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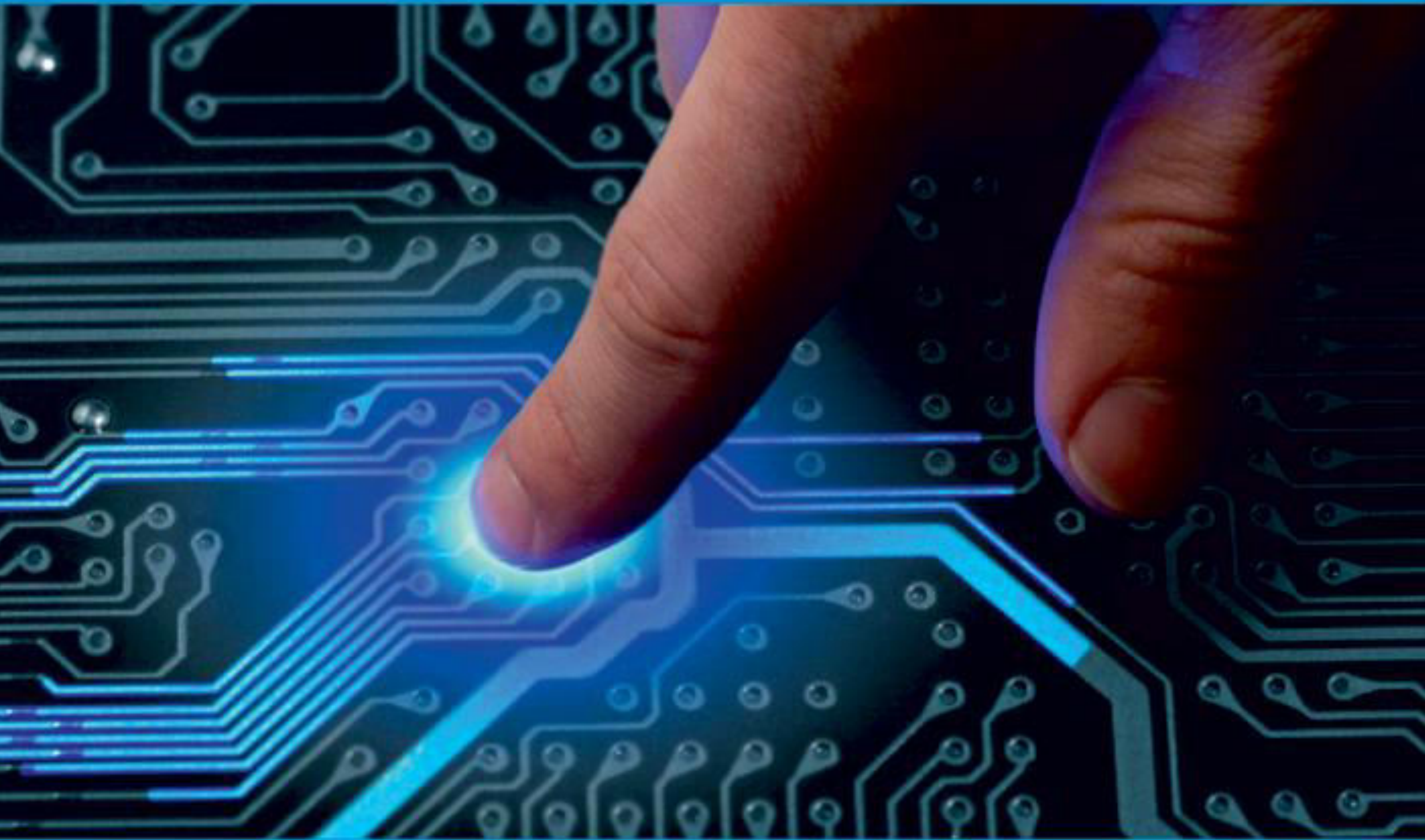

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Automatic Vehicle Speed Controlling System by Detecting Traffic sign boards, Potholes and Speed bumps

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ABSTRACT: This research aims to identify and recognize potholes, speed bumps, and traffic sign boards in varied backgrounds and lighting situations in order to decrease accidents and encourage compliance with traffic laws. Cutting-edge automotive safety and control technology called the "Automatic Vehicle Speed Controlling System by Detecting Traffic Sign Boards, Potholes, and Speed Bumps" is intended to improve road safety and lower vehicle speed. Advanced technologies like computer vision and sensor integration are incorporated into the system to enable autonomous real-time detection and interpretation of potholes, speed bumps, and traffic signs. By applying deep learning algorithms and image processing capacity to automatically detect potholes, speed bumps, and traffic sign boards on roads, this study offers a novel solution to these problems. The method under consideration utilizes computer vision algorithms to examine images obtained from cameras placed on vehicle. The system can precisely recognize and categorize traffic sign boards and road irregularities, such potholes and speed bumps, from the picture data by integrating a deep learning algorithm. The system's primary function entails utilizing a mix of strategically positioned cameras and sensors on the car to record and analyse the surrounding road environment. Speed restrictions, warning signs, and regulatory instructions are among the pertinent information that is extracted from traffic signboards by the computer vision component module. In addition to stabilizing the vehicle speed, the technology uses sensors to simultaneously detect road abnormalities like potholes and speed bumps. The system instantly modifies the vehicle speed to comply with established traffic laws and guarantee a smooth and secure driving experience upon detecting these road factors. When it comes to traffic signs, the system decodes the data and applies the designated speed limits. The system's ability to automatically adjust vehicle speed to reduce pain and potential damage caused by potholes and speed bumps adds an additional layer of safety. Preventing collisions, improving driver comfort, and promoting general road safety are the primary goals of this speed control system.

KEYWORDS*:* Deep Learning, Computer vision, Image processing

I.INTRODUCTION

Recent developments in vehicle technology have concentrated on integrating technological systems to improve driving experiences and increase road safety. The traditional method of regulating a car's speed mostly depends on the driver's knowledge of the road's features, such as the existence of speed bumps and potholes, and their manual interpretation of traffic signs. But this approach offers a real-time, automated solution to these problems by combining deep learning and computer vision technology. Visual data from cameras on vehicle is processed using deep learning models, which are renowned for their capacity to analyse and comprehend intricate patterns in data. These cameras are placed strategically to continuously monitor abnormalities and the road environment. The deep

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learning model can precisely identify and categorize different traffic sign boards, potholes, and speed bumps because it was trained on a wide range of datasets. Real-time analysis and detection of road conditions are achieved simultaneously with the use of computer vision techniques. Using sensors, the system detects potholes, speed bumps, and traffic sign boards. Image processing techniques are then applied to the road surface to identify any anomalies. The output of the deep learning model is then combined with this data to provide a thorough picture of the driving environment. Based on the data gathered by the computer vision and deep learning models, the system's capability is built to dynamically modify the vehicle's speed. The technology reads the information on a traffic signboard, determines the relevant board speed restriction, and applies it. The mechanism automatically modifies the vehicle's speed to provide a safe and comfortable ride when there are potholes and speed bumps.

Initially, training datasets for each detecting feature are gathered and labelled in this way for potholes, speed bumps, and traffic sign boards. Each feature's annotated dataset serves as a training set that the deep learning model uses during its training phase. To guarantee precise model prediction, the model is tested following training. The camera module component mounted on the car records the existence of potholes, speed bumps, and traffic sign boards in the driving environment. It feeds the deep learning model with the acquired image data by using computer vision libraries. With the use of deep learning algorithms, each feature is precisely identified, categorized, and interpreted. The microcontroller connected to the vehicle's wheel provides the motor drivers with the speed restriction, which is then used to manage the vehicle's speed. When a speed limit is detected on a traffic sign board, a motor attached to the wheel changes the vehicle's speed to match the detected limit. By reducing human error in speed regulation, this system not only improves road safety but also makes driving more comfortable.

II.RELATED SURVEY

The main reason behind road accidents are ignorance of traffic rules and improper traffic rules following. Where there are two types of traffic rules traffic signboards and traffic signals. The main focus is on e-Vehicles ADAS which will be a future mode of transportation. The proposed system, Traffic Sign Detection along with Electric Vehicle Speed Control using Deep Learning and CAN protocol will assist the drivers and reduce the road accidents caused by ignorance of traffic rules. In this system, a camera is fixed on the vehicle windshield for capturing the traffic signs on the roads. The camera sensor will send the captured image as a signal to ADAS/AD ECU through Ethernet wire where the captured image undergoes processing. After processing it is identified using the Deep Learning CNN technique in ADAS/AD ECU Microcontroller. Then, the ADAS/AD ECU tells the Transmission ECU to regulate the current speed to a specific speed limit and displays an alert message to the driver in the cluster display using CAN protocol [1]. Since automakers are still having difficulty producing completely functional driverless vehicles, autonomous vehicles are becoming a great topic for both researchers and the automotive industry. Driving a safe vehicle in a real world depends on different conditions, such as distance from other vehicles, pedestrians, animals, speed-breakers, traffic signals and other unpredictable dynamic environments. Automated traffic sign detection and recognition, or ATSDR, is a crucial function for an autonomous car to drive safely. Several deep learning-based models have been employed by numerous researchers for in-the-moment ATSDR. In this research, we have examined several deep learning models that are employed in real-time ATSDR. According to earlier research, YOLO and SSD are better models for ATSDR than other deep learning techniques like CNN, R-CNN, Fast R-CNN, and Faster RCNN and are capable of real-time traffic sign detection [2]. Controlling the speed of a vehicle is one of the most difficult tasks for autonomous driving systems to complete. A Convolutional Neural Network (CNN) algorithm is used in the unique approach suggested for motor managing speed in compliance with speed requirements to scan speed limit sign boards. The system's efficacy depends on CNNs' capacity to accurately identify and categorize items in photos, which are subsequently utilized to retrieve speed limit data from signage. Using the CNN's output, an Arduino microcontroller controls the robot chassis speed. It demonstrate the effectiveness of the system through simulations and experiments on an actual testbed, demonstrating that it can

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maintain the intended speed with a reasonable amount of error [3]. Potholes in the road can lead to a variety of traffic issues. They may result in car problems, deterioration of suspension systems, need for further repairs, and auto accidents. For road maintenance and reconstruction, it is critical to promptly and affordably identify potholes. This demonstrates the necessity for automated technologies that can promptly and accurately identify potential structural issues with roadways. This study suggests the DenseNet121 architecture, a deep learning-based technique, for identifying potholes in roadways. Determining if there are potholes in the road photos in the dataset is the goal of the suggested methodology. Using the DenseNet121 network, potholes on the road were identified in this study with 99.3% accuracy. This dataset was simultaneously processed and compared using the same parameters in the ResNet50, InceptionV3, VGG19, and InceptionResnetV2 models. DenseNet121 produced the best accuracy out of all of these models [4]. When deciding on the best road management strategies and upkeep, pothole identification is essential. In this study, the researcher developed a pothole identification system using Yolov3 and deep learning. YOLOv3, a deep learning method, is utilized to create a model that can accurately detect potholes. It is to be expected that given the wide variety of shapes and sizes of potholes, the detection model's accuracy ranged from 33% to 69%, with an average precision of 95.43% [5]. This study outlines a practical approach to integrating a microcontroller-based speed control system with an artificial intelligence-based detection system for the development of self-driving cars at a reasonable price. The identification of potholes and speed bumps utilizing a camera and artificial intelligence-assisted video feed analysis is the specific emphasis of this work. A well-liked and simple method called SSD (Single Shot Multi box Detector) is utilized to overcome this issue. Being precise enough to run on mobile devices and be used in real-world scenarios, combined with its lightweight design, makes this the best option. The Raspberry Pi has served as the primary processing unit due to its compact size and impressive capabilities. To alert the driver that a pothole or speed bump is approaching, a warning system has been put in place. In order to prevent collisions or damage to the vehicle, this system can also send a signal to the speed controller unit of the vehicle, telling it to slow down. Based on microcontroller technology, the speed control unit makes use of an ATmega328 microprocessor and an L298 motor drive [6]. Speed control in autonomous driving vehicles is heavily dependent on environmental awareness. Autonomous cars are required to abide by the traffic laws as stated in traffic signs. In order to manage the longitudinal velocity of an autonomous vehicle, a novel method for detecting stop signs and calculating their distance is proposed in this study. It is challenging to get the car to stop at the appropriate distance from the stop sign because as it approaches, it disappears from the camera's frame of view. Thus, to determine precisely where to stop the car, knowledge of the stop line's location is necessary. AdaBoost cascade classification is used to detect stop signs. It is based on three distinct feature types: Local Binary Patterns (LBP), Histogram of Oriented Gradients (HOG), and Haar-like features. To choose the best classifier, the performance outcomes of all three are examined and contrasted. A conventional computer vision approach is suggested to locate the stop line. In order to apply a decelerating torque appropriately and slow down the vehicle until it comes to a complete stop, the distance to the stop sign and stop line is evaluated in real time [7]. Technology for autonomous driving is becoming more and more common, but most deep learning algorithms for traffic sign target detection include a lot of parameters and take a long time to infer. This paper proposes a CA-YOLOV4-tiny traffic sign detection algorithm based on the YOLOV4-tiny network. The attention mechanism is incorporated into feature extraction, label smoothing is used to prevent overfitting, and mosaic data is used to improve the model's ability to generalize. Compared to YOLOV4-tiny, the MAP on the TT100K traffic sign dataset is 6.77% higher at 81.71%. The experimental results demonstrate that CA-YOLOV 4-tiny can significantly increase the model detection accuracy without compromising reasoning speed, and that reasoning speed after quantization has also been greatly enhanced. This solves the problem of excessive computing power and slow reasoning speed that the vehicle-side target detection network was experiencing [8]. Potholes in the road annoy commuters and hinder the delivery of goods and services. Existing pothole detection techniques necessitate manual road inspections with specialized sensors mounted on vehicles with unique modifications. It takes a lot of labour and time to complete the process. This work suggests a unique method for pothole identification based on convolution neural networks (CNNs). The method performs pothole detection by combining sensory and visual data. The suggested strategy was able to obtain 87.20% precision, 92.7% recall, and 89.9% F1-Score in the conducted experimental investigations [9]. One of the main concerns of road maintenance during these hard times is making the workplace safe for employees. An autonomous system that seeks to lessen reliance on humans can help achieve this to some extent. Pothole detection and

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dimension estimation is one of these systems that is proposed in this paper. YOLO (You Only Look Once), an algorithm based on deep learning, is used by the suggested system to detect potholes. Additionally, pothole dimension estimate is performed using a triangle similarity metric based on image analysis. Pothole identification and dimension estimate findings from the suggested technique are comparatively accurate. Additionally, the suggested system aids in cutting down on the amount of time needed for road maintenance. The method makes use of a specially created dataset that includes pictures of both dry and wet potholes in a range of sizes and shapes [10]. This study describes a sensor-based approach, machine learning, and image processing technique for detecting potholes and humps. Road safety and avoiding vehicle damage depend on the early detection of potholes and humpbacks. Developing automatic techniques for pothole and hump detection has gained popularity in the last few years. The proposed approach makes use of cameras and sensors to gather information about the state of the roads, evaluate the information, and pinpoint places where there are potholes or speed bumps. By applying deep learning algorithms, data patterns are identified and precise predictions are made. The proposed technique is reliable, reaching the goal with an estimated accuracy of 90% in a variety of lighting and weather scenarios. Real-time implementation and condition testing of the suggested solution are conducted. Using the suggested solution, the analysis is done in terms of increased road safety and decreased maintenance costs [11]. To maintain the integrity of any engineering structure, road pothole detection is crucial. Identifying and categorizing potholes manually requires a lot of human labour. Road inspections now involve fewer human intervention thanks to the implementation of various sensor-based, laser imaging, and image processing systems. However, because machine learning-based techniques need manual feature extraction for the prediction, they have several drawbacks, including great expense, low accuracy, and danger during detection. In order to achieve improved pothole detecting outcomes, this proposed work intends to apply deep learning techniques. Pothole pictures are gathered from several datasets and merged into a single dataset to train the model. A number of pothole datasets are accessible online, and deep learning-based techniques necessitate large amounts of data for training. In order to improve training, augmentation is also used to the dataset. This is because augmentation offers photos from various perspectives, which helps the model be fine-tuned and yields records with approximately 98% accuracy [12].

III.DEEP LEARNING NETWORK MODELS

Deep learning technology is being increasingly applied in the development of automatic vehicle speed controlling systems, particularly for tasks related to perception, decision-making, and control in the context of intelligent infrastructural and transportation systems.

A. Convolutional Neural Network

A popular Deep Learning neural network design in computer vision is the Convolutional Neural Network (CNN). The artificial intelligence discipline of computer vision allows a computer to comprehend and analyze a picture or other visual data. Convolutional neural networks (CNNs) are a type of neural network design used for structured grid data analysis, such as photograph analysis. CNNs have proven to be incredibly effective in computer vision applications like object identification, picture segmentation, and image classification. A CNN's architecture is based on how the human brain processes images and is designed to find patterns in visual input. The primary structural element of a CNN is the convolutional layer. Convolution operations are applied to the input data using learnable filters or kernels, which helps to identify regional patterns and traits. Convolutional processing of the incoming data is accomplished using filters, which are small matrices. By swiping over the input, these filters are able to capture the spatial hierarchies of attributes. The weights of these filters are found during the training phase.

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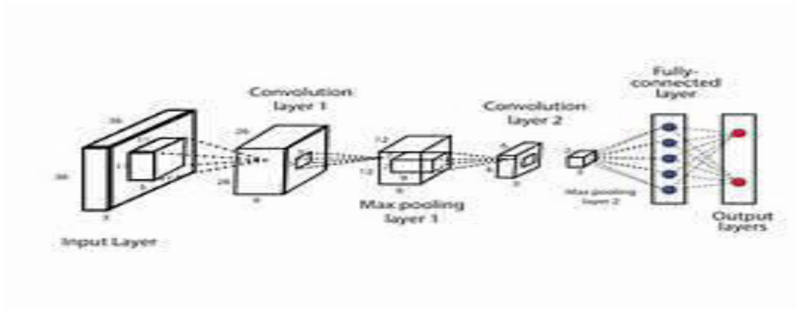

Figure 1: Architecture of Convolutional Neural Network

By employing activation functions like the Rectified Linear Unit (ReLU), convolutional layers give the model non-linearity. ReLU is used to improve non-linearity and support the network's capacity to identify complex patterns.
Pooling layers, like Average or Max Pooling, reduce the spatial dimensions of the data by down sampling the incoming data while retaining the most important information. This reduces computational complexity and strengthens the network's resilience. CNNs usually have numerous convolutional and pooling layers followed by one or more fully connected layers for higher order reasoning and decision making. These layers connect every neuron in the layers that come before and after it. The output of the convolutional and pooling layers is vectorized before the fully connected layers. For CNNs, transfer learning in which previously trained models on large datasets are improved on specific tasks using smaller datasets is a helpful strategy. This improves utilization of taught features and expedites training. CNNs are utilized in a wide range of computer vision applications, including as autonomous vehicles, object detection, picture segmentation, facial recognition, and medical image analysis.

B. Recurrent Neural Network

An architecture for a neural network that is meant to process sequential data and identify dependencies over time is called a recurrent neural network (RNN). RNNs can retain a hidden state that records details about earlier inputs in the sequence because they include connections that form directed cycles, which distinguishes them from typical feedforward neural networks. Speech recognition, time-series prediction, natural language processing, and other applications are among the many applications for RNNs. An RNN keeps track of a hidden state that serves as a memory for earlier sequence inputs. The network uses this hidden state, which is updated every time step, to remember information about previous inputs. Information can be transmitted from one time step to the next in an RNN thanks to its recurrent connections. As a result, the network can recognize patterns and dependencies in sequential data. RNNs' structure can be gradually revealed by conceptually unrolling them. The hidden states are connected between time steps by recurrent connections, with each time step representing a layer in the unrolled network.

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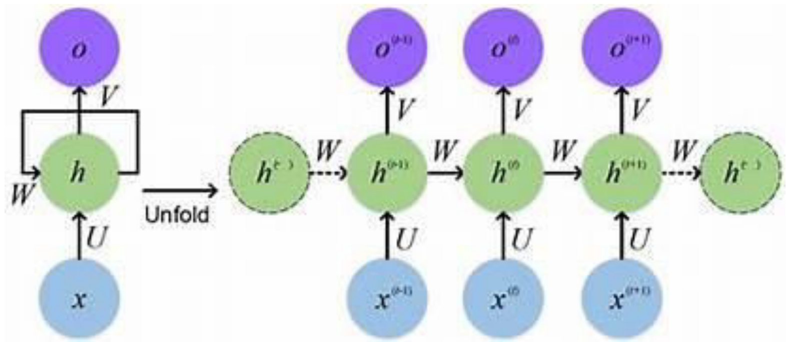

Figure 2: Architecture of Recurrent Neural Network

The capacity of RNNs to preserve context or memory across successive inputs is one of its primary characteristics. An RNN's internal hidden state is modified at each time step based on the input that is received currently and the hidden state that came before it for each unit. RNNs can now recognize patterns and dependencies in sequential data because of this. Many applications, including language modelling, sentiment analysis, and machine translation, include natural language processing and RNNs and their variations. They are also used in time series prediction, speech recognition, and other applications where sequential dependencies are essential.

C. ResNet

A kind of convolutional neural network (CNN) architecture known as a "Residual Network," or ResNet, was developed to overcome the difficulties associated with training extremely deep neural networks. The introduction of residual blocks, which include skip connections (also known as shortcut connections) that let the network bypass one or more layers during training, is the main novelty of ResNet. This makes training very deep networks easier and helps mitigate the issue of disappearing gradients. The training of very deep architectures is made possible by the skip connections, which support the gradient flow across the network. Without these skip connections, gradients find it more and more difficult to propagate across all of the layers during backpropagation as the network gets deeper. When the best transformation for a layer is to have no effect, the residual block turns into a type of identity mapping in the absence of non-linearity in the skip connection (e.g., utilizing identity mapping). The learning process is made easier by this.

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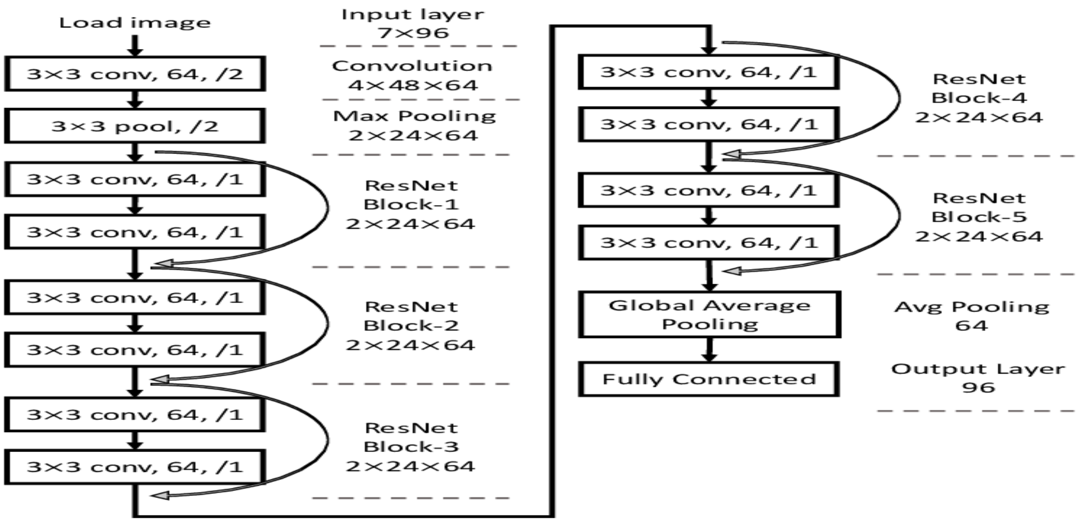

Figure 3: Architecture of ResNet

For a variety of computer vision applications, such as object identification, image segmentation, and image classification, ResNets have been extensively used and modified. Because of their efficiency in training extremely deep networks, they have established themselves as a standard reference architecture for deep learning practitioners. The total number of layers in the network is indicated by the number in the name. ResNet-50, for example, consists of 50 layers.

D. AlexNet

One of the most important convolutional neural network (CNN) architectures that contributed to the renewed interest in deep learning is AlexNet. The ImageNet Large Scale Visual Recognition Challenge (ILSVRC) was won by the system created by Alex Krizhevsky, Ilya Sutskever, and Geoffrey Hinton in 2012. Three fully connected layers and five convolutional layers make up AlexNet's eight learnable parameter layers. Max-pooling layers come after the convolutional layers, and a softmax activation is used in the last layers for classification. The rectified linear unit activation function (ReLU) was heavily utilized by AlexNet's convolutional layers. ReLU speeds up the training process and assists in introducing non-linearity to the model. Following the first and second convolutional layers in AlexNet is a local response normalization layer. The purpose of this layer is to promote local competition between neighboring neurons, which will improve the model's capacity to distinguish between various patterns. Dropout was introduced by AlexNet in the fully linked layers to prevent overfitting. During training, dropout randomly removes a predetermined percentage of neurons, which helps to prevent co-adaptation of neurons and enhances generalization.
The training dataset's size was manipulated by applying data augmentation techniques including flipping and cropping. As a result, the model's capacity to generalize to fresh, untested data was enhanced.

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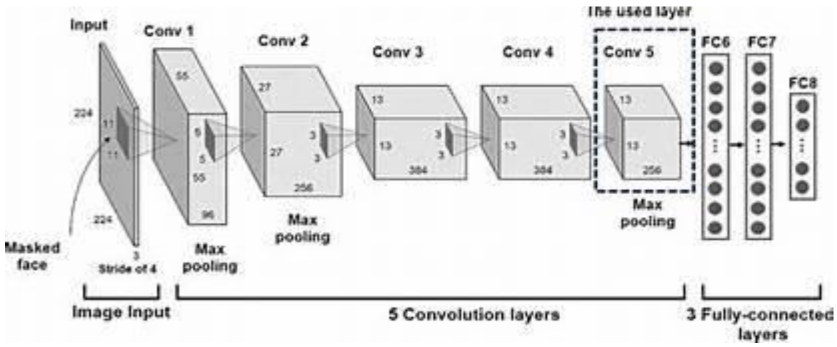

Figure 4: Architecture of AlexNet

One of the earliest CNNs to use GPU (graphics processing unit) acceleration for training was AlexNet. Large neural networks could be trained effectively as a result, and deep learning performed well on picture classification tasks. AlexNet outperformed earlier methods with a top-5 error rate of about 16.4% in the ILSVRC 2012 competition. Its accomplishments showed how effective deep learning is in classifying images.

E. GoogleNet

Google researchers created the convolutional neural network (CNN) architecture known as GoogleNet, formerly called Inception v1. It was first mentioned in the work "Going Deeper with Convolutions" by Andrew Rabinovich, Dragomir Anguelov, Scott Reed, Wei Liu, Yangqing Jia, Pierre Sermanet, and Christian Szegedy. GoogleNet was created to overcome the difficulties associated with training extremely deep neural networks and to achieve a high level of accuracy when classifying images. GoogleNet's unique selling point is its utilization of the "Inception module." Rather than depending on a solitary convolutional layer, the Inception module integrates several filters with varying dimensions (1x1, 3x3, 5x5) and pooling procedures concurrently. As a result, the network can learn a wide range of properties and capture features at various spatial scales. Rather than using the conventional completely connected layers in the last layer, GoogleNet implemented global average pooling. In addition to preventing overfitting, this lowers the number of parameters in the network.

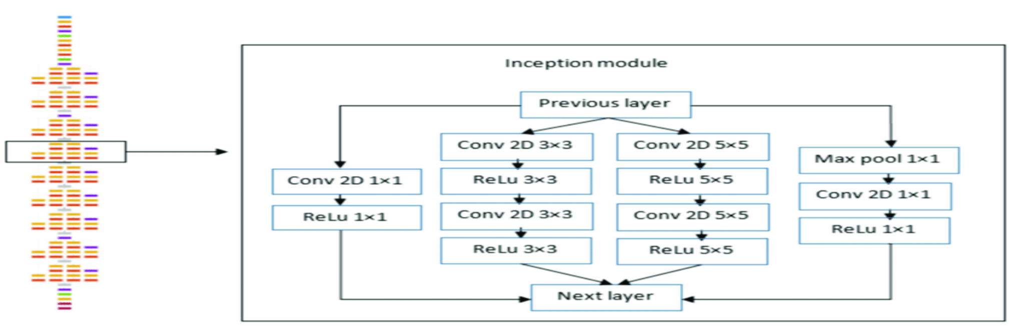

Figure 5: Architecture of GoogleNet

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The architecture of GoogleNet, which has 22 levels, is comparatively deep. Still, the effective architecture of the Inception modules allows it to reach this depth without using an unnecessarily high amount of parameters. The Inception modules employ 1x1 convolutions for two reasons. It first permits dimensionality reduction, which lowers the quantity of input channels. Second, it strengthens the model's representational power by adding non-linearity. During training, GoogleNet adds auxiliary classifiers at intermediate layers in addition to the primary classification output. These auxiliary classifiers are intended to help address the issue of disappearing gradients and to offer more oversight throughout the training process. Subsequent versions of the Inception architecture, including Inception v2, v3, and so on, have been released since then, each of which has improved upon the initial layout. Another architecture that aims to balance depth, width, and computational efficiency in neural networks was inspired by GoogleNet, which has had a major influence on the field of deep learning.

F. MobileNet

A class of neural network topologies called MobileNet was created specifically to be effectively deployed on mobile and edge devices with constrained processing power. Researchers Andrew G. Howard, Menglong Zhu, Bo Chen, Dmitry Kalenichenko, Weijun Wang, Tobias Weyand, Marco Andreetto, and Hartwig Adam from Google presented it. The major goal of MobileNet is to offer a neural network architecture that is both effective and lightweight, yet still maintains a respectable level of accuracy for applications like object identification and image categorization. Using depth wise separable convolutions is one of MobileNet's primary contributions. Conventional convolutions generate a high number of parameters since they apply a filter to every input channel at every spatial position. This is separated into depth wise convolutions and pointwise convolutions using depth wise separable convolutions. This leads to a significant reduction in the number of computations and parameters. By applying a different filter to every input channel, depth wise convolutions are able to individually capture the spatial correlations inside each channel. After depth wise convolutions, pointwise convolutions (1x1 convolutions) are used to combine data from different channels. They aid in capturing connections across channels and producing intricate representations.

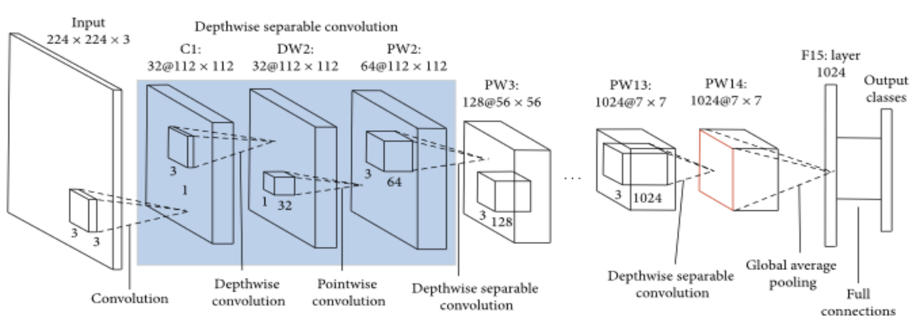

Figure 6: Architecture of MobileNet

MobileNet presents the "width multiplier" (α), a hyperparameter that scales the number of channels in each layer. The model becomes lighter and more computationally efficient as the number of channels is decreased. Users can compromise between accuracy and model size by using the width multiplier. The input resolution can be scaled using a different hyperparameter known as the "resolution multiplier" (ρ). The efficiency of the model is further increased by lowering the input resolution. There are various variations of MobileNet, including MobileNetV1,

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MobileNetV2, and MobileNetV3. Every iteration brings enhancements and refinements over the preceding version. For instance, MobileNetV2 incorporates linear bottlenecks and inverted residuals, whereas MobileNetV3 concentrates on effective neural architecture search for model optimization. MobileNet architectures are frequently employed in embedded and mobile applications with constrained computational resources. They are widely used for applications including object recognition, image classification, and even real-time image segmentation on smartphones and edge devices .

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