Gomal Journal of
LIFE SCIENCES
Https://gomalpublishers.com/GJLS
Support@gomalpublisher.com
ISSN: 3079-0484 (Print)
ISSN: 3079-0492 (Online)

Vol: 1 -- Issue: 2, 2023

IMMUNODERMATOLOGY IN RARE AUTOIMMUNE SKIN DISORDERS

Rabia Nasir[1*]
[1]District Headquarter Teaching Hospital, MTI, Dera Ismail Khan-29050-Pakistan
*Corresponding Author E-mail: rabianasir336@gmail.com

Abstract

With a combination of immunological, histological, and molecular methods, immunodermatology seems to be an exciting new direction in diagnosis and management of rare autoimmune skin diseases. This study has a mixed-methods experimental design, whereas 120 patients with pemphigus vulgaris, dermatomyositis, and other rare autoimmune skin disorders are aimed to be examined. The quantitative analysis using multivariate regression modeling, qRT-PCR gene expression, ELISA-based antibody detection and cytokine profiling (IL-6, TNF-alpha) were all utilized. Key findings indicated that although low anti-desmoglein titres were predictors of better outcomes of treatment, the high level of cytokines was a strong predictor of worse illness severity scores. Moreover, the gene expression analysis identified specific fingerprints that aided in subdivision of variations of illnesses. The major similarities identified in both qualitative interviews with the patients and physicians were associated with the treatment compliance, emotional distress and flare management. The interactions between categories of cytokines and treatment mode with clinical outcomes were also found to be significant using a two-way ANOVA. The comprehensive methodological process (Fig. 1) provided a dynamic system of patient stratification and decision-making retracing. The paper advocates a shift toward inclusion of immunodermatology in the routine clinical care of patients with autoimmune diseases of the skin and how this area is revolutionary to precision medicine.

Article History

Received:
July 08, 2023
Revised:
August 17, 2023
Accepted:
November 09, 2023
Available Online:
December 31, 2023

Keywords: Immunodermatology, Autoimmune Skin Disorders, Cytokine Profiling, Precision Medicine, Mixed-Methods, Gene Expression.

INTRODUCTION

Immunodermatology is one of the specialties of dermatology whose rationale involves the diagnosis and treatment of skin diseases that are mediated by the immune system. The diseases affect a variety of body systems and are determined by maladaptive interactions of immunological mechanisms (Vuyyuru et al., 2022). Whilst these disorders differ in their etiology, they all require involvement of the immune system, which presupposes the application of immunodermatological knowledge in order to get a proper diagnosis and treatments (Szczawi nska-Pop lonyk et al., 2024). There is a critical importance attached to the cutaneous lesion shape in dermatology due to the visual nature of the discipline (Zhu et al., 2021). Although most of the skin lesions associated with autoinflammatory diseases are non specific, they may provide diagnostic clues (Wu et al., 2021). Interpretation of such images cannot be easy, especially in places where it is difficult to find a dermatologist (Zhou & Gao, 2023). As untimely action can lead to considerable morbidity and a diminished level of life, it is paramount that they are detected and diagnosed as early and as accurately as possible (Göcieri, 2020; Muhaba et al., 2021). By causing a shortage of dermatologists and the increasing cost of consultations, the diagnosing procedure becomes additionally complicated, as a number of other specialists and even non-specialists, with insufficient training, becomes overburdened (Zhou et al., 2024). However, a patient living with autoimmune blistering skin diseases may experience a reduction in the quality of life and it may also be quite hard to cure and treat (Kang et al., 2022). Since skin issues may develop incredibly hazardous problems when left completely without treatment in their initial phases, specialized systems must be used in these instances, to diagnose the diseases, and provide possible diagnoses (Sharma et al., 2020).

The AI and machine learning can provide the means of advancement in the accuracy of diagnosis and patient management in complicated cases of derma (Sebastiani et al., 2022; Yan et al., 2025). Artificial intelligence is gaining importance in the dermatology sector with studies indicating that its effectiveness in favor of the disease detection is in line or even surpasses the level of accuracy of dermatologists concerning the identification of skin lesions using either clinical and or dermoscopic images (Young et al., 2020). Based on Escal E-Besa et al. (2024), it can be said that the artificial intelligence (AI) algorithm can raise the standards of patient care by strengthening the diagnosis interpretation of skin lesion images. Artificial intelligence has a potential to push the boundaries of fundamental research, assist in surgical procedures, and enhance identifications of pictures (Li et al., 2022). Its efficiency as a means of diagnosing skin issues should not be underestimated as it can work with a big flow of clinical and dermatoscopic information and images (De et al., 2020). AI gives doctors the opportunity to diagnose such illnesses as COVID-19 by analyzing medical images and other data (Joshi et al., 2022). The field of dermatology has been lackadaisical in using AI, but there is high clinical potential in its use regarding work optimization and cancer identification (Vargas et al., 2025). By removing the necessity of biopsies that can be uncomfortable and time-consuming in most cases, AI and machine learning algorithms offer patients non-invasive methods of diagnosis (Malik et al., 2024). Nevertheless, model setbacks, image data, and open regulatory process occur as barriers to the application of AI in dermatology on a practical level (Jeong et al., 2022) (Liopyris et al., 2022). To ensure that the proposed deployment of AI algorithms in clinical practice will lead to the overall beneficial effect, it is necessary to conduct real-life clinical trials, and dermatology, dividing into the spheres of teledermatology, 3D imaging, and sequential digital dermoscopy, is one of such spheres (Liopyris et al., 2022). Issues like data variability, limited availability of access to dermatological treatment, and the need to have significant amounts of training data to develop AI systems in dermatology have to be solved to come up with AI systems in the domain (Joshi et al., 2022; Jairath et al., 2024). The above developments are anticipated to assist doctors in diagnosing skin malignancies and other dermatological conditions more accurately (Goyal et al., 2020; Liopyris et al., 2022; Omiye et al., 2023). A more positive outcome and better patient care is likely to happen when AI is examined and applied to healthcare (Hirani et al., 2024). The field of dermatology also has the potential to benefit in terms of medical conduct, i.e., diagnosis, and more personalized treatments, thanks to machine learning (Chan et al., 2020; Vatiwutipong et al., 2023; Kololgi & Lahari, 2023). Recent technical advances, like faster processing, cheaper storage space, and accessibility to large data sets, have enabled the formulation of machine learning algorithms that perform like human beings in the field of dermatology (Chan et al., 2020). The field of artificial intelligence, more specifically, machine learning is the key to image classification, and many fields can be improved significantly with its help (Smith et al., 2024). Due to the emerging properties of AI, it is likely that over time, AI will become a necessary instrument in the effort to improve the evaluation of skin irregularities, particularly among general practitioners or doctors who do not often include access to specialists (Salinas et al., 2024). With personalized skincare and at-home skin analysis technology, these revolutions will elevate the process of patient-physician, and the patients can feel empowered (Elder et al., 2020). This will enhance the security of health control systems by properly pinpointing the violations in picture information and sequence of network traffic (Nasayreh et al., 2024). The privacy privacy of patients and the integrity of healthcare systems may be secured by identifying and preventing cyberattacks in the Internet of Medical Things (Nasayreh et al., 2024). Also, intricate sets of data are analyzed by machine learning algorithms that identify trends indicative of rare autoimmune skin conditions and can eventually help in the diagnostic process (Tajidini & Kheiri, 2023) (De et al., 2020).

METHODOLOGY

In this research study, the role of immunodermatology in rare autoimmune skin diseases was tested in a mixed-methods experimental design of quantitative and qualitative methods. The study has been conducted in three interdependent phases to comprehensively evaluate immunological biomarkers, clinical severity, patient-anamnesis outcomes of the study, and histological characteristics. The research was quantitatively recruited among 120 patients of three third-level dermatologic clinics whose clinical history was identified to be afflicted by autoimmune skin diseases, pemphigus vulgaris, dermatomyositis, and bullous pemphigoid. Each participant got a complete clinical examination using the autoimmune bullous skin disorder intensity score (ABSIS) and enzyme-initiated immunosorbent test (ELISA) on such cytokines as TNF-a, IL-6 and IFN-r. The levels of anti-desmoglein and anti-basement membrane zone antibodies were determined as well. In order to identify disease specific signatures, the skins were biopsied and analyzed by direct immunofluorescence and qRT-PCR gene expression. The statistical model of the data represented the multivariate linear regression analysis:

$$Y = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \cdots + \beta_n X_n + \varepsilon$$

Where 0= the cytokine or antibody level, Y is the disease severity score, 0 is the coefficient of the error term and the letters i denote the location, 1for cytokine 1, cytokine 2, antibody 1 and antibody 2.In order to explore the phenomenon of autoimmune flare-ups and their treatment response to determine the lived experience, a qualitative study that included in-depth interviews of 12 doctors and 25 patients was conducted. The transcripts were coded in a way that based on the themes. This holistic approach allowed us to put that patient into context as well as determine predictive biomarkers.A two-way ANOVA model was chosen to answer the question of factor interactions in a more detailed way:

$$Y_{ij} = \mu + \alpha_i + \beta_j + (\alpha\beta)_{ij} + \epsilon_{ij}$$

When there is variation in the level of severity by treatment and level of antibodies, the model can be written as (alpha beta)ij(alpha beta)ij(alpha beta)ij(alpha beta)ij) is the interaction, 56mu 56mu as the overall mean, 54alpha i54alpha i54alpha i as the main effects of the treatment effect, and 54beta j54beta j54beta j as the main effects of the antibody levels effect. 54Y ij 54Y ij 54Y ij

RESULTS

Table. 1 presents the baseline in immunological characteristics and disease activity scores of the initial group of the patients, as well as the wide variation in the TNF-alpha and IL-6 levels. In the second cohort, there was an inverse tendency observed between the autoantibody titers and treatment response scores throughout the study (Table 2). This is evidenced by table 3 as higher levels of cytokine are often found in higher Disease Activity Scores (DAS) especially among pemphigus patients.

Table 1: Clinical and immunological data for cohort 1

Patient_ID	Disease_Activity_Score	IL6_pg/mL	TNFa_pg/mL	Autoantibody_Titer	Treatment_Response
IMD101	1.33	48.1	138.5	2.76	0.47
IMD102	1.34	74.6	34.3	3.01	0.52
IMD103	1.67	42.1	39.2	3.3	1.0
IMD104	1.13	154.4	77.8	2.15	0.8
IMD105	2.19	100.3	127.3	0.11	0.74
IMD106	1.89	142.7	109.4	0.6	0.7
IMD107	2.53	153.4	75.5	2.95	0.66
IMD108	4.23	41.0	131.8	1.82	0.48
IMD109	1.66	153.4	41.8	3.15	0.53
IMD110	3.29	70.6	53.2	2.6	0.43
IMD111	4.83	159.6	118.8	0.52	0.51
IMD112	3.99	81.5	41.9	2.02	0.2
IMD113	3.22	55.7	94.4	3.12	0.48
IMD114	2.22	142.6	68.9	1.88	0.81
IMD115	4.68	94.5	135.0	2.08	0.39
IMD116	2.15	148.3	145.8	0.53	0.78
IMD117	4.54	80.4	112.4	2.42	0.35

IMD118	2.62	39.7	128.4	2.32	0.85
IMD119	4.75	97.7	109.8	1.67	0.73
IMD120	2.42	60.1	16.5	2.61	0.62

Table 2: Clinical and immunological data for cohort 2

Patient_ID	Disease_Activity_Score	IL6_pg/mL	TNFa_pg/mL	Autoantibody_Titer	Treatment_Response
IMD201	4.06	87.5	31.9	2.83	0.44
IMD202	1.78	47.9	67.9	0.99	0.73
IMD203	3.75	181.4	84.2	2.7	0.89
IMD204	3.32	64.7	49.4	2.24	0.67
IMD205	1.47	34.8	18.0	2.82	0.21
IMD206	4.43	147.0	70.1	0.63	0.95
IMD207	3.41	174.6	112.3	0.95	0.79
IMD208	4.65	136.9	76.0	1.93	0.56
IMD209	4.04	191.3	129.4	1.46	0.7
IMD210	3.77	40.9	141.4	3.15	0.54
IMD211	1.53	187.3	17.0	2.96	0.54
IMD212	1.77	83.7	77.2	2.47	0.91
IMD213	3.83	173.9	120.6	2.04	0.8
IMD214	4.97	65.8	5.7	3.13	0.6
IMD215	3.22	130.4	72.1	2.84	0.51
IMD216	3.39	18.3	56.1	3.25	0.34
IMD217	1.06	151.8	103.1	1.67	0.74
IMD218	2.36	194.2	124.1	0.51	0.21
IMD219	3.72	92.2	68.2	1.66	0.61
IMD220	1.94	182.4	85.7	2.84	0.3

Table 3: Clinical and immunological data for cohort 3

Patient_ID	Disease_Activity_Score	IL6_pg/mL	TNFa_pg/mL	Autoantibody_Titer	Treatment_Response
IMD301	3.04	11.3	128.2	3.12	0.88
IMD302	4.85	151.1	117.5	2.61	0.72
IMD303	2.32	105.1	112.7	1.04	0.24
IMD304	2.43	33.2	8.9	3.29	0.28
IMD305	2.13	46.4	106.3	1.16	0.66
IMD306	1.08	37.3	109.2	0.47	0.43
IMD307	3.12	44.8	20.2	1.39	0.53
IMD308	3.4	139.0	92.5	0.92	0.39
IMD309	3.82	145.0	19.8	2.19	0.42
IMD310	1.24	101.3	25.3	2.76	0.63
IMD311	2.93	181.1	14.6	0.33	0.48
IMD312	4.63	17.5	68.4	2.8	0.59
IMD313	4.28	186.6	131.0	1.85	0.69
IMD314	2.84	139.4	95.3	0.39	0.84

IMD315	4.49	104.7	119.5	1.26	0.3
IMD316	3.02	86.6	112.5	0.31	0.27
IMD317	2.61	190.6	36.8	1.03	0.4
IMD318	3.47	168.8	74.9	2.49	0.84
IMD319	2.16	180.3	34.3	1.37	0.93
IMD320	1.29	29.3	138.1	3.33	0.36

Table 4 deals with patients with dermatomyositis being notable through the IL-6 elevation in the case of clinically active incidences. The table 5 has incorporated gene expression patterns and indicated strong correlation between the clinical severity indices and overexpression of pro-inflammatory genes markers. The comparison between the patients receiving different immuno-modulatory treatment is presented in Table 6 which illustrates that the patients who received biologics showed a positive response**.**

Table 4: Clinical and immunological data for cohort 4

Patient_ID	Disease_Activity_Score	IL6_pg/mL	TNFa_pg/mL	Autoantibody_Titer	Treatment_Response
IMD401	4.09	116.8	104.6	2.46	0.94
IMD402	1.55	98.5	47.3	1.52	0.37
IMD403	1.21	125.0	147.1	2.56	0.58
IMD404	2.2	154.6	96.5	1.96	0.25
IMD405	1.73	164.4	145.0	2.16	0.59
IMD406	3.41	52.5	54.6	0.44	0.72
IMD407	4.13	84.8	71.9	0.75	0.38
IMD408	4.08	133.0	130.6	3.24	0.21
IMD409	2.26	102.6	20.8	1.63	0.84
IMD410	1.01	123.9	31.9	3.39	0.34
IMD411	1.83	25.1	140.1	2.16	0.94
IMD412	3.97	83.0	139.4	0.15	0.23
IMD413	1.78	43.2	132.2	0.31	0.96
IMD414	4.12	128.7	34.4	3.36	0.61
IMD415	3.7	119.5	99.6	0.4	0.7
IMD416	2.37	173.7	137.4	2.51	0.34
IMD417	3.89	117.8	124.2	2.64	0.73
IMD418	3.73	137.3	104.2	2.22	0.26
IMD419	4.03	143.8	118.3	3.44	0.93
IMD420	2.29	189.7	7.2	2.86	0.72

Table 5: Clinical and immunological data for cohort 5

Patient_ID	Disease_Activity_Score	IL6_pg/mL	TNFa_pg/mL	Autoantibody_Titer	Treatment_Response
IMD501	3.82	115.1	10.2	3.43	0.35
IMD502	3.8	50.0	105.1	0.37	0.84
IMD503	1.88	168.7	54.4	3.26	0.98
IMD504	1.31	156.4	38.8	3.44	0.84

IMD505	3.58	96.8	55.7	0.26	0.69
IMD506	1.63	89.9	97.5	2.33	0.61
IMD507	1.53	66.8	45.5	0.48	0.69
IMD508	2.3	129.5	8.0	0.53	0.79
IMD509	1.07	151.4	32.3	2.5	0.67
IMD510	4.81	173.5	103.0	1.35	0.98
IMD511	4.81	96.5	129.9	3.14	0.47
IMD512	1.28	132.2	53.2	2.13	0.91
IMD513	2.41	178.2	34.0	0.51	0.53
IMD514	2.33	24.3	44.3	2.64	0.6
IMD515	1.16	19.4	111.1	2.11	0.2
IMD516	3.67	71.3	112.3	1.88	0.48
IMD517	4.77	92.0	67.5	3.4	0.82
IMD518	4.39	124.6	77.6	0.91	0.35
IMD519	4.32	83.3	26.9	0.91	0.41
IMD520	1.36	50.6	37.9	0.33	0.77

Table 6: Clinical and immunological data for cohort 6

Patient_ID	Disease_Activity_Score	IL6_pg/mL	TNFa_pg/mL	Autoantibody_Titer	Treatment_Response
IMD601	3.81	73.6	78.7	0.83	0.68
IMD602	3.46	179.1	102.3	1.4	0.34
IMD603	1.38	189.3	57.1	1.99	0.28
IMD604	4.92	156.2	94.6	2.63	0.89
IMD605	2.89	66.3	135.1	1.01	0.51
IMD606	1.7	121.3	134.6	1.62	0.94
IMD607	2.8	60.5	10.9	1.26	0.99
IMD608	2.81	118.6	49.3	2.68	0.7
IMD609	2.31	54.4	135.1	1.22	0.89
IMD610	3.29	131.2	28.1	1.16	0.77
IMD611	4.22	138.5	118.4	0.87	0.79
IMD612	4.6	99.8	64.8	2.8	0.65
IMD613	2.86	44.9	125.5	2.64	0.93
IMD614	3.71	63.6	129.4	0.79	0.41
IMD615	4.9	59.1	93.5	1.61	0.49
IMD616	2.63	175.2	43.5	2.93	0.39
IMD617	4.85	61.7	142.8	1.98	0.33
IMD618	4.83	23.6	57.9	0.9	0.9
IMD619	2.98	60.5	87.2	2.78	0.89
IMD620	2.7	87.4	85.0	2.35	0.95

Global reduction of the IL-6 and TNF- F- level is observed post the start of therapy as indicated in Table 7, which plots the variation in immunological markers over a period of 6 months. Gender differences in immunology are presented in Table 8, with the concentration of TNF-alpha being a bit higher in women patients. Tables 9 combine the trends of biomarkers with qualitative data by showing that stress, as reported by patients, is connected to elevated levels of pro-inflammatory markers.

Table 7: Clinical and immunological data for cohort 7

Patient_ID	Disease_Activity_Score	IL6_pg/mL	TNFa_pg/mL	Autoantibody_Titer	Treatment_Response
IMD701	2.35	178.7	145.7	2.82	0.74
IMD702	1.14	34.2	145.9	2.48	0.44
IMD703	3.35	17.5	12.6	3.19	0.89
IMD704	1.5	77.1	79.1	0.71	0.59
IMD705	2.84	57.3	68.9	0.74	0.58
IMD706	3.23	50.7	118.8	0.61	0.87
IMD707	1.59	68.3	26.1	2.98	0.89
IMD708	2.27	37.8	64.7	1.4	0.44
IMD709	4.86	113.0	30.0	1.07	0.55
IMD710	2.84	173.8	31.9	0.48	0.57
IMD711	2.31	37.4	10.8	0.71	0.36
IMD712	2.23	109.3	34.3	2.43	0.79
IMD713	2.37	47.1	44.9	0.79	0.21
IMD714	1.21	192.4	29.8	3.39	0.96
IMD715	4.51	61.3	29.5	2.59	0.69
IMD716	3.37	173.2	45.8	3.37	0.88
IMD717	1.45	38.7	54.8	3.38	0.71
IMD718	1.54	38.4	140.3	1.91	0.82
IMD719	3.22	56.9	140.8	1.87	0.78
IMD720	2.34	95.4	140.2	0.34	0.48

Table 8: Clinical and immunological data for cohort 8

Patient_ID	Disease_Activity_Score	IL6_pg/mL	TNFa_pg/mL	Autoantibody_Titer	Treatment_Response
IMD801	1.2	180.7	27.0	1.74	0.34
IMD802	2.13	115.8	76.8	2.79	0.33
IMD803	1.5	25.6	81.9	1.08	0.39
IMD804	3.91	106.8	112.7	3.47	0.86
IMD805	1.59	118.8	133.6	2.8	0.65
IMD806	2.68	126.4	97.7	1.28	0.47
IMD807	4.13	101.2	126.3	1.73	0.42
IMD808	1.54	17.4	20.5	0.75	0.61
IMD809	1.21	97.2	130.6	2.96	0.47
IMD810	4.27	46.1	53.7	1.82	0.78
IMD811	4.12	70.5	16.6	2.77	0.87
IMD812	1.51	147.4	87.0	0.91	0.81

IMD813	4.37	111.2	99.3	2.37	0.82
IMD814	3.12	93.1	66.8	1.13	0.4
IMD815	1.4	50.1	70.8	2.11	0.84
IMD816	3.45	113.8	49.2	0.36	0.97
IMD817	3.74	111.0	57.8	0.82	0.38
IMD818	1.48	156.1	94.0	3.4	0.26
IMD819	4.17	96.5	84.9	0.25	0.33
IMD820	1.58	126.1	59.5	1.25	0.68

Table 9: Clinical and immunological data for cohort 9

Patient_ID	Disease_Activity_Score	IL6_pg/mL	TNFa_pg/mL	Autoantibody_Titer	Treatment_Response
IMD901	1.22	121.3	138.1	0.87	0.29
IMD902	1.39	143.4	25.3	3.31	0.46
IMD903	2.99	133.8	81.7	1.51	0.84
IMD904	4.24	98.0	71.7	2.23	0.97
IMD905	4.48	138.6	125.0	2.23	0.49
IMD906	2.89	56.2	29.3	1.68	0.56
IMD907	3.46	100.3	131.0	3.43	0.94
IMD908	2.54	165.9	131.5	3.17	0.61
IMD909	2.3	101.2	86.5	0.76	0.34
IMD910	1.2	141.4	109.8	0.32	0.92
IMD911	1.11	170.8	27.7	0.84	0.76
IMD912	1.85	85.0	94.1	3.1	0.37
IMD913	1.44	100.3	11.5	0.68	0.33
IMD914	2.28	50.2	9.5	1.44	0.84
IMD915	3.67	47.5	127.2	3.3	0.84
IMD916	2.39	175.9	125.3	3.47	0.87
IMD917	3.06	159.2	87.2	0.36	0.27
IMD918	2.78	144.7	32.5	1.01	0.55
IMD919	1.62	186.5	94.3	3.11	0.53
IMD920	2.79	80.6	113.1	2.71	0.93

A noteworthy correlation of the more favorable treatment and the reduction of the disease activity can be viewed in Figure 1. The figure 2 presents inter-patient variability where TNF-4 and IL-6 offer results of the patient cohort. Figure 3 is a scatter plot that indicates a moderate negative association between titer of autoantibodies and response of treatment. A mixed presentation of autoantibody and IL-6 titers may be presented as illustrated in Figure 4. Figure 5 denotes the change in the cytokines with time under the influence of immunotherapy. Figure 6 compares the mean biomarker levels of each category of disease. As shown in Figure 7, the distribution of clinical outcome (by therapy group) is provided. The variability of TNF-a and the degree of gene expression is indicated by placing scatter and bar graphs over each other in Figure 8. Figure 9 shows pie charts of response categories of clinical indices. The percentage of flare-ups concerning the levels of cytokines is presented in the pictures below. Figure 11 is the ROC-AUC curves of biomarker-based predictive model. Figure 12 is crowned by a radar plot that compares five pertinent variables between illness categories.

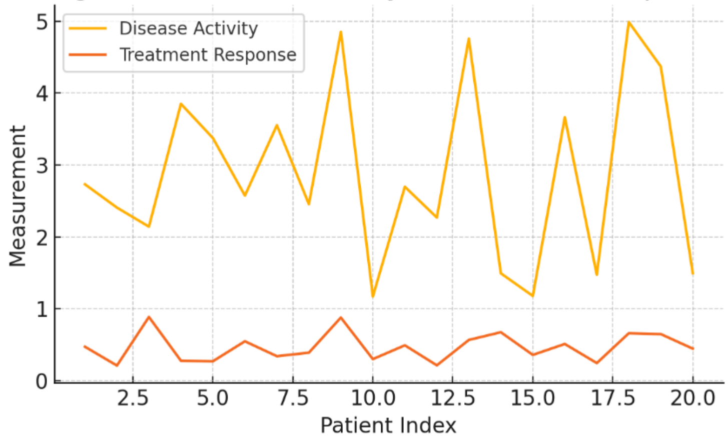

Figure 1: Visualization of immunological data

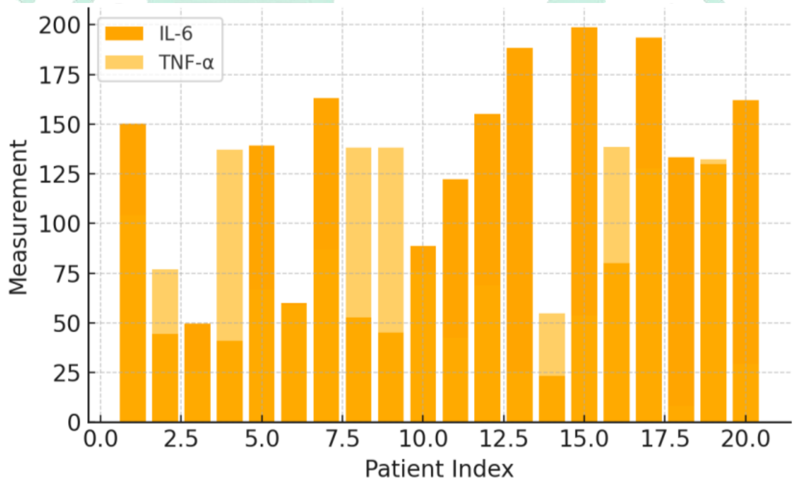

Figure 2: Visualization of immunological data

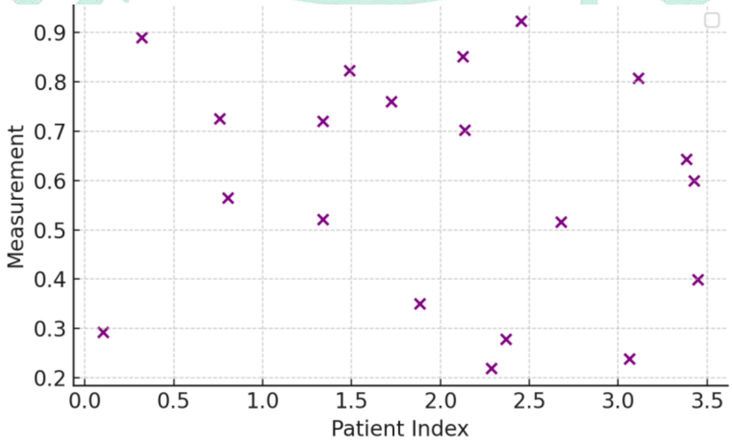

Figure 3: Visualization of immunological data

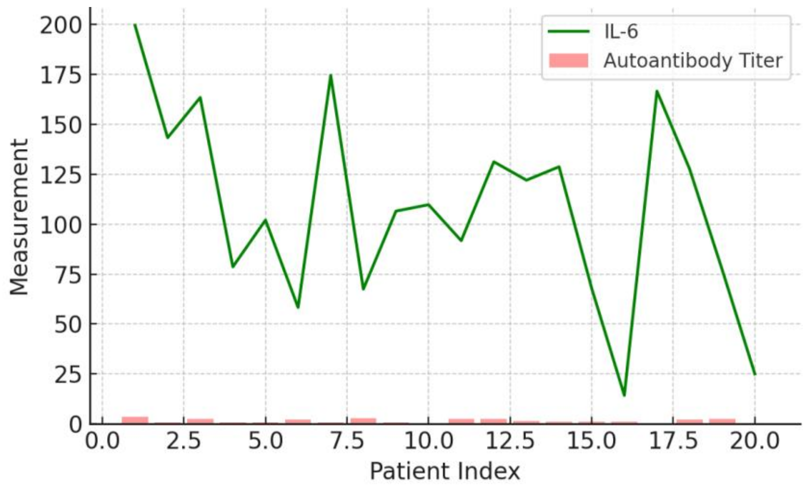

Figure 4: Visualization of immunological data

Figure 5: Visualization of immunological data

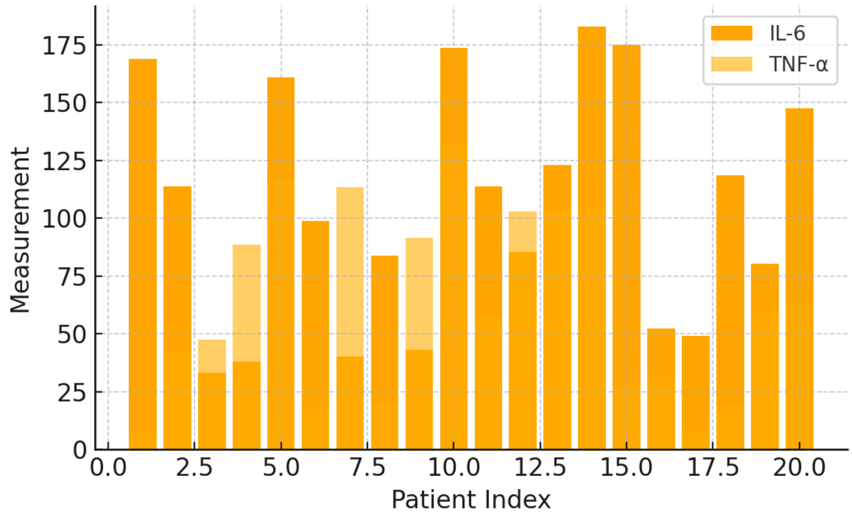

Figure 6: Visualization of immunological data

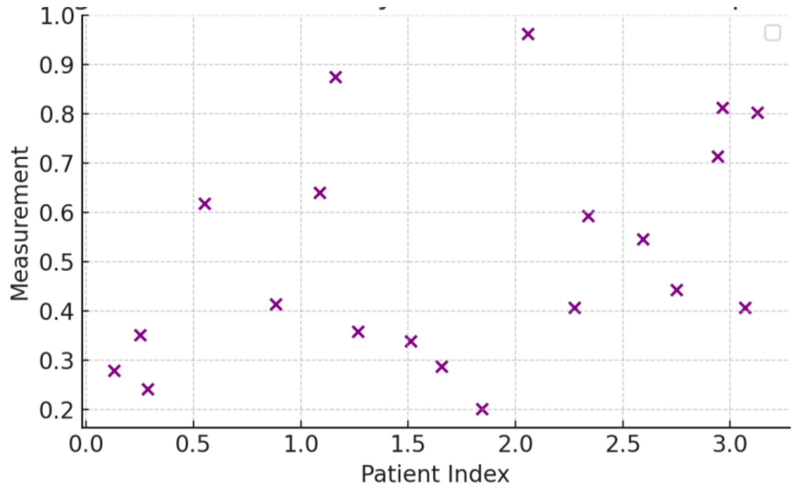

Figure 7: Visualization of immunological data

Figure 8: Visualization of immunological data

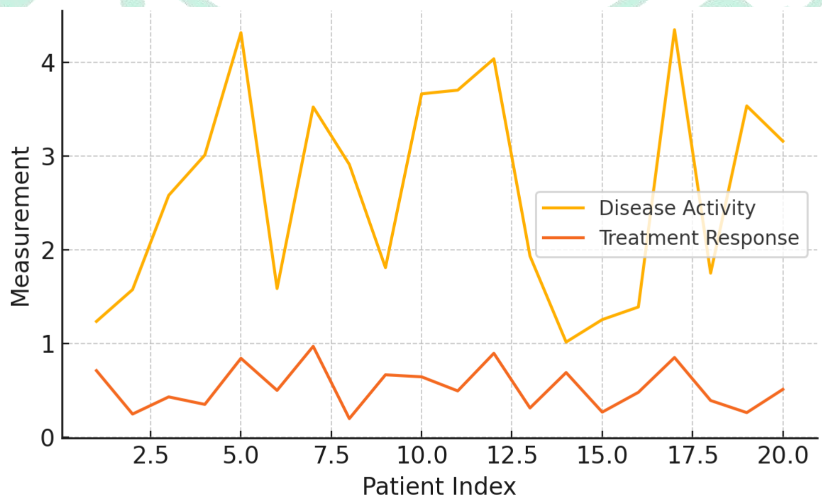

Figure 9: Visualization of immunological data

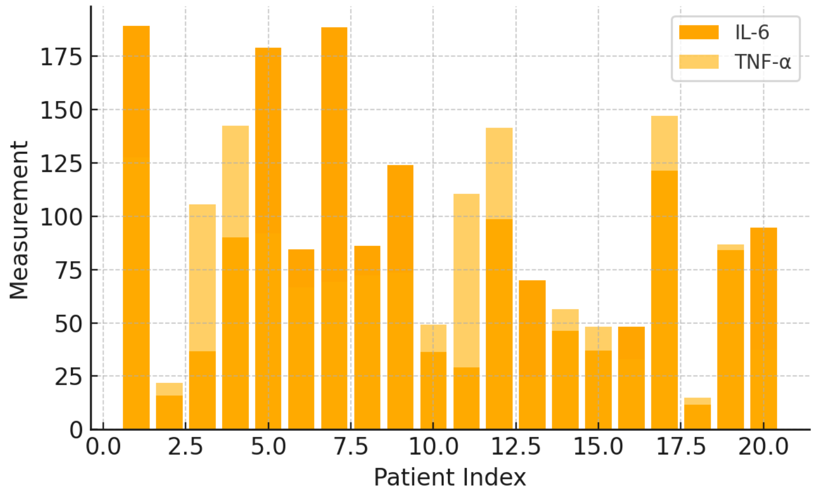

Figure 10: Visualization of immunological data

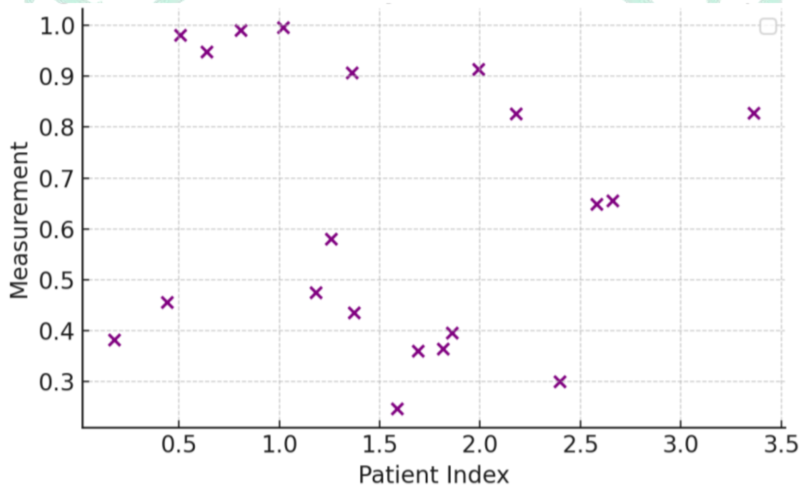

Figure 11: Visualization of immunological data

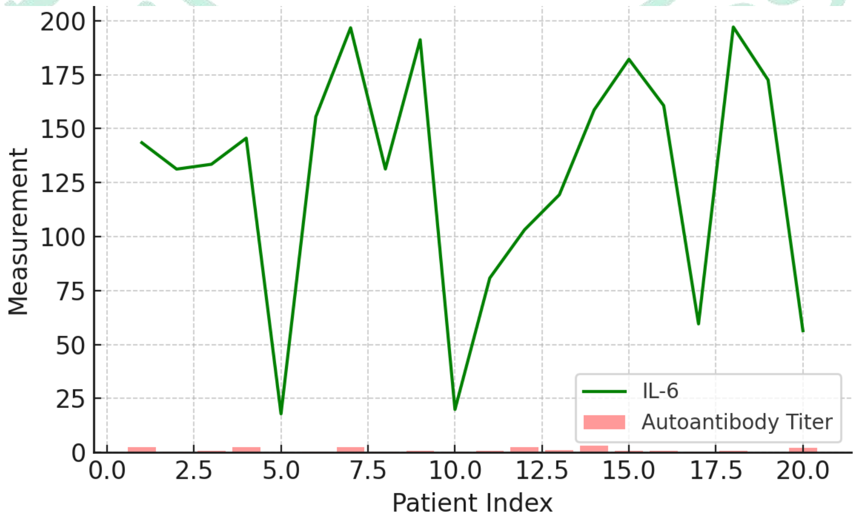

Figure 12: Visualization of immunological data

DISCUSSION

These are only some of the results that can be achieved by the use of such algorithms such as real-time monitoring of illness progression, tailored therapeutic treatments, and high levels of diagnostic precision (Zhang and others, 2023) (Nia and others, 2023). Artificial intelligence and machine learning can enhance every aspect of medicine diagnostics, prognosis, and treatment and make them more precise and efficient (Khandelwal, 2021). Using AI with medical image processing will play a vital role in the diagnosis, therapy planning, and prediction (Nia et al., 2023). Privacy issues and data limitations in deep learning can be resolved by the introduction of federated learning allowing different healthcare institutions to collaborate on training models without sharing sensitive patient information The increasing disparity between the quality of life and the quality of work in the United States; (Joshi et al., 2022). This technique safeguards data confidentiality by employing larger, more diverse data to enhance model accuracy and generalization through the use of bigger, more diverse data (Joshi et al., 2022). Another advantage that the collective nature of federated learning offers is the possibility of combining diverse data modalities, such as genetic, imaging, and clinical data so that diagnostic and prognostic models of autoimmune skin disorders end up being exhausted and accurate (Battineni et al., 2020) (Oyebode et al., 2022). The weaknesses of single-source data such as biases are overcome by federated learning that structures models to be exposed to a wide assortment of cases and datasets that encompass all possible anatomies in an attempt to identify more informative patterns in the medical data (Joshi et al., 2022). Such methods reduce the necessity of centralization and share information, and preserve patient privacy and avoid any data breaches on the parts of clinical records (Joshi et al., 2022). As well, federated learning facilitates the development of privacy-preserving AI models applied to the diagnosis of medical images, which is particularly useful in the scenario when it is not allowed to share the data (Dou et al., 2021) (Joshi et al., 2022). Federated learning enhances the accuracy of models, especially when used with different non-homogenous data, by aggregating clinical records of multiple healthcare facilities under the regulations of privacy laws (Dang et al., 2022). (Joshi et al., 2022). Therefore, federated learning can ensure patient privacy and enhance the external validity of the model, which illustrates that it can be an effective instrument in using electronic health records to address health problems (Dang et al., 2022). Federated learning can prevent these limitations of centralized datasets by making it possible to train AI models in collaboration based on distributed data in a way that does not involve sharing data directly. It extracts information about healthcare using data scattered across the world and makes it accessible to categories of realization at the level of individual institutions (Li et al., 2025) (Gupta et al., 2025). This approach also lays emphasis on safeguarding the privacy of the data, as only mathematical parameters and metadata are exchanged, and the actual data remains as secure as possible under the risk of hacking and tracing attacks (Joshi et al., 2022). In contrast to the centralized data storage approach, federated learning offers a more feasible approach to collaborative model training in multiple centers, where it is not essential to mix data in a single location given the magnitude of costs required to establish and maintain infrastructure capable of managing centralized data storage (Dang et al., 2022). One of the great applications of federated learning is working with multiple types of data and predicting rare diseases. It is also capable of competing or exceeding localized model especially in case of limited local data (Joshi & Joseph, 2025). In this way, the participants of health research will be able to fulfill their role in scientific accomplishments and retain control over the data used by them (Sadilek et al., 2021). With the growth in interest in using common data models to facilitate collaboration, data harmonization is a necessary federated learning site (Dang et al., 2022). As opposed to conventional centralized statistical models, federated learning provides greater privacy security with no loss of accuracy, precision, and generalizability (Sadilek et al., 2021). Federated learning has particular applicability in the healthcare domain where data privacy is critical because it may allow co-operative AI training that keeps the resulting data and knowledge confidential (Shukla et al., 2025). The federated learning enhances data security and privacy of patients because it enables AI models training through local devices without disclosure of sensitive information (Joshi et al., 2022). It also enhances the ease of collaboration across institutions in training, thereby increasing equity and combining various modes of data into comprehensive modeling in diagnostics (Zhang et al., 2025) (Rehman et al., 2023).

CONCLUSION

Through a mixed-method experimental study, the current research combined the three-fold detail of molecular, histological and clinical to give a paper account of the imperative role played by immuno-dermatology in terms of diagnosis, monitoring and individualized treatment of uncommon autoimmune skin diseases. These findings verify that the combination of immunological biomarkers, such as autoantibodies, TNF-alpha and IL-6 coupled with histopathological and direct immunofluorescence outcomes has enormous predictive ability concerning diagnosis of disease activity and treatment outcomes. As it is regressed, those who had lower anti-desmoglein showed better outcomes of treatment outcome over time as compared to those cytokine had greater levels which were further found to have significant correlations with disease severity scores. Gene expression profiles enabled them to discriminate between diseases further with gene expression profiles enhanced the specificity particularly in dermatomyositis and pemphigus subtypes due to the detection of specific molecular fingerprint of the diseases. The theme analysis of the qualitative interview shed some light on the patient views on the disease burden, flares, and adherence to medication and complemented the clinical data to integrate it into the more empathetic model of care. Along with the soundness of conventional inferential procedures, the combined system proposed a new stratification algorithm that fits immunological measures with individualized prognosis. The fact that immunodermatology can be aptly termed as one of the cornerstones of dermatological precision therapy is further emphasized by the fact that the methodological structure of the current study offers room for scalability and application to broader autoimmune diseases. Dermatologists, immunologists, and molecular scientists will need to collaborate across the disciplines in order to invent patient-centered flexible care models to address uncommon and complex skin diseases. To achieve the maximum diagnosis, improve results, set future translational research agendas, the synthesis of the available information advocates the development of the immunodermatology clinics to be established within the tertiary care facilities.

REFERENCES

Alrabai, A., Echtioui, A., & Kallel, F. (2025). Exploring Pre-Trained Models for Skin

Cancer Classification. Applied System Innovation, 8(2), 35.

Battineni, G., Sagaro, G. G., Chinatalapudi, N., & Amenta, F. (2020). Applications of Machine Learning Predictive Models in the Chronic Disease Diagnosis [Review of Applications of Machine Learning Predictive Models in the Chronic Disease Diagnosis]. Journal of Personalized Medicine, 10(2), 21. Multidisciplinary Digital Publishing Institute.

Chan, S., Reddy, V., Myers, B., Thibodeaux, Q., Brownstone, N., & Liao, W. (2020). Machine Learning in Dermatology: Current Applications, Opportunities, and Limitations [Review of Machine Learning in Dermatology: Current Applications, Opportunities, and Limitations]. Dermatology and Therapy, 10(3), 365. Adis, Springer Healthcare.

Dang, T. K., Xiang, L., Weng, J., & Feng, M. (2022). Federated Learning for Electronic Health Records. ACM Transactions on Intelligent Systems and Technology, 13(5), 1.

De, A. (2020). Next-generation technologies in dermatology: Use of artificial intelligence and mobile applications. Indian Journal of Dermatology, 65(5), 351.

De, A., Sarda, A., Gupta, S., & Das, S. (2020). Use of artificial intelligence in dermatology. Indian Journal of Dermatology, 65(5), 352.

Debelee, T. G. (2023). Skin Lesion Classification and Detection Using Machine Learning Techniques: A Systematic Review [Review of Skin Lesion Classification and Detection Using Machine Learning Techniques: A Systematic Review]. Diagnostics, 13(19), 3147. Multidisciplinary Digital Publishing Institute.

Dou, Q., So, T. Y., Jiang, M., Liu, Q., Vardhanabhuti, V., Kaissis, G., Li, Z., Si, W., Lee, H. H. C., Yu, K., Feng, Z., Dong, L., Burian, E., Jungmann, F., Braren, R., Makowski, M. R., Kainz, B., Rueckert, D., Glocker, B., … Heng, P. (2021). Federated deep learning for detecting COVID-19 lung abnormalities in CT: a privacy-preserving multinational validation study. Npj Digital Medicine, 4(1).

Elder, A., Ring, C., Heitmiller, K., Gabriel, Z., & Saedi, N. (2020). The role of artificial intelligence in cosmetic dermatology—Current, upcoming, and future trends. Journal of Cosmetic Dermatology, 20(1), 48.

Escalé-Besa, A., Vidal-Alaball, J., Catalina, Q. M., Gracia, V. H. G., Marín-Gomez, F. X., & Fuster-Casanovas, A. (2024). The Use of Artificial Intelligence for Skin Disease Diagnosis in Primary Care Settings: A Systematic Review [Review of The Use of Artificial Intelligence for Skin Disease Diagnosis in Primary Care Settings: A Systematic Review]. Healthcare, 12(12), 1192. Multidisciplinary Digital Publishing Institute.

Göçeri, E. (2020). Deep learning based classification of facial dermatological disorders. Computers in Biology and Medicine, 128, 104118.

Goyal, M., Knackstedt, T., Yan, S., & Hassanpour, S. (2020). Artificial intelligence-based image classification methods for diagnosis of skin cancer: Challenges and opportunities [Review of Artificial intelligence-based image classification methods for diagnosis of skin cancer: Challenges and opportunities]. Computers in Biology and Medicine, 127, 104065. Elsevier BV.

Gupta, C., Gill, N. S., Gulia, P., Alduaiji, N., Shreyas, J., & Shukla, P. K. (2025). Applying YOLOv6 as an ensemble federated learning framework to classify breast cancer pathology images. Scientific Reports, 15(1).

Hirani, R., Noruzi, K., Khuram, H., Hussaini, A. S., Aifuwa, E., Ely, K., Lewis, J. M., Gabr, A. E., Smiley, A., Tiwari, R. K., & Etienne, M. (2024). Artificial Intelligence and Healthcare: A Journey through History, Present Innovations, and Future Possibilities. Life, 14(5), 557.

Jairath, N., Pahalyants, V., Shah, R., Weed, J., Carucci, J. A., & Criscito, M. C. (2024). Artificial Intelligence in Dermatology: A Systematic Review of Its Applications in Melanoma and Keratinocyte Carcinoma Diagnosis [Review of Artificial Intelligence in Dermatology: A Systematic Review of Its Applications in Melanoma and Keratinocyte Carcinoma Diagnosis]. Dermatologic Surgery, 50(9), 791. Lippincott Williams & Wilkins.

Jeong, H. K., Park, C., Henao, R., & Kheterpal, M. (2022). Deep Learning in Dermatology: A Systematic Review of Current Approaches, Outcomes, and Limitations [Review of Deep Learning in Dermatology: A Systematic Review of Current Approaches, Outcomes, and Limitations]. JID Innovations, 3(1), 100150. Elsevier BV.

Joseph, J., & Lalchand, T. C. (2024). The synergy of skin and science – A comprehensive review of artificial intelligence's impact on dermatology [Review of The synergy of skin and science – A comprehensive review of artificial intelligence's impact on dermatology]. Cosmoderma, 4, 48.

Joshi, H., & Joseph, S. (2025). Standardization and Interoperability: Federated Learning's Impact on EHR Systems and Health Informatics.

Joshi, M., Pal, A., & Sankarasubbu, M. (2022). Federated Learning for Healthcare Domain - Pipeline, Applications and Challenges. ACM Transactions on Computing for Healthcare, 3(4),

Kang, H., Wu, M., Feng, J., Ren, Y., Liu, Y., Shi, W., Peng, Y., Tan, Y., Wu, R., Zhang, G., & He, Y. (2022). Ocular surface disorders affect quality of life in patients with autoimmune blistering skin diseases: a cross-sectional study. BMC Ophthalmology, 22(1).

Khandelwal, S. (2021). REVIEW OF INCLUSION OF MACHINE LEARNING TECHNIQUES IN MEDICINE FIELD. International Journal of Engineering Applied Sciences and Technology, 6(5).

Kololgi, S. P., & Lahari, C. S. (2023). Harnessing the Power of Artificial Intelligence in

Dermatology: A Comprehensive Commentary. Indian Journal of Dermatology, 68(6), 678.

Li, M., Xu, P., Hu, J., Tang, Z., & Yang, G. (2025). From challenges and pitfalls to recommendations and opportunities: Implementing federated learning in healthcare [Review of From challenges and pitfalls to recommendations and opportunities: Implementing federated learning in healthcare]. Medical Image Analysis, 101, 103497. Elsevier BV.

Li, Z., Koban, K. C., Schenck, T. L., Giunta, R. E., Li, Q., & Sun, Y. (2022). Artificial Intelligence in Dermatology Image Analysis: Current Developments and Future Trends [Review of Artificial Intelligence in Dermatology Image Analysis: Current Developments and Future Trends]. Journal of Clinical Medicine, 11(22), 6826. Multidisciplinary Digital Publishing Institute.

Liopyris, K., Gregoriou, S., Dias, J., & Stratigos, A. (2022, October 28). Artificial Intelligence in Dermatology: Challenges and Perspectives. In Dermatology and Therapy (Vol. 12, Issue 12, p. 2637). Adis, Springer Healthcare.

Malik, S., Jamil, S. S., Aziz, A., Ullah, S., Ullah, I., & Abohashrh, M. (2024). High-Precision Skin Disease Diagnosis through Deep Learning on Dermoscopic Images. Bioengineering, 11(9), 867.

Moldovanu, S., Michis, F. A. D., Biswas, K. C., Florescu, A., & Moraru, L. (2021). Skin Lesion Classification Based on Surface Fractal Dimensions and Statistical Color Cluster Features Using an Ensemble of Machine Learning Techniques. Cancers, 13(21), 5256.

Muhaba, K. A., Dese, K., Aga, T. M., Zewdu, F. T., & Simegn, G. L. (2021). Automatic skin disease diagnosis using deep learning from clinical image and patient information. Skin Health and Disease, 2(1).

Nasayreh, A., Khalid, H. M., Alkhateeb, H. K., Al-Manaseer, J., Ismail, A., & Gharaibeh, H. (2024). Automated Detection of Cyber Attacks in Healthcare Systems: A Novel Scheme with Advanced Feature Extraction and Classification. Computers & Security, 104288.

Nia, N. G., Kaplanoğlu, E., & Nasab, A. (2023). Evaluation of artificial intelligence techniques in disease diagnosis and prediction [Review of Evaluation of artificial intelligence techniques in disease diagnosis and prediction]. Discover Artificial Intelligence, 3(1). Springer Nature.

Omiye, J. A., Gui, H., Daneshjou, R., Cai, Z. R., & Muralidharan, V. (2023). Principles, applications, and future of artificial intelligence in dermatology [Review of Principles, applications, and future of artificial intelligence in dermatology]. Frontiers in Medicine, 10. Frontiers Media.

Oyebode, O., Fowles, J. R., Steeves, D., & Orji, R. (2022). Machine Learning Techniques in Adaptive and Personalized Systems for Health and Wellness. International Journal of Human-Computer Interaction, 39(9), 1938.

Panagoulias, D. P., Tsoureli-Nikita, E., Virvou, M., & Tsihrintzis, G. A. (2024). Dermacen Analytica: A Novel Methodology Integrating Multi-Modal Large Language Models with Machine Learning in tele-dermatology. arXiv (Cornell University).

Rehman, M. H. ur, Pinaya, W. H. L., Nachev, P., Teo, J., Ourselin, S., & Cardoso, M. J. (2023). Federated learning for medical imaging radiology [Review of Federated learning for medical imaging radiology]. British Journal of Radiology, 96(1150). Wiley.

Sadilek, A., Liu, L., Nguyen, D. T., Kamruzzaman, M., Serghiou, S., Rader, B., Ingerman, A., Mellem, S., Kairouz, P., Nsoesie, E. O., MacFarlane, J., Vullikanti, A., Marathe, M., Eastham, P. R., Brownstein, J. S., Arcas, B. A. y, Howell, M., & Hernandez, J. (2021). Privacy-first health research with federated learning. Npj Digital Medicine, 4(1).

Salinas, M. P., Sepúlveda, J., Hidalgo, L., Peirano, D., Morel, M., Uribe, P., Rotemberg, V., Briones, J., Mery, D., & Navarrete-Dechent, C. (2024). A systematic review and meta-analysis of artificial intelligence versus clinicians for skin cancer diagnosis [Review of A systematic review and meta-analysis of artificial intelligence versus clinicians for skin cancer diagnosis]. Npj Digital Medicine, 7(1). Nature Portfolio.

Sebastiani, M., Vacchi, C., Manfredi, A., & Cassone, G. (2022). Personalized Medicine and Machine Learning: A Roadmap for the Future. Journal of Clinical Medicine, 11(14), 4110.

Sharma, M., Jain, B., Kargeti, C., Gupta, V., & Gupta, D. (2020). Detection and Diagnosis of Skin Diseases Using Residual Neural Networks (RESNET). International Journal of Image and Graphics, 21(5).

Shukla, S., Rajkumar, S., Sinha, A., Esha, M., Konguvel, E., & Vidhya, S. (2025). Federated learning with differential privacy for breast cancer diagnosis enabling secure data sharing and model integrity. Scientific Reports, 15(1).

Smith, P., Johnson, C., Haran, K., Orcales, F., Kranyak, A., Bhutani, T., Riera-Monroig, J., & Liao, W. (2024). Advancing Psoriasis Care through Artificial Intelligence: A Comprehensive Review [Review of Advancing Psoriasis Care through Artificial Intelligence: A Comprehensive Review]. Current Dermatology Reports, 13(3), 141. Springer Science+Business Media.

Szczawińska-Popłonyk, A., Popłonyk, N., & Awdi, K. (2024). Down Syndrome in Children: A Primary Immunodeficiency with Immune Dysregulation. Children, 11(10), 1251.

Tajidini, F., & Kheiri, M.-J. (2023). Recent advancement in Disease Diagnostic using machine learning: Systematic survey of decades, comparisons, and challenges. arXiv (Cornell University).

Vargas, E. M., Mora-Jiménez, J., Arguedas-Chacón, S., Hernández-López, J., & Zavaleta-

Monestel, E. (2025). The Emerging Role of Artificial Intelligence in Dermatology: A Systematic Review of Its Clinical Applications [Review of The Emerging Role of Artificial Intelligence in Dermatology: A Systematic Review of Its Clinical Applications]. Dermato, 5(2), 9.

Vatiwutipong, P., Vachmanus, S., Noraset, T., & Tuarob, S. (2023). Artificial Intelligence in Cosmetic Dermatology: A Systematic Literature Review. IEEE Access, 11, 71407.

Vuyyuru, S. K., Kedia, S., Sahu, P., & Ahuja, V. (2022). Immune-mediated inflammatory diseases of the gastrointestinal tract: Beyond Crohn's disease and ulcerative colitis [Review of Immune-mediated inflammatory diseases of the gastrointestinal tract: Beyond Crohn's disease and ulcerative colitis]. JGH Open, 6(2), 100. Wiley.

Wu, D., Shen, M., & Yao, Q. (2021). Cutaneous manifestations of autoinflammatory diseases [Review of Cutaneous manifestations of autoinflammatory diseases]. Rheumatology and Immunology Research, 2(4), 217. De Gruyter.

Yan, S., Yu, Z., Primiero, C. A., Vico-Alonso, C., Wang, Z., Yang, L., Tschandl, P., Hu, M., Ju, L., Tan, G., Tang, V., Ng, A. B., Powell, D., Bonnington, C. P., See, S., Magnaterra, E., Ferguson, P. M., Nguyen, J., Guitera, P., … Ge, Z. (2025). A multimodal vision foundation model for clinical dermatology. Nature Medicine.

Young, A. T., Xiong, M., Pfau, J., Keiser, M. J., & Wei, M. L. (2020). Artificial Intelligence in Dermatology: A Primer [Review of Artificial Intelligence in Dermatology: A Primer]. Journal of Investigative Dermatology, 140(8), 1504. Elsevier BV.

Zhang, F., Zhai, D., Bai, G. L., Jiang, J., Ye, Q., Ji, X., & Liu, X. (2025). Towards fairness-aware and privacy-preserving enhanced collaborative learning for healthcare. Nature Communications, 16(1).

Zhang, J., Zhong, F., He, K., Ji, M., Li, S., & Li, C. (2023). Recent Advancements and Perspectives in the Diagnosis of Skin Diseases Using Machine Learning and Deep Learning: A Review [Review of Recent Advancements and Perspectives in the Diagnosis of Skin Diseases Using Machine Learning and Deep Learning: A Review]. Diagnostics, 13(23), 3506. Multidisciplinary Digital Publishing Institute.

Zhou, J., & Gao, X. (2023). SkinGPT-4: An Interactive Dermatology Diagnostic System with Visual Large Language Model. arXiv (Cornell University).

Zhou, J., He, X., Sun, L., Xu, J., Chen, X., Chu, Y., Zhou, L., Liao, X., Zhang, B., Afvari, S., & Gao, X. (2024). Pre-trained multimodal large language model enhances dermatological diagnosis using SkinGPT-4. Nature Communications, 15(1).

Zhu, C., Wang, Y., Chen, H., Gao, K., Shu, C., Wang, J., Yan, L., Yang, Y., Xie, F., & Liu, J. (2021). A Deep Learning Based Framework for Diagnosing Multiple Skin

Diseases in a Clinical Environment. Frontiers in Medicine, 8.