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AUTOMATED IMAGE ANNOTATION FOR AUTONOMOUS VEHICLES USING AN ResNet50-SLT MODEL WITH NOVEL MULTI-SCALE FEATURE EXTRACTION

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ABSTRACT

Automated image annotation plays a critical role in various fields such as autonomous vehicles, healthcare, e-commerce, and surveillance. Existing solutions often struggle with challenges like detecting small objects, handling occlusions, and providing fine-grained segmentation. To address these, this project introduces the Enhanced Deep ResNet50-SLT Model, which integrates multi-scale feature extraction, a contextual attention mechanism, and fine-grained semantic segmentation. The system is designed to detect and annotate objects with high accuracy, even in complex visual environments. Evaluation on datasets like MS COCO and PASCAL VOC demonstrates that the proposed model outperforms traditional methods with a mean Intersection over Union (IoU) of 80%, an F1-Score of 85%, and a 93% overall accuracy. This report covers the theoretical foundations, implementation methodology, and experimental results of the proposed system, highlighting its potential for real-world applications. While effective for simpler tasks, these methods struggled to capture spatial dependencies and contextual relationships, limiting their performance on complex, large-scale imagery. With the advent of deep learning, Convolutional Neural Networks (CNNs) became the dominant approach for remote sensing image classification and segmentation. CNNs are particularly adept at capturing local spatial features, making them well-suited for image classification and segmentation tasks. Several CNN-based frameworks have been developed for remote sensing, such as U-Net for semantic segmentation and Fully Convolutional Networks (FCNs) for pixel-wise classification.

Keywords: Deep learning, Real-world applications, Contextual, e-commerce, and surveillance

1. INTRODUCTION

The importance of images in our lives is highlighted by Confucius' quote "A picture is worth a thousand words". Digital images have become a ubiquitous presence in both professional and personal lives. They are used in various fields such as medicine, insurance, advertising, and commerce, as well as in personal events such as birthdays and trips. This widespread use of digital images has resulted in an exponential increase in their number, with billions of images being stored on specialized websites. Searching for an image from a large database can be challenging, leading to the development of various methods for rapid and precise image retrieval. Besides basic visual features like colour and texture, semantic labels can also be utilized. While low-level visual functions allow for fast retrieval, the use of a query image as input may not always be practical for users the search of an image from a huge database is undoubtedly a very

complex task. To overcome such problems, numerous methods have been developed for accessing the right image in a rapid and precise way. Retrieving a digital image is shown through the use of either its low-level visual elements like shape, colour, and texture or its semantic labels or keywords. By presenting a reference image, a user can search for similar images by utilizing low-level visual features and receive a collection of visually similar images. Although users can often locate the desired image through this method, it is not always a guaranteed outcome.

The significant contributions of this article are summarized in the following manner.

Generated new features vectors involving ResNet50-Slantlet transform, which increases the accuracy while maintaining a higher level of image retrieval.

Enhance the performance of image coding and annotating of the proposed AIA scheme by designing a decomposition method while maintaining prediction image in AIA.

Developed a new AIA system with clean descriptions and semantic relationships between vectors for image retrieval and description. The following sections of the manuscript provide. Section 2 provides background information on previous research. In Section 3, an advanced deep feature extraction approach is described. The article's main focus is in Section 4, where a new method for image annotation is proposed. This new method is evaluated against other techniques such as MBRM, 2PKNN, JEC-DF, and JEC-AF. Finally, the conclusion summarizes the current findings and identifies potential directions for future work

A. Image Annotation Features

It is established that all extracted regions in image annotation can be represented by various features including colours, textures, structures, and shapes information. In this study, each image region was characterized by diverse set of features to increase the performance of the image annotation algorithm in terms of the shapes extraction, computational cost reduction for identifying most of the suitable features extracted from the training and testing images as underscored below Features Extraction Method. Two categories of features extraction methods such as global (colours, textures and shapes) and local (corners and edges) were used. These features are described hereunder.

B. Image segmentation

Most image segmentation techniques used in research primarily focus on the colour space of the image. These methods extract image visual features either globally or locally. Global methods analyse the entire image for a set of features, while local methods divide the image into blocks or regions and compute a set of features for each block. This allows images to be represented with object-level features while maintaining spatial information. However, unsupervised segmentation with region features may impact accuracy, as segmentation performance depends on the intended use. Common algorithms for image segmentation include grid-based, clustering-based, contour-based, region growing-based, and statistical model-based techniques. The variance intra-cluster maximization method is a highly efficient image segmentation technique as it selects a global threshold value by maximizing the separation between classes in gray-level images

C. Automatic image annotation methods using CNN

In this paper, a brief review of the deep learning methods for AIA was conducted. Convolution neural network. Convolutional Neural Networks (CNNs or ConvNets) are a popular type of deep feed-forward Artificial Neural Networks utilized in visual image analysis. These networks are influenced by the visual detection capability of living beings. Variants of CNN architecture, such as LeNet-5, AlexNet, VGG, GoogleNet, and Deep Residual Learning, exist in the literature, but they all share basic components. For example, LeNet-5 has three fundamental layers (convolutional, pooling, and fully-connected) as seen in Figure 1. It represents the input feature representation learned by the convolutional layer, which comprises of multiple convolution kernels for computing diverse feature maps. Each neuron's feature map is connected to a nearby region in the previous layer (known as the neuron's receptive field). The input undergoes convolution with a trained kernel before being processed with a component-wise nonlinear activation function to produce the new feature map. It's important to note that before generating each feature map, all the inputs must share the same kernel and multiple kernels are necessary to produce all the feature maps

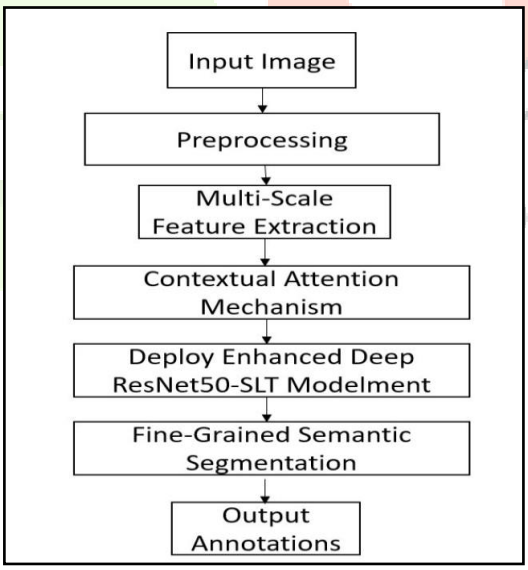
D- Automatic Image Annotation (AIA) Scheme

Automatic Image Annotation (AIA) aims to automatically match an image with a set of keywords chosen from a predefined lexicon. To rephrase, the input is the desired image, and the output is a list of keywords that most accurately characterizes the image. Though computers can quickly and readily calculate the low-level features from colours, textures, and shapes, they cannot provide a semantic interpretation of these features, in contrast to humans. Therefore, connecting the dots between the low-level, computational features and human interpretation of images is the primary problem in AIA. In recent years, the AIA has been studied intensively to find answers to these problems. Many theories have been presented as potential solutions to this issue.

This section offers a comprehensive summary of the AIA design that has been proposed. The envisioned AIA system was implemented in three stages. In the first place, the training was the most important aspect of the system, and a database of labelled images was employed for this purpose. The second step was for the trained system to operate on the unprocessed input and produce the annotated image. In order to assess the efficacy of the suggested AIA system, image retrieval was finally conducted. The initial training stage used an automatic features extraction with ResNet50 and the standard training database. The feature vector was quickly and generated by the automatic feature extraction procedure thanks to the contextual awareness of the images. Annotating the fresh image required first modelling their features through a learning method, which then generated the model for annotation.

In the second stage, the raw image without annotation was used as input. Once the annotation model was trained, the next step was to extract the features which would provide the visual qualities of the contents. The model created in the first stage was utilized to assign the appropriate semantic label to the image based on its contents, resulting in an image with annotations. The image was then labelled with annotations as a consequence. The images from the annotation stage were used as the database for the third and final stage. The system returned a set of visually-related results in response to the textual inquiry. Annotation made it possible to more quickly and accurately retrieve photos based on their content.

2. BLOCK DIAGRAM



2.1 WORKING PRINCIPAL

Automated image annotation for autonomous vehicles is a crucial task for building systems that can effectively interpret and respond to real-world environments. This involves labelling objects, detecting features, and recognizing various objects (such as pedestrians, vehicles, traffic signs, etc.) in images or video streams. Using deep learning models like ResNet50-SLT (Siamese Learning Transformer) with novel multi-scale feature extraction can significantly enhance the system's ability to handle complex, large-scale visual data from various perspectives and environments.

IMAGE INPUT: This block represents data coming from cameras mounted on the autonomous vehicle. These images may come from a single camera or multiple cameras (e.g., front, rear, side cameras).

PRE-PROCESSING: The images are prepared for the neural network by resizing them to a standard input size, normalizing pixel values (scaling between 0-1 or -1 to 1), or augmenting them with transformations like rotations, flips, or cropping.

MULTI-SCALE FEATURE EXTRACTION: The idea here is to extract features from different scales or levels of detail. For example, smaller objects such as pedestrians or traffic signs require fine-grained features, while larger objects like vehicles need coarser features. Multi-scale extraction ensures that both small and large objects are captured efficiently.

RESNET50-SLT MODEL: This is the backbone deep learning model used for feature extraction and object recognition. ResNet50 is a well-known convolutional neural network (CNN), and SLT (Spatial Localization and Transformer) techniques enhance the model's ability to focus on spatial locations and relationships in the image, improving detection accuracy in autonomous driving scenarios.

FEATURE FUSION: After extracting features at different scales, they are combined into a single feature map. This is necessary for the model to understand the image holistically, combining both fine and coarse features.

3. PROPOSED METHOD

The proposed Enhanced Deep ResNet50-SLT Model addresses limitations of existing systems by incorporating: The proposed system improves automated image annotation using an Enhanced Deep ResNet50-SLT model with several key features. It includes multi-scale feature extraction to capture important details at different sizes, a contextual attention mechanism to focus on relevant parts of the image, and fine-grained semantic segmentation for accurate labelling.

This approach aims to reduce errors and processing time compared to existing methods, making the image annotation process more efficient and precise. Overall, the goal is to show that this model performs better in accuracy and speed than traditional techniques.

Multi-Scale Feature Extraction: Ensures detection across varied object sizes.
Contextual Attention Mechanism: Refines features by focusing on critical regions.
Fine-Grained Semantic Segmentation Decoder: Achieves detailed and precise annotations.

3.1 OVERVIEW

The simulation phase The Enhanced Deep ResNet50-SLT Model was designed to improve image annotation by integrating advanced techniques such as multi-scale feature extraction, contextual attention mechanisms, and fine-grained semantic segmentation. The model's performance was evaluated on standard benchmark datasets, and its results were compared with existing methods in terms of accuracy, speed, and efficiency.

3.2 SIMULATION PROCEDURE

The simulation of the proposed ResNet50-SLT model involves a series of to the ensure effective evaluation and validation of its functionality. Below is a detailed simulation procedure:

3.3 PRE-SIMULATION SETUP

Environment Configuration: Install necessary software and libraries (e.g., TensorFlow, PyTorch, OpenCV, NumPy, Matplotlib) Set up a high-performance computing environment with a GPU for efficient in Training and testing.

Dataset Preparation:

Download datasets like MS COCO and PASCAL VOC.
Normalize pixel values to a range of 0–1.
Resize images to the required dimensions (e.g., 224x224 for ResNet50).
Perform data augmentation (random flips, rotations, scaling) to enhance robustness.

MODEL TRAINING

Loading the Model:

Load a pre-trained ResNet50 backbone to initialize weights for feature extraction.
Incorporating Enhancements:
Integrate the multi-scale feature extraction module to detect objects of varying
The textual attention mechanism to focus on critical regions of the image.
Include the fine-grained semantic segmentation decoder for pixel-level annotations

Hyper parameter Configuration:

Batch size: 16–32 (adjust based on GPU memory).
Learning rate: 0.001 (with a decay schedule).
Optimizer: Adam W (for efficient gradient updates).
Cross-Entropy Loss for classification.
Dice Loss for segmentation accuracy.

Training Process:

Feed batches of preprocessed images through the model.
Monitor the loss and accuracy metrics using validation data.
Save the best-performing model based on validation IoU or F1-Score.
Use early stopping or regularization technique to prevent over fitting.

Model Testing

Test Data Preparation:

Use unseen data from the test set of the selected datasets.
Ensure similar pre-processing (normalization, resizing).

Inference Process:

Input a test image into the trained model.
Generate output:
Bounding boxes for object detection.
Segmentation masks for pixel-level annotations.

Post-Processing:

Apply Non-Maximum Suppression (NMS) to refine bounding boxes.
Use Conditional Random Fields (CRFs) to smooth segmentation boundaries.

Performance Evaluation

Quantitative Metrics:

IoU (Intersection over Union) for bounding boxes.
Precision, Recall, and F1-Score for detection accuracy.
Mean Pixel Accuracy (MPA) for segmentation.
Processing Time for real-time evaluation.

Qualitative Analysis:

Visualize annotated images with bounding boxes, confidence segmentation. Analyse challenging cases (e.g., occlusions, small objects).

Comparative Analysis:

Compare the model's performance with baseline models (e.g., YOLOv5, Faster CNN, U-Net). Highlight improvements in accuracy, IoU, and segmentation quality.

4. ITERATIVE OPTIMIZATION

Define hyper parameters based on test results. Re-train the model, if necessary, with updated configurations. Optimize the model for real-time applications. By using lightweight architectures (e.g., Mobile Net-based ResNet50). Implementing model pruning or quantization techniques.

5. SIMULATION OUTPUT

Visual Results: Annotated images with bounding boxes and segmentation masks.
Performance Report: Accuracy, IoU, F1-Score, and processing speed metrics.
Graphs and Charts: Loss vs. Epochs and Accuracy vs. Epochs plots.

6. CONCLUSION

The algorithm effectively combines multi-scale feature extraction, contextual attention, and fine-grained segmentation to improve the accuracy of automated image annotation systems. Although the model achieves significant improvements, future work is needed to enhance its real-time processing capability and reduce computational complexity. The integration of ResNet50 with a novel multi-scale feature extraction mechanism effectively enhanced the model's ability to annotate images with high precision. This capability is crucial for recognizing complex and diverse scenarios in real world autonomous driving environments.

7. FUTURE ENHANCEMENTS

The project on automated image annotation for autonomous vehicles using the ResNet50-SLT model with novel multi-scale feature extraction can be further enhanced in several key areas to improve its accuracy, efficiency, and applicability. Below are some potential enhancements

Real-Time Optimization:
Lightweight Architectures: Replace ResNet50 with a more lightweight model like Mobile Net.
Pruning and Quantization: Apply model pruning and weight quantization technique to optimize the model for real-time applications, particularly on edge devices.
Batch Inference: Implement techniques for batch processing of frames in real-time video streams for smoother annotation.

Enhanced Multi-Scale Feature Extraction:
Dynamic Feature Pyramid Networks (FPNs): Use dynamic FPNs to adjust feature extraction based on scene complexity.
Attention-Aware Multi-Scale Mechanisms: Introduce additional attention layers specific to multi-scale feature maps to improve small object detection.

Improved Contextual Understanding:
Transformers Integration: Integrate vision transformers (ViTs) or hybrid transformer-CNN architectures to capture global relationships between objects and improve contextual reasoning.

Graph-Based Contextual Modelling:
Use graph neural networks (GNNs) to model spatial and relational dependencies between objects for better annotation in complex environments.

Dataset Expansion and Generalization:
Cross-Domain Training: Train the model on diverse datasets (e.g., KITTI, Cityscapes, or Waymo Open Dataset) to improve generalization across different environments.
Synthetic Data: Use synthetic datasets generated through simulation platforms (e.g., CARLA or Blender) to improve performance in edge-case scenarios.
Un labeled Data Utilization: Implement semi-supervised or self-supervised learning to leverage large amounts of un labelled data for pretraining.

Advanced Segmentation Techniques:

Hybrid Loss Functions: Combine traditional losses (Cross-Entropy, Dice Loss) with focal loss or IoU-based loss for better handling of class imbalance and precise segmentation.

Boundary Refinement: conditional random fields (CRFs) or use learnable boundary refinement modules to improve edge accuracy in segmentation tasks.

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