# CLIP-Mamba: CLIP Pretrained Mamba Models with OOD and Hessian Evaluation

Weiquan Huang, Yifei Shen, Yifan Yang \*

### Abstract

State space models and Mamba-based models have been increasingly applied across various domains, achieving state-of-the-art performance. This technical report introduces the first attempt to train a transferable Mamba model utilizing contrastive language-image pretraining (CLIP). We have trained Mamba models of varying sizes and undertaken comprehensive evaluations of these models on 26 zero-shot classification datasets and 16 out-of-distribution (OOD) datasets. Our findings reveal that a Mamba model with 67 million parameters is on par with a 307 million-parameter Vision Transformer (ViT) model in zero-shot classification tasks, highlighting the parameter efficiency of Mamba models. In tests of OOD generalization, Mamba-based models exhibit exceptional performance in conditions of OOD image contrast or when subjected to high-pass filtering. However, a Hessian analysis indicates that Mamba models, making them more challenging to train. The source code is available at https://github.com/raytrun/mamba-clip.

#### 1 Introduction

Foundation models, i.e., models pretrained on massive data and adapted for specific downstream tasks, have emerged as a vibrant field within machine learning. The transformative six years preceding have seen Transformers establish themselves as the principal architecture underpinning foundation models across a multitude of domains Dosovitskiy et al. (2020); Vaswani et al. (2017); Ying et al. (2021); Gong et al. (2021); Zhou et al. (2021); Cui et al. (2024). The core of the Transformer architecture is the self-attention mechanism, which intricately facilitates the flow of information between every token pair. This mechanism is critically acclaimed for its indispensable role in facilitating in-context learning Wen et al. (2024), enhancing reasoning capabilities Yang et al. (2024b), and bolstering out-of-distribution (OOD) robustness Li et al. (2022). Nonetheless, the self-attention mechanism's quadratic computational demands pose significant scalability challenges, particularly concerning window length, thereby emerging as a substantial impediment for practical applications. In response, a wealth of research has been dedicated to devising efficient self-attention mechanisms capable of operating within sub-quadratic time Wang et al. (2020); Katharopoulos et al. (2020); Choromanski et al. (2020). Despite these advancements, such innovations often demonstrate inferior performance when compared with their quadratic-time Transformer counterparts.

Selective state space models (Mamba) Gu & Dao (2023) have recently emerged as promising candidates for the next-generation foundation model backbone as they exhibit better scaling laws than Transformers while enjoying linear-time complexity. In the brief span of the last few months, the Mamba model has demonstrated remarkable success across a spectrum of critical domains, including but not limited to, natural language processing Gu & Dao (2023); Qiao et al. (2024), image processing Zhu et al. (2024); Liu et al. (2024), video analysis Yang et al. (2024c); Li et al. (2024), time-series forecasting Tang et al. (2024); Patro & Agneeswaran (2024), graph theory applications Wang et al.

<sup>\*</sup>Weiquan Huang is with Tongji Univeristy(weiquanh@tongji.edu.cn). Yifan Yang, Yifei Shen are with Microsoft.

Models	Food-101	CIFAR-10	CIFAR-100	CUB	SUN397	Cars	Aircraft	DTD	Pets	Caltech-101	Flowers	MNIST	FER-2013	STL-10	EuroSAT	RESISC45	GTSRB	KITTI	Country211	PCAM	UCF101	Kinetics700	CLEVR	HatefulMemes	SST2	ImageNet
VMamba_B (89M)	48.5	58.0	29.9	36.5	50.4	5.8	8.5	26.5	30.2	64.7	52.8	9.7	19.6	91.9	16.0	30.4	7.9	40.2	10.2	59.9	35.2	25.6	12.6	51.6	50.1	38.3
VMamba_S (50M)	49.4	70.3	34.3	39.1	53.9	6.9	8.4	26.0	31.3	68.7	54.1	10.1	9.8	92.8	17.6	31.4	6.9	23.5	10.9	54.2	38.4	27.1	13.2	50.5	50.0	40.0
VMamba_T220 (30M)	46.5	50.9	22.9	35.6	51.1	5.7	6.8	25.1	31.0	64.9	54.0	10.1	12.5	91.6	13.9	25.4	10.7	32.3	9.9	55.0	34.0	25.1	12.7	53.9	50.6	38.7
Simba_L (66.6M)	52.7	67.4	31.0	39.1	52.7	6.9	9.1	27.8	33.4	68.9	55.9	8.0	16.0	93.9	17.4	32.3	8.9	41.5	11.1	58.1	35.7	27.9	12.1	54.9	50.1	41.6
VIT_B(84M)	50.6	66	34.5	38.8	51.1	4.0	5.4	21.2	28.5	60.9	53.3	8.4	17.3	90.5	30.2	21.5	6.1	35.1	10.5	53.5	28.5	22.1	10.8	52.4	50.7	37.6
VIT_L(307M)	59.5	72.9	41.5	40.3	53.6	6.9	6.4	20.6	27.9	65.4	55	10.3	34.5	94.2	22.7	28.8	5.8	41.4	12.5	54.9	34.3	24.0	12.9	54.3	50.1	40.4
Tab	Table 1: Zero-shot performance of different architectures trained with CLIP.																									

(2024); Behrouz & Hashemi (2024), point cloud processing Liang et al. (2024); Zhang et al. (2024), recommendation systems Yang et al. (2024a), reinforcement learning Rimon et al. (2024), and medical diagnostics Ma et al. (2024); Xing et al. (2024). Focusing on computer vision, a myriad of Mamba-based models have emerged, setting new state-of-the-art baselines in image classification Zhu et al. (2024); Patro & Agneeswaran (2024), object detection Liu et al. (2024), segmentation Liu et al. (2024); Ma et al. (2024), image restoration Zheng & Wu (2024); Guo et al. (2024), and 3D reconstruction Shen et al. (2024). Despite these achievements, current Mamba-based models are trained on a fixed array of predetermined object categories, and lacks of zero-shot generalization capabilities. Bridging this gap necessitates the integration of large-scale language-image pretraining, and this is an indispensable component for the evolution of Mamba-based foundational models.

This technical report presents the first attempt to train Mamba models with contrastive language-image pretraining. Specifically, the conclusions of this technical report summarized as follows:

- **CLIP-Mamba models:** We release the open-sourced CLIP-Mamba models. A Mamba model with 50 million parameters surpasses the performance of an 84 million-parameter ViT model, and a 67 million-parameter Mamba model equates to the performance of a 307 million-parameter ViT model on 26 zero-shot classification datasets. These results underscore the efficiency and effectiveness of Mamba models.
- **OOD generalization evaluation:** Our extensive evaluations on 16 OOD datasets demonstrate that Mamba models consistently outperform ViT models. Mamba-based models show exceptional robustness in conditions of OOD image contrast or when subjected to high-pass filtering.
- Landscape evaluation: Through the visualization of the Hessian, we delve into the training landscape of Mamba models. Our findings indicate that Mamba models exhibit a more "non-convex" and sharper landscape compared to ViT models, suggesting greater challenges in optimization.

## 2 Experiments and Analysis

In this section, we conduct comprehensive experiments and analysis for the CLIP Mamba models versus CLIP Vision Transformer models, in terms of zero-shot classification, OOD generalization, and Hessian spectra.

#### 2.1 Zero-shot Classification

In our study, we train a series of models including VMamba-30M, VMamba-50M, VMamba-89M Liu et al. (2024), and Simba-L 66.6M Patro & Agneeswaran (2024), utilizing the standard CLIP pretraining pipelines. The zero-shot performance of these models is systematically evaluated across a variety of datasets and summarized in Table 1. Notably, the 50M-parameter Mamba-S model demonstrates superior performance over the 84M-parameter ViT-B model in the majority of the datasets examined. When considering the pinnacle of performance, the results are evenly split; the 66.6M-parameter Simba-L leads in half of the datasets, while 307M-parameter ViT-L dominates in the remaining half.







Figure 2: Detailed performance on 16 OOD datasets.

#### 2.2 OOD Robustness and Comparison with Humans

Building upon the methodology outlined by Geirhos et al. (2021), we delve into a comparative analysis involving VMamba, Simba, ViTs (Vision Transformers), and human performance across



Figure 3: Hessian max eigenvalue spectra.

16 Out-of-Distribution (OOD) datasets. The results of this comprehensive comparison are visually represented in Figure 1, which provides an overview of the overall performance, and in Figure 2, which offers a detailed breakdown of performance metrics.

From the aggregate data presented in Figure 1, it's evident that Mamba-based models exhibit superior OOD performance and a pronounced shape bias when compared to their counterparts. This shape bias, indicative of a preference for recognizing the shape of objects over texture, more closely mirrors the image recognition capabilities inherent to human vision Geirhos et al. (2021). Such alignment with human visual processing underscores the potential of Mamba-based models in applications requiring nuanced visual understanding.

The more granular insights provided in Figure 2 further substantiate the dominance of Mamba-based models over those based on ViT architecture. Notably, in conditions where contrast is heightened or a high-pass filter is applied—scenarios, Mamba-based models not only outperform ViT-based models but also surpass human capabilities. On the one hand, both ViTs and human vision exhibit a pronounced bias towards low-frequency components of visual data, as highlighted by Park & Kim (2022). This predisposition renders them less effective in environments where these components are minimized or absent, such as in the presence of a high-pass filter. On the other, the hiddens of the state space model or Mamba are the coefficients of orthogonal polynomials Gu et al. (2020), and thus the frequency-bias is less evident compared with ViT.

#### 2.3 Hessians and Training Landscape

Hessian spectra reflect the training landscape of the models and a desirable loss landscape is characterized by its flatness and convexity. The Hessian eigenvalues serve as indicators of these characteristics, where the magnitude of the eigenvalues reflects the sharpness of the landscape, and the presence of negative Hessian eigenvalues denotes non-convexity. We follow Park & Kim (2022) to conduct the analysis. We utilize 3000 samples with a batch size of 15. For each batch, we compute the top-5 Hessian eigenvalue spectra, the results of which are depicted in Fig. 3. The visualization reveals that VMamba models exhibit a higher number of negative eigenvalues compared to ViT models, indicating a more non-convex nature. Furthermore, Mamba models display a greater number of eigenvalues with large magnitudes, suggesting that their loss landscapes are sharper.

## References

- Ali Behrouz and Farnoosh Hashemi. Graph mamba: Towards learning on graphs with state space models. *arXiv* preprint arXiv:2402.08678, 2024.
- Krzysztof Choromanski, Valerii Likhosherstov, David Dohan, Xingyou Song, Andreea Gane, Tamas Sarlos, Peter Hawkins, Jared Davis, Afroz Mohiuddin, Lukasz Kaiser, et al. Rethinking attention with performers. arXiv preprint arXiv:2009.14794, 2020.
- Haotian Cui, Chloe Wang, Hassaan Maan, Kuan Pang, Fengning Luo, Nan Duan, and Bo Wang. scgpt: toward building a foundation model for single-cell multi-omics using generative ai. *Nature Methods*, pp. 1–11, 2024.
- Alexey Dosovitskiy, Lucas Beyer, Alexander Kolesnikov, Dirk Weissenborn, Xiaohua Zhai, Thomas Unterthiner, Mostafa Dehghani, Matthias Minderer, Georg Heigold, Sylvain Gelly, et al. An image is worth 16x16 words: Transformers for image recognition at scale. arXiv preprint arXiv:2010.11929, 2020.
- Robert Geirhos, Kantharaju Narayanappa, Benjamin Mitzkus, Tizian Thieringer, Matthias Bethge, Felix A Wichmann, and Wieland Brendel. Partial success in closing the gap between human and machine vision. *Advances in Neural Information Processing Systems*, 34:23885–23899, 2021.
- Yuan Gong, Yu-An Chung, and James Glass. Ast: Audio spectrogram transformer. arXiv preprint arXiv:2104.01778, 2021.
- Albert Gu and Tri Dao. Mamba: Linear-time sequence modeling with selective state spaces. arXiv preprint arXiv:2312.00752, 2023.
- Albert Gu, Tri Dao, Stefano Ermon, Atri Rudra, and Christopher Ré. Hippo: Recurrent memory with optimal polynomial projections. *Advances in neural information processing systems*, 33:1474–1487, 2020.
- Hang Guo, Jinmin Li, Tao Dai, Zhihao Ouyang, Xudong Ren, and Shu-Tao Xia. Mambair: A simple baseline for image restoration with state-space model. *arXiv preprint arXiv:2402.15648*, 2024.
- Angelos Katharopoulos, Apoorv Vyas, Nikolaos Pappas, and François Fleuret. Transformers are rnns: Fast autoregressive transformers with linear attention. In *International conference on machine learning*, pp. 5156–5165. PMLR, 2020.
- Bo Li, Yifei Shen, Jingkang Yang, Yezhen Wang, Jiawei Ren, Tong Che, Jun Zhang, and Ziwei Liu. Sparse mixture-of-experts are domain generalizable learners. *arXiv preprint arXiv:2206.04046*, 2022.
- Kunchang Li, Xinhao Li, Yi Wang, Yinan He, Yali Wang, Limin Wang, and Yu Qiao. Videomamba: State space model for efficient video understanding. *arXiv preprint arXiv:2403.06977*, 2024.
- Dingkang Liang, Xin Zhou, Xinyu Wang, Xingkui Zhu, Wei Xu, Zhikang Zou, Xiaoqing Ye, and Xiang Bai. Pointmamba: A simple state space model for point cloud analysis. arXiv preprint arXiv:2402.10739, 2024.
- Yue Liu, Yunjie Tian, Yuzhong Zhao, Hongtian Yu, Lingxi Xie, Yaowei Wang, Qixiang Ye, and Yunfan Liu. Vmamba: Visual state space model. *arXiv preprint arXiv:2401.10166*, 2024.
- Jun Ma, Feifei Li, and Bo Wang. U-mamba: Enhancing long-range dependency for biomedical image segmentation. arXiv preprint arXiv:2401.04722, 2024.
- Namuk Park and Songkuk Kim. How do vision transformers work? arXiv preprint arXiv:2202.06709, 2022.
- Badri N Patro and Vijay S Agneeswaran. Simba: Simplified mamba-based architecture for vision and multivariate time series. *arXiv preprint arXiv:2403.15360*, 2024.
- Yanyuan Qiao, Zheng Yu, Longteng Guo, Sihan Chen, Zijia Zhao, Mingzhen Sun, Qi Wu, and Jing Liu. Vl-mamba: Exploring state space models for multimodal learning. arXiv preprint arXiv:2403.13600, 2024.
- Zohar Rimon, Tom Jurgenson, Orr Krupnik, Gilad Adler, and Aviv Tamar. Mamba: an effective world model approach for meta-reinforcement learning. arXiv preprint arXiv:2403.09859, 2024.

- Qiuhong Shen, Xuanyu Yi, Zike Wu, Pan Zhou, Hanwang Zhang, Shuicheng Yan, and Xinchao Wang. Gamba: Marry gaussian splatting with mamba for single view 3d reconstruction. *arXiv preprint arXiv:2403.18795*, 2024.
- Yujin Tang, Peijie Dong, Zhenheng Tang, Xiaowen Chu, and Junwei Liang. Vmrnn: Integrating vision mamba and lstm for efficient and accurate spatiotemporal forecasting. arXiv preprint arXiv:2403.16536, 2024.
- Ashish Vaswani, Noam Shazeer, Niki Parmar, Jakob Uszkoreit, Llion Jones, Aidan N Gomez, Łukasz Kaiser, and Illia Polosukhin. Attention is all you need. Advances in neural information processing systems, 30, 2017.
- Chloe Wang, Oleksii Tsepa, Jun Ma, and Bo Wang. Graph-mamba: Towards long-range graph sequence modeling with selective state spaces. *arXiv preprint arXiv:2402.00789*, 2024.
- Sinong Wang, Belinda Z Li, Madian Khabsa, Han Fang, and Hao Ma. Linformer: Self-attention with linear complexity. arXiv preprint arXiv:2006.04768, 2020.
- Kaiyue Wen, Xingyu Dang, and Kaifeng Lyu. Rnns are not transformers (yet): The key bottleneck on in-context retrieval. *arXiv preprint arXiv:2402.18510*, 2024.
- Zhaohu Xing, Tian Ye, Yijun Yang, Guang Liu, and Lei Zhu. Segmamba: Long-range sequential modeling mamba for 3d medical image segmentation. *arXiv preprint arXiv:2401.13560*, 2024.
- Jiyuan Yang, Yuanzi Li, Jingyu Zhao, Hanbing Wang, Muyang Ma, Jun Ma, Zhaochun Ren, Mengqi Zhang, Xin Xin, Zhumin Chen, et al. Uncovering selective state space model's capabilities in lifelong sequential recommendation. arXiv preprint arXiv:2403.16371, 2024a.
- Kai Yang, Jan Ackermann, Zhenyu He, Guhao Feng, Bohang Zhang, Yunzhen Feng, Qiwei Ye, Di He, and Liwei Wang. Do efficient transformers really save computation? *arXiv preprint arXiv:2402.13934*, 2024b.
- Yijun Yang, Zhaohu Xing, and Lei Zhu. Vivim: a video vision mamba for medical video object segmentation. arXiv preprint arXiv:2401.14168, 2024c.
- Chengxuan Ying, Tianle Cai, Shengjie Luo, Shuxin Zheng, Guolin Ke, Di He, Yanming Shen, and Tie-Yan Liu. Do transformers really perform badly for graph representation? *Advances in neural information processing systems*, 34:28877–28888, 2021.
- Tao Zhang, Xiangtai Li, Haobo Yuan, Shunping Ji, and Shuicheng Yan. Point could mamba: Point cloud learning via state space model. *arXiv preprint arXiv:2403.00762*, 2024.
- Zhuoran Zheng and Chen Wu. U-shaped vision mamba for single image dehazing. *arXiv preprint* arXiv:2402.04139, 2024.
- Haoyi Zhou, Shanghang Zhang, Jieqi Peng, Shuai Zhang, Jianxin Li, Hui Xiong, and Wancai Zhang. Informer: Beyond efficient transformer for long sequence time-series forecasting. In *Proceedings of the AAAI conference* on artificial intelligence, volume 35, pp. 11106–11115, 2021.
- Lianghui Zhu, Bencheng Liao, Qian Zhang, Xinlong Wang, Wenyu Liu, and Xinggang Wang. Vision mamba: Efficient visual representation learning with bidirectional state space model. *arXiv preprint arXiv:2401.09417*, 2024.