Traffic Sign Classification Project Report

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I. Introduction

Traffic sign recognition is a critical component of autonomous driving and transportation infrastructure, enabling vehicles to interpret and respond to road signs accurately.

The goal of this project is to develop a reliable traffic signage classifier using the image dataset from Kaggle [1]. The dataset consists of images, which are resized to $32 \times 32 \times 3$ pixels (RGB) to ensure computational efficiency while preserving essential features.

This report outlines the methodology, including dataset preprocessing, model selection, hyperparameter tuning, and evaluation, to identify the most effective method of classification amongst Support Vector Classifier kernels (linear, RBF, polynomial) and a Multilayer Perceptron as a baseline. The evaluation metrics include accuracy, precision, recall, F1-score, and a confusion matrix to provide a comprehensive assessment of the model's performance.

II. Data and Application Description

A. Dataset Overview

This project focuses on traffic sign classification using the Flo2607 Traffic Signs Classification dataset [1]. The dataset contains 43 different classes of traffic signs, ranging from speed limits to various warning and regulatory signs.

B. Dataset Structure

- **Total Classes**: 43 different traffic sign categories
- **Image Format**: RGB images with most images being 32×32 in dimension
- **Standardised Size**: All images are resized to $32 \times 32 \times 3$ pixels
- **Data Organisation**: Images are organised in folders numbered 0–42, corresponding to their class labels
- Sample classes include:
  - Speed limits (20 km/h, 30 km/h, 50 km/h, etc.)
  - Regulatory signs (No passing, No entry, Stop, etc.)
  - Warning signs (General caution, Right-of-way, etc.)
  - Prohibitory signs (No vehicles, Vehicles over 3.5 metric tons prohibited, etc.)
  - For the full list, refer to Appendix A

C. Application Purpose

The primary goal is to develop an accurate machine learning model capable of automatically classifying traffic signs from images. This has practical applications in:

- Autonomous vehicle systems
- Traffic monitoring systems
- Driver assistance technologies
- Road safety analysis

III. Model Designs and Configurations

Two primary approaches were evaluated: a Multilayer Perceptron (MLP) as a baseline and Support Vector Classifiers (SVCs) with different kernels. The rationale for model selection, hyperparameter tuning, and configuration is provided in the following sections.

A. Multi-Layer Perceptron Classifier

The MLP is a feedforward neural network designed to learn non-linear feature representations, making it a suitable fit for the $32 \times 32 \times 3$ RGB images in this dataset without requiring the complexity of convolutional neural networks (CNNs). The architecture and optimisation strategy are configured as follows:

- Architecture:
  - **Input Layer**: 3,072 neurons, corresponding to the flattened $32 \times 32 \times 3$ pixel images.
  - **Output Layer**: 43 neurons, one for each traffic sign class.
- Optimisation:
  - **Learning Rate**: Initial learning rate set to `learning_rate_init=0.0001` to provide a good balance between convergence speed and stability.
  - **Maximum Iterations**: Set to `max_iter=100000` to allow sufficient training time and iterations for convergence.
  - **Random Seed**: `random_state=0` for reproducibility of results.
- **Early Stopping**: Enabled with `early_stopping=True`, using a validation fraction of 10% (`validation_fraction=0.1`) and stopping if no improvement is observed for 10 iterations (`n_iter_no_change=10`). This prevents overfitting and reduces training time.

B. Support Vector Classifier (SVC)

To capture the decision boundaries of the dataset, three kernel types are evaluated: linear, radial basis function (RBF), and polynomial (poly). Each kernel is chosen for its ability to handle different types of data distributions:

- **Linear Kernel**: Serves as a strong baseline when features are approximately linearly separable.
- **RBF Kernel**: Provides a flexible non-linear mapping, suitable for complex decision boundaries that may arise due to variations in traffic sign appearances.
- **Poly Kernel**: Captures feature interactions while offering a balance between flexibility and computational cost.

1) Hyperparameter Tuning: To optimise SVC performance, a grid search with cross-validation (`GridSearchCV`) is employed separately for each kernel type (linear, RBF, poly) to identify the best hyperparameters for each. `GridSearchCV` uses 2-5 fold cross-validation on the training data, eliminating the need for a standalone validation set, as it internally evaluates multiple train-validation splits to estimate model performance robustly. The following hyperparameters are explored:

- **C (Regularisation Parameter)**: Controls the trade-off between achieving a wide margin and minimising classification errors. Lower values allow more misclassifications, higher values enforce stricter fitting. Values tested: `[0.1, 1, 10]`.
- **Gamma (Kernel Coefficient, for RBF)**: Determines the influence of individual training points on the decision boundary. Lower gamma produces smoother boundaries, and higher gamma allows more complex, localised boundaries. Values tested: `[0.0001, 0.001, 0.1]`.

`GridSearchCV` is performed with 2-5 fold cross-validation on the training data to identify the best hyperparameter combination for each kernel. The final model for each kernel is refit on the entire training split using the optimal parameters.

For each kernel, `GridSearchCV` identifies the best hyperparameter combination based on cross-validation performance. The final model for each kernel is then refit on the entire training split using these optimal parameters. The resulting models are evaluated on the separate test data to assess their generalisation performance, ensuring an unbiased estimate of their effectiveness on unseen data.

IV. Data Pre-processing

This section outlines the preprocessing steps applied to the dataset to prepare it for model training and evaluation. The preprocessing step ensures consistency in input format, optimises computational efficiency, and preserves the visual features critical for accurate classification.

A. Image Preprocessing Pipeline

The preprocessing stage transforms raw images into a format suitable for the SVC and MLP models. The steps are designed to standardise inputs while preserving the features critical for classification.

1) Resizing: To standardise inputs, all images are resized to a resolution of $32 \times 32 \times 3$ pixels. Since most images in the dataset are already at this resolution, resizing them leaves them unchanged (no up/downscaling), ensuring no loss of visual features while maintaining a consistent input size across all models.

This resolution reduces computational cost while retaining the distinct features (shapes and colours) of the data, which is essential for classification.

2) Normalisation: Images are then converted to `float32` type, scaling pixel values to the range `[0, 1]` for all models, thereby normalising the input data.

3) Data Flattening: Subsequently, each $32 \times 32 \times 3$ image is flattened into a one-dimensional array of $3,072$ features. This representation is compatible with traditional machine learning models like SVC and MLP, which expect tabular input.

B. Data Splitting Strategy

To facilitate robust model training and evaluation, the dataset is split into training and test sets using a stratified split implemented via scikit-learn's `train_test_split` function.

1) Train–Test Split: The test set is made up of 20% of the dataset, with the remaining 80% allocated to training. A random state of 0 is set to ensure reproducibility. Stratification is applied to preserve the per-class distribution across both sets, mitigating bias from potential class imbalances in the 43-class dataset.

2) Rationale for $80:20$ Split: The $80:20$ split provides a sufficient number of training examples to learn generalisable patterns across all classes while reserving enough test samples for reliable evaluation of model performance.

3) Validation Strategy: For SVC models, validation is handled within `GridSearchCV` using 2–5 fold cross-validation on the training data, eliminating the need for a separate validation set. For MLP models, early stopping is enabled (`early_stopping=True`) with a validation fraction of 10% (`validation_fraction=0.1`) to monitor convergence and prevent overfitting by halting training if no improvement is observed after a given number of iterations (`n_iter_no_change=50`).

C. Data Storage Optimisation

To streamline experimentation and minimise preprocessing overhead, the preprocessed data is optimised for efficient storage and retrieval:

1) Pickle Serialization: The resized, normalised, and flattened images are stored in pickle format, eliminating the need for repeated image I/O and resizing operations during subsequent experiments. Data is processed in batches of $1,000$ samples to control peak memory usage during preprocessing.

Metadata, including the number of samples (`n_samples`) and batch size (`batch_size`), is stored alongside the data to enable efficient array reconstruction at load time.

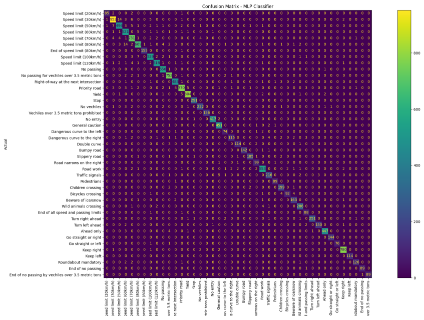

Fig. 1. Confusion Matrix for MLP Classifier

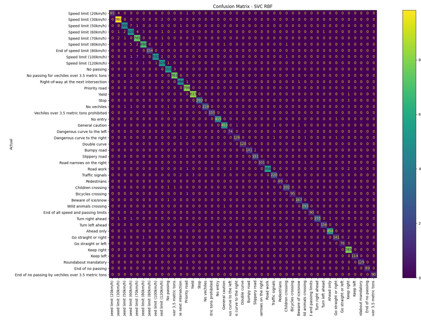

Fig. 4. Confusion Matrix for SVC-RBF Improved

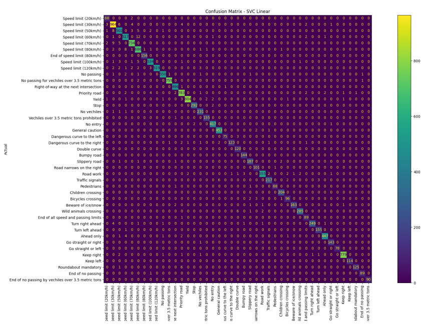

Fig. 2. Confusion Matrix for SVC-Linear

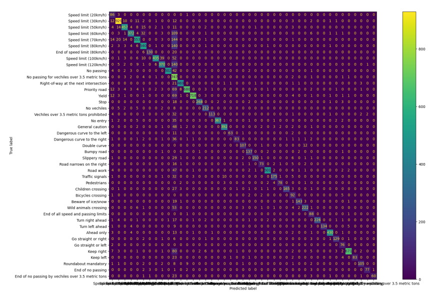

Fig. 5. Confusion Matrix for SVC-Poly

This approach significantly accelerates computationally intensive tasks, such as grid searches, by reducing data loading time and ensuring a consistent and reproducible data handling workflow.

V. Comparative Analysis of Model Performance

This section presents a comparative evaluation of the SVC models with linear, RBF, and polynomial kernels and the MLP model, focusing on their performance in classifying the 43 classes in the dataset. The evaluation was conducted on the test set, 20% of the preprocessed dataset, to assess the models' performance against unseen data. Performance metrics are derived from detailed evaluation reports (see Appendices B, C, D, E for the full reports), supplemented by confusion matrix analyses to identify specific classification challenges. The analysis determines the best-performing model and provides insight into their relative strengths and weaknesses.

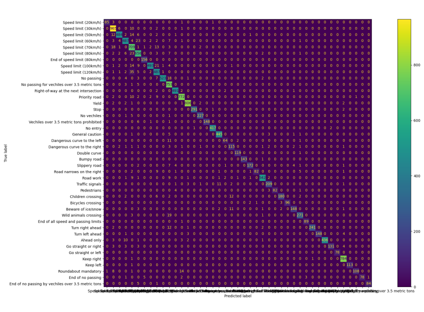

Fig. 3. Confusion Matrix for SVC-RBF Initial

A. Overall Performance Comparison

A comprehensive comparison of the four models across key classification metrics is presented in Table I, based on data from the evaluation reports in Appendices B–E:

TABLE I
Performance Comparison of Classification Models

Model	Accuracy	Precision	Recall	F1
SVC-RBF	99.00%	99.30%	98.63%	98.96%
SVC-Linear	98.14%	97.87%	98.11%	97.97%
MLP	97.34%	97.14%	97.05%	97.07%
SVC-Poly	84.82%	91.07%	84.10%	86.30%

The SVC with an RBF kernel achieves the highest overall accuracy at 99%, outperforming the SVC with a linear kernel by 0.86%, the MLP Classifier by 1.66%, and the SVC with a polynomial kernel by 14.18%. The SVC with a linear kernel demonstrates very competitive performance at 98.14% accuracy, closely followed by the MLP classifier at 97.34%. However, the polynomial kernel significantly underperforms at 84.82%, indicating potential issues with its suitability for this dataset.

B. Model-Specific Performance Analysis

1) SVC-RBF (Best Performance): The SVC with an RBF kernel emerges as the best-performing model, achieving an accuracy of 99% with a balanced precision of 99.3% and a recall of 98.63%. Its strength lies in its consistent high performance across all 43 classes, as evidenced by near-perfect or perfect scores for many categories. Analysis of the confusion matrix in Figure 4, reveals minimal misclassifications, with a strong diagonal dominance, indicating robust generalisation.

2) SVC-Linear: The SVC with a linear kernel follows closely with an accuracy of 98.14%, supported by a macro-averaged precision of 97.87% and recall of 98.11%. Its strength lies in its competitive generalisation, performing well on complex classes. The confusion matrix in Figure 2, exhibits a clean diagonal pattern with a few off-diagonal errors, suggesting effective feature learning.

3) MLP: The MLP classifier achieves an accuracy of 97.34%, with a macro precision of 97.14% but a lower recall of 97.05%, indicating some missed classifications. Its strength is in its high precision, but its weaknesses appear in certain classes with significant missclassifications, as seen in the confusion matrix in Figure 1.

4) SVC-Poly (Poor Performance): The SVC with a polynomial kernel underperforms with an accuracy of 84.82%, despite a macro precision of 91.07%. Its poor recall of 84.1% suggests overfitting, as the model achieves high precision but misses many true positives. The confusion matrix in Figure 5 shows numerous off-diagonal errors, indicating over-prediction of certain classes. This model's complexity appears to be unsuitable for this dataset.

REFERENCES

[1] "Traffic Signs Classification," www.kaggle.com. https://www.kaggle.com/datasets/flo2607/traffic-signs-classification.

APPENDIX A
TRAFFIC SIGN CLASSES

The dataset defines 43 traffic sign classes. Table II lists all class identifiers and their corresponding labels.

TABLE II
LIST OF ALL 43 TRAFFIC SIGN CLASSES.

ClassId	Name
0	Speed limit (20km/h)
1	Speed limit (30km/h)
2	Speed limit (50km/h)
3	Speed limit (60km/h)
4	Speed limit (70km/h)
5	Speed limit (80km/h)
6	End of speed limit (80km/h)
7	Speed limit (100km/h)
8	Speed limit (120km/h)
9	No passing
10	No passing for vechiles over 3.5 metric tons
11	Right-of-way at the next intersection
12	Priority road
13	Yield
14	Stop
15	No vechiles
16	Vechiles over 3.5 metric tons prohibited
17	No entry
18	General caution
19	Dangerous curve to the left
20	Dangerous curve to the right
21	Double curve
22	Bumpy road
23	Slippery road
24	Road narrows on the right
25	Road work
26	Traffic signals
27	Pedestrians
28	Children crossing
29	Bicycles crossing
30	Beware of ice/snow
31	Wild animals crossing
32	End of all speed and passing limits
33	Turn right ahead
34	Turn left ahead
35	Ahead only
36	Go straight or right
37	Go straight or left
38	Keep right
39	Keep left
40	Roundabout mandatory
41	End of no passing
42	End of no passing by vechiles over 3.5 metric tons

Appendix B
Evalutation Report: MLP Classifier

```
====================================================================================================
EVALUATION REPORT: MLP Classifier
====================================================================================================
Confusion Matrix Shape: (43, 43)
Total Predictions: 14628
Correct Predictions: 14239
Incorrect Predictions: 389
```

	precision	recall	f1-score	support
Speed limit (20km/h)	0.98	0.94	0.96	90
Speed limit (30km/h)	0.98	0.97	0.97	984
Speed limit (50km/h)	0.95	0.95	0.95	522
Speed limit (60km/h)	0.93	0.98	0.95	534
Speed limit (70km/h)	0.96	0.97	0.97	750
Speed limit (80km/h)	0.97	0.95	0.96	702
End of speed limit (80km/h)	0.99	0.99	0.99	156
Speed limit (100km/h)	0.97	0.97	0.97	546
Speed limit (120km/h)	0.98	0.97	0.98	534
No passing	0.98	1.00	0.99	558
No passing for vechiles over 3.5 metric tons	0.97	0.99	0.98	762
Right-of-way at the next intersection	0.98	0.97	0.97	498
Priority road	0.98	0.96	0.97	798
Yield	0.99	0.99	0.99	816
Stop	0.99	0.99	0.99	294
No vechiles	0.97	0.95	0.96	234
Vechiles over 3.5 metric tons prohibited	1.00	1.00	1.00	156
No entry	0.99	0.99	0.99	420
General caution	0.98	0.99	0.98	456
Dangerous curve to the left	0.87	0.95	0.91	78
Dangerous curve to the right	0.96	0.87	0.91	132
Double curve	0.97	0.95	0.96	120
Bumpy road	1.00	0.99	0.99	144
Slippery road	0.98	0.96	0.97	192
Road narrows on the right	0.93	0.97	0.95	102
Road work	0.97	0.97	0.97	570
Traffic signals	0.96	0.95	0.95	228
Pedestrians	0.97	0.99	0.98	90
Children crossing	0.94	0.98	0.96	204
Bicycles crossing	0.98	0.90	0.94	102
Beware of ice/snow	0.94	0.97	0.95	168
Wild animals crossing	0.97	0.97	0.97	294
End of all speed and passing limits	0.90	0.98	0.94	90
Turn right ahead	1.00	0.97	0.98	258
Turn left ahead	0.98	0.96	0.97	156
Ahead only	0.99	0.98	0.99	456
Go straight or right	0.99	1.00	1.00	144
Go straight or left	1.00	0.97	0.99	78
Keep right	0.99	0.99	0.99	786
Keep left	1.00	1.00	1.00	114
Roundabout mandatory	0.98	0.95	0.97	132
End of no passing	0.99	0.99	0.99	90
End of no passing by vechiles over 3.5 metric tons	1.00	0.99	0.99	90
accuracy			0.97	14628
macro avg	0.97	0.97	0.97	14628
weighted avg	0.97	0.97	0.97	14628

```
Accuracy: 97.34%
Precision (Macro): 97.14%
Recall (Macro): 97.05%
F1 (Macro): 97.07%
Precision (Weighted): 97.37%
Recall (Weighted): 97.34%
F1 (Weighted): 97.34%
```

APPENDIX C
EVALUTATION REPORT: SVC LINEAR

```
========================================================================================================
EVALUATION REPORT: SVC Linear
========================================================================================================
Confusion Matrix Shape: (43, 43)
Total Predictions: 14628
Correct Predictions: 14356
Incorrect Predictions: 272
```

	precision	recall	f1-score	support
Speed limit (20km/h)	0.93	0.98	0.95	90
Speed limit (30km/h)	0.97	0.98	0.98	984
Speed limit (50km/h)	0.96	0.96	0.96	522
Speed limit (60km/h)	0.96	0.97	0.97	534
Speed limit (70km/h)	0.98	0.98	0.98	750
Speed limit (80km/h)	0.96	0.98	0.97	702
End of speed limit (80km/h)	0.99	1.00	1.00	156
Speed limit (100km/h)	0.98	0.98	0.98	546
Speed limit (120km/h)	1.00	0.97	0.99	534
No passing	0.99	0.99	0.99	558
No passing for vechiles over 3.5 metric tons	1.00	1.00	1.00	762
Right-of-way at the next intersection	0.99	1.00	0.99	498
Priority road	0.97	0.98	0.98	798
Yield	1.00	0.99	0.99	816
Stop	0.99	0.99	0.99	294
No vechiles	0.96	0.99	0.97	234
Vechiles over 3.5 metric tons prohibited	0.98	0.99	0.99	156
No entry	0.99	0.99	0.99	420
General caution	0.98	0.99	0.99	456
Dangerous curve to the left	0.99	0.96	0.97	78
Dangerous curve to the right	0.99	0.93	0.96	132
Double curve	0.92	1.00	0.96	120
Bumpy road	0.97	1.00	0.99	144
Slippery road	0.97	0.97	0.97	192
Road narrows on the right	0.95	0.99	0.97	102
Road work	0.99	0.97	0.98	570
Traffic signals	0.98	0.95	0.97	228
Pedestrians	0.99	0.98	0.98	90
Children crossing	0.98	1.00	0.99	204
Bicycles crossing	0.94	0.94	0.94	102
Beware of ice/snow	0.99	0.97	0.98	168
Wild animals crossing	0.99	0.97	0.98	294
End of all speed and passing limits	0.93	0.99	0.96	90
Turn right ahead	1.00	0.97	0.98	258
Turn left ahead	0.97	0.99	0.98	156
Ahead only	0.99	0.98	0.99	456
Go straight or right	0.98	0.99	0.99	144
Go straight or left	1.00	1.00	1.00	78
Keep right	1.00	0.99	0.99	786
Keep left	1.00	1.00	1.00	114
Roundabout mandatory	0.99	0.95	0.97	132
End of no passing	0.98	0.99	0.98	90
End of no passing by vechiles over 3.5 metric tons	1.00	1.00	1.00	90
accuracy			0.98	14628
macro avg	0.98	0.98	0.98	14628
weighted avg	0.98	0.98	0.98	14628

```
Accuracy: 98.14%
Precision (Macro): 97.87%
Recall (Macro): 98.11%
F1 (Macro): 97.97%
Precision (Weighted): 98.16%
Recall (Weighted): 98.14%
F1 (Weighted): 98.14%
```

APPENDIX D
EVALUTATION REPORT: SVC RBF IMPROVED

```
====================================================================================================
EVALUATION REPORT: SVC RBF Improved
====================================================================================================
Confusion Matrix Shape: (43, 43)
Total Predictions: 14628
Correct Predictions: 14481
Incorrect Predictions: 147
```

	precision	recall	f1-score	support
Speed limit (20km/h)	1.00	0.94	0.97	90
Speed limit (30km/h)	0.98	1.00	0.99	984
Speed limit (50km/h)	0.99	0.97	0.98	522
Speed limit (60km/h)	0.97	0.97	0.97	534
Speed limit (70km/h)	0.98	0.99	0.98	750
Speed limit (80km/h)	0.99	0.98	0.99	702
End of speed limit (80km/h)	1.00	0.99	0.99	156
Speed limit (100km/h)	0.99	0.97	0.98	546
Speed limit (120km/h)	0.99	0.99	0.99	534
No passing	0.99	0.99	0.99	558
No passing for vechiles over 3.5 metric tons	0.99	1.00	0.99	762
Right-of-way at the next intersection	0.99	1.00	0.99	498
Priority road	0.99	1.00	0.99	798
Yield	1.00	1.00	1.00	816
Stop	1.00	1.00	1.00	294
No vechiles	1.00	0.97	0.99	234
Vechiles over 3.5 metric tons prohibited	1.00	0.99	1.00	156
No entry	1.00	1.00	1.00	420
General caution	0.99	0.99	0.99	456
Dangerous curve to the left	0.99	0.95	0.97	78
Dangerous curve to the right	0.99	0.95	0.97	132
Double curve	1.00	1.00	1.00	120
Bumpy road	1.00	0.98	0.99	144
Slippery road	0.99	0.99	0.99	192
Road narrows on the right	1.00	0.99	1.00	102
Road work	0.99	0.99	0.99	570
Traffic signals	0.99	0.96	0.98	228
Pedestrians	1.00	0.99	0.99	90
Children crossing	0.99	0.99	0.99	204
Bicycles crossing	1.00	0.93	0.96	102
Beware of ice/snow	0.99	0.99	0.99	168
Wild animals crossing	0.99	1.00	0.99	294
End of all speed and passing limits	1.00	1.00	1.00	90
Turn right ahead	1.00	0.99	0.99	258
Turn left ahead	0.99	1.00	1.00	156
Ahead only	1.00	1.00	1.00	456
Go straight or right	0.98	0.98	0.98	144
Go straight or left	1.00	1.00	1.00	78
Keep right	0.99	1.00	0.99	786
Keep left	1.00	1.00	1.00	114
Roundabout mandatory	1.00	0.98	0.99	132
End of no passing	1.00	0.99	0.99	90
End of no passing by vechiles over 3.5 metric tons	1.00	1.00	1.00	90
accuracy			0.99	14628
macro avg	0.99	0.99	0.99	14628
weighted avg	0.99	0.99	0.99	14628

```
Accuracy: 99.00%
Precision (Macro): 99.30%
Recall (Macro): 98.63%
F1 (Macro): 98.96%
Precision (Weighted): 99.00%
Recall (Weighted): 99.00%
F1 (Weighted): 98.99%
```

Appendix E
Evalutation Report: SVC Poly

```
==================================================================================================
EVALUATION REPORT
==================================================================================================
                                                    precision    recall  f1-score   support

                              Speed limit (20km/h)       0.49      0.96      0.65        90
                              Speed limit (30km/h)       0.93      0.94      0.94       984
                              Speed limit (50km/h)       0.91      0.88      0.89       522
                              Speed limit (60km/h)       0.94      0.70      0.80       534
                              Speed limit (70km/h)       0.89      0.74      0.81       750
                              Speed limit (80km/h)       0.87      0.77      0.82       702
                       End of speed limit (80km/h)       0.97      0.83      0.90       156
                             Speed limit (100km/h)       0.97      0.80      0.88       546
                             Speed limit (120km/h)       0.86      0.69      0.77       534
                                        No passing       1.00      0.90      0.95       558
      No passing for vechiles over 3.5 metric tons       0.34      0.98      0.51       762
             Right-of-way at the next intersection       0.96      0.94      0.95       498
                                     Priority road       0.98      0.85      0.91       798
                                             Yield       0.99      0.88      0.93       816
                                              Stop       0.98      0.91      0.94       294
                                       No vechiles       0.91      0.91      0.91       234
          Vechiles over 3.5 metric tons prohibited       0.98      0.72      0.83       156
                                          No entry       0.99      0.87      0.93       420
                                   General caution       0.96      0.86      0.91       456
                       Dangerous curve to the left       0.97      0.81      0.88        78
                      Dangerous curve to the right       0.98      0.63      0.76       132
                                      Double curve       0.93      0.89      0.91       120
                                       Bumpy road       0.91      0.95      0.93       144
                                     Slippery road       0.98      0.78      0.87       192
                         Road narrows on the right       0.90      0.72      0.80       102
                                         Road work       0.98      0.88      0.93       570
                                   Traffic signals       0.93      0.77      0.84       228
                                       Pedestrians       0.95      0.87      0.91        90
                                 Children crossing       0.99      0.81      0.89       204
                                 Bicycles crossing       0.62      0.90      0.73       102
                                Beware of ice/snow       0.95      0.85      0.90       168
                             Wild animals crossing       0.91      0.76      0.83       294
               End of all speed and passing limits       0.69      0.98      0.81        90
                                  Turn right ahead       1.00      0.88      0.93       258
                                   Turn left ahead       1.00      0.86      0.92       156
                                        Ahead only       0.98      0.94      0.96       456
                              Go straight or right       0.93      0.90      0.91       144
                               Go straight or left       0.76      0.97      0.85        78
                                        Keep right       0.98      0.85      0.91       786
                                         Keep left       1.00      0.73      0.84       114
                              Roundabout mandatory       0.92      0.80      0.85       132
                                 End of no passing       0.96      0.86      0.91        90
End of no passing by vechiles over 3.5 metric tons       0.98      0.67      0.79        90

                                          accuracy                           0.85     14628
                                         macro avg       0.91      0.84      0.86     14628
                                      weighted avg       0.91      0.85      0.87     14628

Accuracy: 84.82%
Precision (Macro): 91.07%
Recall (Macro): 84.10%
F1 (Macro): 86.30%
Precision (Weighted): 91.12%
Recall (Weighted): 84.82%
F1 (Weighted): 86.61%
Precision (Micro): 84.82%
Recall (Micro): 84.82%
F1 (Micro): 84.82%
```