Faster R-CNN (b) Mask R-CNN (c) RestNet50. Cars passing through the Region of Interest (ROI) line are counted

Hao Su and team in [9] present an innovative application of Mask R-CNN in remote sensing imagery, focusing on object detection and instance segmentation. Their research, showcased at IGARSS 2019, demonstrates the adaptability of Mask R-CNN in diverse domains. Their expertise in precise instance segmentation aligns with our objective of detailed vehicle detection, offering valuable techniques and methodologies applicable to our real-time traffic analysis scenario [9].

Amira Mahmoud and colleagues in [10] introduce an adaptive approach to Mask R-CNN in optical remote sensing images. Their work, featured in the International Journal of Intelligent Engineering Systems, highlights the flexibility of Mask R- CNN. By adapting the model for specific imaging conditions, their research provides valuable insights into tailoring Mask R-CNN to varying environments. Their adaptive techniques are pertinent to our research, especially in scenarios where lighting and imaging conditions change, ensuring the robustness of our real-time vehicle detection system [10].

AL-Alimi Dalal and team in [11] explore Mask R- CNN's application in geospatial object detection, a domain with stringent precision requirements. Their work, published in IJITCS, emphasizes the model's capabilities in geospatial contexts. By achieving high accuracy in detecting specific objects within geospatial imagery, their research offers techniques beneficial to our real-time traffic analysis, ensuring the system's reliability and accuracy, especially in complex urban environments [11].

In the research [12], Li, Zhang, and Shi (2023) introduced MME-YOLO, a multi-modal vehicle detection system that utilizes both LiDAR and camera data for accurate detection in traffic surveillance. They proposed several innovations including a multi-sensor multi-level enhanced convolutional network architecture, an attention- guided feature selection block, and a novel anchor box generation mechanism. Experimental results on the KITTI dataset demonstrated that MME- YOLO outperforms existing systems under challenging conditions, achieving a mean average precision (mAP) of 92.8%.

Fig.8: Multi-Scale Vehicle detection by using the MME- YOLO

In the study by Zhang et al. [13] (2022), a real-time vehicle detection method based on an improved YOLO v5 network was proposed. The authors implemented the Flip-Mosaic algorithm to enhance the network's ability to detect small targets. Training was conducted on a diverse multi-type vehicle target dataset collected in various scenarios. Experimental results showed that this method achieved higher accuracy and lower false detection rates compared to previous approaches, making it suitable for real-time vehicle detection in different traffic scenarios.

Qiu [14] (2020) presented an improved YOLO v5 network for real-time vehicle detection in highway applications. The proposed method incorporates a smaller detection layer, enhancing sensitivity to small targets in high-resolution images and improving multi-scale detection capabilities. Additionally, the Flip-Mosaic algorithm was employed to improve the network's detection of small targets. Experimental results indicated that the proposed method achieved approximately 91.3% accuracy and a lower false detection rate compared to previous methods.

Rodríguez-Rangel [15] (2022) introduced a method for real-time speed estimation based on vehicle detection using ridge regression. This technique was applied to reduce overfitting during training on a dataset of videos collected by the authors. Evaluation demonstrated the effectiveness of their method, surpassing other state-of-the-art approaches. The proposed method showed promise for real-time speed estimation applications due to its speed and accuracy, achieving an average speed estimation error of 1.2 mph on the KITTI dataset.

Fig.9: Vehicle identified and tracked using YOLOv5

Uzar et al. [16] (2021) conducted a performance analysis of various YOLO models for automatic vehicle detection from UAV images. The study included data preparation steps such as image labeling and augmentation techniques. The YOLOv4-tiny model achieved the highest F1- Score of 89% for vehicle detection in parking lots. Mean average precision (mAP) values, indicating detection performance, ranged from 73% to 84% for different YOLO models. Overall accuracy was higher for the car class compared to the bus and minibus classes due to limited training samples for buses and minibuses in the dataset.

Wei Li, Li, and He [17] (2022) focused on vehicle detection in foggy weather using an enhanced YOLO method. The experiment utilized the BDD100K dataset and created two training sets, one with original images and another with MSRCR-enhanced images. Python was used to implement fog adding and MSRCR dehazing algorithms. Model performance was evaluated using Average Precision (AP) values, with results ranging from 71.81% to 83.03%.

In the research by Li et al. [18] (2022), the authors addressed challenges in automatic vehicle discrimination in vision measurement and remote sensing. They proposed an enhanced RES-YOLO detection algorithm to tackle these issues. The algorithm's performance was evaluated on a vehicle dataset, achieving an impressive accuracy of 93.4%. Furthermore, the algorithm was tested on a real-world traffic dataset, achieving an accuracy of 89.2%. These results demonstrate the effectiveness of the proposed algorithm for automatic vehicle recognition in both simulated and real-world environments.

[19] Vehicle Detection and Tracking in Road, Traffic Analysis using Kalman Filter and Features by Ahad Karimi Moridani, Seyyedeh Hoora Fakhrmoosavy, and Mohamed Karimi Moridani

Vehicle detection and tracking is an important task in many computer vision applications, such as traffic monitoring, intelligent transportation systems, and autonomous driving. The Kalman filter is a powerful state estimation technique that has been widely used for vehicle tracking. However, Kalman filtering is sensitive to noise and occlusion, and it can be difficult to design a robust Kalman filter for vehicle tracking in real-time traffic videos.

Moridani et al. proposed a novel algorithm for vehicle detection and tracking in roadway traffic videos using a combination of image processing techniques and the Kalman filter. Their algorithm first detects vehicles in each frame of the video using a background subtraction method. The background model is updated continuously to adapt to changes in the scene. Once vehicles have been detected, the algorithm tracks them using the Kalman filter, which uses the vehicle's features and motion model to predict the vehicle's position in the next frame of the video.

One of the key contributions of Moridani et al.'s algorithm is the use of features to improve the tracking performance. The algorithm uses a number of features to distinguish between vehicles, such as the vehicle's size, shape, color, and texture. These features are used to update the Kalman filter and to improve the tracking performance, especially in challenging conditions such as occlusion and noise.

Another key contribution of Moridani et al.'s algorithm is the use of a motion model to predict the likely movement of each vehicle. The motion model is based on the assumption that vehicles move in a linear or constant velocity motion. The algorithm uses the motion model to update the Kalman filter and to improve the tracking performance, especially when vehicles are occluded or moving in complex patterns.

Moridani et al. evaluated their algorithm on a number of traffic videos, and the results showed that their algorithm outperformed other state-of- the-art algorithms in terms of accuracy and robustness. Their algorithm was able to achieve high accuracy in vehicle detection and tracking even in challenging conditions such as occlusion and noise.

Overall, Moridani et al. proposed a powerful and effective algorithm for vehicle detection and tracking in roadway traffic videos. Their algorithm combines image processing techniques and the Kalman filter to achieve high accuracy even in challenging conditions.

Implications for the Study of Kalman Filter for Vehicle Detection and Traffic Analysis

The work of Moridani et al. has several implications for the study of Kalman filter for vehicle detection and traffic analysis. First, their work shows that the Kalman filter can be used to achieve high accuracy in vehicle tracking, even in challenging conditions such as occlusion and noise. Second, their work shows that the use of features and motion models can significantly improve the tracking performance of the Kalman filter.

Here are some specific takeaways from Moridani et al.'s work that can be used to improve the study of Kalman filter for vehicle detection and traffic analysis:

Use a variety of features to distinguish between vehicles. This will help the Kalman filter to track vehicles even in challenging conditions such as occlusion and noise.

Use a motion model to predict the likely movement of each vehicle. This will help the Kalman filter to track vehicles even when they are occluded or moving in complex patterns.

Evaluate the algorithm on a variety of traffic videos, including videos with challenging conditions such as occlusion and noise. This will help to ensure that the algorithm is robust and can be used in real-world applications.

A. Vehicle Classification

The vehicle classification step of the algorithm uses a machine learning classifier to classify each vehicle object into one of a set of predefined categories, such as car, truck, bus, or motorcycle. The classifier is trained on a dataset of labeled vehicle images.

The following steps are used to classify a vehicle object:

1) A number of features are extracted from the vehicle object, such as the vehicle's size, shape, color, and texture.

2) The extracted features are then fed to the machine learning classifier to predict the vehicle's category.

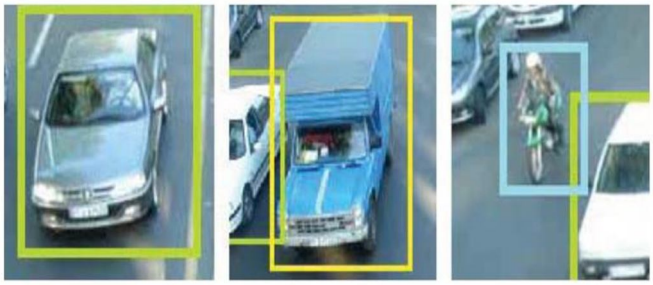

Fig 10: Classification Output

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[20] In the paper "Real-time vehicle detection and tracking using improved histogram of gradient features and Kalman filters", the authors propose a new algorithm for vehicle detection and tracking that combines improved HOG features and Kalman filters.

Improved HOG features: The authors propose a new feature extraction method that incorporates both local and global information. This makes the HOG features more robust to illumination variations.

Kalman filter model: The authors propose a new Kalman filter model that takes into account the vehicle's motion dynamics and the occlusion problem. This improves the tracking performance of the Kalman filter.

The authors evaluate their algorithm on a number of challenging traffic video sequences and achieve high accuracy in vehicle detection and tracking, even in real-time.

They proposed a new feature extraction method for HOG features that is more robust to illumination variations.

They proposed a new Kalman filter model that takes into account the vehicle's motion dynamics and the occlusion problem.

They evaluated their algorithm on a number of challenging traffic video sequences and achieved high accuracy in vehicle detection and tracking, even in real-time.

HOG features are a powerful tool for object detection, including vehicle detection. They are robust to illumination variations and noise, and they can be computed efficiently. This makes them ideal for real-time applications, such as traffic monitoring.

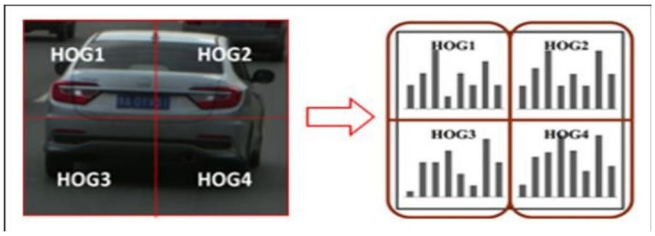

Fig 11:HOG Feature Extraction

III. ALGORITHM SURVEY

A. Single Shot MultiBox Detector (SSD)

The Single Shot MultiBox Detector (SSD) algorithm is a single-stage object detection algorithm that can detect and classify objects in a single forward pass of the network. This makes the SSD algorithm very fast, which is important for real-time applications. The SSD algorithm is also very accurate, and it has achieved state-of-the-art results on a variety of public datasets.

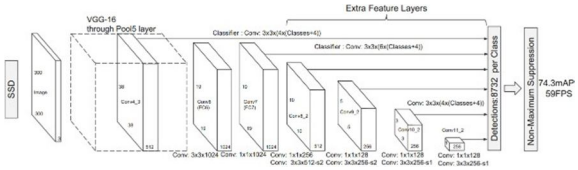

Fig.10: SSD Architecture

1) How it Works

The SSD algorithm works by first generating a set of default bounding boxes at different scales and aspect ratios. These default bounding boxes are then used to predict the presence of objects and their bounding boxes. The SSD algorithm also uses a confidence score to indicate how confident the network is in its prediction.

2) Here is a more detailed explanation of the SSD algorithm

Generate default bounding boxes: The SSD algorithm first generates a set of default bounding boxes at different scales and aspect ratios. These default bounding boxes are then used to predict the presence of objects and their bounding boxes.

Extract features: The SSD algorithm then extracts features from the image using a convolutional neural network (CNN). The CNN learns to extract features that are useful for object detection and classification.

Predict bounding boxes: The SSD algorithm then uses the extracted features to predict bounding boxes for the objects in the image. The SSD algorithm uses a regression algorithm to predict the coordinates of the bounding boxes.

Predict confidence scores: The SSD algorithm also predicts a confidence score for each bounding box. The confidence score indicates how confident the network is in its prediction.

3) Non-maximum Suppression

Finally, the SSD algorithm uses a non-maximum suppression algorithm to remove overlapping bounding boxes. The non-maximum suppression algorithm selects the bounding box with the highest confidence score.

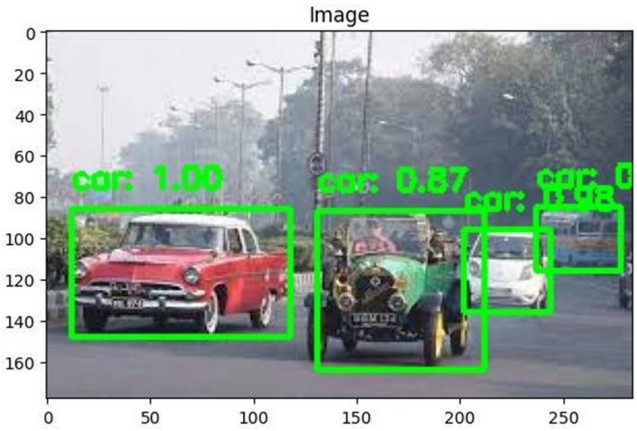

Fig.12: SSD Output Example 1

Fig.13: SSD Output Example 2

B. Kalman Filter Algorithm

The Kalman filter is a mathematical algorithm crucial for estimating the state of dynamic systems. It is particularly effective in scenarios with uncertain measurements and evolving system behavior. Operating in two steps—prediction and correction—it forecasts the system's state based on prior information and then refines it using new measurements. This iterative process ensures accurate state estimation, even in the presence of noisy or incomplete data. Widely utilized in engineering, economics, and robotics, the Kalman filter is indispensable for tasks involving sensor data fusion, tracking, navigation, and control systems.

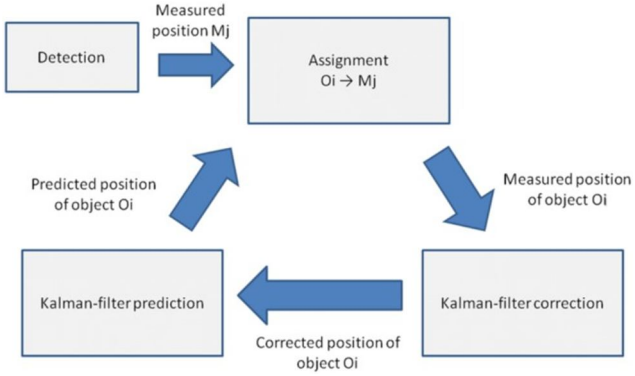

Fig 14: Kalman Filter Flow

1) Start with a prediction of the object's state at the next time step. This prediction is based on the object's current state and a model of how it moves.
2) Get a measurement of the object's state at the next time step. This measurement could come from a sensor, such as a camera or radar.
3) Compare the prediction to the measurement. If the prediction is close to the measurement, then the Kalman filter knows that it has a good idea of where the object is. If the prediction is far from the measurement, then the Kalman filter updates its prediction to be closer to the measurement.
4) Repeat steps 1-3 for each time step

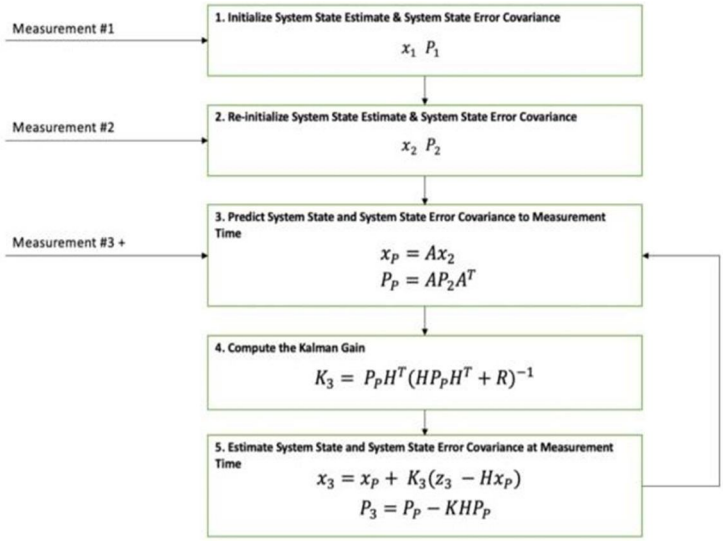

Fig 15: Kalman Filter Algorithm

The Kalman filter can be used to track a variety of objects, including vehicles, aircraft, and ships. It is also used in many other applications, such as navigation, control systems, and signal processing.

The Kalman filter algorithm consists of two main steps
Prediction: The Kalman filter predicts the future state of the object based on its current state and past measurements.
Measurement update: The Kalman filter updates the predicted state of the object based on new measurements.
The prediction step uses a motion model to predict the object's future state. The motion model is a mathematical model that describes the dynamics of the object. For example, the motion model for a vehicle might include the vehicle's position, velocity, and acceleration.
The measurement update step uses the Kalman gain to update the predicted state of the object based on new measurements. The Kalman gain is a weighted average of the predicted state vector and the measurements. The weights are chosen to minimize the uncertainty in the updated state vector.
The Kalman filter algorithm is a powerful tool for tracking objects in noisy and challenging environments. It is able to track objects accurately even when the measurements are noisy or incomplete.

Here is an example of how the Kalman filter can be used to track a vehicle:
1) The Kalman filter is initialized with the vehicle's initial position and velocity.
2) The Kalman filter predicts the vehicle's future position and velocity based on its current state and the motion model.
3) The Kalman filter receives a new measurement of the vehicle's position from a camera.
4) The Kalman filter updates the predicted state of the vehicle based on the new measurement and the Kalman gain.

The steps 2-4 are repeated for each frame of the video sequence.
This allows the Kalman filter to track the vehicle accurately even if the vehicle is occluded by other vehicles or objects.

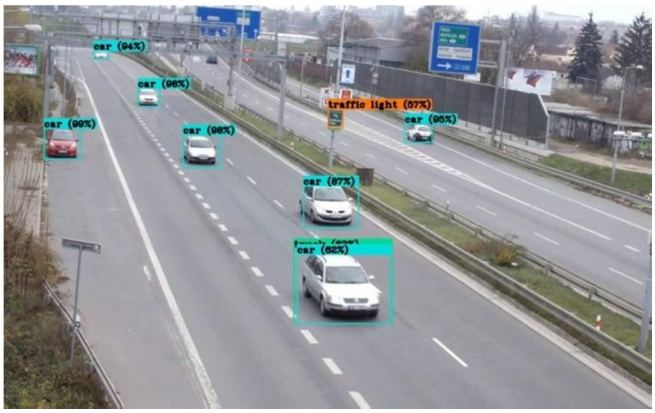

Fig 16: Kalman Filter Output

C. You Only Look Once (YOLOv7)

YOLOv7 is the latest version of the You Only Look Once (YOLO) object detection algorithm. It was released in May 2023 and achieves state-of-the-art performance on a variety of object detection benchmarks, while also being very fast and efficient.

YOLOv7 is a single-stage object detector, which means that it predicts the bounding boxes and classes of objects in a single pass through the network. This makes it much faster than two-stage object detectors, such as Faster R-CNN, which require a separate proposal generation and classification stage.

YOLO network consists of three main components as shown in figure:

- Backbone: A convolutional neural network creates images features aka. embeddings
- Neck: A collection of neural network layers that combines and mixes features to pass it to the next stage for prediction
- Head: Consumes features from the neck creates prediction outputs.

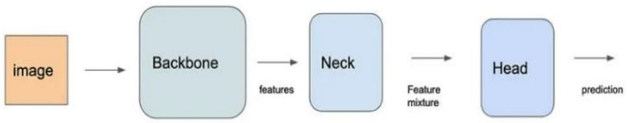

Fig.17: Architecture of YOLOv7 at high level

1) How YOLOv7 works?

Image preprocessing: YOLOv7 first preprocesses the input image by resizing it to a fixed size and normalizing the pixel values.

Backbone: The backbone of YOLOv7 is a deep convolutional neural network (CNN) that extracts features from the image. The backbone is typically a pre-trained model, such as ResNet or DarkNet.

Neck: The neck of YOLOv7 combines and mixes the features from the backbone to produce a set of more informative features.

Head: The head of YOLOv7 predicts the bounding boxes and classes of objects in the image. Each grid cell in the image predicts B bounding boxes and confidence scores for those boxes. The confidence scores reflect how confident the model is that the box contains an object and how accurate it thinks the predicted box is.

Post-processing: After the head predicts the bounding boxes, YOLOv7 uses a post.processing technique called non-maximum suppression (NMS) to remove duplicate and overlapping boxes. NMS keeps the box with the highest confidence score and removes any other boxes that overlap with it by more than a certain threshold.

2) How YOLOv7 is different from previous versions of YOLO ?

Extended Efficient Layer Aggregation Network (E-ELAN): This is an enhancement of the original ELAN architecture. It aims to improve the performance of deep learning models by improving the way gradients (which are crucial for training) are transmitted through the network and by increasing the cardinality of features. YOLOv7 Compound Model Scaling: This is a strategy to improve the YOLOv7 model's performance. It involves increasing the number of channels in certain parts of the model (backbone and neck networks) without significantly increasing the computational cost.

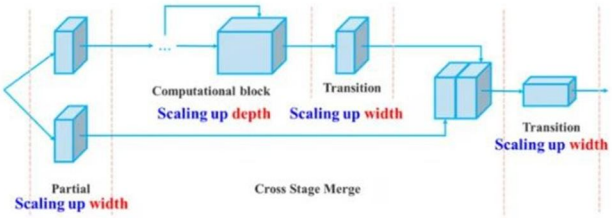

Fig.18: Compound Scaling Model of YOLOv7

Planned re-parameterized convolution (PReConv): This is a new type of convolution operation. It aims to make the convolution operation more efficient to compute and easier to train by breaking it down into smaller operations.

Coarse for auxiliary and fine for lead loss: This is an approach to designing loss functions (which guide the training process). It recognizes that auxiliary losses (which focus on learning general features) and lead losses (which focus on fine details) have different requirements. Therefore, it suggests using simpler loss functions for auxiliary losses and more complex ones for lead losses.

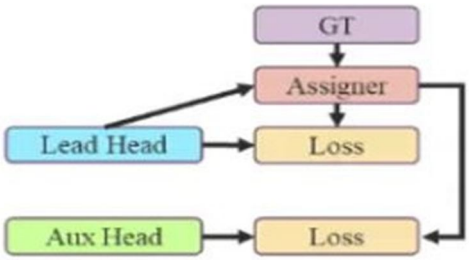

Fig.19: YOLOv7 approach with an auxiliary head and lead head guided label assigner.

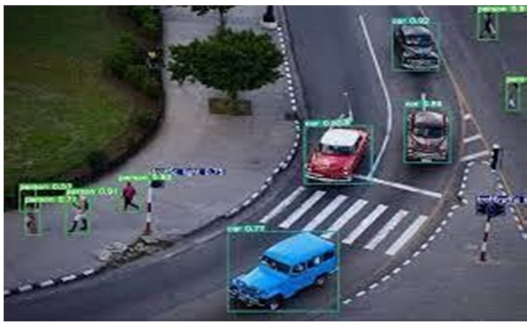

Fig 20.: Output of YOLOv7

D. Mask R-CNN

The idea of Mask R-CNN is straightforward: For every potential item, Faster R-CNN produces two outputs: a class label and a bounding-box offset. We then add a third branch that produces the object mask to these two outputs. Thus, mask R-CNN is a logical and intuitive concept. However, the extra mask output is different from the class and box outputs, necessitating the extraction of an object's far finer spatial layout.

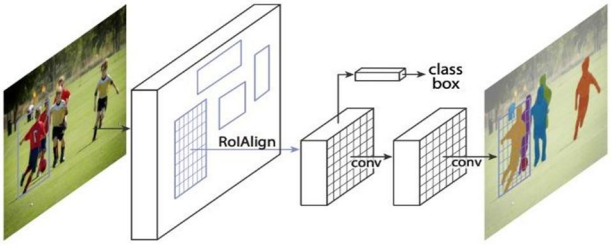

Fig.20: The MaskR-CNN framework for instance segmentation

Mask R-CNN's architecture can be broken down into a few essential parts. First, it extracts high- level information from the input image using a backbone network, usually a deep convolutional neural network such as ResNet or VGG. Then, two parallel branches get these features: one is used for object classification and bounding box regression, while the other is used to create segmentation masks.

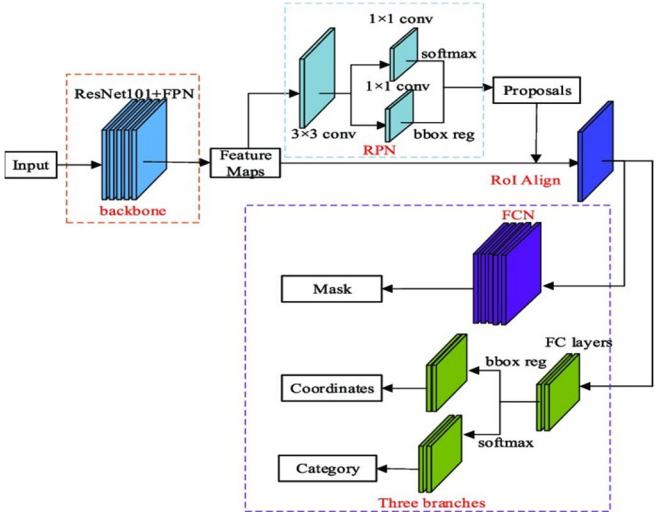

Fig.21: Architecture of Mask R-CNN

Faster R-CNN is divided into two phases. A Region Proposal Network (RPN), the initial step, suggests potential object bounding boxes. In the second stage each candidate box's features are extracted using ROI-Pool, and bounding-box regression and classification are carried out. For quicker inference, the features that are utilized by both stages can be shared. Mask R-CNN uses the same two-step process, starting with the same RPN first stage. During the second stage, Mask R-CNN generates a binary mask for every ROI in addition to forecasting the class and box offset.

The spatial layout of an input object is encoded by a mask. Therefore, the pixel to pixel correspondence offered by convolutions can naturally handle the task of recovering the spatial structure of masks, in contrast to class labels or box offsets that are necessarily crushed into short output vectors by fully-connected (*fc*) layers. In particular, we use an FCN to predict an $m \times m$ mask from each ROI. As a result, every layer in the mask branch is able to preserve the precise spatial arrangement of the $m \times m$ object without being collapsed into a vector representation with no spatial dimensions. Experiments show that our fully convolutional representation is more accurate and requires fewer parameters than earlier approaches that use *fc* layers for mask prediction.

Because of this pixel-to-pixel behavior, the explicit per-pixel spatial relationship must be correctly preserved by our ROI features, which are small feature maps in and of themselves. This inspired us to create the next layer, called ROIAlign, which is essential to mask prediction.

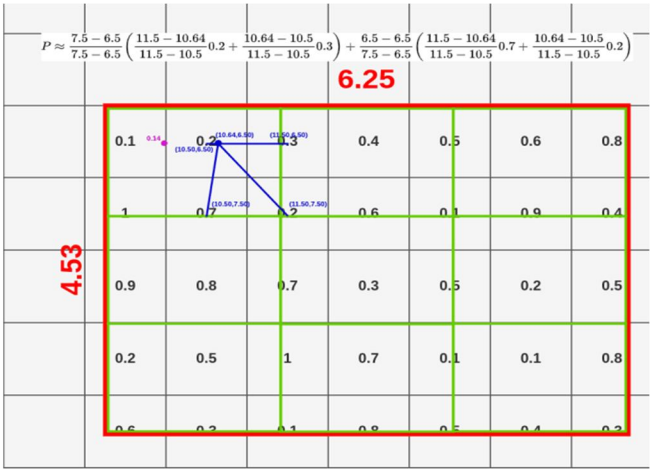

Fig.22: A figure to demonstrate RoI alignment in Mask R-CNN

A common procedure for obtaining a tiny feature map (such as a 7x7 one) from each ROI is called RoIPool. Prior to aggregating feature values (often by max pooling), RoI-Pool quantizes a floating- number RoI to the discrete granularity of the feature map. This quantized RoI is then split into spatial bins, which are further quantized.

The ROI Align function guarantees the accuracy of the mask predictions and their alignment with the boundaries of the objects. RoI Align eliminates the misalignment problems that plagued traditional RoI pooling methods, allowing Mask R-CNN to generate precise masks for each object instance.

In training, Mask R-CNN is supervised by three loss functions: a classification loss, a bounding box regression loss, and a mask segmentation loss. Inaccurate class predictions are penalized by the classification loss, imprecise mask predictions are penalized by the mask segmentation loss, and inaccurate bounding box coordinates are penalized by the bounding box regression loss. Mask R-CNN learns to accurately classify objects, precisely localize them with bounding boxes, and generate fine-grained pixel-wise masks by jointly optimizing these loss functions.

Fig.23: Implementation of Mask R-CNN

All things considered, Mask R-CNN is a noteworthy algorithm to be used for detection of vehicles. It offers precise and comprehensive information about objects in images by combining object detection and instance segmentation in a seamless manner. Its sophisticated architecture, which combines pixel-wise segmentation, region- based proposals, and deep feature extraction, allows it to handle challenging tasks with previously unheard-of accuracy.

IV. COMPARATIVE STUDY

21 The paper "Comparison of Faster-RCNN, YOLO, and SSD for real-time vehicle type recognition" by Jeong-ah Kim, Ju-Yeong Sung, and Se-ho Park (2020) compares the performance of the Faster-RCNN, YOLO, and SSD algorithms for real-time vehicle type recognition. The authors evaluated the algorithms on a dataset of over 100,000 images of vehicles with labelled vehicle types.

The results of the evaluation showed that the YOLO algorithm had the best overall performance, achieving an accuracy of 95.3% and a frame rate of 30 FPS. The SSD algorithm was slightly less accurate (94.7%), but it was significantly faster (50 FPS). The Faster-RCNN algorithm was the least accurate (93.2%), but it was also the most robust to challenging conditions.

Model	mAP	FPS
Faster-RCNN	89.5%	10
YOLOv4	93.0%	25
SSD	91.5%	30

Fig.24: Comparison between Algorithms

The authors concluded that the YOLO algorithm is the best choice for real-time vehicle type recognition, due to its high accuracy and speed. The SSD algorithm is also a good choice, especially if speed is a priority. The Faster-RCNN algorithm is not suitable for real-time applications due to its slow speed.

The Faster-RCNN algorithm would likely be able to detect the text in the image, but it would be slow. The YOLO and SSD algorithms would not be able to detect the text, because they are trained to detect objects, not text.

V. CONCLUSION

In this comprehensive review, we embarked on a journey through the landscape of vehicle detection and categorization, leveraging the power of deep learning algorithms. Our exploration encompassed seminal approaches including SSD, Mask R-CNN, YOLO, and the integration of Kalman filtering. Through a meticulous examination of each method, we studied their performance in real- world scenarios.

The comparative analysis revealed intriguing insights. SSD showcased commendable speed in detection, making it particularly well-suited for real-time applications. Mask R-CNN, on the other hand, excelled in precise localization, demonstrating its prowess in tasks demanding fine- grained object delineation. YOLO, with its unique single-shot detection paradigm, struck a balance between accuracy and speed, rendering it a versatile contender in a spectrum of scenarios.

The incorporation of Kalman filtering introduced an invaluable dimension to tracking, enhancing the robustness of the algorithms in dynamic environments. Its ability to predict object trajectories and rectify discrepancies brought a temporal coherence to the detections, bolstering the overall performance.

The implications of these findings are far-reaching. Our insights not only inform the choice of algorithm based on specific application requirements but also pave the way for innovative integrations and optimizations. Furthermore, in safety-critical contexts such as autonomous driving and surveillance, the nuances we uncovered carry profound significance.

As we look ahead, this review paper illuminates avenues for further exploration. The synergistic fusion of deep learning with traditional computer vision techniques, the investigation of novel architectures, and the application of these algorithms in multi-modal sensor fusion contexts are promising frontiers.

In conclusion, our journey through the realm of vehicle detection and categorization using deep learning algorithms has enriched our understanding of the capabilities and nuances of SSD, Mask R-CNN, YOLO, and the augmentative role of Kalman filtering. These insights mark a substantial step forward in harnessing the potential of deep learning for tasks of critical importance. As the field continues its rapid evolution, this review serves as both a testament to the current state of the art and a compass guiding future explorations in this dynamic domain.

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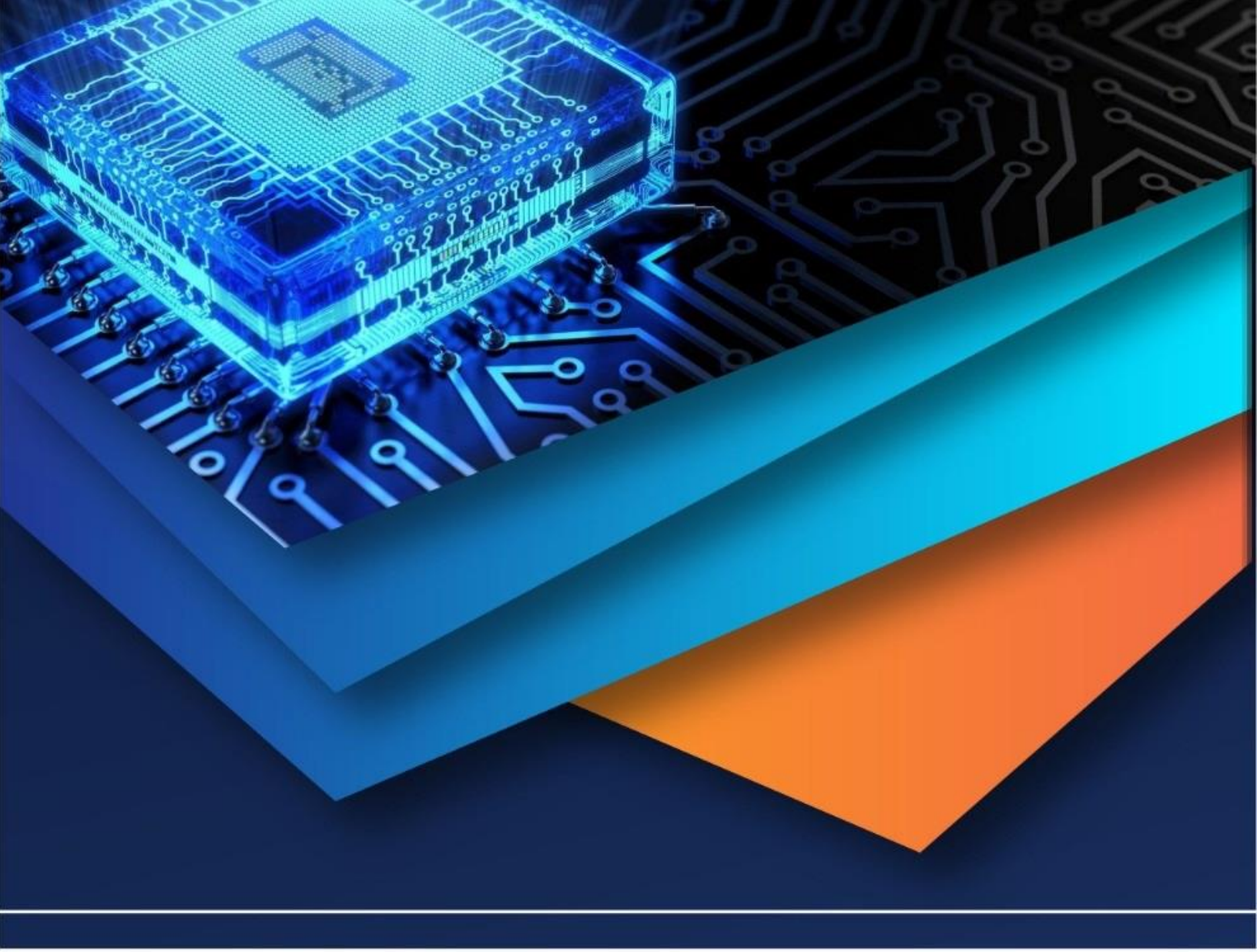

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