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MUNDARIJA *** СОДЕРЖАНИЕ *** CONTENTS		
ANIQ VA TABIIY FANLAR * EXACT AND NATURAL SCIENCES *** ТОЧНЫЕ И ЕСТЕСТВЕННЫЕ НАУКИ**		

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DIAGNOSING THE QUALITY OF HIGHWAYS THROUGH AN INTELLIGENT SYSTEM

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Abstract. *With the ever-increasing demand for efficient and reliable transportation networks, ensuring the quality and safety of highways has become a crucial task for transportation authorities. Traditional methods of diagnosing highway conditions rely on manual inspections, which are time-consuming, subjective, and prone to human errors. In recent years, advancements in intelligent systems and data analytics have opened up new possibilities for automating the process of diagnosing the quality of highways.*

This article proposes an intelligent system for diagnosing the quality of highways using a comprehensive approach. The system leverages state-of-the-art technologies such as machine learning, computer vision, and data fusion to analyze various data sources, including visual imagery, sensor data, and historical records. By integrating these different data types, the system can provide a more accurate and holistic assessment of the highway conditions.

Keywords: *highway, machine learning, artificial intelligence, technologies, computer visions.*

AVTOMOBIL YO’LLAR SIFATINI INTELEKTUAL QAROR QABUL QILUVCHI TIZIM ORQALI DIAGNOSTIKA QILISH

Anotatsiya. *Samarali va ishonchli transport tarmoqlariga talab tobora ortib borayotgan bir sharoitda avtomobil yo'llarining sifati va xavfsizligini ta'minlash transport organlarining hal qiluvchi vazifasiga aylandi. Magistral yo'llarning holatini diagnostika qilishning an'anaviy usullari qo'lda tekshirishga tayanadi, bu ko'p vaqt talab qiladigan injinerlarning subyektiv, obyektiv qarashlariga bog’liqlik holatlari bo’lishi mumkin. So'nggi yillarda intellektual tizimlar va ma'lumotlar tahlili sohasidagi yutuqlar avtomobil yo'llarining sifatini diagnostika qilish jarayonini avtomatlashtirish uchun yangi imkoniyatlar ochdi.*

Ushbu maqolada kompleks yondashuvdan foydalangan holda avtomobil yo'llarining sifatini diagnostika qilishning intellektual tizimi taklif etiladi. Tizim turli ma'lumotlar manbalarini, jumladan, vizual tasvirlar, sensor ma'lumotlari va tarixiy yozuvlarni tahlil qilish uchun mashinani o'rganish, kompyuter ko'rish va ma'lumotlarni birlashtirish kabi eng zamonaviy texnologiyalardan foydalanadi. Ushbu turli xil ma'lumotlar turlarini birlashtirgan holda, tizim avtomobil yo'llarining holatini yanada aniq va yaxlit baholashni ta'minlaydi.

Kalit so’zlar: *Avtomobil yo’llari, mashinali o’qitish, sun’iy intelekt, texnologiyalar, kompyuterli ko’rish.*

ДИАГНОСТИКА КАЧЕСТВА АВТОМОБИЛЬНЫХ ДОРОГ ЧЕРЕЗ ИНТЕЛЛЕКТУАЛЬНУЮ СИСТЕМУ

Аннотация. *В условиях постоянно растущего спроса на эффективные и надежные транспортные сети обеспечение качества и безопасности автомобильных дорог стало важнейшей задачей транспортных органов. Традиционные методы диагностики состояния дорог основаны на ручных проверках, которые отнимают много времени, субъективны и подвержены человеческим ошибкам. В последние годы достижения в области интеллектуальных систем и анализа данных открыли новые возможности для автоматизации процесса диагностики качества автодорог.*

В данной статье предлагается интеллектуальная система диагностики качества автомобильных дорог с использованием комплексного подхода. Система использует самые современные технологии, такие как машинное обучение, компьютерное зрение и объединение данных, для анализа различных источников данных, включая визуальные изображения, данные датчиков и исторические записи. Интегрируя эти различные типы данных, система может обеспечить более точную и целостную оценку состояния дорог.

Ключевые слова: *шоссе, машинное обучение, искусственный интеллект, технологии, компьютерное зрение.*

Introduction. Highways serve as the lifelines of transportation networks, enabling efficient movement of goods and people across vast distances. However, over time, these critical infrastructure components can deteriorate, posing safety risks and leading to increased maintenance costs. Traditional methods of diagnosing highway conditions are often time-consuming, costly, and subjective. Fortunately, with the advent of machine learning, we are witnessing a groundbreaking shift in how highways are diagnosed and maintained. At present, YOLO series deep learning algorithm is one of the most frequently used methods in object detection, which has strong generalization ability. Among them, YOLOv5 has achieved smaller model size and lower computing resource consumption by using modern deep learning technology and structural optimization. It shows high speed and precision in real-time target detection tasks, and is very friendly to practical engineering applications. Therefore, based on YOLOv5, this paper proposes a model combining Swin Transformer and BiFPN model, which shows excellent algorithm robustness and generalization in experiments.

Proposed methodology.

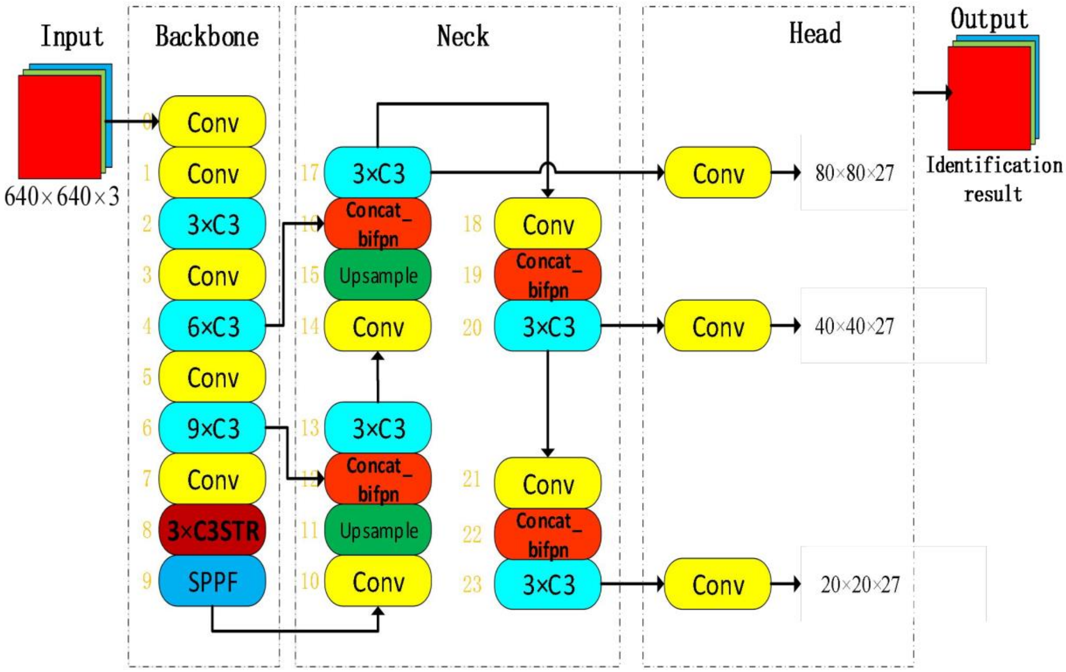


Fig. 1. The architecture of BiTrans-YOLOv5

YOLOv5 is composed of input, backbone, neck, head and output. The backbone of the latest version of YOLOv5 is mainly composed of Conv module, C3 module and SPPF module, which is used to extract image features. Neck uses PANet for multi-scale fusion; head has three groups of output for detection. In addition, YOLOv5 uses mosaic data augmentation, adaptive anchor box computing and image scaling at the input, nms non-maximum suppression at the output and CIOU_Loss as the loss function of Bounding box.

YOLOv5 is divided into four types: Yolo V5s, Yolo V5 m, Yolov5l and Yolo V5x, and the model size and complexity increase one by one. The depth of each CSP structure in the four network architectures and the number of convolution cores in different stages is different. YOLOv5s performs best on devices with limited computing resources and has the fastest detection speed, so it is suitable for mobile devices or edge devices. Considering that road crack detection needs to be integrated into mobile unmanned aerial vehicles before it can be used in engineering, we choose YOLOv5s as the Baseline model.

Based on YOLOv5 network architecture, we use a SwinTransformer in backbone, and use BiFPN instead of PANet to strengthen higher-level feature fusion. The pictures at the input end are uniformly filled or scaled to 640*640. There are three output layers, which correspond to the feature layers of different scales, and their output size is related to the number of classifications (nc). They are 80×80×(3×(nc+5)), 40×40×(3×(nc+5)) and 20×20×(3×(nc+5)) respectively, and nc = 4 in this data set. The architecture of BiTrans-YOLOv5 is shown in Fig. 1.

1) Swin-Transformer

Recently, Transformer has received a lot of attention in the field of computer vision, and achieved outstanding results in a variety of visual tasks. According to the paper, integrating the Transformer Prediction Heads into YOLOv5 can effectively improve the performance of the model, which proves the feasibility of combining transformer and YOLOv5.

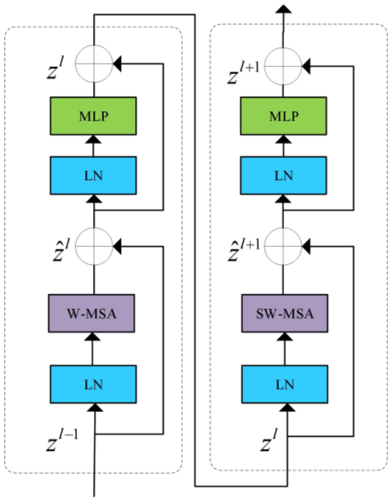


Fig. 2. The architecture of Swin Transformer Layers

Swin Transformer aims to solve the problem of high calculation and memory cost of traditional transformer when processing large-scale images. It introduces a strategy called Shifted Window, which divides the image into uniform local windows and obtains the global context information through the cross attention between windows. Swin Transformer down samples and up samples image features with multiple resolutions through hierarchical structure, so that the model can handle global and local information at the same time. The core component of this hierarchical structure is patch merging and patch partitioning strategy based on Shifted Window. The architecture diagram of two consecutive Swin Transformer Layers is shown in Fig. 2. Each Swin Transformer layer consists of Multi-Head Self-Attention (MSA) and Multi-Layer Perceptron (MLP). Layer Normalization (LN) is used to normalize the input of each layer in the neural network.

We only use Swin Transformer in backbone, and integrate it into C3 module to form C3STR module.

2) Bidirectional Feature Pyramid Network (BiFPN)

Inspired by the paper, we use BiFPN instead of PANet in neck. BiFPN is a feature pyramid network for target detection, which aims to solve the problems of feature fusion and information transmission in multi-scale target detection. BiFPN makes the feature pyramid network more expressive by introducing bidirectional paths, which is suitable for detecting road cracks of tiny pixels. Its architecture diagram is shown in Fig. 3.

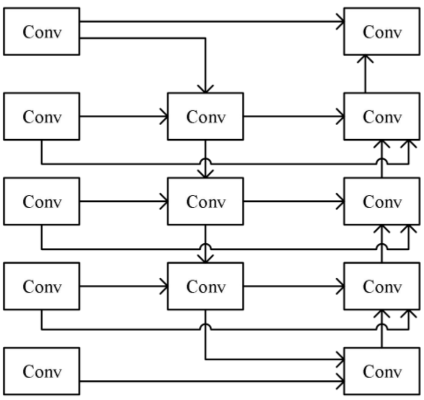


Fig. 3. The architecture of BiFPN

Experiments and results analysis. The first step towards diagnosing highways using machine learning involves collecting vast amounts of data related to road conditions. This data can be acquired through various sources, such as sensors installed on vehicles, GPS systems, satellite imagery, and even crowd-sourced information. These datasets encompass a wide range of parameters, including road surface quality, cracks, potholes, traffic patterns, weather conditions, and more. Machine learning algorithms excel at processing and analyzing large volumes of data, extracting patterns, and uncovering valuable insights. By employing techniques like data preprocessing, feature selection, and normalization, the collected data can be prepared for training models.

We implement BiTrans-YOLOv5 on Pytorch 1.8.1, Python 3.8. The computer configuration used for model training and testing includes: CPU is Xeon-4210, running memory is 32GB, GPU is 2*RTX3090, and the system is Ubuntu 18.04, 64-bit operating system Accuracy is the most commonly used index in classification problems, and it is the ratio of correctly classified predictions to total predictions. However, for unbalanced multi-classification scenarios, Accuracy is deceptive and highly sensitive to data changes, so it is difficult to judge the performance of the model. Therefore, we choose Precision, Recall, F1-Score, AP and mAP@0.5 as evaluation metrics.

Through the confusion matrix, we can know the true positive (TP), true negative (TN), false positive (FP) and false negative (FN), and then we can calculate the precision, recall and F1-score as defined in (1)–(3).

On the smoothed PR curve, take the value of Precision of 10 bisectors (including 11 breakpoints) on the horizontal axis 0-1, and calculate its average value as the final AP, which is defined in (4). When IOU=0.5, the mean Average Precision (mAP) of all crack types is defined in (5).

$$\text{Precision}=\frac{TP}{TP+FP} \tag{1}$$

$$\text{Recall}=\frac{TP}{TP+FN} \tag{2}$$

$$F1=2\times\frac{\text{Precision}\times\text{Recall}}{\text{Precision}+\text{Recall}} \tag{3}$$

$$AP=\frac{1}{11}\sum_{0,0.1\cdots1.0}P_{smooth}(i) \tag{4}$$

$$mAP=\frac{\sum_{i=1}^{4}AP_i}{4} \tag{5}$$

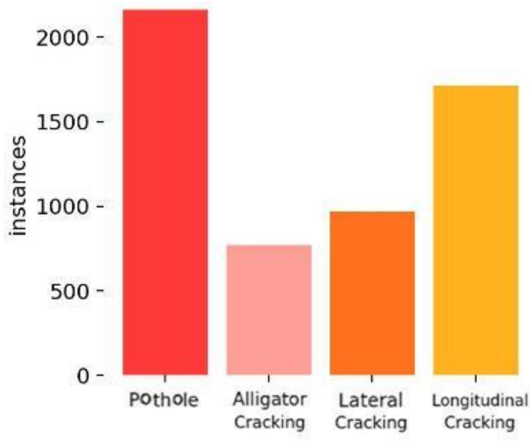


Fig. 4. Label statistics for each category

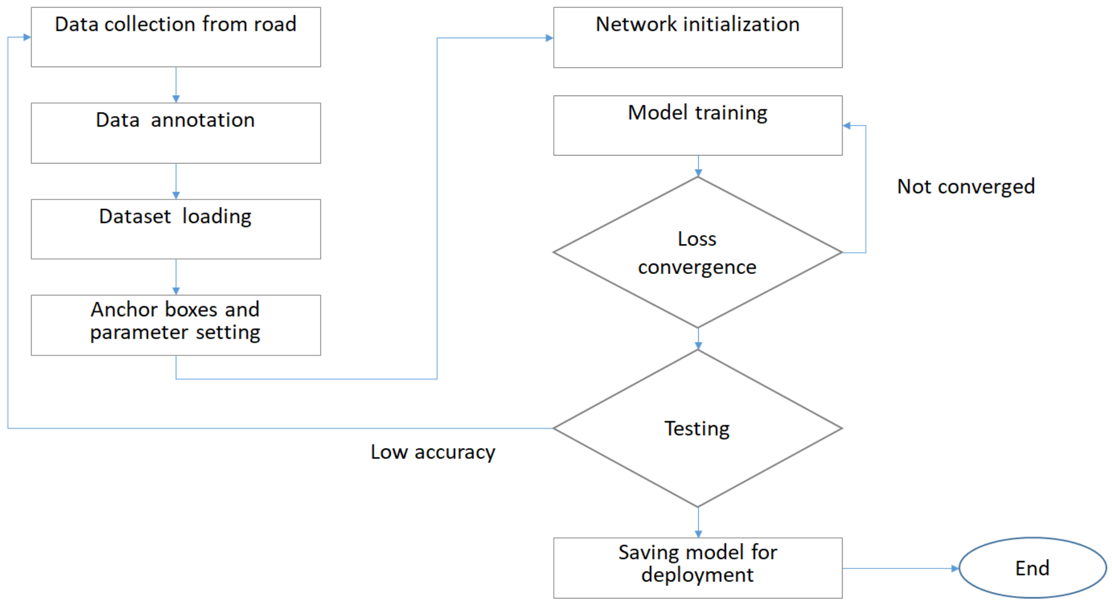
For BiTrans-YOLOv5 model, three kinds of loss curves and three kinds of metrics curves of the training set are drawn as shown in Fig. 5. Cls_loss calculates whether the anchor frame and the corresponding calibration classification are correct. Box_loss is the error between the prediction frame and the calibration frame. Obj_loss calculates the confidence of the network. The smaller the loss, the better the model performance. As shown in Fig. 5, each loss tends to be stable and finally converges to a very small value, and the metrics curve finally tends to be stable, which proves that the hyperparameters set by the model is reasonable.

Methods	Precision (%)	Recall (%)	F1 (%)	mAP@0.5 (%)
YOLOv5	73.6	61.5	61.0	60.0
BiTransYOLOv5	76.3 (↑2.7)	62.8 (↑1.3)	67.0 (↑6.0)	65.4 (↑5.4)

table 1. Ablation study on test-set of road damage

Methods	Pothole (%)	Alligator Cracking (%)	Lateral Cracking (%)	Longitudinal Cracking (%)
YOLOv5	71.7	70.3	35.5	62.6
BiTransYOLOv5	75.5 (↑ 3.8)	73.4 (↑ 3.1)	53.2 (↑ 17.7)	59.7 (↓ 2.9)

table 2. Comparison Of Ap For Each Category



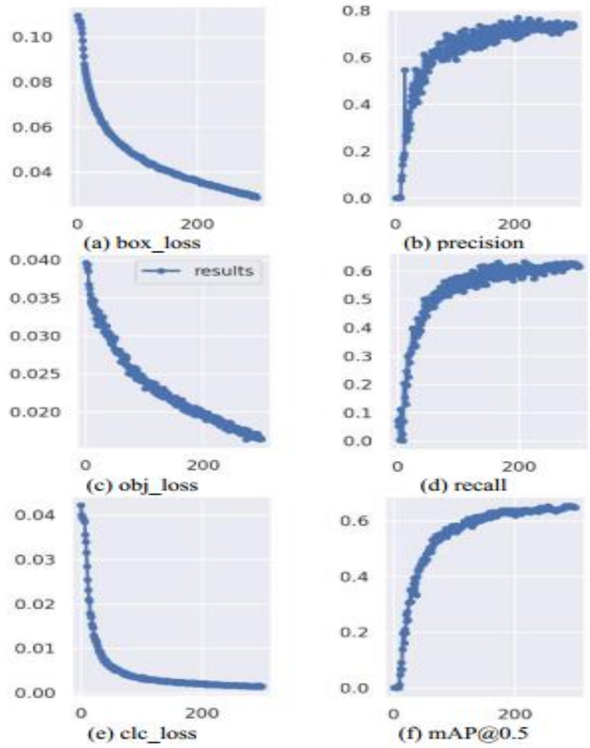
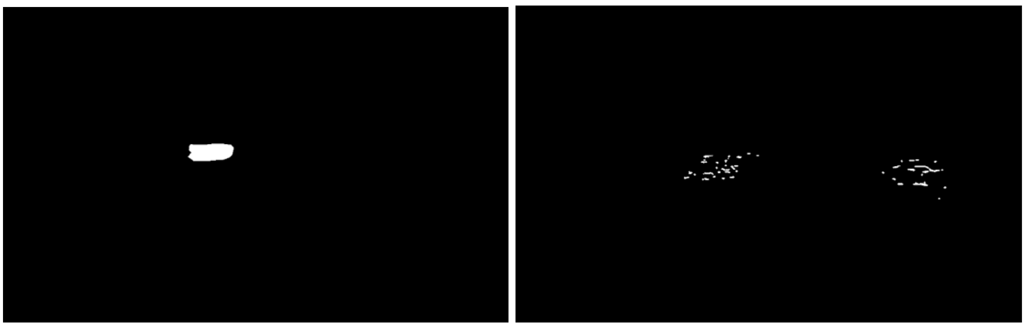


Fig. 5. Loss and metrics

We set the epoch to 300. YOLOv5 and BiTransYOLOv5 were trained respectively. We use the test set independent of the training set and the verification set to evaluate the model performance with IoU=0.5. The obtained model test results are shown in TABLE I. Because we are discussing the multi-classification problem, we also list the AP value of a specific type of crack, as shown in table II.

According to TABLE I, BiTrans-YOLOv5 has improved 2.7% in Precision, 1.3% in Recall, 6.0% in F1 score and 5.4% in mAP@0.5 compared with YOLOv5. This proves that our model improvement is effective.

According to TABLE II, we find that the AP of Lateral Cracking is particularly small. On the one hand, because the samples are not balanced, and on the other hand, because the pixels of Lateral Cracking are too small compared with other kinds, even if we make image weighting reassignment, Lateral Cracking is still more difficult to detect. This also explains that although Alligator Cracking is the least in the statistics of labels in Fig. 4, the AP is very high. Because both the number of samples and the size of the target have an impact on the AP, the size of Alligator Cracking is larger, and it contributes more to the whole picture. It means that even if the number of samples is small, the detection result of large targets may still be good. Anyway, by adding Swin Transformer and BiFPN models, we successfully improved the AP of Lateral Cracking by 17.7%. We choose some pictures of BiTrans-YOLOv5 detected in the test set as the actual results. As shown in Fig. 6, all four types of cracks can be effectively detected.



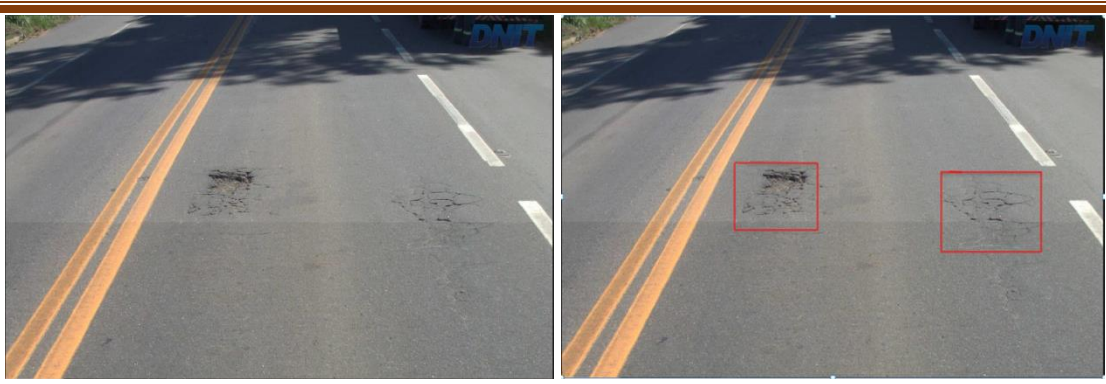


Fig. 6. Visualization result from BiTrans-YOLOv5 on test-set

Literature review. Several studies were carried on for detecting pavement singularities, like road bumps and potholes, based on the analysis of high energy event in vertical acceleration impulse [1–2]. Other researchers have focused on the use of smartphone sensors for evaluating the roughness of the pavement surface and by using the vertical acceleration recorded by a mobile device in a car [2,3]. The International Roughness Index (IRI) was the more investigated parameter and the road surface condition classified by IRI-proxy factors. In identifying the conditions of the pavement, the effect of speed in the study of vertical acceleration must be considered. In this regard, Alessandroni et al. [4] showed how the average value of vertical acceleration is closely related to vehicle speed. The authors developed the "SmartRoadSense" system which aims to monitor road surfaces via smartphones, using a model to calculate an index for the roughness of the pavement. In the same way, Zeng et al. [5] developed a normalized acceleration-based metric for different functional classes of highway by incorporating vehicle speed. An extensive review of 130 papers [6] pointed out an increasing trend of applying artificial intelligence (AI) method, especially Machine Learning techniques, for detection of road anomalies, mainly applied to image analysis. Neural Network (NN)/Artificial Neural Network (ANN) and Support Vector Machine (SVM) are the most common methods applied to data collected by onboard sensors (e.g. speed, vertical displacement and acceleration). Most of studies used ML to detect potholes/humps and estimate roughness (e.g. IRI) [6–8].

Conclusion. Machine learning is revolutionizing the way highways are diagnosed, providing more accurate, efficient, and cost-effective solutions. By harnessing the power of data and advanced algorithms, authorities can monitor road conditions in real-time, predict maintenance needs, and allocate resources effectively. The adoption of machine learning-based diagnostics holds immense potential to enhance highway safety, reduce costs, and improve the overall quality of transportation networks, thereby benefiting society as a whole. In this paper， we propose an improved model BiTransYOLOv5 for Road Damage dataset. First of all, we choose YOLOv5s architecture suitable for embedded development as the baseline, and choose the data set Road Damage for analysis. BiTrans-YOLOv5 is mainly improved in feature extraction layer and neck layer, and the performance of the model can be effectively improved by using Swin Transformer in backbone and BiFPN module in neck. All evaluation metrics selected in this paper have all been improved. In addition, we tested the test set and found that BiTrans-YOLOv5 can still detect four kinds of road cracks well in the noisy background.

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