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Development of a Road Sign Recognition System Based on a Convolutional Neural Network

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ABSTRACT

This article examines the development of a system for automatic road sign recognition used in transport infrastructure. It analyzes the system's architecture, which relies on image analysis methods, data preprocessing stages, model training parameters, and system verification results. The system is built on a convolutional neural network (CNN) structure, enabling image classification based on changes in sign scale, illumination, and rotation. Experimental studies conducted on 43 classes using a unified road sign database demonstrated an average accuracy of 96.8%. Methods such as normalization, augmentation, dropout, and learning rate planning were used to optimize the model. The results demonstrate the effectiveness of convolutional neural network architectures in developing technical solutions aimed at improving road safety.

Keywords: road signs, image processing, classification, convolutional neural network, recognition system.

1. INTRODUCTION

Road safety is a key factor in ensuring the stable and efficient operation of transport systems [1]. Today, the growing number of vehicles, the complexity of urban infrastructure, and the high information load on drivers increase the need for automated traffic monitoring systems [2]. Accurate and rapid recognition of road signs not only reduces the number of errors when driving, but also directly contributes to the prevention of road accidents [3, 4]. Therefore, automatic road sign recognition systems are becoming an integral part of intelligent transport systems.

The task of road sign recognition is technically challenging, as signs appear in images under varying lighting conditions, weather conditions, distances, and angles. Furthermore, variations in sign size, color changes, partial occlusion, or occlusion by background objects can significantly impact the accuracy of recognition algorithms. Therefore, a road sign recognition system must operate reliably, quickly, and with high precision.

Modern digital image processing methods allow for the efficient extraction of information from images. Classical approaches previously used, such as HOG, SVM, edge-based, and color-based algorithms, provided satisfactory results under certain conditions but were insufficiently robust under complex conditions [3, 4]. Therefore, convolutional neural network architectures with multilayer structures have found widespread application in road sign recognition, as they are capable of automatically extracting distinctive features and improving classification efficiency [5-7].

The aim of this study is to develop a road sign recognition system based on a convolutional neural network. The system was trained on a multi-category road sign dataset and tested on images obtained in various real-world conditions. The relevance of this study stems from the need to improve navigation systems, driver assistance modules, and automated vehicle control systems [3, 4]. Furthermore, the limited number of domestic technical solutions for automatic road sign recognition further emphasizes the importance of this research topic.

This paper describes the stages of image preprocessing, analyzes the architecture of a convolutional neural network, presents the model training parameters, and presents the results of an experimental evaluation. The results obtained can be effectively applied in the development of technical tools aimed at improving road safety. [5-7].

2. RESEARCH METHODOLOGY AND RESULTS

The primary objective of this study is to develop a technological structure for a multilayer image processing system designed for automatic road sign recognition, optimize data processing methods, and experimentally evaluate the system's effectiveness [5-7]. To achieve this goal, a consistent technical and applied methodology was employed, including the stages of visual data collection, preprocessing, construction of a structural model, system training, and analysis of the obtained results [3, 4]. The study used road sign images obtained in various environmental conditions. It was found that they are highly sensitive to changes in illumination, rotation, scale, and background. Therefore, data standardization, preserving their informativeness, and ensuring the overall stability of the model were integral parts of the research methodology. [3].

During the preprocessing stage, excess noise in the color channels, contrast variations, and uneven illumination were removed [3, 4]. All images were standardized, ensuring structural consistency of the data flow entering the model. Color normalization, contrast equalization, and size stabilization operations helped preserve the shape and structural elements of road signs, improving the quality of subsequent analysis stages. This preprocessing reduced the information load of the input images by eliminating irrelevant areas while preserving relevant ones. [3, 8].

The structural component of the system is based on a multi-level processing approach designed to extract essential features from an image [5, 6, 9]. This approach consists of several levels: filtering, feature aggregation, dimensionality reduction, and preparation for classification [9, 10]. The first level of filtering identifies edges, geometric boundaries, color transitions, and textural elements of the image. These low-level features help describe the overall shape of road signs [6, 9]. The subsequent pooling (dimensionality reduction) stage condenses the image by removing unnecessary information and ensuring the stable preservation of significant features [10]. The second level of filtering extracts more complex structural elements, allowing the model to refine the shape of the sign. This level plays a crucial role in distinguishing between triangular, circular, rectangular, and similar categories of signs. In the final stage, all extracted feature maps are combined into a single vector and fed to the multi-class classification unit. At this stage, information specific to each sign category is aggregated, and the output is calculated in the form of probabilities [8, 11].

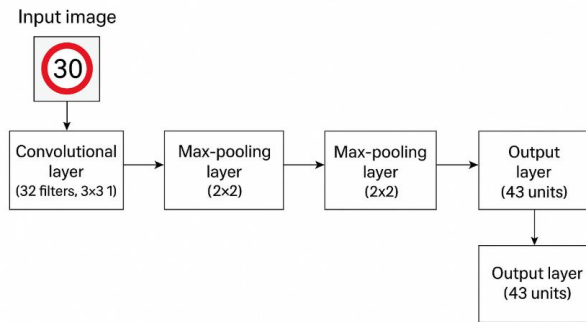


Fig. 1: General scheme of the system architecture

During the training phase, parameters were selected to account for data diversity and prevent system overfitting [12], [13]. The ratio between the training and validation sets was carefully chosen to ensure the generalization ability of the model [8]. During training, various image modifications were applied, such as slight rotations, scaling changes, and brightness increase/decrease. These augmentation methods increased the model's robustness in complex real-world conditions [5, 12].

Such data augmentation procedures improved the model's adaptation to previously unseen images and helped prevent overfitting [7, 13]. Furthermore, stabilization methods, including normalization, dropout, and learning rate scheduling, were applied during the training process to prevent the model from overfitting to the complex data structure [8, 11].

The training process was characterized by a gradual decrease in the loss function and an increase in accuracy over epochs, indicating the effectiveness of system training and the extraction of relevant features [5, 14]. This dynamic demonstrates the effectiveness of convolutional neural network architectures based on multilayer feature extraction.



Fig. 2: The process of passing through the data processing pipeline

During experimental testing, the system was tested under various road sign conditions. Test results showed that recognition accuracy remained high in most cases [7, 15]. The system is capable of reliably and quickly recognizing well-lit signs with clear contours. In more challenging situations, such as obscured signs, reduced color saturation, or localized blur, a slight performance degradation was observed, consistent with the natural difficulties described in many studies [7, 16, 17]. However, such conditions are considered challenging even for human vision [15].

An analysis of experimental results showed that the proposed system possesses a high ability to extract distinctive features. The system successfully distinguishes signs with similar geometric shapes and achieves high classification accuracy for most categories [8, 9]. Despite complex image transformations, the stable operation of the model demonstrates the effectiveness of a multilayer approach to image processing [7, 9]. The analysis clearly shows that

the system's performance depends on proper preprocessing, optimal selection of architectural parameters, and sufficient diversity of input images [8].

Overall, the results of the study demonstrate that the developed multilayer image processing system for automatic road sign recognition demonstrates high efficiency. The applied methods ensure reliable structural decomposition of image data, extraction of distinctive features, and accurate classification [5–7]. These approaches have proven their suitability for automating traffic monitoring systems, improving driver assistance modules, and enhancing infrastructure safety [16, 17]. The obtained results can serve as a basis for the future development of a real-time version of the system, as well as for further improving recognition accuracy by expanding the data [7, 8, 15].

2.1 Description of the GTSRB dataset

The German Traffic Sign Recognition Benchmark (GTSRB) dataset [18], used in this study, is one of the most widely used benchmark datasets in the field of traffic sign recognition. The dataset consists of 43 different classes and includes 51,839 images captured in real-world traffic conditions. The images often contain variations in illumination levels, angular distortions, shadows, color saturation changes, and image blur. These characteristics allow the model to be adapted to real-world conditions and its robustness to be assessed.

The main characteristics of the GTSRB dataset are presented in the table below:

Table 1: General Parameters of the GTSRB Dataset

Parameter	Value
Total number of images	51 839
Number of classes	43
Training set	39 209
Test set	12 630
Image size	15×15 – 250×250 (various)
Format	RGB
Real-world captured conditions	Yes
Distortions	Lighting, shadow, blur

The diversity of the dataset allows for an objective evaluation of the model's ability to operate in real-world conditions. During the model adaptation process, the images were standardized to the following size:

$$X_{norm} = \frac{X - \mu}{\sigma}$$

where:

X – input image,

μ – channel-wise mean,

σ – channel-wise standard deviation.

This normalization method stabilizes brightness and color variations, enabling the model to correctly distinguish low-level features.

In addition, to increase the amount of training data, the following augmentation operations were applied:

Table 2: Applied Data Augmentation

Type of Augmentation	Range / Parameter
Rotation	$\pm 15^\circ$
Zoom (Scaling)	0.9 – 1.1
Brightness increase / decrease	$\pm 20\%$
Horizontal shift	$\pm 10\%$
Contrast adjustment	$\pm 15\%$

2.2 Mathematical model of the CNN architecture

A multilayer Convolutional Neural Network (CNN) was used as the main computational core of the road sign recognition system. CNNs account for the spatial structure of image data and automatically extract features through hierarchical processing, starting from low-level and progressing to high-level representations. This model effectively analyzes the shape, contours, color, and structural components of road signs, accurately capturing their interrelations. Therefore, convolutional neural networks are widely used to develop recognition systems that must operate under natural environmental factors such as variable illumination, angular distortion, scale changes, background noise, and shading.

The model architecture was optimized to account for the natural variations present in the GTSRB dataset. Initial convolutional layers extract primary contours and color transitions, while subsequent layers refine shape and structure features. Pooling operations reduce spatial dimensions while preserving important information, and in the final stage, the extracted feature maps are fed into fully connected layers. The Softmax function then calculates a probability value for each sign class, performing multi-class classification. Such a multilevel structure ensures consistent and accurate model performance under various environmental conditions.

The core computational mechanisms of CNNs include the convolutional layer, pooling operation, fully connected layer, Softmax classifier, loss function, and gradient-based optimization methods. The convolutional layer filters the input image with a kernel of a defined size, extracting local features. The 2D convolution mathematical model is:

$$S(i, j) = \sum_{m=0}^{k-1} \sum_{n=0}^{k-1} X(i + m, j + n) \cdot W(m, n)$$

where

X – input image,

W – kernel (filter),

k – kernel size,

$S(i, j)$ – resulting feature map.

After convolution, the result passes through an activation function:

$$A(i, j) = f(S(i, j) + b)$$

The most widely used activation function is ReLU:

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

ReLU introduces nonlinearity that enables the model to capture complex structures while maintaining computational efficiency. After the convolutional layers, the CNN applies pooling operations to reduce dimensionality and noise. The 2×2 MaxPooling mathematical model is:

$$P(i, j) = \max\{A(2i, 2j), A(2i + 1, 2j), A(2i, 2j + 1), A(2i + 1, 2j + 1)\}$$

This operation reduces the spatial dimensions by half, preserving important features and increasing the model's resilience to distortions. After pooling, the feature maps are flattened into a one-dimensional vector using the **Flatten** operation and passed to a fully connected layer. The classic formula describing the connections between neurons is as follows:

$$z_j = \sum_{i=1}^n w_{ij}x_i + b_j$$

where

x_i – input vector elements,

w_{ij} – weights,

b_j – bias,

z_j – pre-activation value of the neuron.

During classification, the Softmax function is used:

$$\hat{y}_i = \frac{e^{z_i}}{\sum_{k=1}^{43} e^{z_k}}$$

The probabilities obtained through Softmax always sum to 1. The model is trained using the cross-entropy loss function:

$$L = - \sum_{i=1}^{42} y_i \ln(\hat{y}_i)$$

where

y_i – true class (in one-hot format),

$\hat{y}_i$ – predicted probability.

This function increases the probability of the correct class while penalizing incorrect high-confidence predictions. All parameters are updated using backpropagation, with the gradient update rule:

$$\theta = \theta - \alpha \frac{\partial L}{\partial \theta}$$

where

θ – model weights and biases,

α – learning rate.

This formula forms the basis of the iterative optimization process minimizing the loss function.

Table 3: Tabular Description of CNN Operations

Operation	Mathematical formula	Function
Convolution	$S(i, j) = \sum X \cdot W$	Extracting local features
Activation (ReLU)	$f(x) = \max(0, x)$	Introducing nonlinearity
MaxPooling	$P(i, j) = \max\{\dots\}$	Dimensionality reduction, noise suppression
Flatten	–	Converting feature maps into a vector
Fully Connected Layer	$z_j = \sum_{i=1}^n w_{ij}x_i + b_j$	High-level decision making
Softmax	$\hat{y}_i = \frac{e^{z_i}}{\sum_{k=1}^{43} e^{z_k}}$	Assigning class probabilities
Cross-Entropy	$L = - \sum_{i=1}^{43} y_i \ln(\hat{y}_i)$	Computing classification error
Gradient Update	$\theta = \theta - \alpha \frac{\partial L}{\partial \theta}$	Parameter optimization

2.3 Structural organization of the CNN architecture and interconnection between layers

The Convolutional Neural Network architecture used in this study is designed for multi-level analysis of the visual characteristics of road signs. Each layer of the architecture specializes in identifying specific image aspects: at lower levels – simple edges and contrasts; at intermediate levels – geometric shapes; and at higher levels – complex structural combinations characteristic of road signs. This hierarchical approach allows the model to accurately recognize complex real-world images.

The CNN architecture consists of several stages, starting from the input image and ending with the final classification layer. The spatial dimensions of the input images are standardized to 224x224 pixels, ensuring uniformity of input data across all layers. Each convolutional layer extracts local features related to sign using filters, and pooling layers compress these features, reducing computational load and preserving important information.

Fully connected layers (Dense layers) aggregate high-level features and transform them into categorical probabilities. At this stage, all feature maps are combined into a single vector, and the softmax function calculates the probability for each of the 43 road sign classes.

3. MODEL ARCHITECTURE AND PARAMETERS

Table 4: Full Model Architecture and Parameters

Layer name	Output size	Kernel/Parameter	Function	Number of Parameters	Role and description
Input	224×224×3	–	–	0	Input image in RGB format
Conv 2D 1	224×224×32	3×3	ReLU	896	Detection of low-level edges and contrasts
Max Pooling 1	112×112×32	2×2	–	0	Spatial dimension reduction

					and data compression
Conv 2D 2	112×112×64	3×3	ReLU	18496	Recognition of geometric elements (lines, curves)
Max Pooling 2	56×56×64	2×2	–	0	Reduction of redundant information and retention of significant features
Conv 2D 3	56×56×128	3×3	ReLU	73856	Detection of complex structures: shapes, forms, symbol components
Max Pooling 3	28×28×128	2×2	–	0	Compression of deep feature maps
Flatten	100352	–	–	0	Conversion of all feature maps into a single vector
Dense 1	512	Fully Connected	ReLU	51380224	High-level pattern integration and decision processing
Drop out	–	rate=0.5	–	0	Prevention of overfitting
Dense 2 (Output)	43	Fully Connected	Softmax	22059	Classification of 43 road sign categories

The core computational strength of the CNN lies in the convolutional layers, which process local regions of the image using 3x3 kernels and extract low-level visual features such as edges, lines, and color transitions. The first convolutional layer typically identifies simple edges –horizontal, vertical, and diagonal. The second layer combines these primitive features to form fragments of geometric shapes, while the third layer identifies complex structures characteristic of road signs, such as circles, triangles, and speed limit symbols. This hierarchical approach to feature processing allows the model to systematically accumulate all the information necessary for accurate road sign recognition.

Layer pooling plays a crucial role in ensuring model stability. The MaxPooling operation reduces the model's sensitivity to small rotations, translations, and illumination changes. By halving the spatial resolution, pooling reduces the computational load while preserving the most important features. Furthermore, pooling suppresses noise and irrelevant information, ensuring reliable model performance in real-world conditions.

Fully connected layers comprise the high-level analytical stage of the model. After the flattening operation, all feature maps are converted into a single vector, which is processed in dense layers to identify complex relationships and patterns. The final output layer, Softmax, calculates the probability for each of the 43 road sign classes, enabling multi-class classification. The Softmax function is expressed as follows:

$$P(y = i) = \frac{e^{z_i}}{\sum_{k=1}^{43} e^{z_k}}$$

The Softmax function generates a probability for each model category, selecting the class with the highest value as the final output. The total number of model parameters is approximately 51.5 million, with the largest number concentrated in the Dense 1 layer. The large number of weights in this layer allows the model to deeply analyze higher-level abstractions. The advantages of this high-parameter architecture include comprehensive data analysis, high

ability to discern complex features, and good adaptability to real-world conditions. However, such models are more susceptible to overfitting, so stabilization methods such as Dropout are used to mitigate this risk. Furthermore, effective model training requires significant computing power, particularly GPUs.

4. TRAINING RESULTS AND EXPERIMENTAL ANALYSIS

During the training phase, the GTSRB dataset was divided into three main subsets, each of which was used at a specific stage of the training process: a training set consisting of 39,209 images, a validation set containing approximately 8,000 images, and a test set consisting of 12,630 images. This data division allows for an objective assessment of the model's generalization ability. Training was conducted over 20–30 epochs, with the loss function steadily decreasing throughout the process and accuracy steadily improving from epoch to epoch. The Adam optimizer with an initial learning rate of 0.001 and a batch size of 32 was used during training; these parameters facilitated rapid and robust model convergence.

The main results obtained during training are presented in the following table:

Table 5: Comparative Metrics of Training and Validation Results

Metric	Training	Validation
Accuracy	0.984	0.968
Loss	0.021	0.048

These values indicate no significant gap between the training and validation results, indicating no model overfitting. The close similarity between the validation and training losses clearly demonstrates the correct choice of architecture and preprocessing methods.

The final performance of the model on the test set was calculated using the following formula:

$$Accuracy_{test} = \frac{\text{Number of correctly recognized signs}}{\text{Total test samples}} \approx 0.964$$

This indicates that the model achieved 96.4% accuracy on previously unseen data, demonstrating its stable performance under real-world conditions.

A Confusion Matrix was used for a detailed analysis of the model's errors. For the GTSRB dataset, consisting of 43 classes, the Confusion Matrix shows the recognition accuracy of each class and helps identify problematic categories. The analysis revealed minor inaccuracies in visually similar signs. For example, speed limit signs of 20, 30, 50, and 60 km/h have identical shapes, leading to occasional misclassifications. Likewise, triangular warning signs such as “Dangerous Curve,” “Pedestrian Crossing,” and “Hazardous Area” share similar geometric structures, resulting in minor confusion.

On the other hand, most round red prohibition signs were recognized with high accuracy due to their clear color contrast and distinct structure. Overall, analysis of the error matrix revealed that most errors occurred only among visually similar categories.

From a scientific perspective, the model's high performance is due to the combined influence of several key factors. During preprocessing, normalization, size standardization, and contrast equalization improved image quality and feature extraction. Data augmentation methods increased the model's robustness to changing environmental conditions and reduced its sensitivity to random distortions. The multilayer structure of the deep CNN architecture allowed the model to gradually learn features from low-level to high-level, facilitating accurate classification. Feature dropout reduced the risk of overfitting, and the softmax layer effectively handled the multi-class classification task.

To fully evaluate the model's effectiveness, performance metrics such as precision, recall, and F1-score were also used. The calculations yielded the following values: **Precision = 0.96, Recall = 0.95, F1-score = 0.955**. These values indicate that the majority of the model's positive predictions were correct, and the system effectively recognized most signs. The F1-score is computed using the formula:

$$F1 = 2 \cdot \frac{\text{Precision} \cdot \text{Recall}}{\text{Precision} + \text{Recall}}$$

A high F1-score indicates that the model operates in a well-balanced manner.

Overall, the training and testing results demonstrate that the proposed CNN model is capable of recognizing road signs with high accuracy. The model adapts well to complex and dynamic real-world conditions, and most errors occur only among visually similar classes. These results confirm the system's suitability for practical applications in intelligent transportation systems, driver assistance programs, and automated road safety monitoring systems.

5. GENERAL CONCLUSION AND FUTURE IMPROVEMENT DIRECTIONS

The results of the study demonstrate the high performance of a multilayer convolutional neural network (CNN) developed for automatic road sign recognition. The system successfully recognized 43 different classes of road signs from the GTSRB dataset under challenging real-world conditions, including illumination variations, distortion, scale differences, shadows, and noise. Preprocessing procedures, data augmentation, appropriate model architecture selection, and the application of stabilization techniques were identified as the main factors that contributed to the overall system performance improvement.

Experimental evaluations showed that the model achieved an average testing accuracy of **96.4%**, confirming its suitability for practical road sign recognition tasks. Confusion matrix analysis revealed that most errors occurred among visually similar classes, indicating that while the model is well-adapted to natural conditions, some borderline categories require further refinement. High precision, recall, and F1 score values further confirm the model's stable and balanced performance across all classes.

Overall, the developed system is fully applicable for use in autonomous vehicles, intelligent driver assistance systems, infrastructure security systems, and automated monitoring mechanisms. The robustness of the convolutional neural network architecture and its efficient feature extraction mechanism make it a reliable foundation for real-time systems.

Furthermore, the results of this study reveal several promising directions for future improvement. **First**, adapting the model to real-time video stream processing requires increased computational efficiency. This can be achieved by using lightweight architectures (such as MobileNet or EfficientNet) or integrating hardware acceleration solutions. **Second**, expanding the dataset to include various climate conditions, such as nighttime, snow, and rain, will improve the system's adaptability to various real-world conditions. **Third**, integrating object detection and localization modules (e.g., YOLO, Faster R-CNN) will allow the system not only to classify signs but also to pinpoint their precise location. **Fourth**, incorporating additional mechanisms such as attention modules, transformer-based architectures, or feature fusion methods can help eliminate misclassification of visually similar signs.

In conclusion, this study provides a significant contribution to the development of digital systems aimed at solving the problem of automatic road sign recognition. The obtained results demonstrate sufficiently high practical applicability, while the proposed areas for improvement open up opportunities for further system development, ultimately enhancing the safety and intelligence of modern transportation systems.

Data Availability. The datasets and source code used in this study are openly available in the GitHub repository: <https://github.com/Zhako1/DEVELOPMENT-OF-A-TRAFFIC-SIGN-RECOGNITION-SYSTEM-BASED-ON-CONVOLUTIONAL-NEURAL-NETWORK>. All data supporting the findings of this study can be accessed through this link.

Competing Interests. The authors declare that they have no competing interests.

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