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Performance Benchmarking: Pre-trained Models and Custom Convolutional Neural Networks in Deep Learning

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Abstract - Recent advances in computer vision and deep learning, particularly Convolutional Neural Networks (CNNs), have significantly increased road safety. CNNs were used in this work to automatically detect and categorise traffic signs—a crucial task for autonomous vehicles (AVs) and advanced driver assistance systems (ADAS). These technologies' ability to accurately recognize traffic signs enables them to make informed decisions in real time, thereby elevating the standard for overall driving safety. The study uses a large, annotated dataset of images of traffic signs to train and assess the CNN model. We developed a model that can recognize a large number of traffic lights, even in challenging scenarios such as low light levels, adverse weather, or high traffic. CNN image processing enables the system to accurately recognize and categorize traffic signs. Real-time predictions made by the CNN model after training aid ADAS and autonomous vehicles in comprehending road conditions. Real-time recognition is essential for tasks like managing turns, stopping at red lights, and adhering to speed restrictions. The research also addresses real-world challenges to ensure the model performs effectively in light or weather changes. A thorough testing process validates the model's accuracy and reliability. Ultimately, this technology might significantly increase road safety by providing drivers with more precise information, improving ADAS and AV decision-making skills, and reducing the number of accidents caused by drivers misinterpreting traffic signals.

Keywords— Advanced Driver Assistance Systems, Intelligent Transportation Systems, Convolutional Neural Network, Deep Learning, Machine Learning

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1. INTRODUCTION

A key component of contemporary Intelligent Transportation Systems (ITS), which aim to enhance traffic flow and road safety, is the classification of traffic signals. Accurately identifying and classifying traffic signs is essential for

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the development of ADAS, autonomous vehicles, and smart city infrastructure. These systems must have a precise understanding of traffic signs to make informed decisions about modifying vehicle speeds, recognizing pedestrian zones, and obeying traffic rules.

Due to their diverse and often complex designs, traffic signs may be challenging to classify. A dependable and flexible feature extraction and classification system is required due to the large number of symbols and their changes in size, colour, and shape. Real-world factors, including shifting illumination, weather, occlusions, and various angles of view, make the issue more difficult. When it comes to picture identification tasks like traffic sign classification, CNNs are a helpful tool. This is due to its ability to automatically identify and extract hierarchical features from unprocessed visual input. The efficiency and ease of usage of the VGG16 architecture set it apart from previous CNN systems. It has a deep design with tiny receptive fields and sixteen weight levels. Notwithstanding its efficiency, the original VGG16 architecture had drawbacks, especially when it came to managing the complexity and enormous volume of data from traffic signs. The increasing significance of intelligent transportation systems in contemporary society motivates this endeavour. Maintaining road safety and effective traffic management requires accurate and dependable traffic sign recognition, especially considering the development of driver assistance technologies and autonomous cars.

The diversity and intricacy of traffic sign data provide difficulties for traditional techniques and even certain contemporary CNN systems, given the ever-changing real-world environment [1], [2], [3]. The VGG16 architecture works well for general image classification tasks; however, it is not a good fit for the field of traffic sign identification. By carefully altering the VGG16 model and using cutting-edge methods like batch normalization and dropout, we may greatly enhance its performance. The goal of the project is to use these developments to create a more reliable and accurate traffic sign categorization system, which will make transportation networks safer and more effective [4], [5], [6]. The present traffic sign classification system, which mostly uses conventional CNN designs, makes extensive use of the VGG16 model. VGG16 is well known for its depth and simplicity due to its 16 weight layers, which allow for efficient feature extraction from photos. Despite their widespread use, VGG16 and related CNN models have several shortcomings when it comes to traffic sign classification. Some of these problems are a shallow network, which makes it hard to get accurate data, a high risk of overfitting because of not enough regularization, and problems applying to real-life situations where lighting, weather, and viewpoints are different [7-10]. Road signs and traffic signals provide a visual language that drivers can comprehend. They sound warnings, show traffic conditions while on the road, warn of dangers and other difficulties, and help drivers navigate by providing useful information that makes driving simple and safe. A person's physical and mental well-being has an impact on their capacity to recognize visual signals.

A variety of variables, such as weariness and observational skills, may impact these talents in certain situations. Road signs use colours that contrast with the surroundings' terrain to make them stand out. If drivers can recognize these signals in exterior photos taken while driving, they will be able to make the proper judgements faster, with fewer accidents, less pollution, and more safety. [11], [12], [13]. Colour was the major signal for identifying traffic signals in around 62% of the studied literature, with form being employed in the remaining cases. Vitabile and Sorbello create the HSV colour space from RGB photographs, further dividing it into many subspaces (regions). You can use the S and V components to identify the hue's area. Using a predetermined threshold and the H component, we separated yellow.

Information from traffic signs is essential for safe and effective driving and navigation. Therefore, automatic traffic sign identification is one of the most crucial problems for autonomous navigation and driver support systems. For such systems to accurately identify symptoms and detect them in real time, they must be quick and dependable. An algorithm for detection may be based on the colour characteristics of a traffic signal. However, variations in weather and lighting may affect the colour information in the given photographs. Additionally, a few urban non-sign items have design and colour traits in common with transportation signs. It is possible that more sign candidates, longer recognition durations, and false-positive recognitions may cause non-sign items to be mistakenly identified as traffic signs. We employ the sign's geometry information in addition to its colour attributes to overcome this issue. The three main categories of traffic signs are warning signs, restriction signs, and information (or guide) signs. Based on their traits, we may divide these indicators into two categories. The first category consists of "red-bordered" signs, which are warnings and prohibitions. We used a variety of strategies in response to these indicators. We have shown a few of these strategies. Informative signals are included in the second category. Identification of this type of signal is not well studied [14], [15], [16]. The limiting and warning indications are more organised than the informative ones, which explains this. Various formulas and materials may be used. Given the differences in sign structure and processing techniques, grouping is essential. The first group's indicators have red margins. Therefore, we may use a colour-based detecting method. Each group's sign may be divided into three sections: the black "meaning" portion, the white or yellow inner component, and the red border. As a result, we display three colour groups. Even if a sign's colour qualities may aid in detection and extraction, its significance lies in its black zone. As a result, the identification section may be built around form analysis. Limitations and alert indicators are necessary for identification and retrieval. Structures for guiding signs may vary in complexity. Each information sign, however, includes a backdrop (which may be green, blue, or brown) and a symbol that indicates what the sign means. information about traffic signs. Automated recognition and identification of traffic signs have been the subject of several studies. The ability to detect traffic signs is essential for driverless cars, driver assistance systems, and inventory management. This project's goal is to create an inventory system that will allow for the comprehensive documentation of each traffic sign along a certain route, along with details on the signs' condition. We accounted for the detection of red and blue traffic lights for inventory purposes. But instead of emphasising the indicators' identification, that method simply addressed their location [17-20].

- Feature space-based approaches: These include clustering, histogram thresholding, and other neural network algorithms created especially for colour classification. They are based on the colour of each pixel and do not take spatial information into account.
- Image-domain-based approaches: These techniques leverage colour features to generate a similarity score for merging pixels within an area. These methods, which use colour and spatial information, include neural network-based categorisation, edge detection, split-and-merge, and area expansion.
- Methods Based on Physics: This method detects the colour zones in an image by using physical models for surface reflection and propagation. There were 150 references in the colour segmentation provided. This number would rise to over 1000 references if the greyscale approaches were considered, rendering a comprehensive study of the area beyond the purview of a book like this one.

2. METHODOLOGY

Instead of using RGB directly, some researchers use alternate colour spaces. We colour-normalize the red, green, and blue (RGB) components according to their sums to identify strong colours in the picture. In this instance, we used the red component as a reference to establish a distinct connection between the RGB components. Researchers used the YUV colour scheme to detect signs of blue rectangles. The Hue Saturation Intensity (HSI) family of spaces has been used in most studies. These spaces include information about intensity to lower hue and saturation instabilities and prioritise hue and saturation components to avoid lighting dependencies. All the earlier approaches fall within the feature-space-based category. Some techniques substitute structural information based on edge detection for colour information. For example, we processed a gradient of colour pictures, a Laplacian filter with prior smoothing, and a Canny edge detector to process greyscale images. These are just a few of the image-domain methods. Consequently, there are several segmentation options for the current investigation. Finding the best segmentation technique is the difficult part. The optimal segmentation technique in this case, in our opinion, is the one that produces the best recognition outcomes. One essential component of a sophisticated driver assistance system is its ability to detect and recognise traffic signs in real time. For feature extraction, the ROI approach is often successful; however, it is not effective for changing illumination. We describe in this paper a maximum stable extremal regions (MSER) method that includes picture enhancement to greatly increase ROI. We begin by using the original photos and the grey-world technique. We next extract the image-enhanced MSER and raise the contrast ratio of the picture to identify possible locations for traffic signs. To find the ROIs, we take out the geometric features of the traffic signs and look at the characteristic variable and geometric moment invariants.

Finally, after building the HSV-HOGLBP feature, we use the random forest technique to identify the traffic signs. Our suggested method works well in a lot of different rotation and lighting conditions, as shown by tests on real photos and the German Traffic Sign Identification Benchmark (GTSDB) data set. For instance, the TSDR system may notify the driver to slow down if it notices a speed limit sign in front of the car. ADAS significantly lowers the incidence of traffic accidents while simultaneously increasing driving comfort and safety.

As the Intelligent Transportation System (ITS) has developed, researchers have concentrated a significant deal of effort on image processing-based traffic sign identification and recognition. ATSDR technology still faces significant obstacles, despite the effect of the intricate components mentioned above. These studies suggest a real-time traffic sign recognition and identification method that uses MSER and random forests to keep speed and accuracy while dealing with the problems caused by the things listed above, especially changes in lighting. The detection phase and the recognition phase are the two stages of this method. By adjusting illumination during the detection phase, the Grey World approach lessens the effect of light variance. We then determine the ROI of traffic signs using the IE-MSER image enhancement technique, which combines MSER and CLAHE. The purpose of geometric moment invariants and traffic sign geometry characteristic variables is to improve the accuracy of sign positioning. We develop a novel feature descriptor, HSV-HOG-LBP, throughout the recognition procedure.

We provide a method for traffic sign identification based on convolutional neural networks (CNNs). First, we use support vector machines to convert the original picture to a greyscale image. Next, we use convolutional neural networks with learning and fixed layers for detection and identification. By removing boundaries that are very near to the edges of traffic signs, the fixed layer may decrease the number of acknowledged regions. The learnable layers may greatly improve the detection accuracy. Additionally, we use bootstrap techniques to improve accuracy and avoid overfitting. In the German Traffic Sign Detection Benchmark, we performed well. Our area under the precision-recall curve (AUC) was 99.73% in the "Danger" category and 97.62% in the "Mandatory" category. The CNNs produced the best outcomes. For instance, a traffic sign going at 70 or 80 km/h has the same name. Much of the research that employs deep learning [21] to tackle the issue of traffic sign identification merely classifies traffic signs to differentiate between super categories, not between individual classes. The primary challenge in most deep detector investigations is the need for big data sets. There are forty-three types of imbalanced traffic indicators on GTSD. Throughout the categorisation stage, just three super classes – prohibitive, indicative, and warning—are often used. This paper's classification makes use of all forty-three classes. Since traffic sign recognition and identification are two of the most crucial technologies for safe driving, they continue to be hot study issues. Due to its significance, this area has received a lot of attention over the last 20 years, and some noteworthy findings for clean static pictures have been made. According to research that has been published, the two clean benchmark static image datasets, GTSDB and GTSRB, have given 99.67% classification accuracy, about 100% recall, and detection accuracy. CNN (Convolutional Neural Network) technology has been the primary focus of researchers for the identification or location task of generic items. This is particularly true when it comes to its use in autonomous driving traffic sign detection. This is because AlexNet reduced the top-5 error to 15.3% in the ILSVRC-2012 competition. We calculate the top-5 error rate using test images where the model's five most likely labels do not include the correct label.

3. SYSTEM MODULES

We break down the suggested traffic sign classification system, which uses the upgraded VGG16 architecture, into several important parts. Each of these parts is necessary for the system to work well and be useful. These topics cover data preparation and augmentation, assessment and validation, network architecture design, and training and regularisation. The raw traffic sign pictures are ready for training and testing thanks to this module. Effective data preparation is crucial because of the diversity and complexity of traffic signs. This involves scaling the photos to a standard size, typically 224 by 224 pixels, to meet the input specifications of the VGG16 architecture. We also used normalisation to standardise the pixel values to ensure that the data is suitable for training deep neural networks. We use a range of data augmentation techniques to address the issue of limited sample sizes in traffic sign databases. These methods mimic real-world variations, such as various perspectives, lighting conditions, and weather impacts. They include random rotations, translations, scaling, and brightness and contrast alterations.

Enhancing the VGG16 architecture is the main goal of this module. The network becomes stronger as additional convolutional layers are added, enabling the model to comprehend more intricate traffic sign information. Non-linearity is introduced in each convolutional layer using the rectified linear unit (ReLU) activation function. This is necessary to learn complex patterns. The interspersion of pooling layers reduces the spatial dimensions of the feature maps and controls the computational cost of the model. To stabilise and speed up training, the improved architecture also includes batch normalisation layers that normalise the inputs at each layer. To reduce the likelihood of overfitting, dropout layers randomly deactivate a subset of neurones during training. Consequently, no one set of characteristics becomes crucial to the model. As seen in Figure 1, this module controls the neural network's training procedure. Images of enhanced and pre-processed traffic signs are used to train the network. Stochastic gradient descent (SGD) and backpropagation are employed to improve the model parameters. Large weights in the loss function are penalised by regularisation approaches like L2. This compels the model to find more straightforward and useful answers for a wider range of situations.

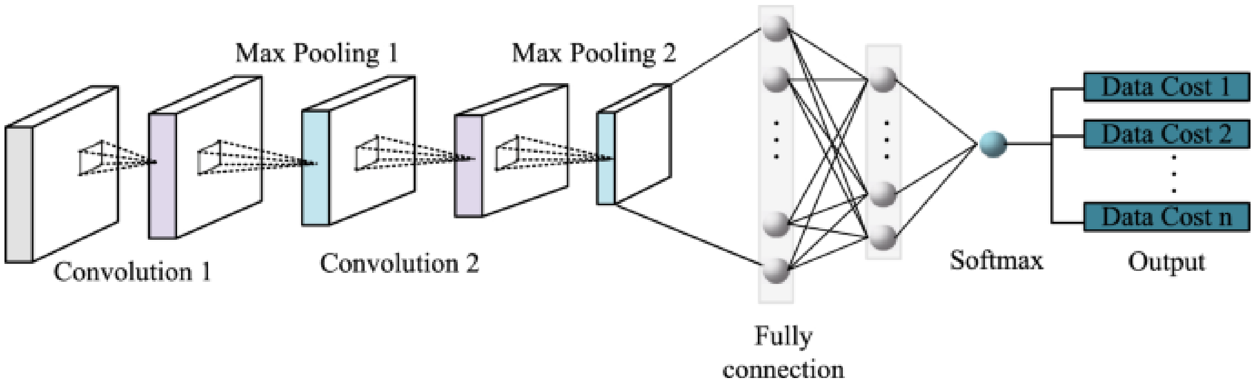

Figure 1. CNN System Model

a. Place the information on hybrid encryption and Python in the relevant section, such as Methodology or System Modules.
b. Describe the main choices made throughout the experimental setup, particularly those concerning performance measures, epochs, and hyperparameter changes.
c. Provide a brief overview of the findings, highlighting the effects of adjusting the hyperparameters and the ways that each statistic affects the overall performance of the model.

4. RESULTS AND DISCUSSION

The implementation details, including the software and technology needed to offer hybrid encryption of data in the cloud environment. Additionally, we built the hybrid encryption in a local cloud environment, and Microsoft updated Windows NT from Windows 8.1 to Windows 10. On July 15, 2015, we sent it to the makers, and on July 29, we launched the product for sale. Users of Windows 10 may upgrade their older computers running Windows 7 or 8 to Windows 10 without having to do invasive system updates or reimaging. Users or IT professionals install Windows 10 from an older version. This process updates all software, settings, preferences, and applications to Windows 10. Both individuals and companies can customise Windows 10 upgrades. Using basic syntactic programming exercises, this approach focuses on the quality of the source code using Python as a writing and scripting tool. This will ultimately make it simpler to maintain a legible and maintainable code base for an application. For many reasons, this artefact production favours Python over other programming languages. Python is an object-orientated, high-level, interpreted programming language. Python aims to be very readable. Python's syntactical characteristics are weaker than those of other languages, and it often uses English terms instead of punctuation. Python is an object-orientated, high-level, interpreted programming language. Python aims to be very readable. It has fewer syntactical structures than other languages, and it often uses English terms instead of punctuation.

After installing Anaconda, one may use the pip command to install any missing library packages. Even though Anaconda comes with a multitude of pre-installed packages, there are instances when certain libraries are missing. To resolve the problem in the Anaconda setup, one may be using Pip, the Python package installer. For instance, you may use the pip install command to quickly add the required libraries to your environment. As shown in Figure 2, this keeps the development environment flexible and equipped with all necessary tools, even if they are not normally part of Anaconda.

Figure 3 illustrates how the recommended website was made using HTML, CSS, and the server-side scripting language DJANGO. Specifically, for traffic sign categorization, this work suggests an enhanced VGG16 architecture to overcome the shortcomings of the current system. By adding more convolutional layers and digging deeper into the network, the suggested method lets the model get more detailed and complete data from traffic signs.

To improve model generalisation and lower the chance of overfitting, we include batch normalisation and dropout in the design. We also use significant data augmentation techniques to improve the training dataset and make the model stronger by simulating the volatility of the real world.

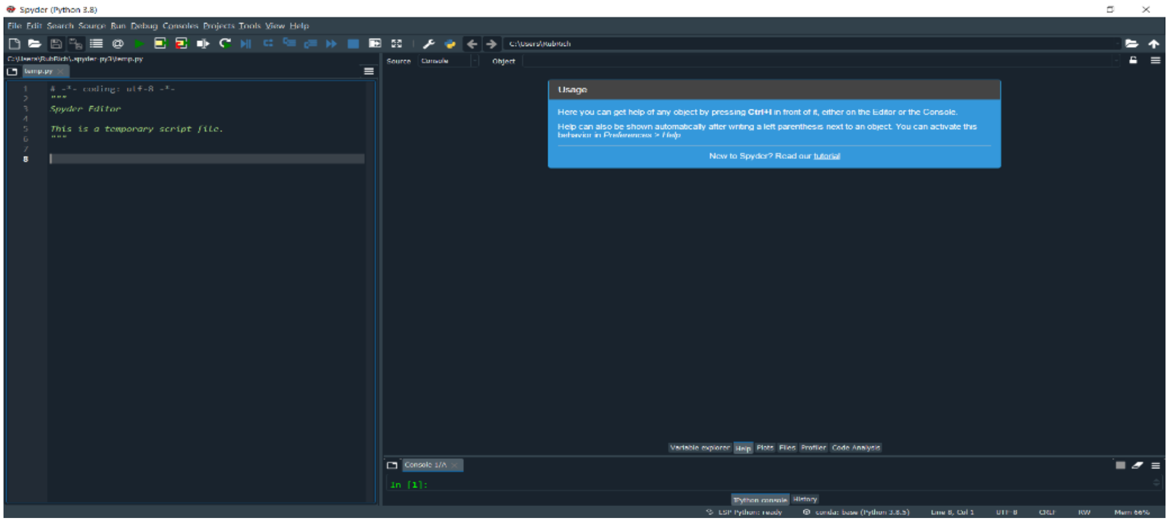

Figure 2. Spyder Environment

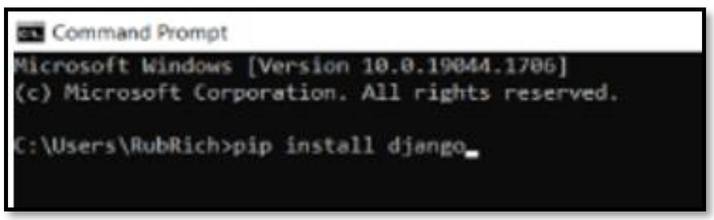

Figure 3. PIP Install using Command Prompt

A crucial step in evaluating the effectiveness of a machine learning model is comparing the accuracy of training and validation, as shown in Figure 4. As shown in Figure 5, training accuracy indicates how well the model fits the training data, while validation accuracy indicates how well the model generalizes to new data. A significant disparity between the training and validation data may indicate overfitting. To install missing Python libraries, use the pip command in the Command Prompt, as shown in Figure 3. For instance, you may use the command prompt to install libraries like TensorFlow or NumPy by running pip install tensor flow or pip install numpy. This ensures that the resources you need for your project will be available. Comparing the testing and training loss gives insight into the model's long-term learning efficacy. While training loss shows the model's error on the training data, testing loss shows the model's error on the testing dataset, as seen in Figure 7. During training, both losses should ideally fall and converge; if the testing loss continues to rise, it might be a sign that the model is not generalising appropriately. The percentage of true positives that the model accurately detects is known as the True Positive Rate (TPR), often called recall. Figure 6 displays the False Positive Rate (FPR), indicating the percentage of incorrectly classified negatives as positives. When assessing model performance, both measures are crucial, particularly when dealing with unbalanced datasets. Finally, a bar chart and prediction label might provide a visual depiction of the model's performance. Figure 8 shows the distribution of accurate and inaccurate predictions in a bar chart that compares predicted and actual values to aid in understanding the model's advantages and disadvantages.

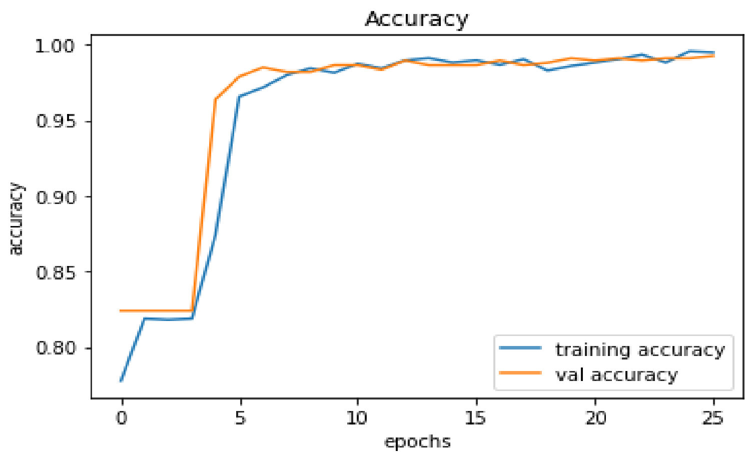

Figure 4. Training and Validation Accuracy Comparison

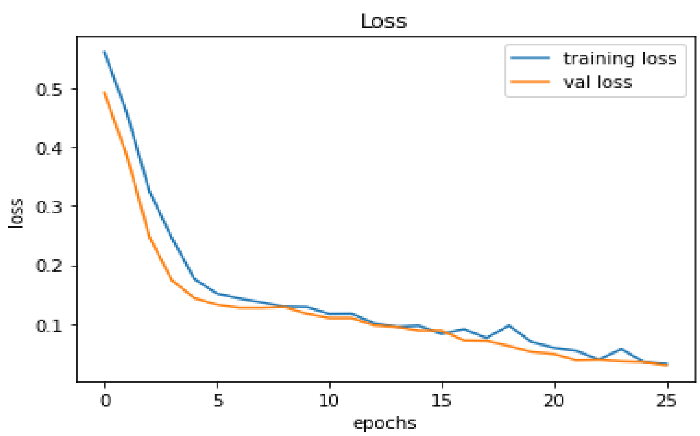

Figure 5. Training and Testing Loss Comparison

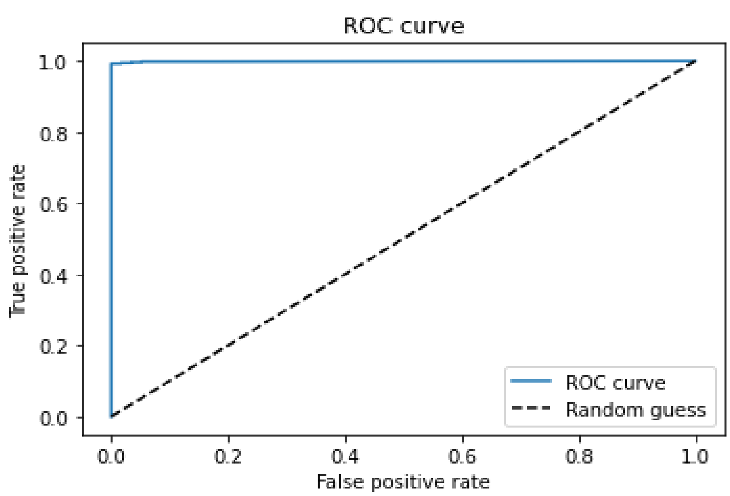

Figure 6. True and False Positive Rate

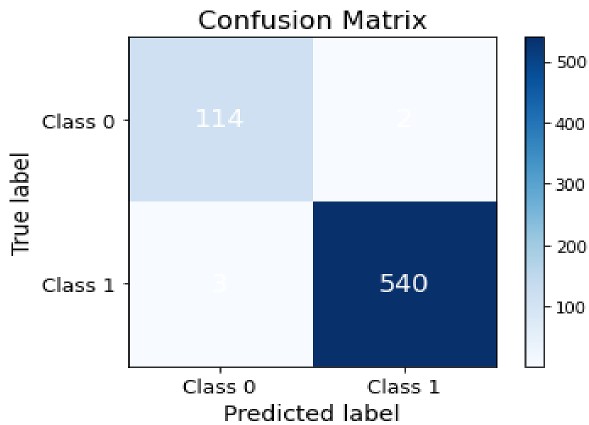

Figure 7. Prediction Label

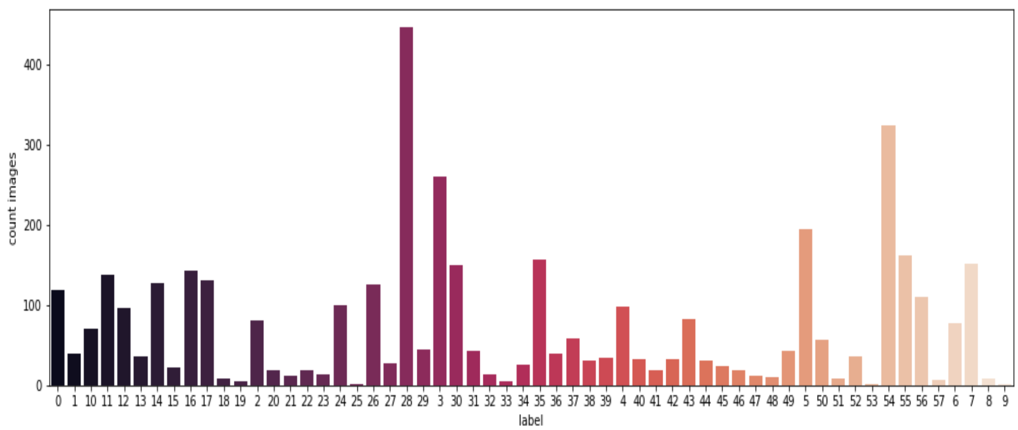

Figure 8. Bar Chart

5. CONCLUSION AND FUTURE SCOPE

This paper presents an improved VGG16 architecture for traffic sign categorisation. Many issues are fixed with the old VGG16 model and other methods that were previously used. To enhance its classification performance and generalization abilities, the new model includes dropouts, batch normalisations, additional convolution layers, and substantial data augmentation techniques. The recommended method is a robust and reliable choice for real-world traffic sign identification applications, demonstrating significant improvements in handling the intricate features and unpredictable nature of traffic signs. The proposed improvements do better than the base VGG16 model and other cutting-edge models, as shown by our extensive testing on benchmark datasets. The project's encouraging outcomes present numerous opportunities for further study and development. Future research could concentrate on integrating autonomous vehicles and advanced driver assistance systems utilizing the enhanced VGG16 architecture.

With the use of recognized cues, such as the ability to recognize and categorize traffic signs in real time, this would allow cars to make logical judgments. Researchers should investigate transfer learning and fine-tuning methods that use models that have already been trained on bigger, more varied datasets to make the traffic sign classification system last longer and work better. We may test and use the updated VGG16 model in practical settings, such as smart city infrastructure and intelligent traffic management systems, to get important insights into its applicability and potential areas for development. The improved VGG16 architecture might be used with other sensory inputs, such as LIDAR or RADAR, to build systems that can interpret traffic signs in several ways. Including a range of data sources would improve the accuracy and dependability of these algorithms in recognizing and categorizing traffic signals. Future research may concentrate on strengthening the model's defences against cyberattacks to ensure that traffic signs are accurately recognized even when unlawfully changed photographs of them are utilized. By including more variants and traffic signs from other nations and areas in the dataset, the model might be made more practical in real life.

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AUTHOR CONTRIBUTIONS

Sheemona Joseph C.: Project Administration, Writing – Review & Editing;
S. Ganesh: Conceptualization, Data Curation, Methodology, Validation, Writing – Original Draft Preparation;
S. Kannadhasan: Conceptualization, Data Curation, Methodology, Validation, Writing – Original Draft Preparation;
K. Selvipriya : Project Administration, Supervision, Writing – Review & Editing.

CONFLICT OF INTERESTS

No conflict of interests were disclosed.

ETHICS STATEMENTS

Our publication ethics follow The Committee of Publication Ethics (COPE) guideline. https://publicationethics.org/

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