

Enhancing Multimodal Understanding with CLIP-Based Image-to-Text Transformation

Chang Che

liamche1123@outlook.com
The George Washington University
Atlanta, Georgia, USA

Qunwei Lin

linqunwei1030@outlook.com
Trine University
Phoenix, Arizona, USA

Xinyu Zhao

lution798@gmail.com
Trine University
Phoenix, Arizona, USA

Jiaxin Huang

jiaxinhuang1013@gmail.com
Trine University
Phoenix, Arizona, USA

Liqiang Yu

rexyu@outlook.com
The University of Chicago
Irvine, California, USA

ABSTRACT

The process of transforming input images into corresponding textual explanations stands as a crucial and complex endeavor within the domains of computer vision and natural language processing. In this paper, we propose an innovative ensemble approach that harnesses the capabilities of Contrastive Language-Image Pretraining (CLIP) models. Our ensemble framework encompasses two significant variations of the CLIP model, each meticulously designed to cater to specific nuances within the image-to-text transformation landscape. The first model introduces an elaborated architecture, featuring multiple layers with distinct learning rates, thereby amplifying its adeptness in capturing intricate relationships between images and text. The second model strategically exploits CLIP's inherent zero-shot learning potential to generate image-text embeddings, subsequently harnessed by a K-Nearest Neighbors (KNN) model. Through this KNN-based paradigm, the model facilitates image-to-text transformation by identifying closely related embeddings within the embedding space. Notably, our ensemble approach is rigorously evaluated, employing the cosine similarity metric to gauge the alignment between model-generated embeddings and ground truth representations. Comparative experiments vividly highlight the superiority of our ensemble strategy over standalone CLIP models. This study not only advances the state-of-the-art in image-to-text transformation but also accentuates the promising trajectory of ensemble learning in effectively addressing intricate multimodal tasks.

CCS CONCEPTS

• **Computing methodologies** → **Information extraction; Ensemble methods**; *Computer vision representations.*

Permission to make digital or hard copies of all or part of this work for personal or classroom use is granted without fee provided that copies are not made or distributed for profit or commercial advantage and that copies bear this notice and the full citation on the first page. Copyrights for components of this work owned by others than the author(s) must be honored. Abstracting with credit is permitted. To copy otherwise, or republish, to post on servers or to redistribute to lists, requires prior specific permission and/or a fee. Request permissions from permissions@acm.org.
ICBDT 2023, September 22–24, 2023, Qingdao, China

© 2023 Copyright held by the owner/author(s). Publication rights licensed to ACM.
ACM ISBN 978-1-4503-XXXX-X/18/06...\$15.00
<https://doi.org/10.1145/3627377.3627442>

KEYWORDS

Image-to-Text Transformation, CLIP, Ensemble Learning, Elaborated Architecture, Zero-Shot Learning, K-Nearest Neighbors, Multimodal Alignment

ACM Reference Format:

Chang Che, Qunwei Lin, Xinyu Zhao, Jiaxin Huang, and Liqiang Yu. 2023. Enhancing Multimodal Understanding with CLIP-Based Image-to-Text Transformation. In *2023 6th International Conference on Big Data Technologies (ICBDT) (ICBDT 2023)*, September 22–24, 2023, Qingdao, China. ACM, New York, NY, USA, 5 pages. <https://doi.org/10.1145/3627377.3627442>

1 INTRODUCTION

In the dynamic landscape of CV(computer vision) and NLP(natural language processing), the conversion of visual input into coherent textual descriptions has emerged as a fundamental yet intricate challenge. Bridging the gap between these two modalities holds profound potential across diverse domains, from enabling visually impaired individuals to enhancing the autonomy of machines. This article addresses the complex task of image-to-text transformation by introducing a novel ensemble approach that harnesses the capabilities of Contrastive Language-Image Pretraining (CLIP) models.

While CLIP models have demonstrated exceptional prowess in aligning text and images, this work propels the field forward by presenting a sophisticated ensemble strategy that leverages their collective strengths. We introduce two distinct adaptations of the CLIP model, meticulously tailored to different facets of the image-to-text transformation endeavor. The first adaptation introduces a multi-layered architecture with the integration of differential learning rates, amplifying the model's discerning power to capture intricate and nuanced image-text relationships. Complementing this, the second adaptation ingeniously exploits CLIP's inherent zero-shot learning capacity, resulting in the generation of contextual embeddings for both images and text. These embeddings seamlessly integrate into a K-Nearest Neighbors (KNN)[9] model, a strategic choice that reverberates throughout the image-to-text transformation process.

The significance of this study reverberates across numerous real-world scenarios, ranging from generating image captions to facilitating content-based image retrieval. Our ensemble approach, by bridging the semantic gap between images and text, contributes to the interpretability and accessibility of visual data.

In subsequent sections, we embark on an exploratory journey into the intricate mechanics of our ensemble approach. We delve into architectural intricacies, elucidate data preprocessing methodologies, unveil the metrics employed for evaluation, and present compelling experimental results. Through meticulous evaluation and comprehensive comparative analysis, we substantiate the distinct advantages of our approach over both standalone CLIP models and traditional methods. As we navigate the complex landscape of image-to-text transformation, our study not only advances the boundaries of current capabilities but also underscores the burgeoning potential of ensemble learning to unravel the complexities inherent in multimodal tasks.

2 RELATED WORK

Within the domain of converting images to text, extensive research has been undertaken to improve the caliber and pertinence of the generated captions. This section provides an overview of key advancements and approaches that have contributed to the development of our proposed ensemble model for image captioning.

J Devlin et al.[3] introduce BERT, a transformer-based language model pre-trained on extensive text data. BERT’s bidirectional context comprehension and contextual embeddings have propelled it to achieve state-of-the-art performance across diverse NLP tasks, including image captioning, significantly enhancing language understanding for such tasks. A Karpathy et al.[7] propose an attention-based model that aligns visual and semantic spaces, producing detailed image descriptions by focusing on relevant regions of the image. By allowing the model to attend to specific image regions while generating each word, the approach improves the relevance and contextual understanding of generated captions. Q. Wu et al. (2016) explore high-level concepts’ role in bridging vision and language, specifically their impact on image captioning. By incorporating high-level semantic concepts, the model gains a better understanding of the image content, leading to improved caption quality that is more aligned with human perception. J Gu et al.[5] propose a stack-captioning model that employs a coarse-to-fine approach to generate captions, demonstrating improved performance by iteratively refining the captioning process. Utilizing a hierarchy of captioning modules, this approach enables the model to encompass global and local details, yielding captions that are more contextually enriched and coherent. SJ Rennie et al.[12] introduces self-critical sequence training, a reinforcement learning approach for image captioning, which improves caption quality by directly optimizing caption-level evaluation metrics. By using a reinforcement learning framework to fine-tune the captioning model, this approach encourages the generation of captions that receive higher scores according to the chosen evaluation metric. P Sharma et al.[13] present the Conceptual Captions dataset, enhancing image caption quality and model training through improved annotations and hypernymic captions. J Johnson et al.[6] introduce DenseCap, a model merging convolutional and recurrent networks for dense image captioning. It generates captions for multiple image regions, enhancing description detail by covering various objects and regions within images. D Elliott et al.[4] introduce the Multi30K dataset, a multi-lingual extension of the English-German image description dataset, facilitating cross-lingual research in image captioning. This dataset

enables the evaluation and development of captioning models for multiple languages, contributing to the advancement of multilingual captioning. R Vedantam et al.[14]proposes the CIDEr metric, a consensus-based evaluation measure for image captioning that considers consensus among multiple reference captions, addressing limitations of previous metrics. CIDEr takes into account multiple valid caption variations and provides a more robust and comprehensive evaluation of caption quality. Utilizing the Twins-PCPVT model, Weinan Dai et al.[1] converts fundus images into embeddings, enhancing the efficiency and accuracy of diabetic retinopathy detection. A Radford et al.[11] Generative Adversarial Networks (GANs) showcased potential in generating images from text descriptions. However, the unidirectional nature of the approach restricted its applicability to image-to-text tasks. Saad M.Darwith et al.[2] investigate the use of Type-2 Fuzzy Logic as a means to bridge the semantic gap in Content-Based Image Retrieval (CBIR) systems. Their findings highlight the potential of this approach in enhancing image retrieval accuracy by addressing inherent uncertainties in semantic interpretations. J Lu et al.[8]showcased advancements in vision-and-language tasks by jointly pretraining on multiple vision and language tasks. However, the focus was broader, and the fine-grained image-to-text transformation remained a challenge.

In the subsequent sections, we delve into our ensemble approach, unveiling its architectural intricacies, data preprocessing strategies, evaluation metrics, and empirical findings. Through comprehensive analysis, we highlight the distinct advantages of our approach, thereby contributing to the broader landscape of image-to-text transformation.

3 ALGORITHM AND MODEL

Our ensemble learning approach harnesses the power of two intricately designed models, both of which are built upon the foundation of the CLIP framework. Collectively, they collaborate to amplify the image-to-text transformation process, harnessing the exceptional abilities of CLIP.

3.1 CLIP Model

The CLIP model, which incorporates elements of the Vision Transformer (ViT), forms the foundation of our approach, providing a powerful framework for processing both images and text and generating embeddings in a shared semantic space. The architecture of the CLIP model, which includes ViT, is illustrated in Figure 1[10].

The CLIP model consists of a shared vision and language encoder. Leveraging the capabilities of ViT, the model employs self-attention mechanisms to capture intricate details within images. This integration allows CLIP to effectively process and represent visual information. Given an input image and text, the model projects them into a common space where the similarity between their embeddings reflects their semantic correspondence. This inherent ability of CLIP, enhanced by ViT, forms the basis for our subsequent enhancements.

The Vision Transformer (ViT)[16] is a crucial component integrated into the CLIP model. ViT is an image processing model that utilizes self-attention mechanisms to analyze and capture the relationships between different parts of an image. By incorporating ViT, the CLIP model gains the capability to understand images

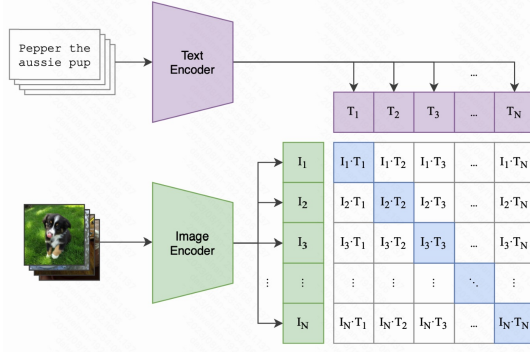


Figure 1: Architecture of the CLIP Model

at a more granular level, enabling it to extract meaningful visual features and representations. This integration not only enhances the model’s ability to process images but also contributes to the generation of semantically meaningful embeddings.

3.2 Model A - Enhanced Image-to-Text Transformation

To optimize the process of image-to-text transformation, we introduce Model A, which enhances the capabilities of the CLIP model through the incorporation of additional neural network layers. Model A is designed to refine the visual embedding of an input image and generate an enriched text embedding.

The computation within Model A begins with passing the input image through the pre-trained CLIP vision model, resulting in a high-dimensional visual embedding denoted as Image_Embedding. This visual representation captures the salient features of the image in the context of semantic understanding.

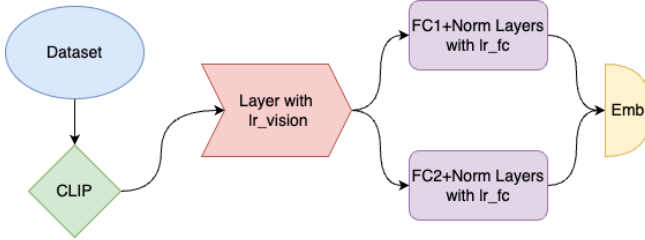


Figure 2: Architecture of Model A - Enhanced Image-to-Text Transformation

To enhance the visual embedding, Model A introduces two additional fully connected layers, FC1 and FC2, followed by layer normalization operations Norm1 and Norm2. These layers iteratively refine the feature representation, extracting intricate relationships inherent in the image data.

The out of FC1 is computed as follows:

$$FC1_Out = FC1(Image_Emb) \quad (1)$$

Subsequently, the output is normalized using layer normalization to yield Norm1_Out:

$$Norm1_Out = Norm1(FC1_Out) \quad (2)$$

Similarly, FC2 and Norm2 operations further enhance the features, resulting in Norm2_Out.

To produce the enriched text emb, Model A employs a weighted combination of Norm1_Out and Norm2_Out using the following equation:

$$Final_Text_Emb = \alpha \cdot Norm1_Out + (1 - \alpha) \cdot Norm2_Out \quad (3)$$

This fusion mechanism empowers Model A to adaptively integrate the refined visual features, resulting in an enriched text embedding that encapsulates both the original visual content and its semantic nuances.

To facilitate effective training, we employ a differential learning rate strategy. Specifically, the pre-trained CLIP vision model is fine-tuned using a relatively small learning rate lr_{vision} , while the newly introduced fully connected layers FC1 and FC2, along with layer normalization operations Norm1 and Norm2, use a larger learning rate lr_{fc} . This method guarantees a harmonious parameter adjustment between the existing pre-trained model and the freshly incorporated layers. The pre-trained CLIP model, having been optimized on an extensive dataset, demands nuanced tweaks, while the newly added layers necessitate more substantial updates owing to their random initialization.

3.3 Model B - Zero-Shot Learning and KNN-based Fusion

Model B capitalizes on the inherent zero-shot learning [15] capabilities of the CLIP model, extending its applicability to image-to-text transformation tasks. The architecture of Model B integrates image embeddings with their corresponding text embeddings through a K-nearest neighbors (KNN) based fusion approach. This enables a seamless cross-modal interaction, leveraging the rich semantic understanding of CLIP for enhanced image-to-text transformation.

The first step of Model B[10] involves utilizing the CLIP model to generate both image embeddings and text embeddings for a diverse set of images and their corresponding textual descriptions. This forms a basis for zero-shot learning, enabling Model B to generalize to unseen image-text pairs during testing.

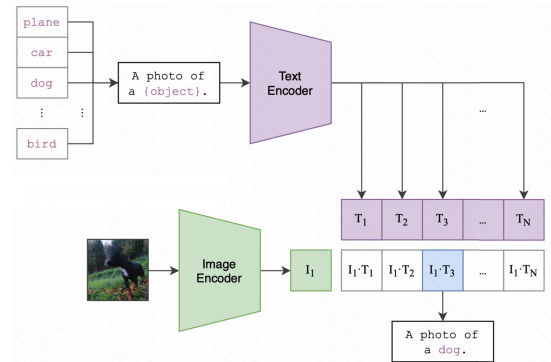


Figure 3: Zero-Shot Learning Architecture in Model B

For each image embedding, Model B employs a K-nearest neighbors (KNN) model to retrieve a set of nearest neighbor text embeddings. The KNN-based approach introduces a distance-based weighting mechanism, which captures the relevance and contextual significance of each neighbor. This distance-based weighting is calculated using the following formula:

$$\text{Weight}(i) = \frac{1}{\text{Distance}(i)^{\text{Distance_Dim} + \delta}} \times \text{Coef} \quad (4)$$

Where $\text{Distance}(i)$ is the Euclidean distance between the query image embedding and the i th neighbor text embedding, Distance_Dim controls the influence of distance, and δ is a small positive constant to ensure numerical stability, and Coef is a coefficient to prevent overflow.

The weighted contributions from all neighbors are then aggregated to form the final text embedding. Mathematically, given an image embedding Image_Emb , the KNN-based fusion mechanism generates the text embedding Text_Emb as:

$$\text{Text_Emb} = \frac{1}{K} \sum_{i=1}^K \text{Weight}(i) \times \text{KNN_Text_Emb}_i \quad (5)$$

Here, K represents the number of nearest neighbors, KNN_Text_Emb_i refers to the i th nearest neighbor text embedding.

In summary, Model B extends the zero-shot learning capabilities of the CLIP model to image-to-text transformation. The KNN-based fusion approach intelligently combines image and text emb, with distance-based weighting to capture contextual relevance, resulting in an enriched text representation that reflects the underlying semantics.

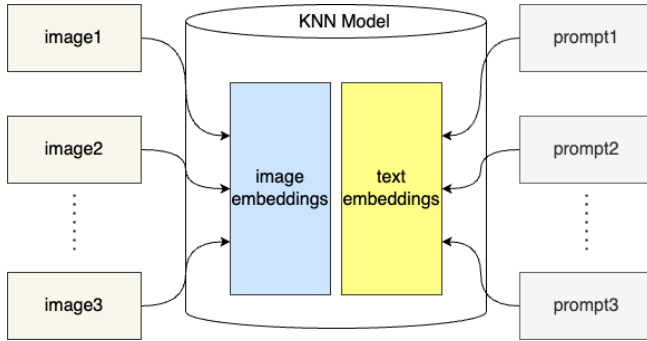


Figure 4: K-Nearest Neighbors Fusion in Model B

3.4 Model Ensemble

This ensemble leverages the strengths of each constituent, yielding a powerful image-to-text transformation framework.

The integration process merges the semantically rich embeddings from the trained CLIP model with the contextual embeddings produced by the CLIP kNNRegression model. This fusion aims to leverage CLIP’s interpretive capabilities alongside the nuanced contextual understanding of kNNRegression, creating a unified ensemble embedding. The ensemble embedding is calculated as follows:

$$\text{Ens_Emb} = \alpha \times \text{A_Emb} + (1 - \alpha) \times \text{B_Emb} \quad (6)$$

Where α represents the adjusted weighting coefficient.

The model ensemble embodies the symbiotic relationship between the model A and model B, resulting in a dynamic and versatile image-to-text transformation framework. The subsequent sections delve into empirical evaluation and findings, substantiating the effectiveness and potential of our ensemble approach.

3.5 Data Preprocessing

Effective data preprocessing is pivotal to the success of our ensemble learning approach for image-to-text transformation. We employ a series of meticulous steps to enhance the quality and suitability of our input data.

3.5.1 Data Augmentation. Data augmentation is employed to enhance the diversity and robustness of our training dataset. For images, we apply random transformations such as rotations, flips, and crops to generate augmented versions of the original images. For text, we perform synonym replacement and random word shuffling to create variations of the input text descriptions.

3.5.2 Cosine Similarity Filtering. To streamline the dataset and enhance model performance, we transform textual prompts into embedding. These embedding encapsulate intricate semantic information within the embedding space. To quantify the resemblance between two embedding vectors, we utilize the cosine similarity formula:

$$\text{Cosine Similarity}(v_i, v_j) = \frac{v_i \cdot v_j}{\|v_i\| \cdot \|v_j\|} \quad (7)$$

Here, v_i and v_j denote the embedding vectors associated with two distinct textual prompts.

For each textual prompt within the training dataset, we compute the cosine value with the embedding vectors of other prompts. By applying a designated similarity threshold (e.g., 0.85), in cases where the similarity between a prompt and any other prompt surpasses this threshold, we opt to remove one of the samples to ensure a diverse dataset composition.

This filtering step not only enhances model performance but also leads to improved training efficiency. Specifically, the reduction in dataset size from 90K to 60K instances has resulted in an enhancement of the model’s metric, along with a reduction in training time per epoch from 6 hours to 4 hours. These improvements collectively contribute to the effectiveness and efficiency of our ensemble learning approach for image-to-text transformation tasks.

3.6 Performance Measurement

To gauge model performance, we utilize the following metric:

$$\text{Avg-Cos} = \frac{1}{N} \sum_{i=1}^N \text{CosSim}(\text{GT-Embed}_i, \text{Pred-Embed}_i) \quad (8)$$

Where Avg-Cos denotes the average cosine similarity, N signifies the total image-text pairs, and $\text{CosSim}(\text{GT-Embed}_i, \text{Pred-Embed}_i)$ represents the cosine value between the groundtruth text embedding and the predicted embedding for the i -th pair. This metric

Table 1: Average Cosine Similarity Results

Model	Avg-CosSim
CLIP	0.5642
CLIP with data filter1	0.5684
CLIP with data filter2	0.5721
Model A	0.5753
Model B	0.5531
Ensemble Model	0.5961

quantifies the alignment and semantic coherence between images and their textual descriptions. Higher Avg-CosSim values indicate more robust semantic alignment and enhanced image-to-text transformation, showcasing the effectiveness of our ensemble learning approach.

3.7 Experiment Results

We conducted comprehensive experiments to evaluate the performance of our proposed ensemble approach for image-to-text transformation. In our experiments, we employ the Average Cosine Similarity (Avg-CosSim) as the evaluation metric, assessing the correspondence between the embeddings generated by the model and the actual ground truth representations.

The outcomes presented in Table 1 unmistakably showcase the efficacy of our ensemble approach. The Ensemble Model achieves the highest Avg-CosSim, indicating a superior alignment between the generated embeddings and ground truth representations compared to other individual models. Model A, with its elaborated architecture, also outperforms the standalone CLIP models and Model B. These findings underscore the value of our ensemble strategy in enhancing image-to-text transformation.

The comparative experiments validate the promising trajectory of ensemble learning in addressing intricate multimodal tasks and further contribute to advancing the state-of-the-art in image-to-text transformation.

REFERENCES

- [1] Weinan Dai, Chengjie Mou, Jun Wu, and Xuesong Ye. 2023. Diabetic Retinopathy Detection with Enhanced Vision Transformers: The Twins-PCPVT Solution. In *2023 IEEE 3rd International Conference on Electronic Technology, Communication and Information (ICETCI)*. IEEE, 403–407.
- [2] Saad M Darwish and Raad A Ali. 2015. Observations on using type-2 fuzzy logic for reducing semantic gap in content-based image retrieval system. *International Journal of Computer Theory and Engineering* 7, 1 (2015), 1.
- [3] Jacob Devlin, Ming-Wei Chang, Kenton Lee, and Kristina Toutanova. 2018. Bert: Pre-training of deep bidirectional transformers for language understanding. *arXiv preprint arXiv:1810.04805* (2018).
- [4] Desmond Elliott, Stella Frank, Khalil Sima'an, and Lucia Specia. 2016. Multi30k: Multilingual english-german image descriptions. *arXiv preprint arXiv:1605.00459* (2016).
- [5] Jiuxiang Gu, Jianfei Cai, Gang Wang, and Tsuhan Chen. 2018. Stack-captioning: Coarse-to-fine learning for image captioning. In *Proceedings of the AAAI conference on artificial intelligence*, Vol. 32.
- [6] Justin Johnson, Andrej Karpathy, and Li Fei-Fei. 2016. Densecap: Fully convolutional localization networks for dense captioning. In *Proceedings of the IEEE conference on computer vision and pattern recognition*. 4565–4574.
- [7] Andrej Karpathy and Li Fei-Fei. 2015. Deep visual-semantic alignments for generating image descriptions. In *Proceedings of the IEEE conference on computer vision and pattern recognition*. 3128–3137.
- [8] Jiasen Lu, Dhruv Batra, Devi Parikh, and Stefan Lee. 2019. Vlbnet: Pretraining task-agnostic visiolinguistic representations for vision-and-language tasks. *Advances in neural information processing systems* 32 (2019).
- [9] Leif E Peterson. 2009. K-nearest neighbor. *Scholarpedia* 4, 2 (2009), 1883.
- [10] Alec Radford, Jong Wook Kim, Chris Hallacy, Aditya Ramesh, Gabriel Goh, Sandhini Agarwal, Girish Sastry, Amanda Askell, Pamela Mishkin, Jack Clark, et al. 2021. Learning transferable visual models from natural language supervision. In *International conference on machine learning*. PMLR, 8748–8763.
- [11] Alec Radford, Luke Metz, and Soumith Chintala. 2015. Unsupervised representation learning with deep convolutional generative adversarial networks. *arXiv preprint arXiv:1511.06434* (2015).
- [12] Steven J Rennie, Etienne Marcheret, Youssef Mroueh, Jerret Ross, and Vaibhava Goel. 2017. Self-critical sequence training for image captioning. In *Proceedings of the IEEE conference on computer vision and pattern recognition*. 7008–7024.
- [13] Piyush Sharma, Nan Ding, Sebastian Goodman, and Radu Soricut. 2018. Conceptual captions: A cleaned, hypernymed, image alt-text dataset for automatic image captioning. In *Proceedings of the 56th Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers)*. 2556–2565.
- [14] Ramakrishna Vedantam, C Lawrence Zitnick, and Devi Parikh. 2015. Cider: Consensus-based image description evaluation. In *Proceedings of the IEEE conference on computer vision and pattern recognition*. 4566–4575.
- [15] Yongqin Xian, Bernt Schiele, and Zeynep Akata. 2017. Zero-shot learning—the good, the bad and the ugly. In *Proceedings of the IEEE conference on computer vision and pattern recognition*. 4582–4591.
- [16] Li Yuan, Yunpeng Chen, Tao Wang, Weihao Yu, Yujun Shi, Zi-Hang Jiang, Francis EH Tay, Jiashi Feng, and Shuicheng Yan. 2021. Tokens-to-token vit: Training vision transformers from scratch on imagenet. In *Proceedings of the IEEE/CVF international conference on computer vision*. 558–567.