Traffic Sign Recognition with Deep Learning

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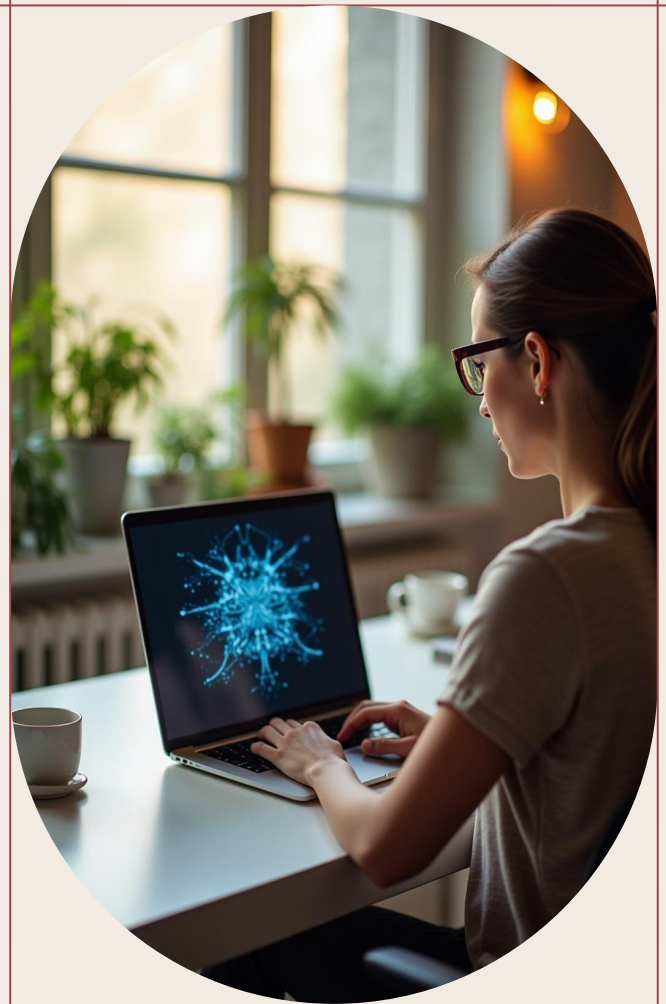
Introduction

- Traffic sign recognition is essential for autonomous driving and advanced systems.
- This project implements a compact CNN model to classify traffic signs with high accuracy.
- Our aim is to demonstrate practical deep learning applications for traffic sign understanding in real-time scenarios.

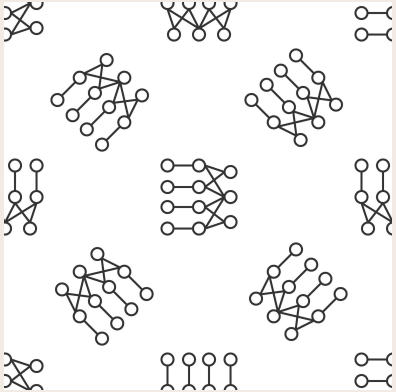


Dataset Description and Preprocessing


```
traffic_sign_small/
    labels.csv
    traffic_Data/
        DATA/
            0/
            1/
            2/
            ...
```

- The dataset consists of over 50 traffic sign classes, each represented by 32×32 RGB images.
- Data variation includes lighting, blur, and perspective challenges.
- Images are normalized and split into 80% training and 20% validation sets to ensure reliable performance evaluation.

Overview of Convolutional Neural Networks (CNNs)



- **Definition**
- **The "Flashlight" Analogy**
- **Spatial Patterns**
- **Feature Hierarchy**

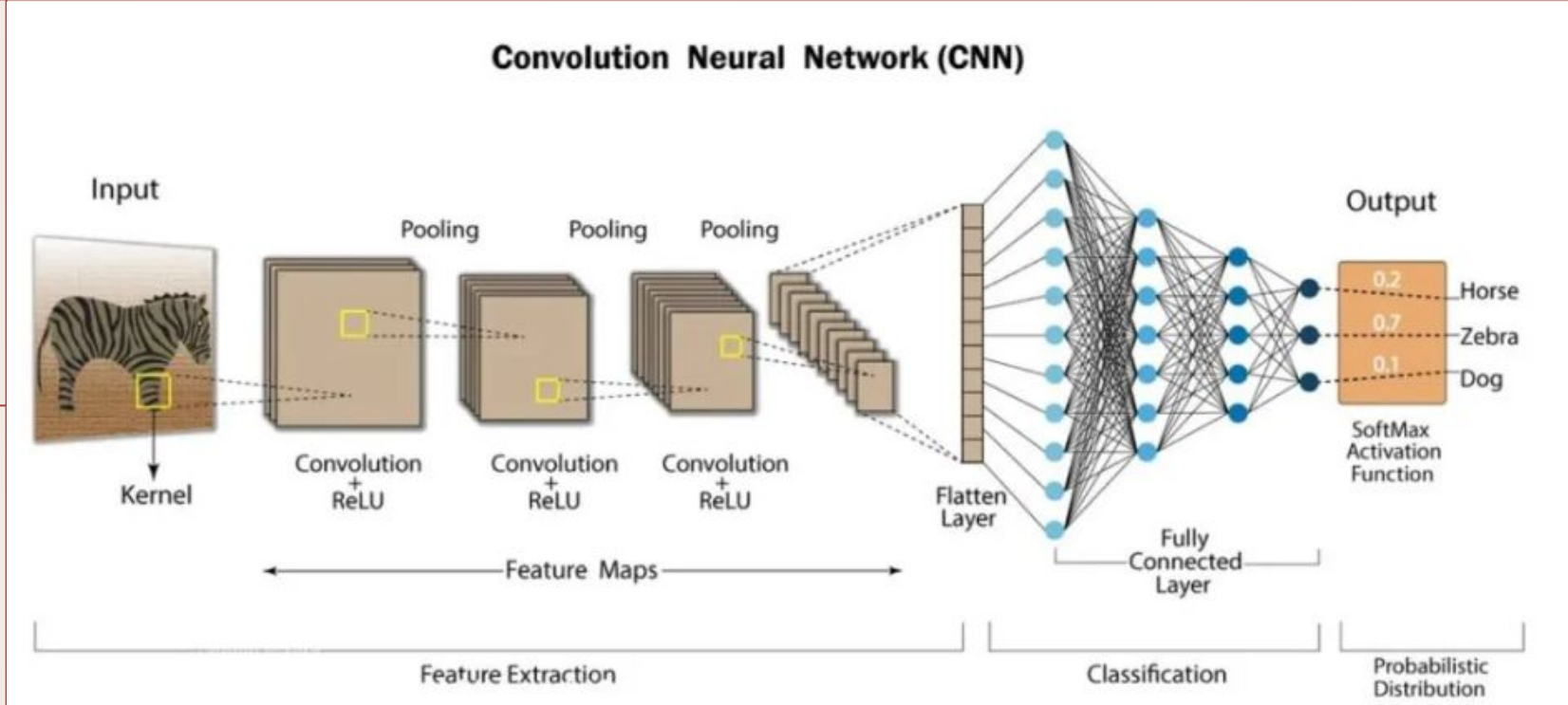


Fig. 2 “Convolution Neural Network”

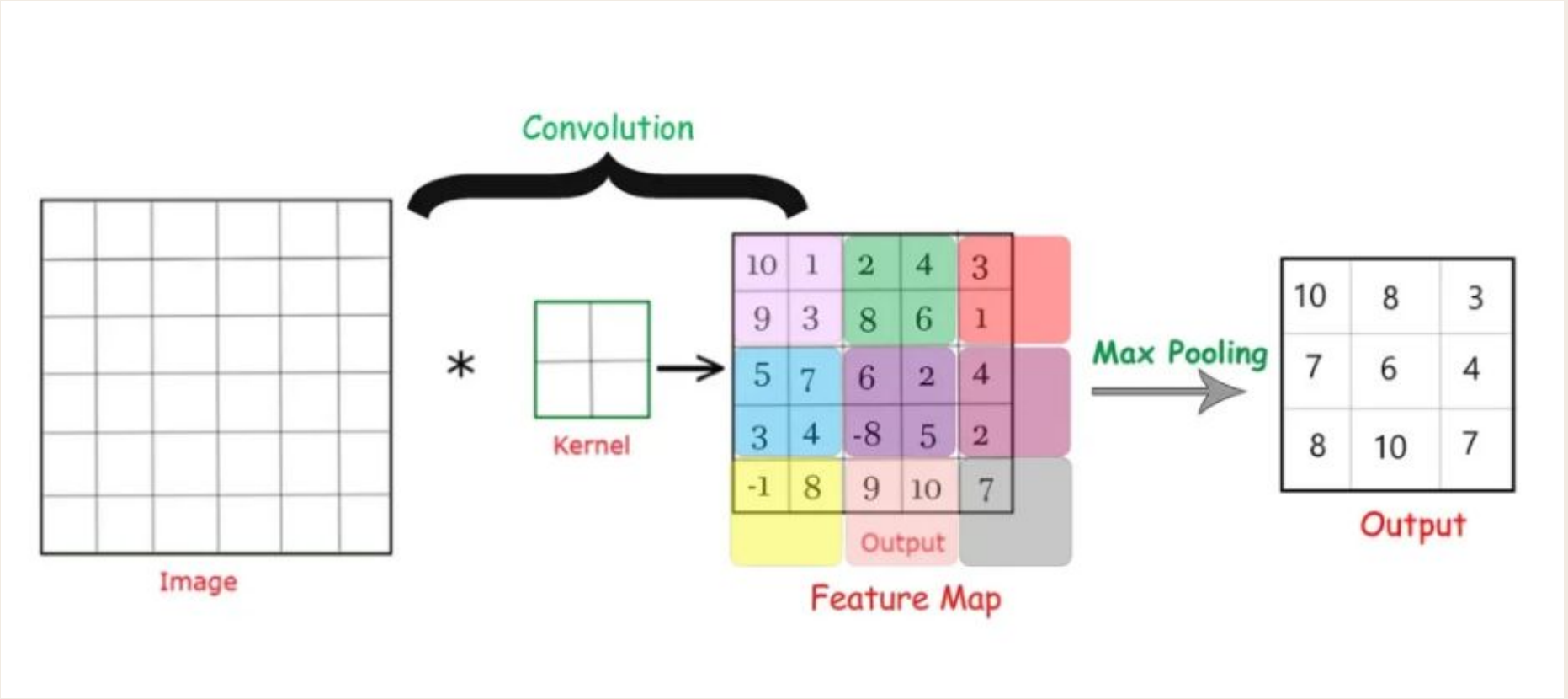


Fig.1: “CNN Visualised”

Mathematics of CNN

- The Convolution Operation
- The Activation
- Pooling Operations
- Fully Connected Layers
- The Softmax Output
- Learning: Loss and Backpropagation

The Convolution Operation

$$S(i,j) = \sum_{c=1}^{C} \sum_{m=1}^{K_H} \sum_{n=1}^{K_W} I(i+m-1, j+n-1, c) K(m,n,c) + b$$

- **Purpose:** To extract local spatial features (e.g., edges, textures) from the input data.
- **I**: The input volume with **C** channels (e.g., C=3 for RGB).
- **K**: The learned kernel (filter) of size K_H times K_W times **C**.
- **b**: A single, learned scalar bias added to every element of the output feature map **S**.
- **Parameters**: The weights in **K** and the bias b are the parameters learned during training.

The Activation

$$\sigma(x) = \max(0, x)$$

- **Purpose:** To introduce non-linearity element-wise into the feature maps.
- **x**: An input value from the feature map **S**.
- **sigma(x)**: The activated output value.
- **Mechanism:** negative input values to zero
- **Benefit:** efficient and helps mitigate the vanishing gradient problem

Pooling Operations

$$P(i,j) = \max_{m=1}^{F} \max_{n=1}^{F} A(i \cdot s + m - 1, j \cdot s + n - 1)$$

- **Purpose:** To downsample the feature map
- **A:** The input feature map to the pooling layer.
- **P(i, j):** The output value at position (i, j) in the pooled map.
- **F:** The size of the pooling filter (e.g., 2).
- **s:** The stride (step size) used to slide the pooling window.
- Mechanism: Selects the maximum value within the **F** times **F** sliding window.

Fully Connected Layers

$$H = \sigma(W \cdot F + B)$$

- F is the input vector from the previous layer.
- W and B are the learned weight matrix and bias vector.

The Softmax Output

$$\hat{y}_k = \text{Softmax}(z)_k = \frac{e^{z_k}}{\sum_{j=1}^{K} e^{z_j}}$$

- **Purpose:** To convert raw output scores into probabilities for multi-class classification.
- **z_k:** The raw output score (logit) for class k.
- **y_k:** The predicted probability for class k.
- **Property:** The resulting probabilities y_k sum to 1.
- **Usage:** Used as the activation function for the final output layer in a classification task.

Learning: Loss and Backpropagation

$$\mathcal{L}(y, \hat{y}) = -\sum_{k=1}^{K} y_k \log(\hat{y}_k)$$

$$\Delta W = \frac{\partial \mathcal{L}}{\partial W} \quad \text{and} \quad \Delta b = \frac{\partial \mathcal{L}}{\partial b}$$

- **Purpose:** To quantify the error (loss) between the model's prediction and the ground truth label.
- **y_k:** The true probability (1 or 0, for one-hot encoding) for class k.
- **Goal:** The training process seeks to find parameters that minimize this loss function
- **Backpropagation:** The gradient is calculated via the chain rule (backpropagation) to update the parameters W.

Implementation

Classification report:

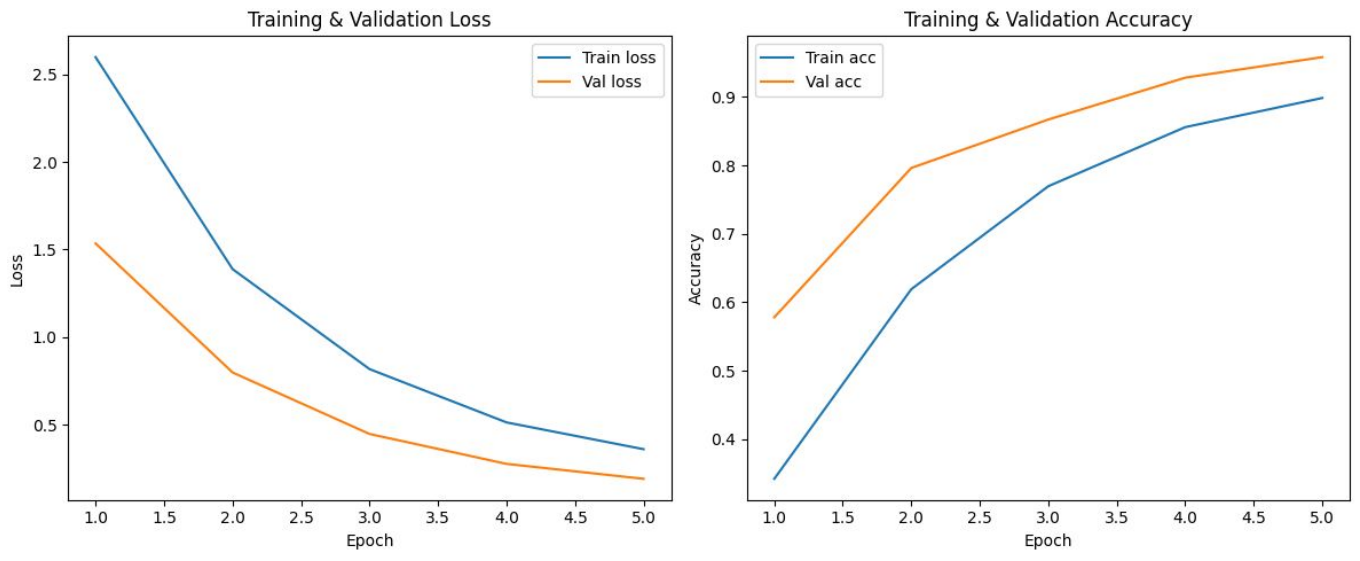
	precision	recall	f1-score	support
Speed limit (5km/h)	1.000	1.000	1.000	20
Speed limit (15km/h)	1.000	0.778	0.875	9
Dont Go straight	1.000	1.000	1.000	15
Dont Go Left	1.000	1.000	1.000	23
Dont Go Left or Right	1.000	1.000	1.000	21
Dont Go Right	1.000	1.000	1.000	6
Dont overtake from Left	1.000	1.000	1.000	22
No Uturn	1.000	0.800	0.889	5
No Car	0.976	1.000	0.988	40
No horn	1.000	1.000	1.000	30
Speed limit (40km/h)	1.000	1.000	1.000	1
Speed limit (50km/h)	0.000	0.000	0.000	0
Speed limit (30km/h)	0.824	1.000	0.903	14
Go straight or right	1.000	1.000	1.000	3
Go straight	1.000	0.667	0.800	3
Go Left	1.000	1.000	1.000	1
Go Left or right	1.000	1.000	1.000	1
Go Right	1.000	1.000	1.000	18
keep Left	0.000	0.000	0.000	1
keep Right	0.933	1.000	0.966	14
Roundabout mandatory	1.000	1.000	1.000	3
watch out for cars	1.000	1.000	1.000	109
Horn	1.000	0.750	0.857	8
Speed limit (40km/h)	1.000	1.000	1.000	43
Bicycles crossing	1.000	1.000	1.000	40
Uturn	0.889	1.000	0.941	8
Road Divider	1.000	0.600	0.750	5
Traffic signals	1.000	1.000	1.000	1
Danger Ahead	0.000	0.000	0.000	6
Zebra Crossing	0.455	1.000	0.625	30
Bicycles crossing	1.000	0.545	0.706	11

- Google Collab
- Python
- Requirements

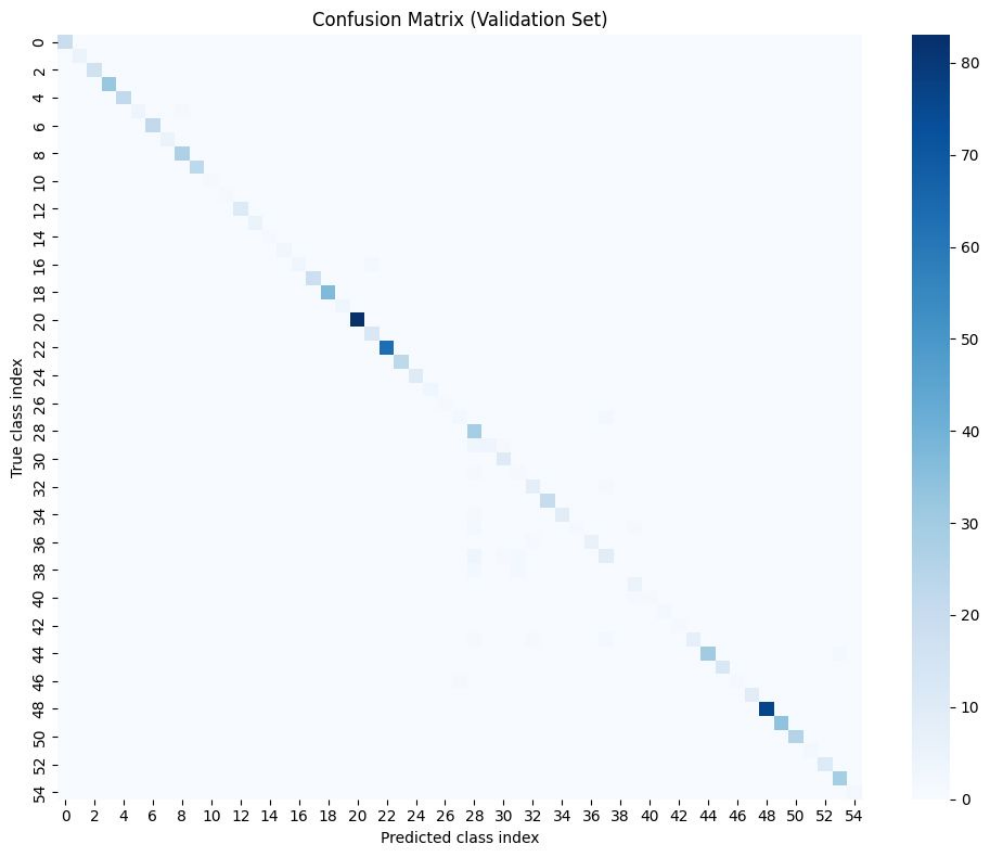
Results

- The model achieves high accuracy with tightly correlated training and validation metrics
- The confusion matrix reveals accurate classification with only a few confusions for visually similar signs.
- Inference takes approximately 4.51 milliseconds per

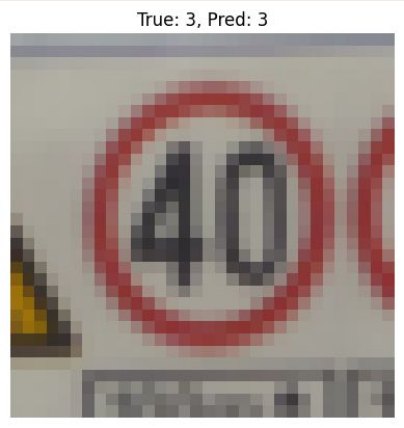
Training Accuracy

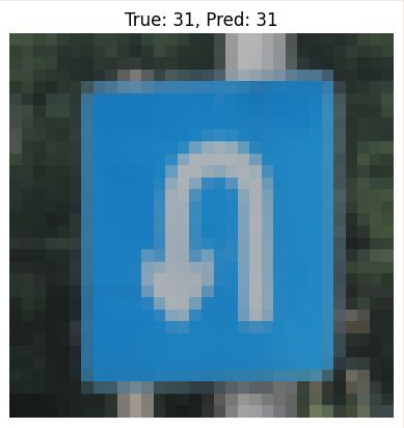


Confusion Matrix



Predicted Images





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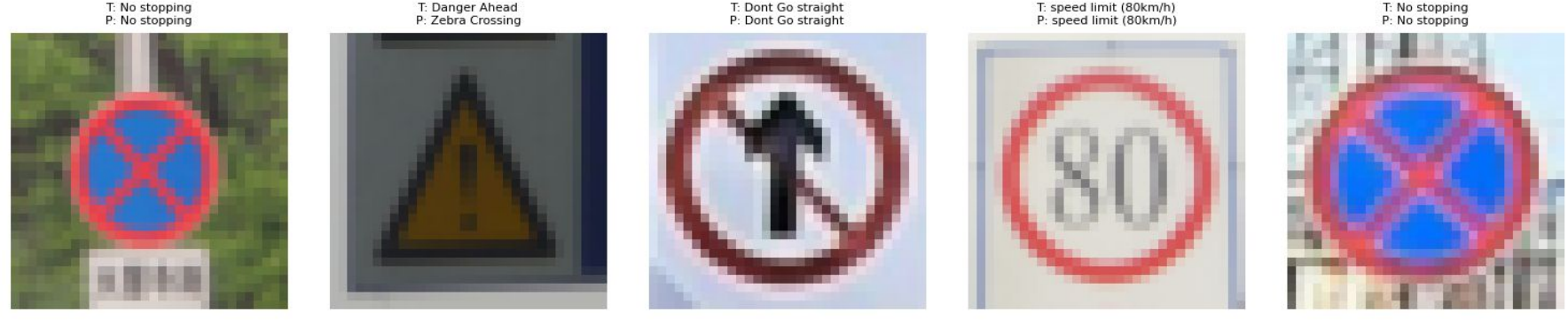
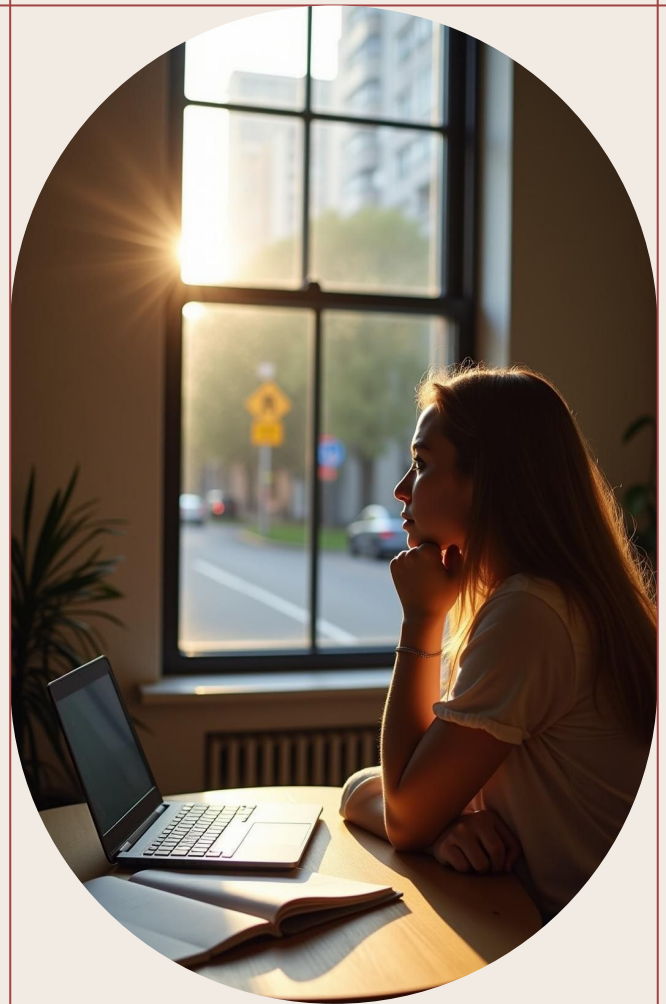


Conclusions

- The compact CNN model effectively classifies traffic sign images
- Limitations include sensitivity to data diversity and lighting changes



THANK YOU

Do you have any questions?

Citations

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***All Images are from google stock images or created by implementation or screenshots from my paper except:**

Fig 1. "CNN Visualised" - Link: https://svitla.com/blog/cnn-for-image-processing/

Fig 2. "Convolutional Neural Network" - Link: https://svitla.com/blog/cnn-for-image-processing/