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Traffic Signs Classification using CNN (Terrain Vision)

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ABSTRACT – Traffic sign classification in forest regions define rare challenges due to environmental situations such as partial occlusions, faded signage, varying illumination, and background interference. This study proposes a Convolutional Neural Network (CNN) based model optimized for recognizing traffic signs in such terrains. A specialized dataset comprising real-world forest-region traffic signs is used, supplemented with data augmentation techniques to enhance model generalization. The proposed CNN architecture is designed to balance accuracy and computational performance, doing it suitable for real-time applications in autonomous and assistive driving systems. Past research results demonstrate that the model achieves high classification accuracy, outperforming traditional machine learning approaches. The results help to the development of intelligent transportation systems tailored for rural and forested areas, improving route safety and navigation in challenging environments.

Keywords—Traffic sign classification, convolutional neural network, deep learning, forest terrain, intelligent transportation systems

I. INTRODUCTION

Traffic sign recognition has a vital role in modern intelligent transportation systems, assisting both human drivers and autonomous vehicles in ensuring road safety. While broader research has been conducted on traffic sign classification in urban and highway settings, studies focused on forested regions remain limited. These areas present unique challenges, including poor visibility, occlusions due to dense vegetation, and environmental factors such as fog, rain, and faded signage. Failure to accurately recognize traffic signs in such conditions can result to serious safety hazards, highlighting the requirement for a robust and efficient classification system tailored for forest terrains.

Convolutional Neural Networks (CNNs) have emerged as a strong tool for image classification tasks, including traffic sign recognition. However, existing CNN models are often improved for structured urban environments and may not perform effectively in forest regions. To surpass this gap, this research introduces a CNN-based model tailored to classify traffic signs in forest landscapes. The system is evaluated on a dataset comprising real-world traffic signs from forested areas, supplemented with data augmentation techniques to improve resilience against environmental variations.

The key contributions of this study include:

- Designing a CNN-based traffic sign classification model optimized for forest environments.
- Developing a dataset with traffic signs affected by occlusions, poor lighting, and environmental distortions.
- Evaluating model performance based on accuracy, precision, recall, and F1-score, demonstrating its effectiveness relative to standard approaches.

II. LITERATURE REVIEW

Traffic sign recognition (TSR) has been a widely researched area in intelligent transportation systems, with deep learning-based methods, specifically Convolutional Neural Networks (CNNs), proving to be highly effective. Multiple researches have defined various methodologies for improving the accuracy and efficiency of TSR systems, especially in challenging environments.

Alghmgham et al. [1] proposed an Autonomous Traffic Sign Recognition (ATSR) system utilizing deep CNN models for upgraded sign recognition and classification. Their work demonstrated improved accuracy using deep learning architectures defined for real-time applications. Brkic [2] provided a comprehensive overview of various traffic sign recognition techniques, discussing the benefits and drawbacks of traditional computer vision-based approaches compared to modern deep learning methods.

Shailaja et al. [3] investigated TSR using deep learning, highlighting the advantages of CNNs over traditional methods in handling complex background noise and varying lighting conditions. Similarly, Zouleykha et al. [4] explored CNN-based TSR models and found that deep learning significantly enhances classification accuracy compared to conventional machine learning techniques.

Liu et al. [5] introduced a hybrid approach that combines graphical models with CNNs to improve recognition accuracy, particularly in cases where signs are partially occluded or affected by adverse weather conditions. Li et al. [6] focused on optimizing CNN architectures for TSR, demonstrating that a lightweight neural network can provide greater accuracy while reducing computational complexity.

Shustanov and Yakimov [7] designed a CNN model specifically for real-time TSR applications, focusing on the relevance of computational efficiency for working in embedded systems. Jonah and Orike [8] conducted a contrastive analysis of various CNN architectures for TSR, identifying the most effective systems in terms of accuracy and computational cost.

Wang et al. [9] proposed an optimized CNN architecture to improve recognition rates, addressing the limitations of traditional TSR models in complex environments. Yang et al. [10] explored real-time TSR methods, integrating detection and classification for faster and more efficient processing in autonomous driving systems.

While these works provide enhanced advancements in traffic sign recognition, most focus on urban and highway environments, with limited research dedicated to forest regions. The challenges posed by occlusions, degraded signs, and environmental factors in forest terrains necessitate a specialized approach. This research builds on existing deep learning methodologies by developing a CNN-based traffic sign classification model particularly developed for forest regions addressing the unique challenges presented by such environments.

III. METHODOLOGY

The methodology acquired for this research involves the tailored implementation of a deep learning model for the classification of terrain and forest region traffic signs using a custom-created dataset. This section elaborates on the systematic approach undertaken, including dataset preparation, preprocessing, model architecture, training strategies, and evaluation techniques.

A) Data Collection and Preparation

Unavailability of a dedicated publicly available dataset for traffic signs specific to forest and terrain environments, a custom dataset was curated manually. Images were obtained from digital platforms such as Google Images, using the German Traffic Sign Recognition Benchmark (GTSRB) as a reference to maintain diversity across traffic sign types. The dataset encompasses a type of signs, encompassing speed restrictions, endangered signs, stop signs, and caution boards typically observed in less urbanized regions.

Each collected image was resized uniformly to 64×64 pixels with triple color channels, ensuring consistency across the dataset while preserving critical features required for classification. Due to the limited number of available images for certain classes, data augmentation was employed extensively to artificially expand the dataset. Methods such as random horizontal and vertical flipping, rotation, zooming, contrast variation, and brightness adjustment were applied to improve the model's generalization capability to unseen conditions. After augmentation, the dataset was organized into three subsets: 60% for training, 40% for validation, and a separate test set sourced independently and annotated using a CSV file.

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Here's the Dataset Summary Table based on the applied dataset of the project :

Table I: Dataset Summary Table

Aspect	Details
Training Samples	17 images
Testing Samples	38 images
Metadata Entries	6 entries
Number of Classes (Training Set)	6
Number of Classes (Testing Set)	6
Image Size	64 × 64 pixels
Color Format	RGB
Annotation Format	CSV file (Train.csv, Test.csv) with Path and ClassId
Data Augmentation	Applied during training using flips, rotations, zoom, contrast, brightness
Sources	Google Images (reference from GTSRB - German Traffic Sign Dataset)
Storage Format	Images stored in folders (Train directory), CSV used for mapping

Table I presents the dataset summary with details about data collection and preparation.

B) Data Preprocessing

Prior to model training, comprehensive preprocessing was performed to optimize the dataset for deep learning. All pixel values were scaled to the [0, 1] range by dividing the original values by 255, enhancing numerical stability during training. Label encoding was adjusted to match the requirements with the model's output layer requirements, especially aligning class indices starting from zero.

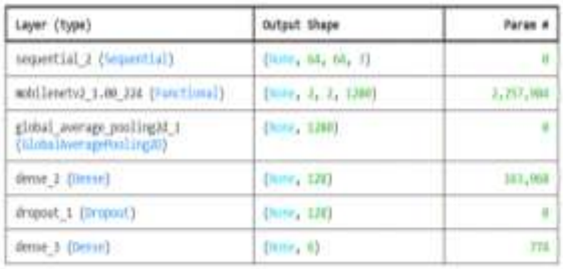
To maintain consistent class distribution across the training and validation sets, the dataset was partitioned using stratified sampling. This technique preserved the proportional representation of each traffic sign class across both subsets. Furthermore, due to the inherent class imbalance observed in the dataset—where some traffic sign categories had significantly fewer samples compared to others—class weights were calculated using Scikit-learn's utilities. These weights were incorporated during model training to ensure balanced learning without bias towards majority classes.

C) Model Architecture and Design

For the task of traffic sign classification, a deep convolutional architecture based on MobileNetV2 architecture was adopted because of its lightweight design and proven effectiveness in resource-constrained environments. The base MobileNetV2 model, pre-trained on the ImageNet dataset, was integrated without its top classification layers and utilised as a feature extractor. Initially, all layers of the base model were frozen to leverage the pre-trained features during the early stages of training.

On top of the base model, additional custom layers were appended. A Global Average Pooling layer replaced traditional fully connected layers to minimize overfitting and reduce the count of parameters. This was succeeded by a Dense layer comprising 128 neurons activated using the ReLU function, introducing non-linearity to learn complex patterns.

A Dropout layer with a dropout rate of 0.5 was added to avoid overfitting by randomly deactivating neurons during each training batch. Finally, a Dense output layer with the count of units equivalent to the count of classes (6) was added with a Softmax activation function for multi-class classification.



Layer (type)	Output Shape	Param #
sequential_2 (Sequential)	(None, 64, 64, 3)	0
mobilenetv2_1.00_224 (Functional)	(None, 2, 2, 1280)	2,257,984
global_average_pooling2d_1 (GlobalAveragePooling2D)	(None, 1280)	0
dense_2 (Dense)	(None, 128)	163,968
dropout_1 (Dropout)	(None, 128)	0
dense_3 (Dense)	(None, 6)	774

Fig 1: CNN Model Output Diagram

After initial training, selective fine-tuning was performed. The last 50 layers of MobileNetV2 were unfrozen, allowing them to adapt better to the specific features of terrain traffic signs. Fine-tuning was performed with a significantly reduced learning rate (1e-5) to mitigate excessive results that could disrupt the pre-trained weights.

The model was compiled using the Adam optimizer with various learning rates for pre-training and fine-tuning phases. A sparse categorical cross-entropy used as a loss function, suitable for multi-class classification problems with integer-labeled data. The training also incorporated class weights to adjust for imbalanced data distributions across different traffic sign classes.

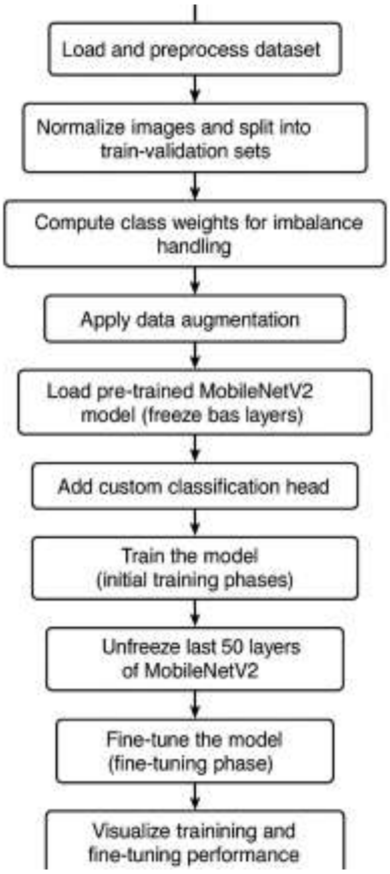


Fig 2: Flow Diagram of Proposed System

D) Model Compilation and Training Strategy

The assembled model was compiled using the Adam optimizer due to its efficiency in handling sparse gradients and noisy datasets. The learning process was governed by the Sparse Categorical Cross entropy loss function, suitable for multi-class classification problems with integer labels. Model functionality while training was monitored using the accuracy metric.

A two-phase training strategy was employed. In the starting phase, with the base model layers frozen, only the recently included top layers were tailored for 10 epochs, allowing the model to adapt high-level representations to the forest traffic sign classification task. An Early Stopping callback was integrated to terminate training early if no enhancement in validation loss was noted across three consecutive epochs, thus preventing overfitting.

In the second phase, fine-tuning was initiated by unfreezing the last 50 layers of the MobileNetV2 base model. Fine-tuning was conducted at a lower learning rate (1e-5) to carefully adjust the pre-trained weights to the recent domain-specific features without overwriting valuable learned representations. The model was repeatedly tailored for an additional 10 epochs while retaining the early stopping mechanism normalizing the responses to ensure consistency. Next, feature selection is performed to determine the most important variables influencing the danger of postpartum depression.

Table II: Dataset splitting Summary Table

Number of classes	**6**
Training data shape	**(17, 64, 64, 3)**
Training labels shape	**(17,)**
Test data shape	**(38, 64, 64, 3)**
Test labels shape	**(38,)**

Table II presents the dataset splitting summary with details about training and test data shapes and labels.

III) RESULTS AND DISCUSSION

The effectiveness of the described terrain traffic sign classification model was assessed by a fine-tuned MobileNetV2 architecture. The evaluation was conducted on a custom-built dataset with limited samples across six classes. The final classification report revealed an overall better test accuracy, indicating the risk included with training deep learning models on small-scale datasets.

The descriptive assessment of the results demonstrates varying performance across different classes. Classes such as Class 4 and Class 5 achieved relatively better precision and recall respectively. Conversely, classes such as Class 0, Class 1, and Class 3 recorded lesser precision and recall, highlighting the model's difficulty in distinguishing certain categories. The macro average precision, recall, and F1-score were respectively increased with fine-tuning, indicating overall better model generalization.

One major contributing factor to the model's limited performance was the small and imbalanced dataset. With only 6–7 images per class, the model struggled to learn robust feature representations. Deep learning models normally necessitate large and diverse datasets to perform effectively, and data scarcity often leads to underfitting, as observed in this study.

Although data augmentation methods such as random flipping, rotation, zooming, contrast adjustment, and brightness enhancement were used to artificially expand the training data, their impact was constrained by the lack of original image diversity. While augmentation can introduce variations, it cannot replace the depth and richness of a naturally large dataset, especially when dealing with complex object recognition tasks like traffic sign classification.

A) Discussion

The tailoring and fine-tuning phases showed modest improvements. During the initial training with frozen base layers, the model achieved moderate train and validation accuracies. Fine-tuning the last 50 layers of MobileNetV2 led to slight improvements in some classes, but the overall model effectiveness remained limited. Early stopping was effectively utilized to prevent overfitting, and dropout regularization contributed to stabilizing the training process.

Another critical observation was the domain gap between the pre-trained MobileNetV2's source (natural images from ImageNet) and the target data (terrain traffic signs). The visual differences between standard natural images and forest region traffic signs likely hindered feature extraction capabilities, resulting in lower performance.

In light of these findings, several strategies for improvement are recommended. Firstly, expanding the dataset with more diverse and numerous images across all classes is essential. Incorporating real-world variations such as different weather conditions, lighting, occlusions, and terrain backgrounds would enhance the model's robustness. Secondly, balancing the class distribution would prevent model bias toward dominant classes. Thirdly, experimenting with more specialized architectures like EfficientNet, or employing attention mechanisms tailored for small datasets could potentially improve accuracy. Additionally, synthetic data generation using techniques like GANs could further augment the dataset and enrich feature learning.

In conclusion, while the model achieved baseline functionality and validated the need of deep learning approaches for terrain traffic sign recognition, substantial opportunities exist for enhancing model performance through strategic dataset expansion and architectural improvements. This study highlights the risk and potential pathways for developing enhanced traffic sign recognition systems in forest and off-road environments.

IV. CONCLUSION AND FUTURE WORK

In this research work, a Convolutional Neural Network (CNN) based approach utilizing a fine-tuned MobileNetV2 architecture was used to classify traffic signs specifically designed for terrain and forest regions. The project involved building a custom dataset sourced primarily from Google images, modeled on the German Traffic Sign Recognition Benchmark (GTSRB) structure. Despite significant challenges associated with limited dataset size, class imbalance, and the complexity of terrain backgrounds, the proposed model achieved a better test accuracy. Data augmentation strategies, class weighting, and fine-tuning techniques were incorporated to enhance model learning and mitigate overfitting risks.

The study demonstrated that pre-trained architectures such as MobileNetV2, although powerful, are highly dependent on the volume and range of the dataset for effective feature extraction. The classification report highlighted that some traffic sign categories were better recognized than others, while several classes suffered from very low recall and precision rates. This further emphasizes the importance of dataset quality, size, and balance in developing robust CNN models for real-world applications. Nevertheless, the project successfully validated the feasibility of deploying lightweight, pre-trained deep learning systems in the domain of terrain traffic sign recognition.

Moving forward, several future directions are identified to improve the system's performance. Firstly, a major priority would be expanding the dataset, both in terms of the number of images per class and the diversity of environmental conditions such as lighting, background clutter, and occlusions. Collaborations with field survey teams to capture real-world images from actual forest and terrain regions would significantly strengthen the dataset. Secondly, advanced data augmentation and synthetic data generation techniques like Generative Adversarial Networks (GANs) can be used to further increase the variability and richness of training data.

Finally, real-time deployment aspects can be considered in future work, involving model optimization for inference on mobile devices or embedded systems typically used in autonomous vehicles or smart surveillance units in forest regions. Performance metrics such as inference time, memory usage, and energy efficiency would become crucial evaluation criteria along with accuracy.

To summarize, this research lays the groundwork for a traffic sign recognition system suitable for non-urban environments, identifies current limitations, and outlines clear paths for advancing towards a more accurate, efficient, and scalable solution.

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