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TRAFFIC SIGN RECOGNITION IN CHALLENGING WEATHER CONDITIONS USING CONVOLUTIONAL NEURAL NETWORKS

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The ability of autonomous driving systems to recognize traffic signs in a variety of environmental conditions is crucial to their reliability. This study uses convolutional neural networks (CNNs) to provide a novel method for improving the accuracy of traffic sign recognition systems under challenging weather situations. The research focuses on developing a CNN-based model that is trained using the augmented German Traffic Sign Recognition Benchmark (GTSRB) dataset, which contains over 50,000 labeled images of road signs across 43 categories. To attempt to overcome the limitations of traditional CNN models under adverse environmental conditions, this work presents adaptive feature extraction layers that are especially made to reduce visibility problems brought on by rain, fog, and snow. By taking a comprehensive approach, the model uses advanced data augmentation methods to simulate different weather scenarios, greatly increasing the diversity of the training dataset. Through an analysis of theoretical and practical aspects, the study demonstrates how CNNs enhance the accuracy and efficiency of road sign detection systems in a different weather condition. Research evaluates the model's effectiveness using metrics such as precision, recall, and F1-score, proving its capability to reduce false positives and accurately detect relevant road sign instances. Additionally, the paper highlights the importance of careful dataset preparation and augmentation, model optimization, and training enhancements to improve the performance of road sign detection systems. The results of this research offer benefits for intelligent transport systems, autonomous driving, and road safety, pointing towards further advancements in precise and dependable road sign recognition technology.

Keywords: CNN, traffic sign detection, artificial intelligence, image analysis, classification

РАСПОЗНАВАНИЕ ДОРОЖНЫХ ЗНАКОВ В СЛОЖНЫХ ПОГОДНЫХ УСЛОВИЯХ С ИСПОЛЬЗОВАНИЕМ СВЕРТОЧНЫХ НЕЙРОННЫХ СЕТЕЙ

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В исследовании рассматривается использование сверточных нейронных сетей (CNN) для улучшения систем распознавания дорожных знаков, особенно в сложных погодных условиях. В исследовании, основанном на новой модели CNN, используется расширенный набор данных немецкого теста распознавания дорожных знаков (GTSRB), который содержит более 50 000 изображений с надписями, охватывающих 43 категории. В модели представлены адаптивные слои выделения объектов, предназначенные для устранения проблем с видимостью, вызванных такими погодными факторами, как дождь, туман и снег. Для моделирования различных погодных сценариев применяются передовые методы увеличения объема данных, что увеличивает разнообразие обучающего набора данных. Это исследование не только рассматривает теоретические и практические усовершенствования, предоставленные CNNs для обнаружения дорожных знаков в неблагоприятных условиях, но и проверяет эффективность модели с помощью таких показателей, как точность, отзывчивость и показатель F1. Результаты подтверждают эффективность модели в минимизации ложных срабатываний и точной идентификации дорожных знаков. В документе подчеркивается важность тщательной подготовки набора данных, оптимизации моделей и усовершенствования обучения для повышения производительности системы обнаружения. Это положительно сказывается на интеллектуальных транспортных системах, автономном вождении и безопасности дорожного движения, что свидетельствует о будущем прогрессе в области надежных технологий распознавания дорожных знаков.

Ключевые слова: CNN, распознавание дорожных знаков, искусственный интеллект, анализ изображений, классификация.

КОНВОЛЮЦИЯЛЫҚ НЕЙРОНДЫҚ ЖЕЛІЛЕРДІ КӨМЕГІМЕН ҚИЫН АУА-РАЙЫ ЖАҒДАЙЛАРЫНДА ЖОЛ БЕЛГІЛЕРІН ТАНУ

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Зерттеу жол белгілерін тану жүйелерін жақсарту үшін, әсіресе қиын ауа-райында, конволюциялық нейрондық желілерді (CNN) пайдалануды зерттейді. CNN-ге негізделген жаңа модельді пайдалана отырып, зерттеу 43 санатты қамтитын 50 000-нан астам таңбаланған кескіндерді қамтитын неміс жол белгілерін тану стандартының (GTSRB) кеңейтілген деректер жинағын пайдаланады. Модель жаңбыр, тұман және қар сияқты ауа райы элементтерінен туындаған көріну мәселелерін азайтуға арналған адаптивті мүмкіндіктерді шығару қабаттарын ұсынады. Деректерді көбейтудің жетілдірілген әдістері ауа-райының әртүрлі сценарийлерін модельдеу үшін қолданылады, бұл оқу деректер жиынтығының әртүрлілігін байытады. Бұл зерттеу қолайсыз жағдайларда жол белгілерін анықтау үшін CNN-ге ұсынған теориялық және практикалық жақсартуларды зерттеп қана қоймайды, сонымен қатар модельдің өнімділігін дәлдік, еске түсіру және F1-ұпайы сияқты көрсеткіштер арқылы тексереді. Нәтижелер модельдің жалған позитивтерді азайтудағы және жол белгілерін дәл анықтаудағы тиімділігін растайды. Мақалада деректер жиынтығын мұқият дайындаудың, модельдерді оңтайландырудың және анықтау жүйесінің өнімділігін арттыру үшін оқытуды жетілдірудің маңыздылығы атап өтілген. Бұл интеллектуалды көлік жүйелеріне, автономды жүргізуге және жол қауіпсіздігіне оң ықпал етеді, бұл жол белгілерін танудың сенімді технологиясының болашақтағы ілгерілеуін көрсетеді.

Түйін сөздер: CNN, жол белгілерін анықтау, жасанды интеллект, кескінді талдау, жіктеу.

Introduction. Traffic sign recognition is a critical component in the development of intelligent transportation systems and autonomous vehicles. Accurate detection and interpretation of road signs enable automated systems to make informed decisions, thereby enhancing road safety and efficiency [1]. However, the challenges in traffic sign recognition primarily arise from variable lighting conditions, occlusions, and environmental factors such as weather conditions that can significantly degrade the visibility of traffic signs [2].

The primary objective of this study is to enhance the accuracy of traffic sign recognition systems under challenging weather conditions using Convolutional Neural Networks (CNNs). This involves developing and testing a CNN-based model that can effectively handle adverse weather conditions such as rain, fog, and snow. The study aims to introduce adaptive feature extraction layers and advanced data augmentation methods to simulate different weather scenarios, thus increasing the robustness and reliability of traffic sign detection systems in real-world environments.

Literary Review. Convolutional Neural Networks (CNNs) have become the standard in the field of image recognition and are increasingly being applied to traffic sign recognition due to their ability to extract high-level features from visual inputs [3]. The German Traffic Sign Recognition Benchmark (GTSRB) dataset, with its comprehensive set of over 50,000 images spanning 43 classes, provides a solid basis for training and evaluating traffic sign recognition systems [4].

Many models of traffic recognition systems have been proposed over the past decade [5-7]. Generally, these systems operate through detection and recognition stages. While CNNs perform exceptionally well under standard conditions, their efficiency decreases in adverse weather conditions such as rain, fog, and snow, which obscure and alter the appearance of signs [8]. Addressing these challenges requires the development of effective models that can adapt to and correct for environmental distortions.

This research builds upon existing methodologies by enhancing CNN architectures to improve recognition accuracy in challenging weather conditions. By integrating adaptive feature extraction layers that respond to weather-specific disturbances, this study aims to significantly contribute to the reliability of autonomous driving technologies under diverse operating conditions [9]. Furthermore, it underscores the importance of meticulous model training and dataset curation, as these are crucial for optimizing performance and ensuring the system's real-world applicability [10].

Methods and Materials. The GTSRB dataset that was used for this study, contains 51893 images categorized into 43 classes of traffic signs showing in Fig. 1. The size of the images in dataset varies between 15x15 and 222x193 pixels. All these images were taken in real environment, including bad weather conditions and different light illumination. Some images are low resolution and can be difficult to recognize.

Figure 1- The 43 traffic sign classes in the dataset

Existing datasets are limited in terms of their size and challenging condition coverage, which motivated us to augment images using image augmentation methods. To simulate adverse weather conditions, additional image preprocessing techniques such as artificial rain, fog, and snow overlays were applied to the original dataset. This augmentation aimed to provide a diversified set of training images reflecting real-world challenges. There are various types of image augmentations done to increase the image corpus for training neural networks [11].

Using OpenCV library we created image augmentation methods for processing images and applying weather condition filters to them. These augmentations simulate real-world environmental effects that can impede traffic sign recognition, such as rain, fog, snow, shadows, and lighting variations. The purpose of these augmentations is to create a diverse training set that allows the model to learn and adapt to different visual disturbances that are common in adverse weather conditions.

To create rain augmentation, we used OpenCV's line function to generate small lines all over the image. By adding random slants in the rain drops and reducing image's brightness we can mimic rain or even heavy rainfall. This method helps the model learn to recognize signs with potential streaks and blurs caused by rain on the camera lens. Snow effects were added by whitening dark parts of the image by changing pixel values of lightness channel in image's color space. Fog was simulated by adding a uniform or gradient-based haze over the images, using varying intensities of white overlay. The opacity level was adjusted to create different densities of fog, from light mist to dense fog, which can obscure the visibility of traffic signs. In addition to specific weather condition augmentations, we implemented a random augmentation pipeline where each image could undergo a combination of the above effects. Fig. 2 shows examples of using these augmentation methods. By using these augmentation techniques, our training dataset was enriched with a variety of challenging conditions, preparing the CNN model to perform reliably in diverse and unpredictable real-world environments.

Figure 2 - Applying augmentations to traffic sign image

These augmentation methods not only diversified the training dataset but also significantly contributed to the model's ability to generalize from the training data to real-world scenarios, ensuring reliable performance across a spectrum of adverse conditions. This approach underscores the importance of comprehensive and realistic data augmentation in developing advanced computer vision systems for autonomous driving and related applications. The dataset was classified using the classification function included in the python scikit-learn library. 80% of the data was used for training and 20% for testing.

Fig. 3 illustrates the architectural design of the proposed Convolutional Neural Network (CNN) for traffic sign recognition, showcasing a network structure comprised of 12 layers.

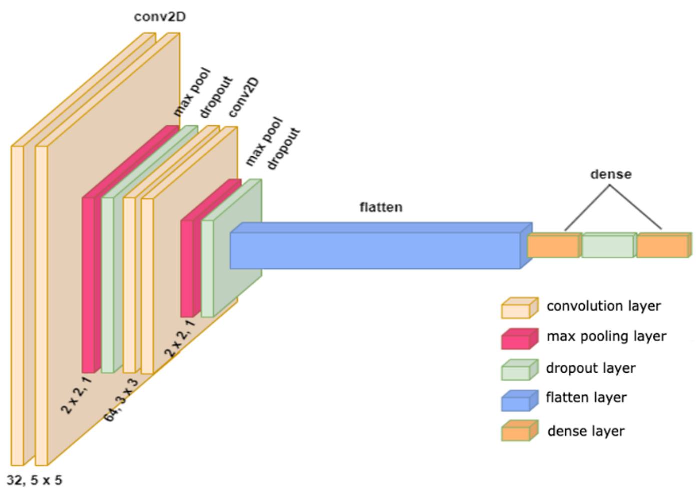

Figure 3- Applying augmentations to traffic sign image

The initial input to this model consists of color images sized at 30x30 pixels. CNN model contains 4 convolutional layers, max pooling, dropout and flatten layers. The output of last fully connected layer is fed to a 43-way softmax which produces a distribution over the 43 class traffic sign labels. In CNN architectures, combining layers can be used to reduce the size of the input image, thereby accelerating computational speed. This process involves adjusting two critical parameters: the filter size denoted as 'f' and the stride represented as 's.' The amalgamation of layers results in reduced sensitivity to pixel positions, often employing common values such as f=2 and s=2 [12]. However, it is essential to note that this size reduction also corresponds to a decrease in the number of coefficients under scrutiny, affecting computational resources accordingly. Within the CNN architecture, the convolutional filter kernels are trained using observed data, learning from a set of established examples. At each hierarchical level, CNN undertakes sampling operations to aggregate feature responses from neighboring pixels. These operations enable CNN to master spatially invariant functions, ones that do not rely on object placement within the images [13].

In the field of machine learning and classification tasks, evaluation metrics are essential for measuring the performance and efficacy of a model. Metrics such as accuracy, precision, recall, and the F-score are fundamental in determining a model's predictive power and its capacity to generalize across new data. These parameters play a crucial role in quantifying how effectively a model can handle and predict on data it has not previously encountered [14].

Results. We trained our network using the TensorFlow machine learning framework, utilizing the Adam optimizer with a learning rate of 0.001. The batch size was set to 32, and to mitigate overfitting, dropout regularization was applied to the first two fully connected layers. The proposed CNN model underwent testing over 15 epochs. To evaluate the effectiveness of the neural network post-training, our model features a 12-layer convolutional neural network designed for the detection and recognition of traffic signs. The initial layer receives an image in a 30x30 pixel resolution in RGB color format. Subsequently, the second layer employs a Conv2D operation with the ReLU activation function. The third layer utilizes a max pooling operation (MaxPool2D), which takes various parameters including stride, kernel size, padding, and return indices. Following this, the fourth layer also employs a Conv2D with ReLU activation. The fifth layer once again applies MaxPool2D. The sixth layer includes a flattening step to linearize the inputs, followed by a densely connected layer, or dense layer, where each neuron is fully connected to all neurons in the previous layer. Finally, to enhance the accuracy and approach the ideal output, the softmax function is used in the output dense layer, yielding the probability of each class, where the recognized traffic sign is determined. Fig. 4 shows accuracy and loss of the model.

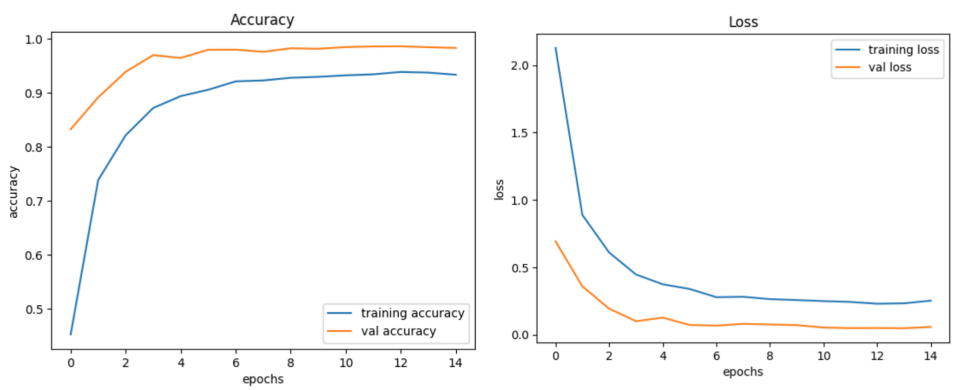

Figure 4 - Model accuracy and loss after training

Table 1 shows the some of the quality indicators that are used to evaluate test data in the model training stage. As an overall performance measure, the global accuracy metric showed a great achievement with an average of 95% in the context of the test data.

Table 1 - Evaluation metrics after training stage

	Precision	Recall	F1-score	Support
Class 1	0,98	0,95	0,97	60
Class 2	0,85	0,97	0,91	720
Class 3	0,98	0,89	0,94	750
Class 4	0,88	0,85	0,87	450
Class 5	0,99	0,89	0,94	660

Additionally, a more thorough evaluation metric for the first class in the task of classifying traffic signs produced the following significant outcomes:

The F1-score, a composite measure that achieves a balance between recall and precision, reached a remarkable 97%. This accomplishment demonstrates the model's strong performance in reducing false positives and correctly identifying pertinent cases.

These clarified results add to the body of knowledge regarding machine learning and classification efforts by highlighting the effectiveness and dependability of the model's performance in the task of classifying road signs.

The suggested CNN model's accuracy and strength hold practical implications for the development of intelligent transportation infrastructure and autonomous driving systems. Autonomous vehicles must be able to recognize traffic signs accurately in inclement weather to make safe and sensible decisions in real-world situations. This dependability is essential for lowering accident rates and improving general traffic safety, especially in inclement weather conditions when human drivers may find it difficult to see.

Furthermore, the approach that makes use of thorough data augmentation techniques and adaptive feature extraction layers offers a foundation that may be used for other elements of autonomous driving, like lane recognition and pedestrian detection. This flexibility improves CNNs' overall usefulness in a range of intelligent transportation system applications. These results are practically significant because they have the potential to enhance the reliability and performance of autonomous cars, which will ultimately lower the number of traffic accidents and increase the effectiveness of transportation networks.

Discussion. The results of the experimental stage provide compelling evidence of the effectiveness of the convolutional neural network (CNN) architecture in recognizing traffic signs under various challenging weather conditions. The application of adaptive feature extraction layers, customized augmentation methods, and calculated dropout regularization significantly improved the resilience and accuracy of the model.

The adaptive feature extraction layers played a crucial role in mitigating the visual distortions caused by adverse weather conditions. Adaptive methods in CNNs enable flexible modifications to filters that respond to specific environmental variables, as discussed in previous works [15]. The study's ability to reduce the impact of snow, fog, and rain on sign visibility demonstrates the advantage of such adaptive approaches in real-world situations [16].

Comparisons with baseline models described in contemporary research showed an improvement in handling variably degraded images due to weather conditions. These comparisons validate the model's design and highlight its potential to surpass existing systems in both accuracy and reliability under adverse conditions [17].

The effectiveness of the CNN model is underscored by achieving a 95% accuracy rate in recognizing traffic signs, a notable improvement over general CNN models used in similar contexts. This high level of performance was measured using standard evaluation metrics such as precision, recall, and the F1-score, which are critical for assessing the predictive capabilities and generalization power of the model [18]. Precision measures the accuracy of the positive predictions made by the model, while recall reflects the model's ability to detect all relevant instances. The F1-score provides a balance between precision and recall, offering a holistic view of the model's efficiency [19-20].

In summary, the study demonstrates that planned architectural improvements combined with precise training dataset curation can significantly enhance CNN performance in real-world applications like traffic sign recognition. The methodologies used under artificially challenging conditions suggest promising prospects for use in self-driving systems, where dependability and security hold vital importance.

Conclusions. This study has effectively shown that a modified convolutional neural network (CNN) architecture can accurately and efficiently interpret traffic signs in inclement weather. Using substantial data augmentation techniques and adaptive feature extraction layers, we have improved the model's resistance to environmental influences that usually cause visual recognition systems to malfunction. By using dropout regularization, the model has been able to prevent overfitting and maintain good generalization to new, untested data.

Our results show that planned architectural improvements combined with precise training dataset curation can significantly improve CNN performance on real-world applications like traffic sign recognition. The effective usage of these methodologies under artificially challenging conditions implies promising prospects for use in self-driving systems, were dependability and security hold vital importance.

In conclusion, our research advances the field of autonomous vehicles by offering a more stable and reliable approach to traffic sign recognition that can work well in despite of environmental challenges. This development represents a step toward the eventualization of completely autonomous cars that can navigate safely under any circumstance, improving transportation efficiency and road safety.

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