Vitiligo Image Segmentation Using Segment Anything Model

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***Abstract*—Introducing a unique promptable segmentation task to enable zero-shot picture segmentation through two basic modes: automated everything and human prompt (e.g., points and boxes), the Segment Anything Model (SAM) is a trailblazing foundation model for universal image segmentation. SAM has proven to be highly effective in a variety of natural image segmentation tasks. Nevertheless, because of its complicated modalities, fine anatomical structures, ambiguous and complex object borders, and various object scales, using it for vitiligo image segmentation (VIS)[18] poses more difficulties. Reducing annotation time and improving visual image analysis are potential benefits of achieving zero-shot and efficient VIS. As a result, SAM becomes a potentially useful technique, and its effectiveness must be confirmed on big datasets of vitiligo images. Three open source datasets were gathered and arranged for this work, which produced a large medical segmentation dataset with 834 photos of healthy skin and 368 images of skin damaged by vitiligo. Using the Vitiligo dataset, an extensive analysis of several SAM testing procedures is carried out. Numerous tests demonstrate that SAM performs better in prompt mode than in everything mode when given manual suggestions, like boxes and points, for object recognition in vitiligo images. Furthermore, in certain photos, SAM performs admirably, while in other cases, it performs poorly or fails. Lastly, a study of the effects of several variables on SAM's segmentation effectiveness is provided.**

Keyword: Segment Anything Model, Vitiligo, Box prompt, Auto prompt

I. Introduction

Large language models that have been pre-trained with billions or even trillions of parameters are the main AI trend of the last few years. Prominent instances comprise ChatGPT[11] and LLaMA[12], which function as flexible instruments capable of accommodating diverse assignments and situations without necessitating extra instruction or optimization. These models, which are also called foundation models, demonstrate remarkable zero-shot generalization skills by just asking them to activate pertinent information. While most foundation model advances are found in domains such as natural language processing (NLP)[13] or in cross-modality tasks like image-text retrieval, the dearth of training data in the computer vision[17] domain poses a challenge, especially in tasks like segmentation. As such, the Segment Anything Model (SAM) was the first segmentation foundation model that performed exceptionally well in zero-shot inference across a variety of domains. Within the field of medical image analysis, where organs, abnormalities, cancers, and more must be distinguished through segmentation[16], current approaches frequently depend on customized model[10] architectures that have been trained on large amounts of data. This work tackles the requirement for a foundation model that may generalize to new domains or tasks in vitiligo picture analysis with little prompts, taking into account the modality differences and domain discrepancies inherent in vitiligo image tasks. The study investigates SAM's potential as the foundation model for vitiligo image analysis segmentation tasks, given the impracticality of obtaining webscale pictures and annotations.

Skin depigmentation, or vitiligo[14], is a dermatological disorder that poses a challenge to medical image analysis, especially when it comes to image segmentation. The loss of melanocytes brought on by this inflammatory disease causes white spots to appear on the skin. The multiple modalities, fine anatomical structures, ambiguous and complex object borders, and wide-ranging object scales associated with vitiligo present particular hurdles to image segmentation models, notwithstanding their progress. Precisely dividing the skin affected by vitiligo is essential for diagnosing the condition and devising a treatment strategy.

For generic image segmentation, the Segment Anything Model (SAM), a ground-breaking foundation model, has shown impressive results in a range of natural picture segmentation applications. However, because vitiligo is a complex disorder, its application to picture segmentation calls for a detailed examination. With the use of an extensive dataset that includes photos of both healthy skin and skin affected by vitiligo, this study attempts to evaluate how well SAM performs in segmenting vitiligo images. This study aims to improve our understanding of the model's applicability and limits in the context of vitiligo image analysis by a thorough review of SAM's testing procedures and their impact on segmentation outputs.

We conduct our experiment in two stages, both of which are intended to fully accomplish the goals of our investigation. In the first step, we carefully examine the Segment Anything Model's (SAM) auto-prompt mode performance. Our results demonstrate a significant constraint on SAM's zero-shot generalization in this mode, suggesting that it is not strong enough to effectively challenge well-established baseline models. This crucial result forces us to reorient our strategy, focusing on examining the box-prompt mode of the SAM model to learn more about its zero-shot generalization potential. Starting the second phase of our study, we carry out several thorough tests that are specifically intended to assess the box-prompt mode's performance. The outcomes are impressive, showing continuously better dice accuracy than its auto-prompt cousin.

Interestingly, we find a clear pattern in our observations: adding jitters to the bounding boxes has a substantial effect on prediction accuracy. This deep understanding leads us to a clear conclusion: the box-prompt method performs better than the auto-prompt strategy in the domain of zero-shot generalization[15]. This amalgamation of our data not only contributes to our comprehension of SAM's capabilities but also bears significant consequences for the improvement and adjustment of segmentation models, especially in situations where zero-shot generalization is crucial. The recognition of the higher performance of the box-prompt method highlights the need for careful thought when optimizing SAM in various applications and provides opportunities for improving segmentation tactics.

II. Related work

More than eight months after it was published[9], the ”Segment Anything” paper has had a significant and long-lasting influence on the academic community. More than sixty pre-print publications devoted to the investigation and use of the Segment Anything Model (SAM) have been found through a recent search on arXiv. This explosion of research effort demonstrates how widely used SAM is and how interested academics from a variety of disciplines—including artificial intelligence, computer vision, and image processing—have become in it. Researchers in these interdisciplinary fields have given SAM a great deal of attention and involvement, indicating that it has become a hub for innovative research. The growing quantity of pre-print articles indicates the applicability and significance of SAM in a wide range of study fields. Studies on the model's adaptability and possible applications have exploded, demonstrating the model's capacity to tackle a wide range of problems in picture segmentation and related domains. We expect a steady increase in the number of studies that use and expand upon SAM's core ideas as long as it continues to draw the interest of scholars. This continuous upsurge in attention is encouraging for the further development and incorporation of SAM into various research approaches and applications soon.

A. About Vitiligo

The dermatological condition vitiligo is characterized by a progressive loss of skin pigmentation that leaves behind depigmented patches. The immune system's specific death of melanocytes, the cells that produce the color melanin, is the fundamental mechanism behind this autoimmune illness. The exact cause of vitiligo is still unknown and complex, with immunological, environmental, and genetic factors all playing a role, even after much research. Vitiligo's characteristic depigmented patches, which are frequently encircled by skin that is normally pigmented, can appear anywhere on the body, and each affected person's distribution and severity will differ greatly. In addition to being a significant cosmetic issue, vitiligo can have a significant negative effect on a person's mental health. The stigma and misconceptions surrounding the disorder are often linked to society, which exacerbates the difficulties faced by individuals impacted. Vitiligo is a complicated and diverse condition, further accentuated by the distinctive distribution of depigmented patches that characterize each case individually. To develop comprehensive approaches to diagnosis, treatment, and support for individuals navigating the challenges posed by this dermatological condition, research must continue to uncover the intricate aspects of vitiligo, including its cosmetic and psychological dimensions[19].

B. Segment Anything

Large Language Models (LLM) have caused a paradigm change that has profoundly altered the research goals of AI researchers, with a renewed focus on building large and fundamental models. This paradigm has become widely accepted and has become a recurrent topic of discussion in the field of artificial intelligence research. There is a common assumption in academia that real breakthroughs in capacity are closely related to model parameter expansion, which is thought to result in previously unheard-of levels of intelligence processing. As a result, researchers in AI are aggressively focusing their efforts on creating basic models; this tendency is especially noticeable in the field of computer vision (CV). The idea that improving model parameters is the key to achieving higher-order cognitive capacities has sparked a group effort to investigate and develop basic models in CV. This investigation is motivated by the realization that building strong models requires a detailed comprehension and separation of different elements in the CV domain. In this ever-changing environment, developing a thorough base model becomes essential to the quest for increasing AI capabilities. It is anticipated that this model will be able to recognize and classify various elements in the intricate field of computer vision and that it will serve as a foundation for future advancements[9]. AI researchers contribute to the evolution of AI as well as the wider range of technology advancements in Computer Vision as they negotiate the opportunities and problems posed by the search for larger and foundational models.

C. Accuracy of SAM in Medical Image Segmentation

In the study ”Segment-Anything Model for Medical Image Segmentation,”[7] the zero-shot generalization skills of the Segment Anything Model (SAM) are methodically evaluated on a range of 12 different medical datasets. Originally created for image segmentation challenges, SAM is a fundamental computer vision segmentation paradigm. SAM has been trained on a large dataset with more than 1 billion masks that were taken from 11 million natural photos. It is capable of zero-shot segmentation using cues like boxes, points, and masks.The accuracy of SAM is compared in the research to that of other cutting-edge deep learning models that have been specially trained on medical pictures, such as U-Net[5] and U-Net++[6]. Organs (brain, breast, chest, lung, liver, colon, pancreas, and prostate), image modalities (2D X-ray, histology, endoscopy, and 3D MRI and CT), and medical states (normal, lesioned) are only a few of the many factors that are evaluated. The results show that, even with SAM's impressive training on a large dataset, SAM is not as accurate as other deep learning models that specialize in medical picture segmentation when re-trained on real photos. The report describes in detail the experimental configurations used to assess SAM, including auto-prompt, single-point prompt, and bounding-box prompt techniques. When comparing the performance of different models across the 12 datasets, the Dice accuracy measure is used as a benchmark, which consistently shows that deep learning models particularly designed for medical pictures perform better than other models.

D. SAM in Zero-shot medical image segmentation

The analysis presented in the paper "Zero-Shot Medical Image Segmentation with the Segment Anything Model" [8] is a thorough investigation of the performance of the Segment Anything Model (SAM) in the complex field of medical image segmentation. The main focus of this study is on SAM's native zero-shot performance, which is achieved without the need for extra model training, especially in the difficult task of segmenting abdominal organs in CT scans. SAM is meticulously guided through the segmentation process using visually intuitive signals, such as bounding boxes and pointers, by utilizing the AMOS22 Abdominal CT Organ Segmentation dataset.The study results show how well SAM can identify and segment previously undetected structures. This performance is especially evident when bounding boxes with a moderate amount of jitters are used. This subtle insight highlights the potential of SAM as a zero-shot approach to medical image segmentation. Its ability to provide rapid and semi-automated segmentation with low user intervention—achieved with just a few clicks or bounding box indicators—is especially remarkable.The paper's conclusion underscores the potential of SAM, stating that it can improve interactive segmentation pipelines and speed up clinical operations without sacrificing the critical component of segmentation accuracy. In addition to highlighting SAM's present capabilities, the study opens up new avenues for investigation and application, signaling a bright future for SAM's use in improving medical picture segmentation techniques.

E. Comparison with other techniques

After reviewing numerous articles and approaches, we compared five cutting-edge segmentation networks into three groups. First, We evaluated attention-based models (Attention U-Net), transformer-based models (UCTransNet and Trans U-Net), and pure U-Net models (UNet and U-Net++). To ensure fair evaluation, the models were trained on 80% of the dataset and tested on 20%. To assess accuracy in Dice overlap, researchers extracted 2D slices along the z-axis for training and testing, concatenated the findings into 3D, and analyzed the resulting pictures[7]. Additionally, we compared SAM to RITM, SimpleClick, and FocalClick, three interactive segmentation approaches. RITM employed an iterative mask correction approach using HRNet-18 as the backbone segmentation model. SimpleClick and FocalClick used SegFormer and plain-ViT instead. To improve performance and speed up inference times for interactive segmentation tasks, each technique used unique features such as click embedding and progressive merging[3].

Our findings indicated significant differences between the SAM and bench-marked SOTA models. SAM shown substantial improvement with human prompts, notably in precisely selecting vitiligo-affected regions, but encountered difficulties with fine anatomical features and complicated borders in auto-prompt mode, requiring manual input for maximum performance. Conversely, models such as U-Net demonstrated resilience in medical image segmentation but required substantial fine-tuning for dermatological applications. SAM's flexibility to manual instructions gave it a substantial edge for accurate segmentation in dermatology. Integrating SAM with other SOTA models might combine the capabilities of each technique, resulting in more accurate and efficient dermatological image segmentation.

III. Methods

A. Dataset and methodology

As part of our painstaking research project, we carefully choose and curated two publicly available datasets to act as thorough representations of various skin disorders. Photographs depicting the essence of healthy skin were included in one dataset, and images especially showcasing symptoms linked with vitiligo were included in another. After all was said and done, an enormous dataset including 1202 images was produced, of which 834 showed examples of skin in good condition and 368 showed signs of vitiligo.

Looking more closely at our process, we decided to take a more complex approach by utilizing the powerful segmentation capabilities provided by the Segment Anything Model (SAM). We were able to perform accurate and sophisticated analyses by immediately applying SAM to the test sets that were incorporated into our dataset. More specifically, SAM helped us identify and define the fine lines that separate skin that is healthy from skin that has vitiligo. By utilizing SAM's sophisticated segmentation capabilities, we were able to considerably improve the accuracy of our analysis. This allowed us to define and identify the small lines that distinguish healthy skin from vitiligo-affected areas. This methodology not only enhanced the precision of our conclusions but also furnished a more in-depth comprehension of the unique attributes included in the gathered images [1][2].

B. Utilizing SAM with diverse prompt modes.

Our goal in this work is to compare the performance of two different prompt modes for medical image segmentation tasks. Three unique operating modes are available for the Segment Anything model (SAM): auto-prompt, point-prompt, and box-prompt. When using the auto-prompt mode, SAM creates a set of masks on its own for every point prompt in a standard

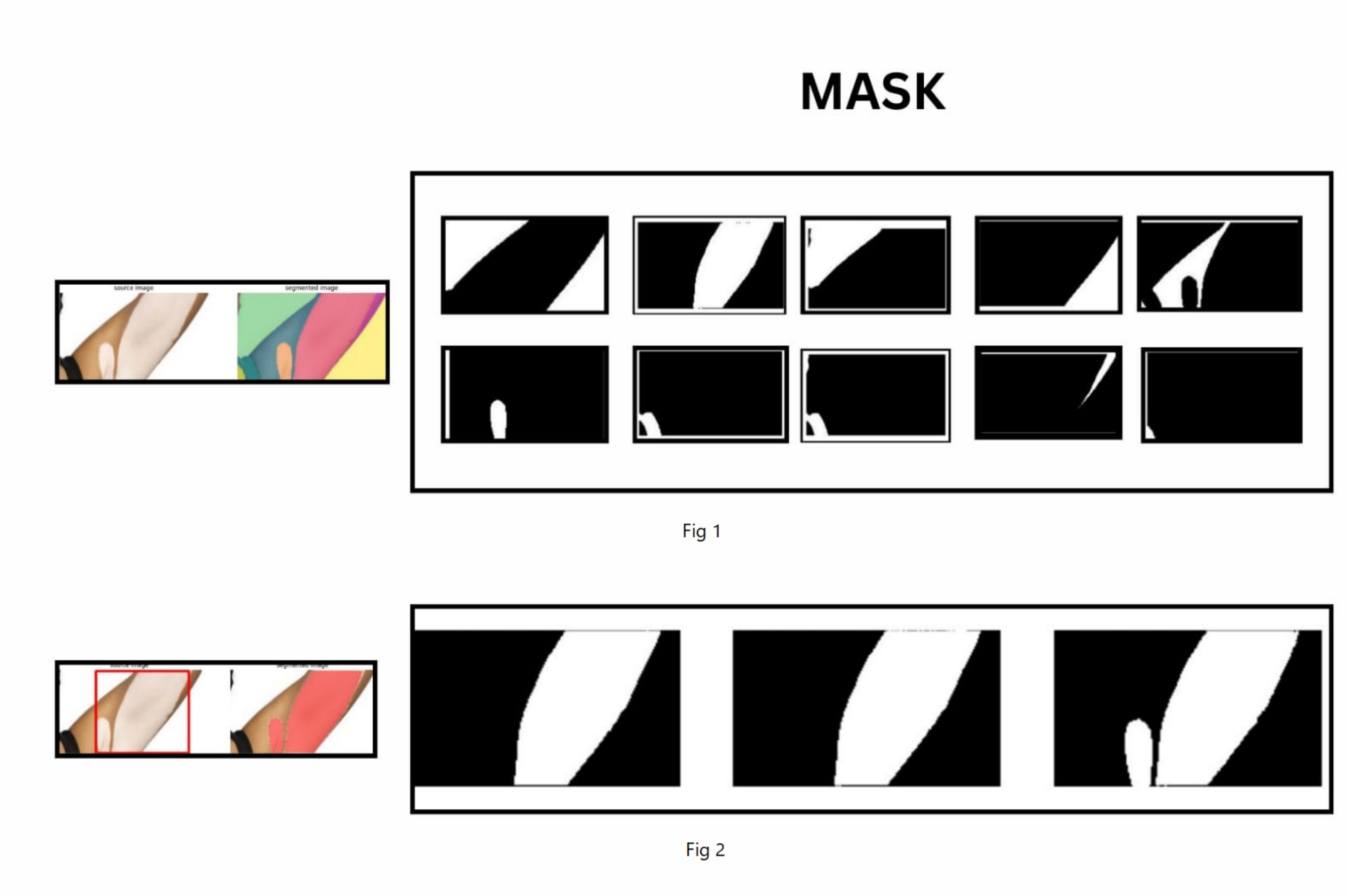

Fig. 1. illustrates the mask generated by the SAM model in auto-prompt mode, while Fig 2 shows the mask produced in box-prompt mode. It can be observed that the accuracy in box-prompt mode is substantially more accurate than in auto-prompt mode. In auto-prompt mode, SAM struggles to separate the vitiligo-affected skin, but in box-prompt mode, the mask precisely targets the vitiligo-affected regions.

point grid. On the other hand, we take a different approach in the box-prompt mode, where we start the process by using the ground truth to create bounding boxes for every object. Then, these carefully designed bounding boxes with different scales are presented to SAM as commands.

It is important to note that our methodology differs from traditional methods applied in SAM model evaluations. Notably, we deviated from conventional evaluation procedures by purposefully choosing not to use the ground truth mask's center point as a stimulus. This choice is based on the understanding that an irregular shape's center point frequently lies beyond the bounding box, which could result in less-than-ideal SAM prompts. Moreover, we recognize the drawbacks of using the center point only, particularly in the case of non-contiguous masks. In these situations, relying just on the center point could unintentionally push it into the background and fool the SAM model. This thoughtful analysis is consistent with earlier findings, as described in [3].Our methodological decisions are motivated by the need to provide more precise and consistent cues, taking into account the complexities of non-contiguous masks and irregular shapes in medical picture segmentation tasks.

C. *Appropriate method for prompting SAM*

One significant trend that can be observed in the examination of prediction accuracy is a steady decrease that is correlated with the jitters scale's augmentation. This trend was noted, and a hypothesis was developed based on the observation that the bounding box tends to cover more background or less important areas with higher jitters and disturbance. As a result, it is clear that the Segment Anything Model's (SAM) prediction quality is greatly influenced by the bounding box's size and reliability [4].

This finding leads one to conclude that the development of appropriate and consistent box-prompts is an interesting area for future research, especially when using SAM across domains. This implies that improving bounding box requirements and keeping them consistent in terms of size and dependability is essential to improving SAM's accuracy and performance across a range of applications. Through examining the nuances of box-prompts, scholars may be able to identify ways to counteract the reported decrease in prediction accuracy linked to higher jitters scale, which would enhance and strengthen SAM in many contexts.

IV. Results and Discussion

A. Overall Accuracy

A thorough examination of the visual aids in Figures 1 and 2 provides strong evidence of the enhanced performance of the Segment Anything Model (SAM) in the complex process of vitiligo image segmentation, especially when used in the box-prompt mode. When we examine the details of the auto-prompt mode, we find that although it is all-inclusive, it adds a variety of elements—including unnecessary noise—to the pictures. Even with its thoroughness, this inclusion adds another level of complexity to the segmentation process.On the other hand, the box-prompt mode stands out due to its remarkable capacity to extract only the relevant parts from the photos through discrimination. Through the creation of masks that are limited to the region bounded by the assigned bounding box, this targeted approach not only simplifies the segmentation procedure but also mitigates the difficulties caused by superfluous elements. The box-prompt mode's targeted precision plays a crucial role in improving the segmentation process's efficiency, highlighting its superiority in practice for vitiligo picture analysis.

Importantly, it is necessary to recognize that, despite the fact that SAM's zero-shot outcomes frequently fall short of those of other state-of-the-art techniques (SOTA) [20], an obvious path toward improvement is apparent. The diligent improvement of the model in conjunction with the incorporation of superior image datasets illustrates the unrealized possibility for substantial progress. This crucial realization emphasizes how flexible SAM is and how sensitive it is to improvement initiatives. SAM's versatility and potential for further advancement in this specific domain are shown by the possibility of a significant increase in accuracy for vitiligo image segmentation through deliberate model tweaks and the use of high-quality data. This creates a strong basis and opens up new directions for investigation and study in the exciting field of vitiligo image segmentation.

B. Evaluation Metrics

In assessing SAM's performance for vitiligo picture segmentation, three key metrics—F1 score (0.8060), precision (0.9500), and recall (0.7000)—provide insight into its efficacy and dependability. SAM strikes a great balance with its F1 score, which reflects both precision and recall. From Fig. 3 we can see, with a high precision of 0.9500, SAM reliably detects vitiligo areas while avoiding false positives. Meanwhile, its recall of 0.7000 provides complete coverage of vitiligo-affected regions while reducing false negatives. These measures demonstrate SAM's ability to effectively distinguish vitiligo lesions from healthy tissue, with intriguing implications for clinical applications in vitiligo diagnosis and therapy monitoring.

C. Factors Affecting SAM's Performance

- Modality Advantage: SAM performs better with endoscopic and dermoscopic pictures because it is trained on RGB data, which is consistent with the nature of the images produced by RGB cameras.
- Difficulties with Zero-Shot Segmentation: SAM struggles with zero-shot segmentation tasks, especially when dealing with pictures that contain continuous branching structures such as blood vessels. This restriction extends beyond medical imaging and includes non-medical settings such as tree branches.
- Comparison with Domain-Specific Models: While SAM performs well in zero-shot segmentation for medical pictures, it frequently falls short of models designed expressly for this imaging domain. SAM's Dice coefficients often lag behind cutting-edge models by 0.1-0.4, in some cases reaching 0.65.[7]
- Potency of Fine-Tuning: Preliminary studies indicate that fine-tuning can greatly improve SAM's performance in medical picture segmentation tasks, as seen in trials with retinal vascular data.
- Analysis of Influencing Factors: Single and multi-factor analyses reveal relationships between SAM accuracy and numerous characteristics like as contrast, segmentation ability, picture dimension, and modality. Notably, segmentation difficulty and relative target region size are strong predictors of SAM performance.

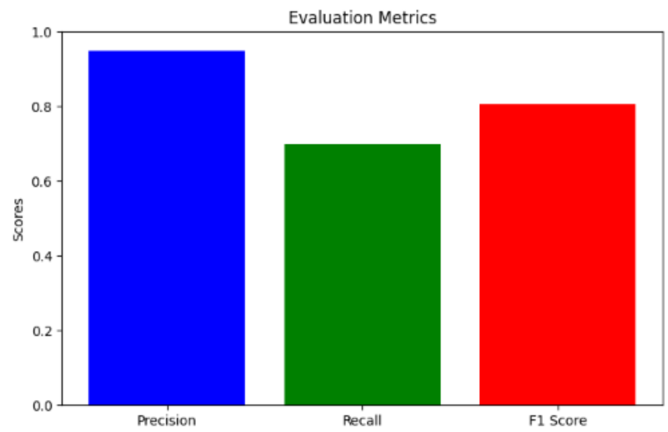

Fig. 3. Bar plot of Evaluation metrics of SAM

D. Benefits of Using the SAM model

- Strong Performance with Large Datasets: SAM performs well when dealing with large datasets, enabling for robust analysis and processing of massive volumes of picture data.
- Comprehensive Object Identification: The model excels at recognizing all of the elements in an image, and the box prompt feature makes it easier to delineate specific areas of interest within the image.
- Use of Zero-Shot Learning: SAM takes advantage of zero-shot learning capabilities, which allow it to learn from new objects and pictures without the need for further information. This flexibility increases its applicability across many situations and datasets.

- Diverse Output Capabilities: SAM's outputs may be used as three-dimensional models, offering a detailed representation of the recognized items and their spatial connections within the picture.
- Real-Time Object Recognition: SAM can quickly recognize things in real-time photos, making it useful in applications that need immediate analysis and reaction.

E. Drawbacks of SAM model

- Prompt Selection Limitations: The success of segmentation is strongly dependent on the quality of the prompts used, and considerable prompts are required for effective zero-shot learning.
- Semantic Segmentation Challenges: Because of the availability of varied colors, textures, and forms, as well as a lack of extensive ground truth annotations, SAM finds it difficult to segment accurately.
- Feasibility in Large-Scale assessment: Using randomly provided "ground prompts" might lead to imitation, whereas manually produced prompts are unsuitable for large-scale assessment scenarios.

V. Conclusion

This extensive paper provides a thorough benchmark analysis of the Segment Anything Model (SAM) on a wide range of visual image segmentation zero-shot tasks. Our testing' main goal is to identify the particular difficulties SAM is currently facing in this area. Interestingly, our study takes a novel approach by using a predetermined set of stimuli that are purposefully unrelated to medical terminology. This deliberate decision seeks to cover a broad range of visuals, offering a comprehensive comprehension of SAM's performance.Further studies can explore important factors to maximize SAM's effectiveness in medical imaging, especially when vitiligo is included. These include investigating precise and interactive cues, incorporating specific feature extraction techniques designed for medical and skin imaging, and improving ways for fine-tuning huge vision models that were first trained on natural images. It is critical to take care of these things in order to guarantee that generalist models operate as well as possible given the unique difficulties presented by vitiligo imaging.Moreover, our results highlight the requirement that big medical vision models possess cross-domain generalizability, similar to the flexibility exhibited by medical professionals. This flexibility is essential to avoid any possible negative impact on diagnostic precision resulting from the use of new instruments and processes. All things considered, our findings highlight the possible use of SAM in vitiligo picture segmentation tasks, which represents a noteworthy advancement in the field of medical imaging. Furthermore, our work establishes the groundwork for future developments and enhancements in this crucial field, encouraging continued study and enhancements in SAM's suitability for problems in medical image segmentation.

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