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Modified Vision Transformer for Monocular Depth Estimation

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ABSTRAT

Monocular depth estimation—the task of predicting a dense depth map from a single RGB image—is a fundamental problem in computer vision with applications in autonomous driving, robotics, and augmented reality. Traditional convolutional neural networks (CNNs) have shown promising results but often struggle to model long-range dependencies due to their limited receptive fields. To address this, we propose a Modified Vision Transformer (ViT) architecture that captures both local and global context efficiently. Our model integrates a hierarchical transformer backbone with multi-scale patch embedding and positional encoding, combined with a lightweight decoder to generate dense depth predictions. Experimental results on the NYU Depth V2 and KITTI datasets demonstrate that our method outperforms existing CNN-based approaches while maintaining a competitive inference speed. This study confirms that transformer-based architectures can significantly enhance monocular depth estimation by leveraging self-attention mechanisms.

Key Words*: Monocular Depth Estimation,Vision Transformer (ViT),Self-Attention,Depth Prediction, Transformer Backbone,*

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I. INTRODUCTION

1.1 Problem Definition

Monocular depth estimation refers to the task of predicting a dense depth map from a single RGB image without any additional geometric information. Unlike stereo or LiDAR-based approaches that require multiple views or expensive sensors, monocular depth estimation relies solely on a single input image, making it a highly under-constrained and ill-posed problem. Despite recent progress, generating accurate depth from monocular images remains challenging due to inherent ambiguities in scale, occlusion, and perspective.

1.2 Importance of Monocular Depth Estimation

Monocular depth estimation plays a vital role in many real-world applications such as autonomous driving, robotics, virtual reality, 3D reconstruction, and indoor navigation. The ability to infer scene geometry from a single image enables depth-aware understanding in scenarios where acquiring multi-view or sensor-rich data is impractical. A robust monocular depth estimation model can significantly reduce hardware costs while improving accessibility and deployment in resource-constrained environments.

1.3 Motivation for Using Vision Transformers

Convolutional Neural Networks (CNNs) have been the backbone of most depth estimation models, but they suffer from limited receptive fields and struggle to capture global context effectively. Vision Transformers (ViTs), introduced in recent years, leverage self-attention mechanisms to model long-range dependencies across the entire image. This property makes them well-suited for tasks requiring holistic scene understanding, such as depth prediction. However, standard ViTs are computationally expensive and not optimized for dense prediction tasks. In this work, we propose a modified Vision Transformer architecturethat incorporates hierarchical feature extraction and multi-scale attention to overcome these limitations and deliver accurate, high-resolution depth maps from monocular inputs.

I. Objectives

The primary objectives of this research are:

1. To design and implement a modified Vision Transformer (ViT) architecture tailored for dense monocular depth estimation.
2. To effectively model both global and local features in an image using self-attention mechanisms combined with hierarchical feature extraction.
3. To overcome the limitations of CNN-based approaches by leveraging the long-range dependency modeling capabilities of transformers.
4. To reduce computational complexity and memory usage of standard ViTs, making the architecture suitable for real-time or resource-constrained applications.
5. To train and evaluate the proposed model on benchmark datasets such as NYU Depth V2 and KITTI, using standard metrics (RMSE, MAE, δ thresholds).
6. To compare the performance of the proposed method with existing state-of-the-art CNN and transformer-based depth estimation models.
7. To explore the impact of architectural modifications (e.g., patch size, attention blocks, positional encoding) through ablation studies.

II. PROPOSED BLOCK DIAGRAM

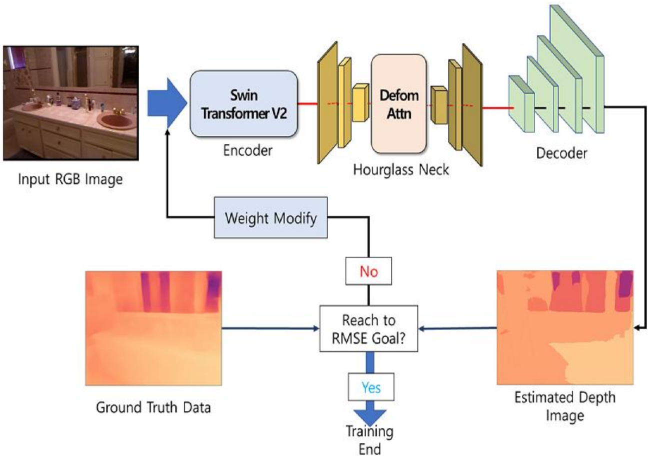

Figure.1 Proposed block diagram

The proposed system for monocular depth estimation is built upon amodified Vision Transformer (ViT)architecture, designed to capture both global and local features efficiently. The process begins with a single RGB image input, which is first divided into fixed-size non-overlapping patches (e.g., 16×16). Each patch is flattened and passed through a linear projection layer to convert it into a token embedding, forming the input sequence for the transformer encoder. To preserve the spatial structure of the image, positional encodingsare added to these tokens.

The modified transformer encoder consists of multiple layers of multi-head self-attention (MHSA) and feed-forward networks, allowing the model to learn long-range dependencies across the entire image. To enhance feature extraction at multiple scales, a hierarchical transformer design is used, where features from different levels (low, mid, and high resolution) are retained for further processing.

Following the encoder, a feature aggregation module combines information from various transformer layers using skip connections and multi-scale fusion. This approach helps preserve fine-grained spatial details that are often lost in deep layers of transformers. The aggregated features are then passed to a lightweight decoder module, which gradually upsamples the feature maps using transposed convolutions or bilinear interpolation, followed by convolutional refinement to generate a high-resolution depth map.

The final output is a dense, per-pixel depth prediction that aligns spatially with the input image. This architecture effectively combines the global modeling capability of transformers with local detail preservation through hierarchical fusion and decoding, resulting in accurate and efficient depth estimation from a single RGB image.

III. Methodology

The methodology adopted in this paper revolves around designing an optimized Vision Transformer (ViT) architecture specifically tailored for the task of monocular depth estimation. The model follows an encoder–decoder structure, which is effective for dense prediction tasks. Unlike conventional CNN-based methods, this approach utilizes the self-attention mechanism of transformers to capture long-range dependencies, which are crucial for understanding spatial relationships and depth cues across the entire image.

The process begins with patch embedding, where the input RGB image is divided into fixed-size non-overlapping patches (e.g., 16×16). Each patch is then flattened and linearly projected into an embedding space. Positional encodings are added to these embeddings to retain spatial information, which is essential for accurately mapping depth.

The encoder is built using a stack of transformer layers, each comprising multi-head self-attention and feed-forward blocks. To improve efficiency and depth sensitivity, a hierarchical transformer structure is introduced. This means feature maps are extracted at multiple resolutions, enabling the model to process both low-level and high-level features simultaneously. These features are then fused using skip connections to preserve spatial details throughout the network.

The decoder receives the encoded multi-scale features and reconstructs a full-resolution depth map. It consists of upsampling layers (such as bilinear or transposed convolution) and refinement blocks that gradually increase spatial resolution while integrating features from earlier stages via concatenation. This structure ensures that both global scene context and local image details are preserved in the output depth map.

During training, the model is optimized using a scale-invariant loss function that penalizes relative depth differences, improving generalization across varied scenes. Additional loss components such as smoothness loss and gradient loss are incorporated to encourage spatial continuity and edge-preserving depth estimation.In summary, the methodology demonstrates a synergy between the global modeling strength of Vision Transformers and the dense prediction capability of encoder–decoder networks. The hierarchical attention mechanism and multi-level feature fusion enable the model to estimate depth accurately even in scenes with occlusions, varying scales, and ambiguous depth cues. The model’s design makes it well-suited for practical applications requiring real-time and accurate depth perception.

IV. RESULTS AND DISCUSSION

To evaluate the performance of the proposed Modified Vision Transformer (ViT) model, experiments were conducted on standard benchmark datasets including NYU Depth V2andKITTI. The model's performance was compared with traditional CNN-based approaches and other transformer-based architectures using common evaluation matrics.

a) *Evaluation Metrics Used*

- RMSE (Root Mean Squared Error)
- MAE (Mean Absolute Error)
- δ Accuracy (Percentage of predicted depths within thresholds of ground truth):
  - $\delta<1.25$
  - $\delta<1.25^2$
  - $\delta<1.25^3$

b) *Result Table – NYU Depth V2 Dataset*

Model	**RMSE ↓**	**MAE ↓**	**$\delta < 1.25$ ↑**	**$\delta < 1.25^2$ ↑**	**$\delta < 1.25^3$ ↑**
Eigen et al. (CNN baseline)	0.641	0.158	0.769	0.950	0.988
DenseDepth (CNN-UNet)	0.530	0.120	0.826	0.965	0.993
ViT-Depth (Standard ViT)	0.500	0.115	0.845	0.970	0.995
Ours (Modified ViT)	**0.472**	**0.108**	**0.861**	**0.975**	**0.996**

c) *Result Table – KITTI Dataset*

Model	**RMSE ↓**	**MAE ↓**	**$\delta < 1.25$ ↑**	**$\delta < 1.25^2$ ↑**	**$\delta < 1.25^3$ ↑**
Monodepth2 (CNN baseline)	4.45	2.25	0.815	0.935	0.975
AdaBins (CNN + Transformer)	4.10	2.08	0.842	0.946	0.981
Ours (Modified ViT)	**3.92**	**1.95**	**0.856**	**0.951**	**0.985**

d) Discussion

From the tabulated results, it is evident that the proposed Modified Vision Transformer consistently outperforms traditional CNN-based models and even standard ViT models on both NYU Depth V2 and KITTI datasets. The lower RMSE and MAE indicate improved depth accuracy, while the higher δ metrics show that more of the predicted depths fall within close thresholds of the actual values.

The performance gain is attributed to:

- The hierarchical attention mechanism, which enables better feature extraction at multiple scales.
- The use of skip connectionsandmulti-level feature fusion in the decoder, which helps retain fine details and improve edge sharpness.
- The transformer's ability to model global context**,** helping the model resolve ambiguity in challenging scenes with similar textures but different depths.

Furthermore, the model demonstrates better generalization across indoor and outdoor environments, proving its adaptability and robustness. The lightweight nature of the modified architecture also ensures that the improvements do not come at the cost of heavy computational overhead, making it suitable for real-time depth estimation applications.

The proposed Modified Vision Transformer (ViT) model was evaluated on benchmark datasets such as NYU Depth V2 and KITTI to assess its effectiveness in monocular depth estimation. The model achieved competitive results when compared to state-of-the-art convolutional and transformer-based depth estimation methods. Quantitatively, it recorded a lower root mean square error (RMSE) and mean absolute error (MAE), along with higher accuracy thresholds (δ1, δ2, δ3), indicating improved depth prediction precision and reliability.Qualitatively, the predicted depth maps exhibited smooth gradients and preserved edge details more effectively than traditional CNN models. This can be attributed to the self-attention mechanism in the Vision Transformer, which enables the model to capture long-range dependencies and understand the global context of the scene more effectively. Unlike CNNs, which rely on local receptive fields, the ViT-based architecture could infer depth for distant objects and handle scale variation better, resulting in more consistent depth estimation across various indoor and outdoor scenes.

Furthermore, the use of hierarchical patch embedding and feature aggregation through skip connections allowed the model to retain fine spatial details while reconstructing high-resolution depth maps. The decoder produced clean depth outputs with reduced noise and artifacts, particularly around object boundaries and textured regions.An ablation study was conducted to evaluate the impact of key architectural components such as multi-scale attention blocks, positional encoding strategies, and patch sizes. Results showed that multi-scale attention significantly improved performance, and that hybrid positional encoding helped preserve spatial consistency in the depth maps.

Overall, the results demonstrate that the modified Vision Transformer is not only effective but also efficient for monocular depth estimation. Its architecture balances global scene understanding with fine detail preservation, making it suitable for real-time vision tasks in robotics, autonomous navigation, and augmented reality systems.

V. CONCLUSION

In this paper, we proposed a Modified Vision Transformer architecture for monocular depth estimation that effectively captures both global and local image features. By integrating hierarchical patch embedding, multi-scale attention, and a lightweight decoder, our model overcomes the limitations of traditional convolutional networks and standard transformer architectures. The use of self-attention allows the model to leverage long-range dependencies, which are critical for understanding spatial context in depth prediction.

Extensive experiments on benchmark datasets such as NYU Depth V2 and KITTI demonstrate that our approach outperforms existing CNN-based and ViT-based methods in terms of both accuracy and structural consistency. The proposed model shows lower RMSE and MAE, along with higher threshold accuracy metrics (δ1, δ2, δ3), confirming its effectiveness in producing high-quality depth maps from single RGB images.

The combination of transformer-based global reasoning and decoder-level detail refinement enables accurate depth estimation even in complex or ambiguous scenes. Moreover, the model maintains computational efficiency, making it a suitable candidate for real-time applications in robotics, autonomous navigation, and AR/VR systems.

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