CNN

BASED

ROAD SIGN

CLASSIFICATION-

DEEP LEARNING

INTRODUCTION:

Road signs are essential for regulating traffic and ensuring road safety. Automating road sign recognition using deep learning can significantly contribute to traffic management and autonomous driving systems. This project focuses on developing a **Convolutional Neural Network (CNN)-based Road Sign Classification Model** capable of identifying and categorizing road signs into 30 distinct classes with high accuracy. The labeled images of various road signs, which are preprocessed through resizing, normalization, and augmentation to enhance model performance. The project follows a structured workflow, starting with data collection and preprocessing, followed by building and training a CNN model with optimized architecture. Finally, the model is deployed using **Streamlit**, providing an interactive UI for real-time classification and accuracy visualization. This system aims to assist in traffic monitoring and autonomous navigation by accurately recognizing road signs in diverse conditions.

OBJECTIVE:

The primary objective of this project is to develop a road sign classification system using Convolutional Neural Networks (CNNs). With the increasing adoption of intelligent transportation systems and autonomous vehicles, accurately identifying road signs is crucial for ensuring road safety, assisting drivers, and enhancing automated navigation. This project aims to build a deep learning model that can classify various traffic signs using a dataset of labeled images.

The system leverages computer vision and machine learning techniques to automatically recognize traffic signs from images. The dataset contains a diverse range of road signs captured in real-world scenarios, helping the model generalize well to different lighting, angles, and environmental conditions. The goal is to create a robust model that can accurately classify signs into their respective categories, enabling applications such as driver assistance systems, automated traffic monitoring, and smart city infrastructure.

DATASET DESCRIPTION:

The dataset used in this project consists of traffic sign images categorized into multiple classes. It is designed for training, validating, and testing a Convolutional Neural Network (CNN)-based classification model. The dataset plays a crucial role in enabling the model to recognize and differentiate between various road signs commonly found on streets and highways. The dataset actually holds csv file and some image folder. The label data consists of 30 distinct classes, each representing a unique traffic sign. Some of the most common sign categories include:

* Stop Sign
* Speed Limit Signs (e.g., 30 km/h, 50 km/h, etc.)
* Horn
* No Entry
* Traffic Light Ahead
* Roundabout
* Yield Sign

Each class is labeled numerically in labels.csv, ensuring correct mapping between images and their corresponding sign categories. The image folders are

* DATA Folder: Contains images of road signs categorized into subdirectories, each representing a different class.
* TEST Folder: Holds images meant for final evaluation after training.

The images are in standard formats such as jpg, png and the dimensions Initially, images may vary in size, but they are resized to 64x64 pixels for uniform processing. Images are in RGB format, ensuring that the model captures color-based sign distinctions.

DATASET PREPROCESSING:

Data preprocessing is a crucial step in preparing the dataset for training a robust Convolutional Neural Network (CNN) model. It ensures that the data is properly formatted, normalized, and augmented to enhance the model’s generalization ability. The dataset is provided as a ZIP file containing images of road signs along with their corresponding labels. The ZIP file is extracted, and the images are loaded using TensorFlow’s [image\_dataset\_from\_directory] function. This method automatically assigns labels based on the directory structure.Since images in the dataset may have varying dimensions, they are resized to a uniform shape of 64x64 pixels. This standardization ensures consistency in input dimensions, which is essential for CNNs to process the data efficiently.

* **Resizing**: All images are resized to (64, 64, 3), where 3 represents the RGB color channels.
* **Normalization**: The pixel values, which originally range from 0 to 255, are scaled to a range of 0 to 1 by dividing by 255. This normalization step speeds up model convergence and prevents numerical instability during training.

To improve the model’s ability to recognize road signs under different conditions, various data augmentation techniques are applied. Data augmentation artificially increases the dataset’s diversity by generating modified versions of existing images. The following transformations are used:

* Random Flipping: Horizontally flips images to simulate different orientations of road signs.
* Random Rotation: Rotates images by a small degree to account for variations in how road signs appear in real-world settings.
* Random Zooming: Zooms into images to help the model recognize signs at different distances.
* Cropping and Clipping: Helps the model learn to recognize partially visible signs.

These augmentation techniques enhance the model’s robustness by reducing overfitting and improving its ability to generalize to unseen data. Once preprocessing is complete, the dataset is divided into three subsets to facilitate effective training and evaluation:

* Training Set (70%): Used for training the CNN model by learning patterns in the road sign images.
* Validation Set (15%): Used to fine-tune hyperparameters and monitor model performance during training. This helps prevent overfitting.
* Test Set (15%): Used for final model evaluation, ensuring that the trained model can generalize to unseen images.

METHODOLOGY

The methodology for this road sign classification project is structured into several key stages: data preprocessing, model development, training, evaluation, and deployment. Each phase has specific steps to ensure the model is robust, efficient, and capable of high accuracy. Below is a detailed breakdown of the methodology used:

**1.Data Augmentation:** To simulate real-world conditions and reduce overfitting, the augmentations applied are Random flipping (horizontal), Random rotation (small degree), Random zooming, Random cropping and clipping. These transformations help improve the model’s generalization by providing more diverse training samples.

**2.CNN Model Architecture:** The Convolutional Neural Network (CNN) used for classification is built with several layers to effectively learn the spatial hierarchies in the image data

* + **Convolutional Layers:** Extract features such as edges, shapes, and textures from the images.
  + **Max-Pooling Layers:** Reduce dimensionality and retain essential features.
  + **Fully Connected Layers:** Classify the extracted features into the 30 predefined classes of road signs.
  + **Softmax Activation:** Used in the final layer to output probabilities for each class.

The model is optimized using the Adam optimizer, and categorical cross-entropy is employed as the loss function, suitable for multi-class classification.

**3.Model Training:** The model is trained for a fixed number of epochs with a batch size of 20. The model’s accuracy and loss are tracked, and early stopping is applied to avoid overfitting.

**4.Model Evaluation:** After training, the model is evaluated on the test set to determine its generalization ability:

* + **Accuracy on Test Set:** The model achieves an accuracy of 98% on the test set, indicating its capability to classify road signs effectively.
  + **Confusion Matrix:** Used to visualize misclassifications across different classes, helping identify areas for potential improvement.

**5.Streamlit Deployment:** To make the model accessible for real-time predictions, a simple web application is created using Streamlit:

* + The UI allows users to upload images of road signs, which are then passed through the trained model.
  + The model’s predicted label and confidence score are displayed in the app.
  + The UI also provides a visualization of the input image and the corresponding predicted label.

METHODOLOGY

1. **High Model Accuracy:**
   * The CNN model achieved a remarkable 99% accuracy on the training set and 98% accuracy on the test set, demonstrating its high performance in classifying road signs.
2. **Effectiveness of Data Augmentation:**
   * Data augmentation techniques, including random rotation, flipping, and zooming, helped the model become more robust. These transformations allow the model to recognize road signs from different angles, lighting conditions, and perspectives, which is crucial for real-world applications.
3. **Class Imbalance:**
   * Some classes may have fewer images than others, potentially leading to slight biases in the model’s predictions. Future improvements could include using techniques like class weights or oversampling for underrepresented classes.
4. **Real-Time Deployment:**
   * The Streamlit interface provides an intuitive way to use the model in real-time for image classification. This is beneficial for applications such as autonomous driving systems, where quick and accurate recognition of road signs is crucial for safety.
5. **Model Interpretability:**
   * While the model performs well, further analysis such as Grad-CAM visualization can help understand which parts of the images contribute most to the classification decision. This would improve model transparency, especially for high-stakes applications like autonomous vehicles.

RESULTS

* **Training Accuracy:** 99%
* **Test Accuracy:** 98%
* **Confusion Matrix:** Shows the distribution of correct and incorrect predictions across the 30 classes.
* **Predictions:** The model accurately classifies images of road signs into their respective categories with high confidence.
* **Streamlit UI:** The deployed application allows real-time image uploads and predicts road signs with visual feedback.

CONCLUSION

In this project, a robust Convolutional Neural Network (CNN)-based model for road sign classification was successfully developed and deployed. The model was trained on a comprehensive dataset of road signs and achieved an impressive accuracy of 99% on the training set and 98% on the test set, demonstrating its strong ability to generalize to unseen data. The preprocessing techniques, including resizing, normalization, and data augmentation, played a vital role in improving the model's performance and robustness. By simulating real-world variations such as different orientations and distances, the model learned to recognize road signs in diverse conditions. The use of a CNN architecture with multiple convolutional and pooling layers enabled the model to extract essential features from the images and classify them into 30 distinct categories of road signs. Furthermore, the deployment of the model using Streamlit created a user-friendly, interactive interface for real-time predictions. This makes the model accessible for practical applications, such as traffic monitoring systems and autonomous vehicles, where accurate and timely road sign recognition is critical for safety and efficient navigation. While the model achieved excellent performance, some areas for improvement remain. These include addressing potential class imbalances, enhancing model interpretability for better transparency, and further fine-tuning to improve performance under various environmental conditions. Additionally, expanding the dataset with more diverse images could further improve the model’s generalization ability. Overall, this project contributes significantly to the field of automated traffic sign recognition, providing a solid foundation for integrating such systems into real-world traffic management and autonomous driving technologies. With further enhancements and refinement, this system could be an integral part of intelligent transportation solutions, improving road safety and supporting the advancement of autonomous driving capabilities.