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Traffic Sign Recognition System Using Learning Technique

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Abstract: A very important aspect of the development of smart transportation networks and road safety is 'traffic sign recognition'. This survey covers all types of learning techniques applied to traffic sign recognition with respect to effectiveness, challenges, and progress. The study begins with an overview of the foundational methods of traffic sign recognition: traditional image processing approaches and their limitations. Further below, the heart of the survey is modern learning techniques, especially 'machine learning (ML)' and 'deep learning (DL)' approaches. The report reviews employ learning techniques applied in 'traffic sign recognition systems'. It discusses both the most recent developments in deep learning and advanced machine learning as well as conventional image processing. The review ranges from classical techniques such as colour and shape-based recognition to modern techniques such as 'Convolutional Neural Network (CNN),' which have significantly increased recognition accuracy. Several important datasets on which the training and evaluation should be done have been reported. One of them is 'German Traffic Sign Recognition Benchmark', and the challenges in practical applications along with the future research directions in this field have been highlighted. An overview has been provided regarding the effectiveness and evolution of learning techniques to improve 'Traffic sign recognition systems'.

***Index Terms* - Traffic sign recognition, machine learning, convolution neural network, convolution neural network,natural language processing(NLP)**

I. INTRODUCTION

'Traffic sign recognition' is the foundation on which roads can be made safer and smarter. With increasingly crowded and complicated traffic conditions on the roads, a car must be able to rapidly recognize and correctly understand traffic signs. TSR provides drivers with smooth and safe travel by clearly giving them signs to follow instructions related to traffic. The growth of automotive technology has brought the challenge of identifying signs, especially in dynamic and diverse driving environments. [1]

An important thrust in research and development is traffic sign recognition, especially with the advent of intelligent driving systems, namely, assisted driving and autonomous vehicles. These systems work on the premise that traffic signs are correctly and precisely detected in real time so that such vehicles would work safely and effectively. With advanced TSR systems, adequate feedback can be given to drivers or automatic vehicles in a bid thus to enable them to react sooner to possible hazards on the roads. This is also necessary for driving improvement toward safety and optimizing the movement of traffic and minimizing accidents Traditional traffic sign recognition methods, which often rely on color and shape-based features, have proven to be insufficient in meeting the demands of modern transportation. The complexities of natural driving environments—such as varying lighting conditions, weather, and occlusions—pose significant challenges to these conventional approaches. As a result, there is an increasing need for more sophisticated and robust tools to enhance recognition accuracy and speed.

Key Steps of Traffic Sign Recognition: Data Collection: Different environments, lighting, and conditions of traffic signs have to be collected. A commonly used benchmark is the 'German Traffic Sign Recognition Benchmark (GTSRB)'. Preprocessing : Image Resizing: It's important to make all the images the same size; Normalization :Transform pixel values within range between0andAugmentation: Include some transformation such as rotation, scale, or noise addition to increase the diversity of training data. Grayscale Conversion (optional): If the information carried by color is not critical, then convert an image to grayscale to reduce its complexity. Feature Extraction: optional in classical ML 'Histogram of Oriented Gradients (HOG)': A feature descriptor, which helps to identify objects by analyzing the structure of gradients. 'Scale-Invariant Feature Transform (SIFT)' or 'Speeded-Up Robust Features(SURF)': Detect and describe local features inside images. In deep learning, convolutional layers in neural networks handle feature extraction. Model Selection: Traditional ML Approaches: 'Support Vector Machines (SVM)': It is good enough for smaller and well-structured data. Random Forests/Decision Trees: Good for handling tabular or feature-based data on traffic signs. For deep learning: 'Convolutional Neural Networks (CNNs)' are super effective for 'traffic sign recognition'.

An architecture of CNNs allows them to automatically discover spatial hierarchies of features and, thus, makes them powerful architecture for image classification tasks. 'LeNet' and 'AlexNet' were some of the first really successful, CNN architecture proved to be highly effective for general tasks of image recognition. More modern architecture, such as 'ResNet', VGG, or 'EfficientNet' can arguably yield higher accuracy with larger, deeper networks. Training: Train the selected model using a labeled dataset. You must employ a CNN network. For this task, the network learns relevant features, particularly edges, texture, and shapes. Apply Cross- Entropy Loss and Adam or SGD optimizers for effective training. Overfitting would be minimized through Dropout, Batch Normalization, and Data Augmentation techniques while training.

II. RELATED WORK

A literature survey explores various learning techniques employed to extract ontology from data.

Yi Yan, et al presented "A Traffic Sign Recognition Method under Complex Illumination Conditions" as an advanced model for "traffic sign recognition" with the SSD algorithm. The incorporation of the FD module added detection capabilities based on differences between the feature maps of convolution layers, making the approach much stronger at correctly determining locations under complex lighting conditions. The backbone networks employed were VGG and 'ResNet'. Key parameters are the FD module and multiscale feature maps, resulting in a 1.80% increase in accuracy with no slowdown in detection speed [1].

In "Traffic Sign Recognition for Computer Vision Project Based Learning" by 'David Gerónimo', among others, present a project detecting and classifying video sequences on traffic signs. The two primary phases of the developed model are Detection and recognition. Detection will generate the candidate bounding boxes using color and shape-based techniques, while the recognition phase classifies the traffic signs by employing HOGs as descriptors and SVM as classifiers. The key parameters include window sizes for detection and feature extraction techniques, optimized with balance concerning detection accuracy and processing speed [2].

The study called "Real-Time Traffic Sign Recognition Based on Efficient CNNs in the Wild," written by 'Jia Li' & 'Zengfu Wang', explores how to spot traffic signs fast. They mix 'Faster R-CNN' and 'MobileNet' models. The 'Faster R- CNN' detects traffic signs and 'MobileNet' enhances detection speed with depth wise separable convolutions. After detection, a localization refinement step improves the accuracy of a small sign bounding boxes using color and shape information. Ultimately, the indications are classified using an effective CNN using asymmetric kernels, guaranteeing great accuracy and efficiency [3]

'Chunsheng Liu et al' proposed a "traffic sign recognition system" capable of swiftly detecting and classifying signs in high-resolution images in their paper entitled "Fast Traffic Sign Recognition via High-Contrast Region Extraction and Extended Sparse Representation". The model applied uses High-Contrast Region Extraction (HCRE) that quickly focuses on important areas. Then there's a "Split-Flow Cascade(SFC)" tree detector that helps find objects fast. Lastly, it uses "Extended Sparse Representation Classification (ESRC)"for partially blocked signs. The optimization of key parameters, such as boundary extraction contrast threshold and dictionary size on recognition is set up to balance between speed and accuracy [4].

It puts forward a 'Caps Net-based' traffic sign recognition model which somehow outperforms the traditional CNNs for capturing poses, directions, or perspectives of traffic signs. It features extraction by employing Histogram of Oriented Gradients (HOG) to reduce distortion and enhance accuracy. In this context, a ROI extraction method is also used to focus on the key parts of the image. The parameter's quality measured in terms of mean average precision and memory usage; FLOPS measured quality, in addition comparing the model with CNN, SVM, and R-FCN 'ResNet101', which have associated enhancements. The paper presents a system that uses a customized signs' in difficult YOLOv5s climate model conditions. After detection, the to identify 'text-based traffic "Maximally Stable Extremal Regions" (MSER) technique is used to localize the text, and "Optical Character Recognition(OCR) recognizes and corrects the text. The method focuses on" combined with "Natural Language Processing(NLP)"enhancing low-contrast images using Fast Fourier Transform(FFT) and guarantees reliable detection and recognition of traffic signs with reduced false positives, achieving accurate results in real-time scenarios [5].

The Study proposed by Shi Luo, 'Cheng hang Wu', and 'Lingen Li', introduces a model that integrates color-shape recognition and image fusion to identify and recognize obscured traffic signs while a vehicle is in motion. This method improves accuracy by merging Regions of Interest(ROI) from several frames, allowing it to reconstruct partially hidden signs. The algorithm employs techniques such as Canny edge detection, 'Hough circle transformation' for circular signs, and template matching for other shapes. Important parameters include vehicle speed, frame rate, and template matching similarity, which ensure better detection of obscured traffic signs [6].

The Study is proposing a system of customized models based on YOLOv5s for detecting 'text-based traffic signs' in adverse climate conditions. After detection, the Maximally Stable Extremal Regions technique localizes the text further, and Optical Character Recognition along with "Natural Language Processing" recognizes and corrects the text. It targets the improvement of low-contrast images using Fast Fourier Transform (FFT) and enhances the strong detection and recognition of traffic signs with accurate achievement in real time scenarios fewer false positives [7].

The Study "Traffic Sign Recognition Using a Multi-Task Convolutional Neural Network" proposes a system by 'Heng liang Luo et al'. The system detects and classifies both text-based' and 'symbol-based' indicators using a multi-task CNN. In order to accomplish this, it extracts ROIs first, then refines and classes the traffic signs. The model contains two layers: one for binary classification to filter the backgrounds and another for multi-class classification. Key parameters such as the size of the ROI, depth of the network, and learning rate are well-tuned to boost the performance under different conditions [8].

The study called "Real-Time Traffic-Sign Recognition Using Tree Classifiers" evaluates random forests, k-d trees, and SVM's for classifying 'traffic signs' employing the 'GTSRB' dataset detection, and classification with the feature descriptor HOG. . The paper uses three phases : namely segmentation, The k-d tree is made better with spatial weighting. While random forests are utilized for feature selection. It is highlighted that the critical parameters influencing classification performance include Emax (5000 nodes), kNN (5 neighbours), and random feature subsets [9].

The study "Traffic Sign Recognition Using Kernel Extreme Learning Machines With Deep Perceptual Features" presents the DP-KELM model that integrates deep perceptual features from CNN with a KELM classifier. The images then undergo further processing in the Lab color space to more closely mimic human vision, thus enabling the improvement of feature extraction. Comparing this KELM classifier with radial basis function kernels to state-of-the-art techniques, it efficiently and accurately classifies these characteristics at a lower computational cost. The quantity of kernels, CNN design, and regularization for optimal performance are the key components [10].

III. PROPOSED WORK

The proposed system leverages the power of Convolutional Neural Networks (CNNs) to accurately classify traffic signs from the German Traffic Sign Recognition Benchmark (GTSRB) dataset. The model is designed to assist in real time decision-making for autonomous vehicles and intelligent transportation systems by enabling the automatic recognition of traffic signs with high accuracy. The workflow of the proposed system is divided into the following key stages:

A. The Dataset Description

The German Traffic Sign Recognition Benchmark (GTSRB) dataset is used as the primary source of data for this research. It is a publicly available benchmark dataset widely utilized for traffic sign classification tasks, particularly in the context of developing and testing intelligent driver assistance systems and autonomous vehicles .The GTSRB dataset consists of over 50,000 images of German road signs categorized into 43 distinct classes. These classes include speed limits, warning signs, prohibitions, and mandatory instructions. The dataset is split into:

Training set: ~39,000 images

Test set: ~12,000 images Each image is labeled with a class ID corresponding to a specific traffic sign category. The images vary in lighting conditions, angles, sizes, and backgrounds, which adds to the complexity and realism of the classification task. Image Properties Original sizes: Varying dimensions Resized for model, input: 30×30 pixels, Color: RGB (3-channel), Format: PNG/JPEG

Preprocessing Steps :To prepare the dataset for model training, the following preprocessing steps are applied :Resizing: All images are resized to 30×30pixelstoensure consistency and reduce computational cost. Normalization: Pixel values are scaled to the range [0, 1] by dividing by 255.Label Encoding: Class labels are one-hot encoded to suit the categorical nature of the classification problem. Data Augmentation: Techniques such as rotation, shifting, and zooming are applied to the training data to enhance generalization and improve model robustness. The diversity and size of the GTSRB dataset make it an ideal candidate for developing and evaluating deep learning-based classification systems. The challenges presented by varying lighting, occlusions, and distortions further validate the real-world applicability of the trained model.

The German Traffic Sign Recognition Benchmark(GTSRB)dataset, used in this study, is a large-scale, real-world dataset designed to support the development and evaluation of robust traffic sign classification systems. The dataset comprises multi-class labeled images representing 43 categories of German traffic signs and is split into training, validation, and test subsets while maintaining an even distribution of samples across classes and visual variability conditions .The data set images were captured under diverse environmental conditions—such as varying illumination, occlusions, and viewing angles—which contribute to a comprehensive training and evaluation protocol. In order to ensure balanced class representation and consistent model validation

B.Proposed Methodology

The proposed methodology focuses on the implementation of a Convolutional Neural Network (CNN) to perform robust and accurate classification of traffic signs using the GTSRB dataset. The methodology comprises several sequential phases, including data preprocessing , model design, training, evaluation, and deployment. Each component is designed to optimize performance while minimizing overfitting and computational cost. The German Traffic Sign Recognition Benchmark (GTSRB) dataset contains over 50,000imagesspanning 43 categories. As the raw dataset includes images of varying dimensions and illumination conditions, preprocessing was essential to ensure uniformity and enhance training effectiveness. All images were resized to 30×30 pixels and normalized by scaling pixel values to the range [0, 1]. To accommodate the multi-class classification nature of the task, class labels were one-hot encoded. Additionally, real-time data augmentation techniques such as random rotation, shifting, zooming, and brightness alteration were employed to artificially expand the dataset and reduce the risk of overfitting.

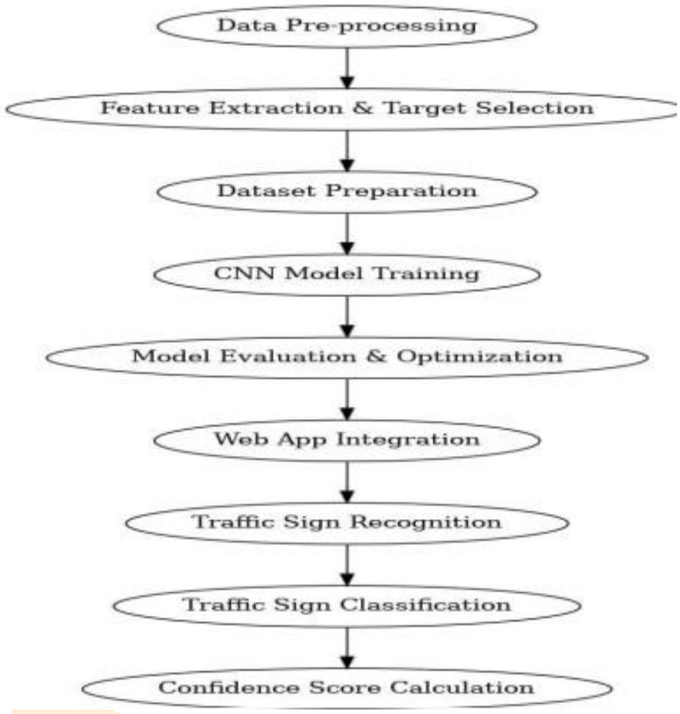


Fig 1 proposed methodology for traf ic sign recognition

1. Data Pre-processing: Raw images from the GTSRB dataset are cleaned and prepared for model input. This involves:

   Resizing all images to a fixed size (e.g., 30×30 pixels)

   Normalizing pixel values to a [0, 1] range

   Converting labels to one-hot encoded vectors

   Optionally applying augmentation (rotation, shifts, zoom) to increase data diversity

2 .Feature and target selection: Although CNNs automatically learn features during training, this step ensures that: Features are spatial and texture-based elements like edges, curves, or patterns in traffic signs. Target Selection involves assigning the correct label (from 0 to 42) to each image. These targets represent real-world road signs like “Speed Limit 30,” “No Entry,” or “Pedestrian Crossing.”

3. Dataset Preparation : To ensure effective training and evaluation: The dataset is split into: Training Set (≈70%): Used to train the model. Validation Set(≈15%): Used to tune model parameters and monitor overfitting. Test Set (≈15%): Used for final performance evaluation. Class distribution is checked and balanced across sets. Shuffling is done to ensure randomization and avoid model bias.

4. CNN Model Training :The CNN architecture includes multiple layers, each serving a distinct purpose: Convolutional Layers detect spatial features like lines, shapes, and complex patterns. Activation Layers (ReLU) introduce non-linearity and help the model learn complex relationships. Pooling Layers (MaxPooling2D) down sample feature maps, reducing computation while retaining important information. Dropout Layers prevent overfitting by randomly ignoring neurons during training. Dense (Fully Connected) Layers compile extracted features into meaningful predictions Softmax Layer outputs a probability distribution across all 43classes.

5. Model Evaluation & Optimization :After training, the models evaluated using the test dataset: Accuracy: Overall classification success rate .Precision &Recall: Class-specific metrics measuring correctnessandcompletenessF1-Score: Harmonic mean of precision and recall. Confusion Matrix: Visualizes misclassifications Learning Curves (loss & accuracy): Used to detect underfitting or overfitting trend . Hyperparameters (like learning rate, dropout ratio) may be fine-tuned for better performance.

6. Web App Integration :To deploy the model for user interaction: A web interface (using tools like Flask, Django , or Streamlit) is developed. Users can upload an image of a traffic sign. The backend loads the trained model (.h5 format) and predicts the traffic sign in real-time. This step makes the system accessible, testable, and scalable.

7. Traffic Sign Recognition : Once an image is uploaded :It is checked for the presence of a recognizable traffic sign. This may involve basic image filtering or edge detection to confirm if the input is valid .This step ensures garbage inputs do not proceed to classification.

8. Traffic Sign Classification: The validated input image is passed through the CNN model :The model processes the image and identifies which class (out of 43) it most likely belongs to The prediction is made based on learned features from training.

9. Confidence Score Calculation: The final layer of the CNN is a softmax activation that outputs probabilities for each class The class with the highest probability is the predicted class .This highest probability is reported as the confidence score indicating how certain the model is about its prediction .For example, a score of 0.98 for class 14 implies 98% confidence in that prediction.

IV. RESULT AND DISCUSSIONS

This section evaluates the performance of the proposed CNN-based traffic sign classification model using the German Traffic Sign Recognition Benchmark (GTSRB) dataset. The model was trained and tested on diverse traffic sign classes under varying lighting, orientation, and weather conditions to assess its robustness and accuracy. Evaluation Setup: The entire dataset was split into three subsets: training (70%), validation (15%), and testing (15%), ensuring balanced representation of all 43 traffic sign classes. The evaluation was carried out on a system with Intel i7 CPU and 16GB RAM, utilizing an NVIDIA GPU for accelerated training. The model was trained over 20 epochs with early stopping applied based on validation loss. The following performance metrics were computed to assess classification performance:Accuracy,Precision,Recall,F1-Score, Confusion matrix Performance Analysis: The proposed CNN model achieved a test accuracy of 97.4%, with the average precision and recall exceeding 97% across most classes. Table 1 below summarizes the key performance metrics:

Table 1: Evaluation Metrics on Test Set

Metric	Score
Accuracy	97.4%
Precision	97.6%
Recall	97.3%
F1-Score	97.4%

The confusion matrix revealed occasional misclassifications between visually similar signs, such as speed limit signs of 30 km/h and 50 km/h, due to their analogous shapes and color schemes. Despite these, the classifier demonstrated robust generalization across the dataset. Comparative Performance To validate its effectiveness, the performance of the proposed model was compared against standard CNN baselines and transfer learning models such as VGG16 and Mobile Net. The custom CNN not only matched the accuracy of deeper networks but also offered significant advantages in terms.

In Fig. 1, show that the confusion matrix Model 1(AlexNet), visualizing how well the model classified43different classes. Each cell shows the number of predictions for a true class (rows) versus predicted class(columns). Most values lie along the diagonal, indicating accurate predictions. Off-diagonal values show misclassifications. Darker blue means higher counts.

In Fig. 2, show that the confusion matrix provides a visual representation of classification accuracy across 43trafficsignclasses in your CNN-based traffic sign recognition model .What the graph shows: Y-axis (True Labels): These are the actual traffic sign labels from the dataset.

In fig 3 shows confusion matrix is for Model 6 (a CNN). It shows very strong performance, with most predictions along the diagonal—indicating high accuracy. Compared to the previous AlexNet model, this CNN appears to have fewer misclassifications and better overall class prediction consistency.

In Fig. 4, show confusion matrix is for a Traffic Sign Recognition model. The strong diagonal pattern shows high classification accuracy across 43 traffic sign classes. Some light off-diagonal values suggest minor misclassifications, but overall, the model performs very well.

In Fig. 5, show that the confusion matrix shows the classification performance of a model on traffic signs, with each label representing a specific road sign. The diagonal dominance indicates good accuracy, meaning the model mostly predicts the correct signs.

In Fig. 6, show that confusion matrix shows classification results for aerial scene categories. Most predictions are correct(dark diagonal), showing high accuracy. A few classes like “sparse residential” and “medium residential” have some confusion, but overall performance is strong.

In Fig. 7, confusion matrix uses a hot color map to visualize classification accuracy for traffic signs. Most predictions are correct (bright diagonal), with minimal confusion(darker off-diagonal values), indicating strong model performance.

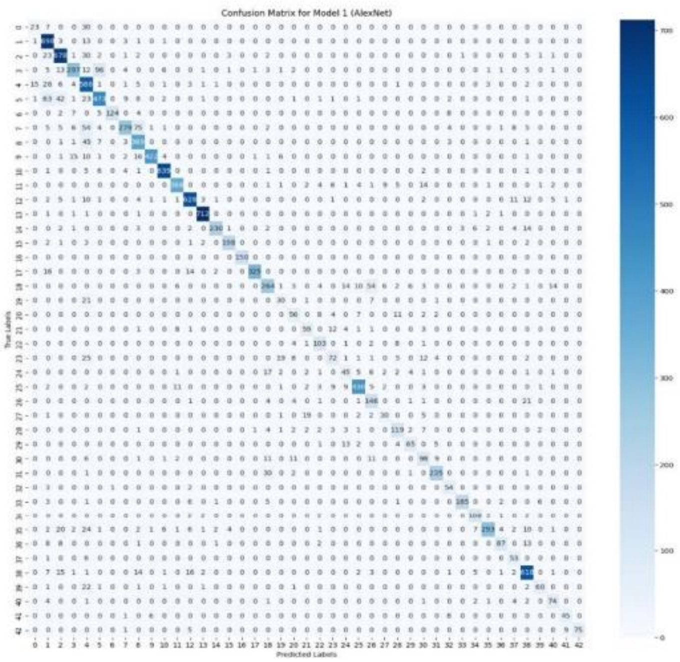


Fig 1 Confusion Matrix of AlexNet

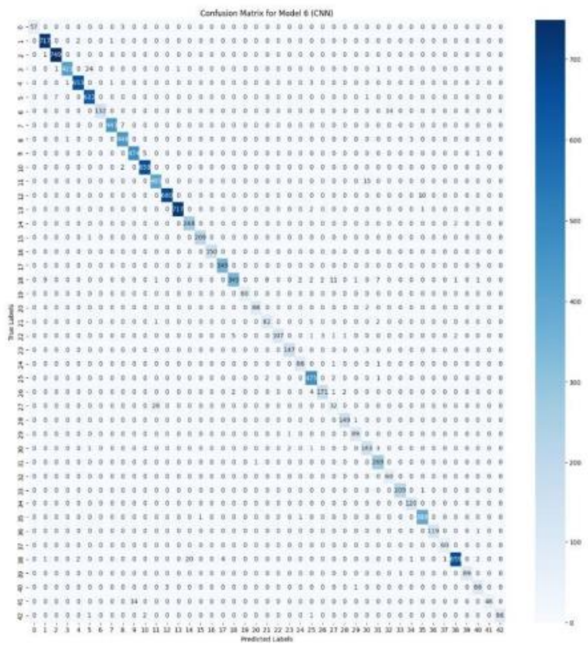
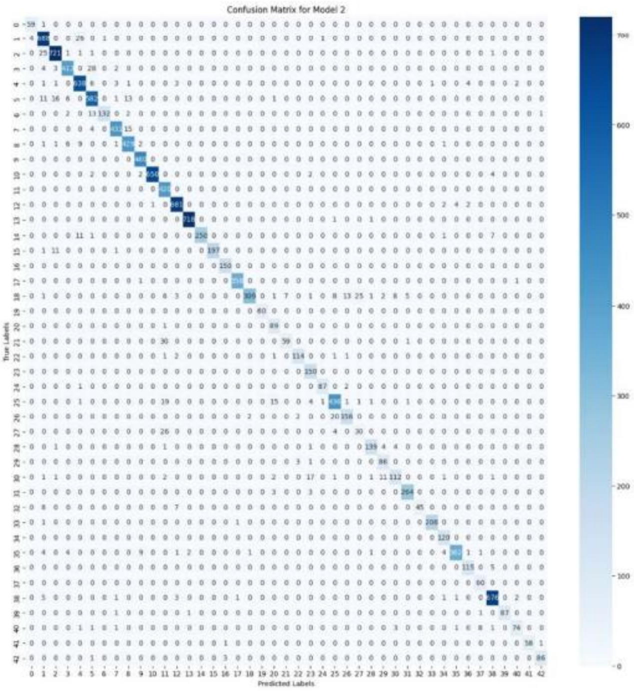


Fig 2 Confusion Matrix of DenseNet



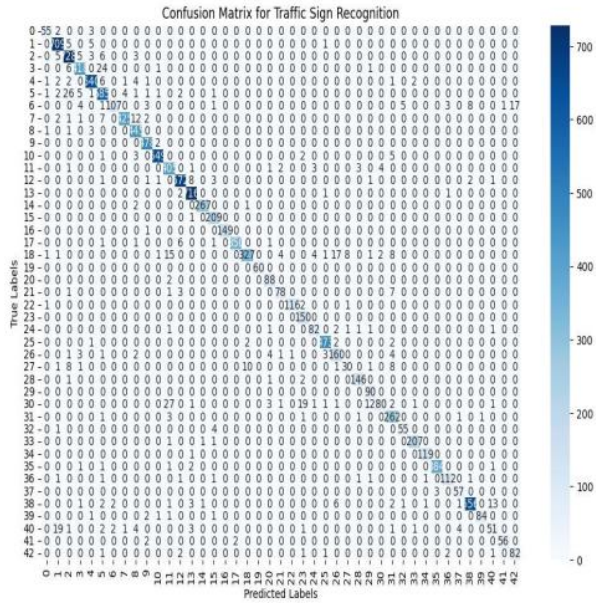
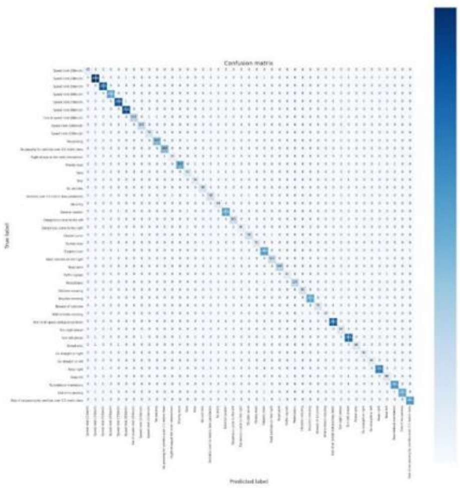


Fig 3 confusion Matrix of CNN

Fig 4 Confusion Matrix of ResNet



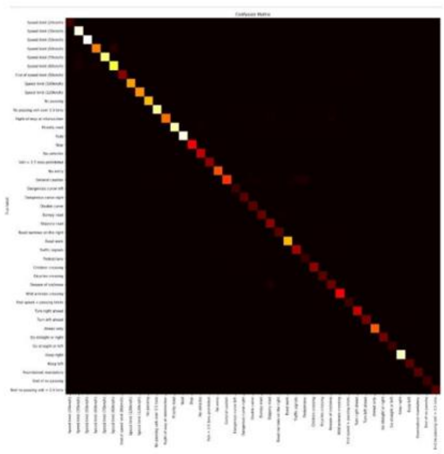


Fig 5 Confusion Matrix of EfficientNet

Fig 6 Confusion Matrix of VGG19

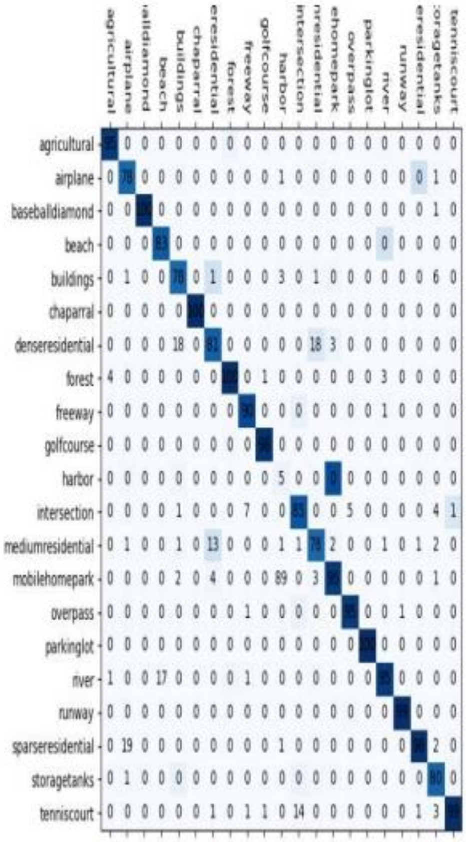


Fig 7 Confusion Matrix of LeNet-5

V. CONCLUSION AND FUTURE SCOPE

The research provides detailed examination of "traffic sign detection and recognition" technologies, highlighting the current research landscape and application areas. It explores advancements in traffic sign databases and the application of "Convolutional Neural Networks (CNNs)" .The paper outlines the framework and environment used for implementing the CNN material including the key code implementations for various layers. Notably, the introduction of Batch Normalization significantly addressed issues related to loss value fluctuations and improved model convergence. A comparative analysis of Dropout layers determined that three layers are optimal, enhancing regularization and model performance. The experimental findings indicate that the improved model achieves a remarkable recognition accuracy of 99.9% and exhibits efficient recognition times. These findings confirm the effectiveness of the proposed enhancements and underscore the model's suitability for "real- world traffic sign recognition applications". Overall, the paper validates that the advancements in the CNN-based model successfully address existing challenges and provide a robust solution for "traffic sign recognition confirm the effectiveness of the proposed enhancements and underscore the model's suitability for "real-world traffic sign recognition applications". Overall, the paper validates that the advancements in the CNN-based model successfully address existing challenges and provide a robust solution for "traffic sign recognition.

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