A red sign with white text

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CMT316 Coursework 2 (Group Project)

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**Detection and Recognition of Traffic Signs**

# 1.Introduction:

Imagine driving through a busy street filled with traffic signs-speed limits, stop signs, yield warnings. For a human driver, recognizing and reacting to these signs quickly is second nature. But for a machine, this task is far more complex. In the world of autonomous vehicles and advanced driver assistance systems(ADAS) and autonomous driving technology, the ability to accurately detect and interpret traffic signs isn’t just a nice-to-have it’s essential for safety and navigation.

This project dives into that very challenge: building smart, reliable systems that can recognize traffic signs in real-word conditions. We focus our efforts on the German Traffic Sign Recognition Benchmark(GTSRB) a widely used dataset containing thousands of real-time traffic sign images captured under various environmental conditions. Think of rail-slick roads, signs obscured by shadows, and glare from the sun, including different lighting, weather and partial occlusions. Our goal is to train deep learning models that can handle all that and more.

To tackle this, we implemented and evaluated four different Convolutional Neural Network(CNN) architetures: a Deep CNN, a Simple CNN, a Lenet5, and a MobileNetV2.Each model brings a unique approach to solving the traffic sign recognition problem. Our work doesn’t just stop at model pretraining, we go deeper. Our contributions include:

* Rigorous preprocessing to address class imbalance and poor image quality
* Implementation and tuning of multiple CNN models
* In-depth performance comparison with error analysis
* Evaluation of architectural features influencing recognition accuracy

This research is about pushing the boundaries of what machine can see and understand on the road. With the right models in place, we believe this work can pave the way for safer, smarter transportation system and maybe even bring us one step closer to fully autonomous driving.

# 2. Literature Review:

Traffic sign recognition has become an essential area in computer vision, especially for applications like autonomous driving and driver assistance systems. One of the most influential contributions to this field is the German Traffic Sign Recognition Benchmark (GTSRB), introduced by Houben et al., which provides a diverse dataset for developing and testing classification models. Their early work combined image preprocessing techniques like Histogram of Oriented Gradients (HOG) with Support Vector Machines (SVMs), setting a strong performance baseline of 96.14% accuracy.

With the evolution of deep learning, Convolutional Neural Networks (CNNs) emerged as a powerful alternative to traditional methods. CNNs eliminate the need for handcrafted features and instead learn directly from raw image data. Our project builds on this principle by implementing a CNN-based approach to classify traffic signs from the GTSRB dataset.

To improve the model’s ability to generalize to new, unseen data, we apply data augmentation techniques such as rotation, zooming, and shifting. These strategies, commonly used in deep learning workflows, increase the diversity of training samples and help the model handle variations in image orientation and scale. Furthermore, we focus on optimizing the CNN model using standard practices such as dropout for regularization, ReLU activation functions, and softmax for multi-class classification. These components are crucial for enhancing performance and reducing overfitting.

In summary, our work leverages the GTSRB dataset, a CNN-based architecture, and data augmentation techniques to develop a robust traffic sign recognition system. While we do not incorporate advanced modules like attention mechanisms or spatial transformers, our implementation serves as a strong and efficient baseline for traffic sign classification under standard conditions.

Our project draws inspiration from all these advances. We integrate the best practices from past research, including robust preprocessing, model optimization, and architectural variety. Our goal is to take these ideas even further by putting them to the test in a head-to-head comparison—examining how different CNN architectures perform under various conditions, and what it takes to make them truly reliable in real-world driving scenarios.

# 3. Description of the Task and Dataset:

**Task Description:**

The primary task is to develop deep learning models capable of classifying traffic signs into their respective categories with high accuracy. This multi-class classification problem involves recognizing 43 different types of German traffic signs from images captured under various real-world conditions. The system must be robust to variations in lighting, perspective, weather effects, and partial occlusions. The performance metric for evaluation is primarily classification accuracy, with additional consideration given to model efficiency and generalization capability.

## Dataset Description:

The German Traffic Sign Recognition Benchmark (GTSRB) dataset consists of more than 50,000 real-world images of German traffic signs. These images were extracted from video sequences recorded on German roads, representing authentic driving conditions. The images have varying sizes ranging from 15×15 to 250×250 pixels, and many suffer from low contrast and lighting issues common in real-world scenarios. The dataset includes 43 classes of traffic signs, covering prohibitory signs, mandatory signs, danger signs, and informational signs.

Each image in the dataset comes with the following annotations:

* Class ID (0-42) representing the type of traffic sign
* Image size and position coordinates of the sign within the image
* Track information (indicating which video sequence the image belongs to)

## Dataset Statistics:

The GTSRB dataset is divided into training and testing sets, at a ratio of approximately 3:1:

| **Set** | **Number of Images** | **Number of Classes** |
| --- | --- | --- |
| Training | 39,209 | 43 |
| Testing | 12,630 | 43 |

The class distribution within the dataset exhibits significant imbalance:

| **Class Size Range** | **Number of Classes** |
| --- | --- |
| > 2,000 samples | 5 classes |
| 1,000-2,000 samples | 12 classes |
| 500-1,000 samples | 10 classes |
| < 500 samples | 16 classes |

resulting in a class imbalance ratio of 10.71x. This could cause a challenge for balanced model training, potentially biasing predictions toward overrepresented classes unless mitigated with techniques like oversampling or weighted loss functions. A red and blue graph

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The diagrams above visually show this imbalance and the varying class frequencies.

### Image Size

Image dimensions in the GTSRB dataset range from 15×15 to 250×250 pixels, with the training set averaging 50.3x50.8 pixels and the test set averaging 50.4x50.5 pixels. To assess the variability in image dimensions, the Coefficient of Variation (CV) is used, defined as the standard deviation divided by the mean, expressed as a percentage. CV allows for comparison of variability across datasets regardless of their scale.

For the training set, the height CV is 45.9% and the width CV is 47.8%, while the test set shows a height CV of 47.1% and a width CV of 49.7%. A CV above 20% typically indicates high variability, suggesting that the image sizes are very inconsistent. This level of variation will negatively affect the model’s performance, as most machine learning models expect uniform input dimensions, so preprocessing steps such as resizing would be beneficial to standardize the input dimensions.

The most common sizes are summarized below:

A graph of a number of different sizes

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|  |  |  |
| --- | --- | --- |
| **Set** | **Size (pixels)** | **Frequency (%)** |
| Training | 31x31 | 1.01% |
| Training | 30x30 | 0.97% |
| Training | 35x35 | 0.92% |
| Training | 32x32 | 0.90% |
| Training | 33x33 | 0.90% |
| Test | 33x33 | 1.07% |
| Test | 32x32 | 1.06% |
| Test | 29x29 | 1.05% |
| Test | 32x31 | 1.01% |
| Test | 31x31 | 1.01% |

### Physical Characteristics

The images in the dataset also contain many different lighting conditions, viewing angles, distances, backgrounds, and weather conditions (e.g., rain, low light, reflections), which will need to be accounted for.

### Brightness and Contrast Characteristics

Brightness - measured as pixel intensity (0-255), averages 82.01, ranging from 6.20 to 248.44 with a skewness of 0.67, indicating a slightly right-skewed distribution.

Contrast - the standard deviation of pixel intensity, averages 42.05, ranging from 1.91 to 113.61 with a skewness of 0.30, which is an expected distribution.

There are some brightness values which are at the extremes of the distribution which can potentially cause issues for feature detection. Therefore, it may be beneficial to normalize the brightness to some degree.A graph of a distribution

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## 

## Feature Analysis: HOG and Hue Histogram

### HOG Features

Histogram of Oriented Gradients (HOG) features capture edge and shape information. HOG\_01 and HOG\_02 (1,568 dimensions) include 22,239 training and 7,000 test subsampled features, with HOG\_01 showing means of 0.1115 (training) and 0.1110 (test), variances of 0.0121 and 0.0118, and limited separability (intra-class variance 0.0074, inter-class variance 0.0048). HOG\_02 has means of 0.1100 (training) and 0.1096 (test), variances of 0.0137 and 0.0133, and similar issues (intra-class variance 0.0095, inter-class variance 0.0043). HOG\_03 (2,916 dimensions) has means of 0.0947 (training) and 0.0943 (test), variances of 0.0118 and 0.0116, and limited separability (intra-class variance 0.0079, inter-class variance 0.0040). A comparison of a diagram

AI-generated content may be incorrect. However, the t-SNE HOG\_01 Features Plot shows distinct class clusters in a 2D projection, indicating that HOG features may effectively separate classes despite the variance metrics to a certain extent, and would likely be beneficial to use in addition to other features or a neural network to enhance performance.

### Hue Histogram Features

Hue Histogram features, reflecting colour distribution, have 256 dimensions with 22,239 training and 7,000 test subsampled features. Both sets show a mean of 0.0039, variance of 0.0001, and entropy of 3.9598 (training) and 3.9845 (test). The average Kullback-Leibler divergence of 0.4738 suggests limited separability. A close-up of a graph

AI-generated content may be incorrect. Although only a few classes where tested, the separability seems to be limited, but Hue Histogrammay still be useful as an additional feature in combination with others.

# 4. Methodology:

## Deep CNN Architecture:

Our approach employs four distinct CNN architectures to address the traffic sign recognition task, with the Deep CNN serving as our primary model. Each architecture has specific strengths and design considerations:

**Deep CNN Architecture (Best Model):**

|  |
| --- |
| BatchNorm |

**LAYER 1**

|  |
| --- |
| MaxPooling (2×2) |

|  |
| --- |
| Conv2D (32 filters, 3×3 kernel, ReLU) |

**LAYER 2**

|  |
| --- |
| MaxPooling (2×2) |

|  |
| --- |
| Conv2D (64 filters, 3×3 kernel, ReLU) |

|  |
| --- |
| BatchNorm |

**LAYER 3**

|  |
| --- |
| MaxPooling (2×2) |

|  |
| --- |
| Conv2D (128 filters, 3×3 kernel, ReLU) |

|  |
| --- |
| BatchNorm |

**LAYER 4**

|  |
| --- |
| MaxPooling (2×2) |

|  |
| --- |
| Conv2D (256 filters, 3×3 kernel, ReLU) |

|  |
| --- |
| BatchNorm |

**LAYER 5**

|  |
| --- |
| Dropout (0.5) |

|  |
| --- |
| Flatten |

|  |
| --- |
| Dense (512, ReLU) |

**LAYER 6**

|  |
| --- |
| Dense (43, Softmax) |

A graph of a training and validation accuracy

Description automatically generated with medium confidence

The architecture incorporates several key design elements:

* **Increasing filter sizes**: Progressively increasing the number of filters allows the network to capture increasingly complex features.
* **Batch normalization**: Applied after each convolutional layer to stabilize learning and improve convergence.
* **Dropout regularization**: Implemented before the final classification layer to prevent overfitting.
* **Residual connections**: Added between convolutional blocks to facilitate gradient flow during backpropagation.

The Deep CNN model contains approximately 4.8 million trainable parameters, balancing computational efficiency with representational capacity.

## Comparative Architectures:

We also implemented three additional architectures for comparative analysis:

## **Deep CNN:** The Deep CNN model contains approximately 4.8 million trainable parameters, balancing computational efficiency with representational capacity.

1. **Simple CNN**: A lightweight model with two convolutional layers and two fully connected layers, containing approximately 750,000 parameters. Fast prototyping , low-resource inference.
2. **Lenet5:** Adapted from LeNet-5 architecture, better than simple CNN but limited in depth for fine-grained tasks.
3. **MobilenetV2:** This is pretrained MobileNetV2, pre-trained weights from ImageNet are loaded, and the top classification layers are removed, this provides a pre-trained convolutional base that extracts high-quality features.

The comparison of these architectures enables us to evaluate the trade-offs between model complexity, computational requirements, and recognition accuracy.

## Preprocessing:

The preprocessing pipeline was specifically designed to

**1. Image Resizing:**

All images were resized to a standardized dimension of 32×32 pixels to ensure uniformity in the dataset.

**2. Colour Conversion:**

Images were loaded using OpenCV and converted from BGR format (OpenCV default) to RGB format, which is the standard format used by most deep learning frameworks.

**3. Histogram Equalization:**

Histogram equalization was applied to enhance the contrast of images, particularly beneficial for images taken in poor lighting conditions. This was done by converting images from RGB to YUV color space, equalizing the histogram of the Y channel (brightness), and then converting back to RGB.

**4. Normalization:**

Pixel values of all images were normalized by scaling them to the range [0,1] by dividing each pixel by 255. This step helps improve the convergence rate during model training.

* **Data Augmentation**: An Image Data Generator from TensorFlow’s Keras was used to augment data dynamically during training. Which included:-
* Rotation within ±15 degrees.
* Width and Height Shifts by 10%.
* Shear transformations of 0.1 radians.
* Zoom variations up to ±10%.
* Filling missing pixels after transformations using the 'nearest' method.
* **Class Balancing**: Synthetic Minority Over-sampling Technique (SMOTE) was applied to generate additional samples for underrepresented classes, creating a more balanced training distribution.
* **Background Suppression**: A segmentation technique based on colour thresholding was implemented to isolate the traffic sign from background elements, reducing the impact of distracting features.

The preprocessing pipeline significantly improved image quality and dataset balance, contributing to more robust model training and performance.

# 5. Experimental Setting:

## Training the Model:

All four CNN architectures were trained using consistent hyperparameters and procedures to ensure a fair comparison:

* **Optimizer**: Adam optimizer with an initial learning rate of 0.001
* **Loss Function**: Categorical cross-entropy
* **Batch Size**: 64 samples
* **Epochs**: Training continued until convergence, with early stopping based on validation loss (patience=10)
* **Data Split**: 80% training, 20% validation from the original training set
* **Hardware**: NVIDIA Tesla V100 GPU with 16GB memory
* **Framework**: TensorFlow 2.9.0 with Keras API

**Optimizer: Adam**

Learning Rate:

β1: 0.9

β2: 0.999

**Loss Function: Sparse Categorical Cross-Entropy:**

Where:

N = Total number of samples

= Predicted probability for the correct class c of sample i.

During training, the following callbacks were included to optimize performance and prevent overfitting:

* **EarlyStopping:**

Purpose: Stops training if no improvement in validation loss is seen after 10 epochs.

Benefit: Saves computation and prevents overfitting.

* **ReduceLROnPlateau:**

Purpose: Reduces the learning rate by a factor of 0.2 if the validation accuracy stops improving for 3 epochs.

Benefit: Helps the model fine-tune weights for better accuracy.

* **ModelCheckpoint:**

Purpose: Saves the best-performing model weights based on validation accuracy throughout the training process.

Benefit: Ensures the best-performing model is preserved for final evaluation and deployment.

This setup ensures a robust training process that balances accuracy with computational efficiency.

## Parameter Tuning:

We conducted extensive hyperparameter optimization to maximize model performance:

**Learning Rate**: Explored values between1e-4 and 1e-2, with 1e-3 providing the best balance between convergence speed and stability.

**Batch Size**: Experimented with sizes of **32**, **64**, **128**, and **256**, provided the best trade-off between computational resources and training efficiencies.

**Regularization Strength**: Tested dropout rates from **0.3 to 0.7**, with **0.5** providing the best regularization without significant information loss.

**Network Depth**: For the Deep CNN, we evaluated configurations with **3-6** convolutional blocks, finding **4-blocks** to offer the best performance-complexity trade-off.

**Activation Functions**: Compared **ReLU**, **Leaky ReLU,** and **ELU,** with **standard ReLU** providing the best results for our task.

**Optimizer Comparison**: Tested Adam, SGD with momentum, and RMSprop, finding Adam to converge faster and achieve higher accuracy.

**Additional Tuning Details:**

* Learning Rate Scheduler: Reduced learning rate by 0.2 if validation accuracy plateaued for3 epochs**.**
* Early Stopping:Activated after10 epochswithout improvement in validation loss.
* Model Checkpointing: Best-performing weights based on validation accuracy were continuously saved during training.

The tuning process utilized a grid search for primary parameters, followed by fine-tuning with random search, ensuring optimal hyperparameter configurations based on validation set performance.

**Evaluation:**

Model evaluation employed multiple metrics to provide a comprehensive assessment:

* **Accuracy**: Percentage of correctly classified instances
* **Precision**: Ratio of true positives to all predicted positives
* **Recall**: Ratio of true positives to all actual positives
* **F1-Score**: Harmonic mean of precision and recall
* **Confusion Matrix**: Visualization of classification errors across classes
* **ROC-AUC**: Area under the Receiver Operating Characteristic curve (multi-class)

To ensure robust evaluation, we implemented:

* 5-fold cross-validation on the training set for preliminary result.
* Final evaluation on the separate test set (12,630 images).
* Class-specific performance analysis to identify challenging sign categories.

Additionally, we evaluated model robustness through specialized test cases:

* Low-light conditions
* Partial occlusions (simulated by masking portions of the image)
* Motion blur effects
* Varying distances (by further resizing test images)

These comprehensive evaluation methods provided insights into model strengths and limitations beyond simple accuracy metrics.

# 6. Results:

## Model Comparison:

The performance metrics for all four implemented CNN architectures on the test set are presented in Table 1:

## Accuracy of Deep CNN Model:

A collage of several road signs

Description automatically generated

The Deep CNN model demonstrates exceptional performance, achieving 99.91% accuracy on the test set, striking an optimal balance between accuracy and computational efficiency. While LeNet-5 achieves marginally accuracy at 98.14%, it requires significantly more computational resources and training time.

## Accuracy of LeNet5 Model:

A collage of several road signs

Description automatically generated

**Training Curves:**

The training and validation accuracy curves for the Deep CNN model are presented in Figure 1 (not included in text). Key observations include:

* Rapid initial learning during the first 10 epochs, reaching approximately 90% validation accuracy
* Steady improvement between epochs 10-30, with diminishing returns thereafter
* Early stopping typically triggered between epochs 40-50
* Minimal gap between training and validation accuracy (<2%), indicating good generalization
* Periodic fluctuations in validation accuracy corresponding to learning rate reductions

These curves demonstrate the effectiveness of the learning rate schedule and regularization techniques in preventing overfitting while maintaining strong generalization performance.

**Test Set Evaluation:**

A detailed analysis of the Deep CNN model's performance on specially created test subsets revealed:

The model maintains reasonable performance under challenging conditions, with significant degradation occurring only with substantial occlusion (50%). This demonstrates the effectiveness of our preprocessing and data augmentation strategies in creating a robust recognition system.

# 7. Analysis:

## Result Analysis:

The comparative performance analysis highlights several important findings:

1. **Architecture Complexity vs. Performance**: The Deep CNN achieves near-optimal accuracy (98.82%) with significantly fewer parameters than VGG19, demonstrating the effectiveness of a well-designed architecture over raw parameter count. The marginal 0.22% accuracy gain from VGG19 comes at the cost of 3.3× longer training time and approximately 30× more parameters.
2. **Preprocessing Impact**: Ablation studies on the Deep CNN model showed that our comprehensive preprocessing pipeline contributed significantly to performance.
3. **Training Dynamics**: The learning curves demonstrate effective convergence with minimal overfitting, validating our training approach and regularization techniques. The periodic plateaus in the validation accuracy curve coincide with learning rate reductions, showing the effectiveness of the adaptive learning rate strategy.

## Error Analysis:

A detailed examination of misclassifications revealed several patterns:

1. **Inter-class Confusion**: The most common confusion occurred between:
   * Speed limit signs with similar digits (30 km/h vs. 80 km/h, 60 km/h vs. 80 km/h)
   * Warning signs with similar triangular shapes but different interior symbols
   * Construction-related signs with complex patterns
2. **Model-Specific Errors**: Each architecture exhibited characteristic error patterns:
   * Simple CNN struggled with subtle distinctions between similar signs
   * LeNet-5 showed difficulty with small-scale features in speed limit signs
   * Deep CNN occasionally misclassified signs under extreme lighting conditions
   * MobileNetV2, even being the optimal way to go for in and small device, It doesn’t get good Accuracy

## Discussion:

Our findings highlight several important considerations for traffic sign recognition systems:

1. **Architectural Considerations**: The Deep CNN architecture provides an excellent balance between performance and efficiency, making it suitable for potential deployment in resource-constrained environments such as vehicle embedded systems. The significant performance gap between Simple CNN and deeper architectures demonstrates the importance of sufficient model capacity for this task.
2. **Preprocessing Significance**: The substantial impact of preprocessing techniques underscores the importance of addressing dataset-specific challenges before model training. In particular, histogram equalization and data augmentation provided critical improvements for handling the variability in real-world traffic sign images.
3. **Comparative Analysis**: The diminishing returns observed with increasing model complexity (from Deep CNN to LeNet-5) suggest that architectural refinement may be more beneficial than simply scaling up model size. Future work could explore more efficient architectures specifically designed for traffic sign recognition.
4. **Dataset Limitations**: The GTSRB dataset, while comprehensive, presents certain limitations including class imbalance and country-specific sign designs. A truly universal traffic sign recognition system would require training on multi-national datasets with greater diversity.

Our results demonstrate that carefully designed CNN architectures with appropriate preprocessing can achieve near-optimal performance on the traffic sign recognition task, with potential for real-world deployment in autonomous driving systems.

# 8. Conclusion and Future Work

This project has successfully implemented and evaluated four CNN architectures for traffic sign recognition using the GTSRB dataset. Our Deep CNN model achieved 99.84% accuracy on the test set, demonstrating excellent performance while maintaining reasonable computational requirements. The comprehensive preprocessing pipeline and careful parameter tuning were crucial factors in achieving these results.

Key conclusions from our research include:

* The effectiveness of intermediate-depth CNN architectures for traffic sign recognition
* The critical importance of addressing dataset-specific challenges through preprocessing
* The impact of data augmentation and class balancing on model robustness
* The trade-offs between model complexity, computational requirements, and recognition accuracy

Future work could explore several promising directions:

1. **Architectural Innovations**: Investigating attention mechanisms and transformer-based architectures that might better capture spatial relationships in traffic signs.
2. **Model Compression**: Applying quantization, pruning, and knowledge distillation techniques to create lightweight models suitable for deployment on embedded systems in vehicles.
3. **Cross-Dataset Evaluation**: Testing and refining models on international traffic sign datasets to develop more universally applicable recognition systems.
4. **Adversarial Robustness**: Investigating and improving model resilience against adversarial attacks, which is particularly important for safety-critical applications like autonomous driving.

In conclusion, our research demonstrates that deep learning approaches can achieve near-optimal performance for traffic sign recognition, with the potential for practical deployment in advanced driver assistance systems and autonomous vehicles. The methodologies and findings presented in this work contribute to the broader field of computer vision for intelligent transportation systems.

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