

Tongue Image Analysis as a Low-Cost Screening Modality for Polycystic Ovarian Syndrome

Authors: Vanya Gupta¹, Aaryesh Chandratre², Vinay Vishwakarma³

Affiliation: Student, Fravashi International Academy, India^{1,2}; Mentor, On My Own Technology Pvt. Ltd., India³

Email: vanya280908@gmail.com¹, aaryeshc@gmail.com², vinay.vishwakarma@onmyowntechnology.com³

DOI: 10.26821/IJSHRE.13.10.2025.131005

Abstract—polycystic ovarian syndrome (PCOS) is one of the most common but least recognized endocrine disorders for women of reproductive age in general and in low-resource settings specifically. Standard diagnostic policies tend to use expensive diagnostic laboratory tests and previous clinical experience which creates delays in diagnosis. We report the use of tongue image analysis as an innovative, low-cost, and non-invasive screening test for PCOS, usefully borrowing from a previous traditional method and with emerging scientific evidence in support of the practice. A machine learning framework was produced to classify the tongue images by severity of symptoms, using CNNs that performed far better than Vision Transformers. The method achieved validation accuracy of 97.1% thereby indicating there is potential for it to be developed as a screening tool. In addition, by combining tongue features with other BMIs and menstrual histories, it is a scalable diagnostic method that can often be performed in under resourced settings. This research uses evidence from a historical diagnostic method combined with the sophistication in modern deep learning techniques to address urgent needs in women's health diagnostics.

Keywords— Polycystic Ovarian Syndrome (PCOS), Tongue Image Analysis, Deep Learning, Convolutional Neural Networks (CNN), Vision Transformer, Noninvasive Screening, Medical Image Processing, Low-cost Diagnostics, Artificial Intelligence (AI), Women's Health.

I INTRODUCTION

Polycystic Ovarian Syndrome (PCOS) is a prevalent endocrine disorder that affects approximately 8–13% of women of reproductive age globally, with a significant portion remaining undiagnosed. PCOS is characterised by the growth of multiple small, fluid-filled sacs (cysts) in the ovaries, resulting in hormonal imbalances. These imbalances disrupt regular menstrual cycles, often leading to irregular or prolonged periods and, in many cases, infertility. While the precise cause of PCOS remains unclear,

researchers have linked the disorder to factors such as genetic predisposition and lifestyle changes. In particular, the modern lifestyle, marked by sedentary habits and poor dietary choices, contributes to insulin resistance, a key factor associated with PCOS. Insulin resistance not only exacerbates the symptoms of PCOS but also increases the risk of long-term health complications, such as type 2 diabetes, cardiovascular disease, and obesity, all of which severely impact a woman's quality of life. Despite the widespread prevalence of PCOS, up to 70% of affected women remain undiagnosed, particularly in regions with limited access to healthcare, such as many developing countries. In India, where socio-economic disparities and inadequate healthcare infrastructure exist, the lack of awareness and diagnostic accessibility exacerbates the issue. Early detection of PCOS is crucial in managing the condition and preventing its progression to more severe health complications. To address the diagnostic challenges in such resource-limited settings, our project investigates a novel and non-invasive method: tongue image analysis. This method draws inspiration from traditional systems like Ayurveda and Traditional Chinese Medicine (TCM), where the tongue is considered a reflective surface of internal health. Scientific literature has increasingly supported the hypothesis that systemic disorders—such as metabolic and endocrine abnormalities—can manifest as visible changes in tongue colour, texture, and coating. Our approach aims to quantify and classify these tongue characteristics to predict the likelihood of PCOS. In our preliminary trials, we explored various machine learning architectures to automate and standardise the analysis of tongue images. Initially, we experimented with Convolutional Neural Networks (CNNs) due to their proven effectiveness in image classification tasks. CNNs allowed us to progressively extract meaningful features across multiple layers from low-level details like colour gradients and edges, to high-level abstractions like patterns associated with

tongue coating severity. Our model achieved classification of images into three categories: healthy, moderate coating, and severe coating, correlating with symptom severity and potential PCOS likelihood. To explore potential performance improvements, we later tested the Swin Transformer, a vision transformer architecture that operates on shifted windows for hierarchical representation. Although theoretically more robust in handling spatial dependencies and global context, the Swin Transformer underperformed in our specific use case. This was likely due to the relatively small dataset size and subtle visual variations across tongue images, which CNNs handled more efficiently through localised feature extraction. As a result, we reverted to CNNs as our primary architecture for further development and fine-tuning. Our goal is to create a lowcost, scalable, and easily deployable PCOS screening tool that leverages tongue images as a diagnostic input. By combining traditional parameters like BMI and menstrual cycle characteristics with deep learning analysis of tongue morphology, our system offers a more holistic diagnostic approach. This is particularly valuable for under-resourced areas, where access to trained gynaecologists and diagnostic labs is limited. Early and accessible detection of PCOS can empower affected individuals to seek timely medical care, thus reducing the risk of chronic health issues and improving quality of life.

II LITERATURE REVIEW

Polycystic Ovarian Syndrome (PCOS) remains one of the most common and frequently under-recognised endocrine disorders worldwide. This review synthesises current evidence on PCOS epidemiology, pathophysiology, diagnostic challenges in low-resource settings, and emerging work on automated tongue image analysis as a non-invasive screening tool. Special attention is paid to the comparative performance of Convolutional Neural Networks (CNNs) and Vision Transformers, the integration of tongue features with clinical parameters, and the public health implications for India and other developing regions.

Polycystic ovary syndrome represents a significant global health challenge, with meta-analyses indicating that PCOS affects between 6% and 13% of women worldwide [1] [2], though prevalence estimates vary depending on the diagnostic criteria employed. The scale of this condition has expanded dramatically over recent decades, as evidenced by the Global Burden of Disease 2021 update, which documented 65.77 million

prevalent cases globally representing an alarming 89% increase since 1990 [3]. This growing burden is further reflected in the disability-adjusted life-years (DALYs) attributable to PCOS, which have risen by 87% over the same three-decade period from 1990 to 2021 [3]. Perhaps most concerning is the substantial gap in diagnosis and care, with up to 70% of affected women remaining undiagnosed worldwide, highlighting the critical need for improved awareness, screening, and healthcare access to address this widespread yet underrecognized condition [1] [4].

Women with PCOS face a constellation of serious long-term health consequences that extend far beyond reproductive concerns. The condition significantly elevates the risk of metabolic disorders, including insulin resistance and type 2 diabetes [5][6][7], while also increasing susceptibility to dyslipidaemia and hypertension, which collectively contribute to heightened cardiovascular event risk. These metabolic complications create a cascade of health challenges that can persist throughout a woman's life. The impact of PCOS also extends to pregnancy-related complications, with affected women experiencing increased rates of gestational diabetes and pre-eclampsia [6], which pose risks to both maternal and fetal health. Additionally, women with PCOS face an elevated risk of certain malignancies, particularly endometrial cancer, likely related to the hormonal imbalances and irregular menstrual patterns characteristic of the condition. This broad spectrum of complications underscores the importance of comprehensive, long-term medical management and monitoring for women diagnosed with PCOS [8] [6].

The underlying mechanisms of PCOS involve a complex interplay between genetic predisposition, hyperandrogenism, and chronic low-grade inflammation, which interact with various lifestyle factors to produce selective insulin resistance—recognized as the central metabolic lesion driving the syndrome [5] [9] [10]. This insulin resistance leads to compensatory hyperinsulinaemia, which in turn exacerbates androgen excess through both ovarian and adrenal pathways, creating a self-perpetuating cycle [9]. The elevated insulin levels stimulate ovarian theca cells to produce excess androgens while simultaneously reducing sex hormone-binding globulin production in the liver, thereby increasing free androgen availability. This hyperandrogenic state disrupts normal ovarian follicular development and ovulation, contributing to the characteristic reproductive features of PCOS including irregular

menstrual cycles and infertility. The chronic inflammatory state further amplifies insulin resistance and androgen production, establishing a pathophysiological framework where metabolic, hormonal, and inflammatory processes continuously reinforce one another [5] [9] [10].

The burden of PCOS in India varies significantly depending on diagnostic criteria and study populations, with systematic reviews demonstrating a pooled prevalence of 11.33% when using Rotterdam criteria compared to 5.8% with the more restrictive NIH criteria [11] [12]. A recent comprehensive national sampling study across 28 states revealed an even higher weighted prevalence of 19.6% using Rotterdam criteria among 9,824 women aged 18–40 years, suggesting the condition may be more widespread than previously recognized [13]. Regional variations are substantial, as evidenced by studies ranging from 4.17% prevalence in Haryana to 22.5% in Mumbai's younger population, highlighting geographic and demographic disparities in PCOS occurrence [11] [14]. The **Bharali et al.** multi-state study reported an 11.34% prevalence across women aged 10–45 years, while urban populations like those studied by **Joshi et al.** in Mumbai showed higher rates, particularly among younger women [11] [14]. These varying prevalence estimates underscore the importance of standardized diagnostic approaches and the need for population specific screening strategies to better understand the true burden of PCOS across India's diverse regions and demographics [13].

The healthcare system's response to PCOS in India reveals significant gaps in awareness and infrastructure, with only 28% of surveyed public facilities having ever conducted PCOS awareness programs and fewer than 35% maintaining dedicated PCOS registries [15]. This systemic under-recognition translates directly into missed diagnoses, as demonstrated by an urban Delhi NCR cohort study that found a 17.4% prevalence rate, yet nearly 30% of these cases were newly detected during routine screening, indicating substantial numbers of undiagnosed women in the community [16]. The diagnostic disparities are particularly pronounced among socioeconomically vulnerable populations, where language barriers and limited healthcare access compound the problem [17]. Provider knowledge deficits further exacerbate these challenges, creating a cascade of missed opportunities for early detection and intervention [17]. These systemic gaps highlight the urgent need for comprehensive healthcare provider training, improved

screening protocols, and targeted awareness campaigns to address the substantial under-recognition of PCOS across India's healthcare system [15] [16] [17].

The diagnosis of PCOS relies on three major criteria sets NIH 1990, Rotterdam 2003, and AES 2006 each with distinct requirements that significantly impact prevalence estimates and clinical management approaches. The NIH criteria require both hyperandrogenism and oligo-anovulation, while Rotterdam criteria offer more flexibility by requiring only two of three features (hyperandrogenism, oligo-anovulation, or polycystic ovaries on ultrasound), and AES criteria mandate hyperandrogenism with either ovarian dysfunction or polycystic ovaries [18] [21]. Each diagnostic approach faces practical challenges in the Indian context, including the need for high-quality hormone assays to accurately assess hyperandrogenism, unreliable menstrual tracking in low-literacy settings, and limited ultrasound access in rural areas [18] [19] [20]. The Rotterdam criteria's broader inclusion parameters increase detected prevalence but also introduce greater phenotypic heterogeneity among diagnosed women, which complicates the development of standardized treatment algorithms [18] [21]. These diagnostic limitations underscore the need for context-appropriate screening tools and improved healthcare infrastructure to ensure accurate and accessible PCOS diagnosis across diverse Indian populations [18] [19] [20] [21].

The concept of tongue assessment as a diagnostic tool draws from centuries-old practices in Traditional Chinese Medicine and Ayurveda, which have long regarded the tongue as a reflection of systemic health status. Modern scientific validation of this approach has emerged through spectroscopy and computer vision studies that demonstrate measurable correlations between tongue color metrics, particularly when analyzed in CIE-Lab color space, and various metabolic diseases including diabetes, non-alcoholic fatty liver disease, and more recently, PCOS [22] [23] [24]. This convergence of traditional wisdom with contemporary technology provides a compelling foundation for developing non-invasive screening tools that could revolutionize PCOS detection. The accessibility and cost-effectiveness of tongue imaging make it particularly attractive for resource-limited settings where conventional diagnostic methods may be unavailable or prohibitively expensive [22] [23] [24]. Furthermore, the real-time nature of tongue assessment could enable rapid screening in community

health settings, potentially addressing the significant diagnostic gaps currently observed in PCOS care [23] [24].

The biological mechanisms underlying tongue changes in PCOS are rooted in the condition's characteristic metabolic disturbances, particularly insulin resistance and associated dysbiosis, which directly influence oral microbiota composition and tongue appearance [23] [24]. These metabolic alterations lead to changes in sulfur compound metabolism, resulting in the formation of thicker, yellower tongue coatings that can be quantitatively measured using color analysis techniques [23] [24]. Research has demonstrated that PCOS patients exhibit significantly lower L-values (indicating darker tongues) and a-values, while showing higher b-values (indicating increased yellowness) compared to healthy controls, providing objective evidence for the visual changes observed in traditional medicine practices [25]. The chronic inflammatory state associated with PCOS further contributes to these tongue alterations through its effects on local tissue metabolism and microvascular changes. This scientific understanding of the pathophysiological basis for tongue changes in PCOS strengthens the rationale for using tongue assessment as a legitimate screening tool rather than merely an empirical observation [23] [24] [25].

The development of machine learning approaches for tongue-based PCOS screening has been built upon carefully constructed supervised datasets, with one notable study utilizing 285 PCOS patients compared against 201 controls to identify seven key tongue color and pulse features that demonstrate predictive value for PCOS diagnosis [25]. Support Vector Machines emerged as the highest-performing algorithm in this analysis, achieving the best area under the receiver operating characteristic curve (AUROC) for PCOS prediction based on these extracted features [25]. However, the field faces significant challenges related to dataset limitations, as public tongue image repositories remain relatively small and exhibit substantial heterogeneity in imaging conditions, lighting, and population characteristics, which hampers external validation and generalizability of developed models [26]. The feature engineering process requires careful consideration of color space transformations, texture analysis, and coating thickness measurements to capture the subtle but significant differences between PCOS and control populations. These dataset limitations underscore the need for larger, more standardized collections of tongue images across

diverse populations to enable robust model development and validation [25] [26].

Convolutional Neural Network architectures have demonstrated remarkable success in tongue image analysis for PCOS screening, with specific implementations including YOLOv5s6 for tongue detection, UNet for precise segmentation of tongue regions, and MobileNetV3 for feature classification achieving greater than 93% accuracy in multi-label tongue feature recognition tasks [22]. The strength of CNNs lies in their exceptional ability to learn and identify localised colour patterns and texture features that are critical for discriminating coating thickness variations and subtle colour gradations associated with PCOS [22]. These deep learning models excel at capturing the hierarchical features present in tongue images, from low-level edge detection to high-level pattern recognition that corresponds to clinically relevant changes. The combination of detection, segmentation, and classification networks creates a comprehensive pipeline that can accurately identify tongue regions, isolate relevant features, and make predictions about PCOS status. However, the success of these CNN approaches depends heavily on adequate training data and careful preprocessing to standardise lighting conditions and image quality across different acquisition settings [22].

The Swin Transformer architecture represents a newer approach to tongue image analysis, offering hierarchical self-attention mechanisms across shifted windows that can theoretically capture global relationships within tongue images more effectively than traditional CNNs [27]. While Vision Transformers have demonstrated superior performance compared to CNNs in certain medical imaging applications, particularly oral cancer detection tasks, their application to tongue-based PCOS prediction has yielded mixed results [28]. The Swin Transformer's under-performance in PCOS tongue image analysis appears to be attributable to the limited sample sizes available for training and the particularly subtle color gradations that characterize PCOS related tongue changes, which require high spatial resolution and may be better captured by CNN architectures optimized for local feature detection [25]. Vision Transformer-based generators within Generative Adversarial Network frameworks show promise for medical image translation tasks, but these approaches demand substantially larger datasets than are currently available for tongue-based PCOS screening [29]. The future success of Vision Transformers in this domain will

likely depend on the availability of larger, more diverse training datasets and potential hybrid architectures that combine the global attention mechanisms of transformers with the local feature extraction capabilities of CNNs [25] [27] [29].

PCOS imposes a growing metabolic and reproductive burden, particularly among underdiagnosed women in developing countries. Evidence shows that machine learning analysis of tongue images—long a staple of traditional diagnostics offers a promising, non-invasive adjunct for early PCOS screening. CNN-based architectures currently outperform Vision Transformers on limited datasets; however, continued dataset expansion and hybrid modelling may alter this landscape. Integrating tongue features with basic anthropometric and menstrual data could provide an accessible, scalable tool for community health workers, bridging critical diagnostic gaps in India and similar settings. Sustained research investment, standardised imaging protocols, and robust evaluation of cost-effectiveness are imperative to translating this innovative approach from pilot studies to public health impact.

III METHODOLOGY

The tongue image dataset was systematically collected following rigorous data collection guidelines to ensure consistency, quality, and clinical relevance across all captured samples. Images were obtained from participants using standardised protocols that included controlled lighting conditions, consistent camera positioning, and specific instructions for tongue protrusion to minimise variability in image characteristics. Each participant was asked to extend their tongue fully while maintaining a relaxed posture, and multiple images were captured per individual to account for natural variations in tongue positioning and surface moisture. The data collection process adhered to established medical imaging guidelines, incorporating proper informed consent procedures, participant privacy protection, and standardised demographic and clinical data recording alongside each tongue image. Quality control measures were implemented throughout the collection process, including immediate image review for focus, lighting adequacy, and proper tongue visibility, with any substandard images being recaptured to maintain dataset integrity. The systematic approach to data collection ensured that the resulting tongue image repository would provide a robust foundation for subsequent machine learning model development and validation while maintaining the highest standards of research ethics and data quality that are essential for

reliable clinical screening tool development.

The training pipeline begins by loading labelled image data from two distinct folders PCOS and not,PCOS stored on Google Drive. Each image is resized to a uniform resolution of 224×224 pixels and partitioned into training and validation datasets using an 80%/20% split. All pixel intensities are normalised to the range $[0,1]$ using a rescaling layer that divides each channel value by 255. The model architecture is a sequential convolutional neural network (CNN) composed of three convolutional blocks with 3×3 kernels and increasing filter depths (16, 32, and 64), each followed by a 2×2 max-pooling operation. These are followed by a flattening layer, a fully connected dense layer with 128 neurones using ReLU activation, and a final dense output layer with two units and a softmax activation. The forward propagation through the CNN is governed by standard convolution and activation operations, where each convolutional feature map is computed as

$$z_k = b_k + \sum_{c=1} w_{kc} * x_c$$

followed by non-linear transformation

$$a_k = \max(0, z_k),$$

and max-pooling over local 2×2 regions. The model is trained using sparse categorical cross-entropy loss defined

$$L = -\log y_c$$

where y_c is the predicted probability corresponding to the ground truth class. Training is conducted over 200 epochs, with metrics including training accuracy, validation accuracy, and loss tracked across epochs. The training logs are saved externally for post-hoc analysis. While no formal early stopping or learning rate scheduling is applied, the validation performance is monitored per epoch to evaluate model generalisation during training.

IV OBSERVATION

Image	Predicted class	Actual class
	Healthy	Healthy
	Severe	Severe

	Severe	Severe
	Healthy	Healthy
	Moderate	Moderate

	Severe	Moderate
	Healthy	Healthy
	Severe	Severe

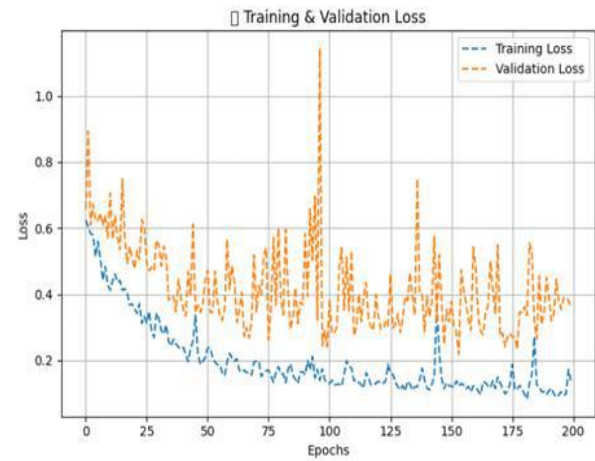


Fig. 1: Training and Validation Loss



Fig. 2: Training and Validation Accuracy

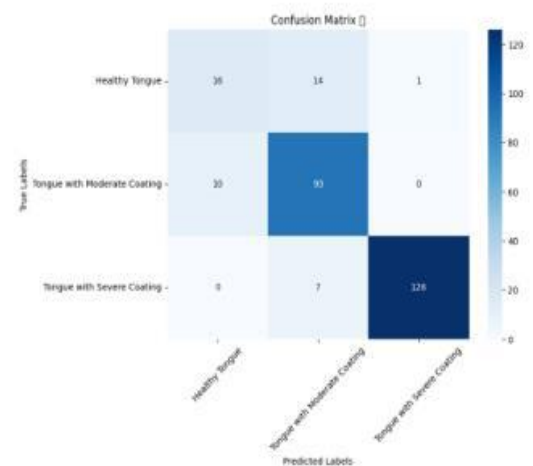


Fig. 3: Confusion Matrix

V CONCLUSION

At convergence, the model achieves a training accuracy of 99.6% and a validation accuracy of 97.1%, indicating strong learning capacity with minimal overfitting on the available dataset. The testing phase involves loading the trained model weights and applying the same preprocessing steps to unseen images, followed by inference and label prediction using the softmax output. Although the results are promising, the limited size and homogeneity of the dataset imply a need for further evaluation. To establish clinical reliability, future work should incorporate independent external validation, preferably through k-fold cross-validation or multi-institutional datasets, to assess model robustness across diverse patient demographics, imaging conditions, and equipment settings.

REFERENCES

- [1] World Health Organization, "Polycystic ovary syndrome," WHO Fact Sheets. [Online]. Available: <https://www.who.int/news-room/fact-sheets/detail/polycystic-ovary-syndrome>. [Accessed: Jul. 23, 2025].
- [2] PubMed, "PMID: 38922413." [Online]. Available: <https://pubmed.ncbi.nlm.nih.gov/38922413/>. [Accessed: Jul. 23, 2025].
- [3] Frontiers in Public Health, "pubh.2025.1514250." [Online]. Available: <https://www.frontiersin.org/journals/public-health/articles/10.3389/fpubh.2025.1514250/full>. [Accessed: Jul. 23, 2025].
- [4] U.S. Department of Veterans Affairs, "Up to 70% of women with PCOS remain undiagnosed- Polycystic ovary syndrome affects 1 in 10 women," Sheridan Health Care Stories. [Online]. Available: <https://www.va.gov/sheridan-health-care/stories/up-to-70-of-women-with-pcos-remain-undiagnosed-polycystic-ovary-syndrome-affects-1-in-10-women>. [Accessed: Jul. 23, 2025].
- [5] PubMed Central, "PMC9665922." [Online]. Available: <https://pmc.ncbi.nlm.nih.gov/articles/PMC9665922/>. [Accessed: Jul. 23, 2025].
- [6] PubMed Central, "PMC4527566." [Online]. Available: <https://pmc.ncbi.nlm.nih.gov/articles/PMC4527566/>. [Accessed: Jul. 23, 2025].
- [7] Wiley Clinical Online Library, Endocrinology. "DOI: [Online]. 10.1111/cen.14609," Available: <https://onlinelibrary.wiley.com/doi/10.1111/cen.14609>. [Accessed: Jul. 23, 2025].
- [8] Johns Hopkins Medicine, "Polycystic Ovary Syndrome (PCOS)," Health Conditions and Diseases. [Online]. Available: <https://www.hopkinsmedicine.org/health/conditions-and-diseases/polycystic-ovary-syndrome-pcos>. [Accessed: Jul. 23, 2025].
- [9] PubMed Central, "PMC3277302." [Online]. Available: <https://pmc.ncbi.nlm.nih.gov/articles/PMC3277302/>. [Accessed: Jul. 23, 2025].
- [10] Clue, "The link between PCOS and insulin resistance," Cycle A-Z. [Online]. Available: <https://hellocycle.com/articles/cycle-a-z/the-link-between-pcos-and-insulin-resistance>. [Accessed: Jul. 23, 2025].
- [11] PubMed Central, "PMC9826643." [Online]. Available: <https://pmc.ncbi.nlm.nih.gov/articles/PMC9826643/>. [Accessed: Jul. 23, 2025].
- [12] Cureus, "Prevalence of Polycystic Ovarian Syndrome in India: A Systematic Review and Meta-Analysis," Article 126192. [Online]. Available: <https://www.cureus.com/articles/126192-prevalence-of-polycystic-ovarian-syndrome-in-india-a-systematic-review-and-meta-analysis.pdf>. [Accessed: Jul. 23, 2025].
- [13] JAMA Network Open, "Full Article: 2825233." [Online]. Available: <https://jamanetwork.com/journals/jamanetworkopen/fullarticle/2825233>. [Accessed: Jul. 23, 2025].
- [14] PubMed Central, "PMC6902362." [Online]. Available: <https://pmc.ncbi.nlm.nih.gov/articles/PMC6902362/>. [Accessed: Jul. 23, 2025].
- [15] Indian Journal of Public Health, "Public health system's preparedness to address," vol. 68, no. 2, Apr. 2024. [Online]. Available: https://journals.lww.com/ijph/fulltext/2024/04000/public_health_system_s_preparedness_to_address.6.aspx. [Accessed: Jul. 23, 2025].
- [16] PubMed Central, "PMC12039125." [Online]. Available: <https://pmc.ncbi.nlm.nih.gov/articles/PMC12039125/>. [Accessed: Jul. 23, 2025].
- [17] Journal of Clinical Endocrinology & Metabolism, "Article: 7819206," vol. 110, no. 6, pp. 1657. [Online]. Available: <https://academic.oup.com/jcem/article/110/6/1657/7819206>. [Accessed: Jul. 23, 2025].

- [18] PubMed Central, “PMC10047373.” [Online]. Available: <https://pmc.ncbi.nlm.nih.gov/articles/PMC10047373/>. [Accessed: Jul. 23, 2025].
- [19] American Family Physician, “AAFP Publications,” Jul. 15, 2016, pp. 106. [Online]. Available: <https://www.aafp.org/pubs/afp/issues/2016/0715/p106.html>. [Accessed: Jul. 23, 2025].
- [20] Mayo Clinic, “PCOS- Diagnosis and treatment,” Diseases and Conditions. [Online]. Available: <https://www.mayoclinic.org/diseases-conditions/pcos/diagnosis-treatment/drc-20353443>. [Accessed: Jul. 23, 2025].
- [21] Indian Journal of Medical Research, “Epidemiology, pathogenesis, genetics & management,” vol. 150, no. 4, 2019. [Online]. Available: <https://journals.lww.com/ijmr/fulltext/2019/50040/epidemiology,pathogenesis,geneticsmanagement.5.aspx>. [Accessed: Jul. 23, 2025].
- [22] PubMed Central, “PMC9600321.” [Online]. Available: <https://pmc.ncbi.nlm.nih.gov/articles/PMC9600321/>. [Accessed: Jul. 23, 2025].
- [23] Frontiers in Cellular and Infection Microbiology, “DOI: 10.3389/fcimb.2022.787143.” [Online]. Available: <https://www.frontiersin.org/journals/cellular-and-infection-microbiology/articles/10.3389/fcimb.2022.787143/full>. [Accessed: Jul. 23, 2025].
- [24] PubMed Central, “PMC8417575.” [Online]. Available: <https://pmc.ncbi.nlm.nih.gov/articles/PMC8417575/>. [Accessed: Jul. 23, 2025].
- [25] PubMed Central, “PMC10281487.” [Online]. Available: <https://pmc.ncbi.nlm.nih.gov/articles/PMC10281487/>. [Accessed: Jul. 23, 2025].
- [26] PubMed Central, “PMC8097848.” [Online]. Available: <https://pmc.ncbi.nlm.nih.gov/articles/PMC8097848/>. [Accessed: Jul. 23, 2025].
- [27] Microsoft, “Swin-Transformer,” GitHub Repository. [Online]. Available: <https://github.com/microsoft/Swin-Transformer>. [Accessed: Jul. 23, 2025].
- [28] PubMed, “PMID: 38473348.” [Online]. Available: <https://pubmed.ncbi.nlm.nih.gov/38473348/>. [Accessed: Jul. 23, 2025].
- [29] Frontiers in Oncology, “DOI: 10.3389/fonc.2022.942511.” [Online]. Available: <https://www.frontiersin.org/journals/oncology/articles/10.3389/fonc.2022.942511/full>. [Accessed: Jul. 23, 2025].