INTERNATIONAL JOURNAL OF LATEST TECHNOLOGY IN ENGINEERING, MANAGEMENT & APPLIED SCIENCE (IJLTEMAS)

ISSN 2278-2540 | DOI: 10.51583/IJLTEMAS | Volume XV, Issue VI, June 2026

A Systematic Review of Machine Learning Approaches for Predicting Heat-Related Skin Diseases under Climate Change

Sowmya S, Kavyashree Nagarajaiah

Research Scholar, SSAHE University Tumakuru, Karnataka, India.

Associate Professor, Department of MCA SSIT, SSAHE University, Tumakuru, Karnataka, India

DOI: https://doi.org/10.51583/IJLTEMAS.2026.150600091

Received: 28 June 2026; Accepted: 03 July 2026; Published: 08 July 2026

ABSTRACT

Climate change has intensified the frequency, duration, and severity of extreme heat events, posing significant risks to human health, particularly through the increasing burden of heat-related skin diseases. Elevated temperatures, prolonged ultraviolet radiation exposure, air pollution, and changing environmental conditions have contributed to the rising incidence of conditions such as heat rash, sunburn, skin infections, dermatitis, and skin cancer, with children and older adults being especially vulnerable. Recent advances in machine learning (ML) have enabled the development of predictive models for disease diagnosis and health risk assessment; however, existing studies predominantly focus either on general heat-related health outcomes or on skin disease classification using clinical images, with limited integration of climatic, environmental, and demographic factors for forecasting heat-related skin disease risk under future climate scenarios. The survey presents a comprehensive review of the current literature on climate-driven heat-related skin diseases and the application of machine learning techniques for their prediction. The review examines major climatic and environmental determinants, vulnerable population groups, commonly used datasets, feature selection methods, and predictive algorithms, including Random Forest, Support Vector Machine, Decision Tree, Artificial Neural Networks, Gradient Boosting, and Deep Learning models. It further compares model performance, interpretability, and limitations. The survey highlights emerging research directions for developing robust and interpretable predictive frameworks capable of forecasting future heat-related skin disease risks under climate change.

Keywords: Climate Change; Heat-Related Skin Diseases; Machine Learning; Predictive Modeling; Environmental Determinants; Skin Disease Risk Assessment; Extreme Heat; Artificial Intelligence.

INTRODUCTION

The skin is the largest organ of the human body and serves as the primary protective barrier against environmental hazards [1-2]. It performs several essential physiological functions, including regulating body temperature, preventing dehydration, protecting against harmful ultraviolet (UV) radiation and infectious agents, and facilitating sensory perception. Despite its protective role, the skin is continuously exposed to environmental stressors such as excessive heat, solar radiation, humidity, and air pollutants, making it highly susceptible to a variety of heat-related skin diseases. Common conditions include heat rash, sunburn, dermatitis, fungal infections, bacterial infections, and, with prolonged exposure, an increased risk of skin cancer. Early detection and accurate prediction of these diseases are essential for timely intervention, reducing disease severity, and improving public health outcomes [3-6].

Climate change has emerged as one of the greatest global public health challenges of the twenty-first century. Rising global temperatures have increased the frequency, intensity, and duration of extreme heat events and heat waves across many regions of the world [7-10]. These climatic changes have resulted in significant health consequences, including increased mortality, hospital admissions, and healthcare resource utilization. Although cardiovascular, respiratory, and renal diseases have received considerable attention in heat-health research, heat-related skin diseases remain comparatively underexplored despite being among the earliest and most visible

ISSN 2278-2540 | DOI: 10.51583/IJLTEMAS | Volume XV, Issue VI, June 2026

health effects of prolonged heat exposure. Vulnerable populations, particularly children, older adults, outdoor workers, and individuals with chronic illnesses or low socioeconomic status, are disproportionately affected due to reduced thermoregulatory capacity and greater exposure to extreme environmental conditions.

The growing availability of environmental monitoring systems, electronic health records, satellite observations, and climate datasets has created new opportunities for data-driven disease prediction. In recent years, artificial intelligence (AI), particularly machine learning (ML), has demonstrated remarkable potential in healthcare by identifying complex and non-linear relationships among large-scale datasets. ML algorithms such as Random Forest, Support Vector Machine, Decision Tree, Gradient Boosting, Artificial Neural Networks, and Deep Learning have been widely applied in disease diagnosis, medical image analysis, epidemiological forecasting, and environmental health studies. Compared with traditional statistical approaches, these techniques can efficiently analyze heterogeneous data, improve prediction accuracy, and support evidence-based decision-making [11-14].

Several review studies have summarized the application of machine learning in dermatology, environmental epidemiology, air pollution, vector-borne diseases, and heat-related health outcomes [15-18]. However, existing reviews primarily focus on either image-based skin disease classification or general heat-related illnesses such as heatstroke, mortality, and hospital admissions. Very limited attention has been given to integrating climatic variables, environmental determinants, demographic characteristics, and future climate projections for predicting heat-related skin disease risk. Furthermore, issues such as model interpretability, explainable artificial intelligence, spatiotemporal analysis, climate scenario integration, and region-specific prediction remain insufficiently investigated.

To address these gaps, this survey presents a comprehensive review of machine learning techniques for modeling heat-related skin disease risk under climate change. The review examines the influence of climatic and environmental determinants, identifies vulnerable population groups, summarizes commonly used datasets and predictive algorithms, and compares their strengths and limitations. It also discusses model evaluation techniques, interpretability methods, and emerging trends, including explainable AI and climate-informed predictive modeling. Finally, the survey highlights current research challenges and future directions for developing robust, interpretable, and climate-resilient machine learning frameworks that can support early disease prediction, healthcare planning, and evidence-based public health interventions in the face of increasing global temperatures.

LITERATURE REVIEW

Recent research demonstrates that climate change has emerged as one of the most significant environmental challenges affecting human health, particularly through increasing heat stress, extreme weather events, and the growing prevalence of skin and cardiovascular diseases. Lee and Kwon (2023; 2024) emphasized that rising global temperatures and ultraviolet (UV) radiation adversely affect skin health, leading to increased risks of dermatitis, psoriasis, melanoma, photoaging, and other dermatological disorders. Their systematic reviews highlighted the growing role of artificial intelligence (AI)-based customized cosmetics and sustainable heat-resistant ingredients, such as Hsian-Tsao, in improving skin protection and supporting climate-adaptive healthcare. Similarly, Basha et al. (2022) investigated the relationship between climatic variables and erythemato-squamous skin diseases, demonstrating that machine learning techniques can successfully identify highly correlated weather parameters responsible for disease occurrence, thereby improving predictive healthcare systems. Several review studies have focused on the application of machine learning in climate-sensitive healthcare. Boudreault et al. (2025) conducted a comprehensive review of machine learning applications for modelling extreme heat-related health outcomes and concluded that Random Forest remains the most widely adopted algorithm, while future studies should incorporate deep learning models with high-resolution spatiotemporal datasets. Likewise, Ssebyala et al. (2024) reviewed machine learning techniques for predicting health risks from climate-sensitive extreme weather events and found that algorithms such as Logistic Regression, Random Forest, Decision Trees, Support Vector Machines, and Bayesian approaches effectively predicted mortality, heat-related illnesses, and post-traumatic stress disorders. However, the authors emphasized the urgent need for standardized climate-health datasets to improve model generalizability.

ISSN 2278-2540 | DOI: 10.51583/IJLTEMAS | Volume XV, Issue VI, June 2026

The integration of multimodal environmental and healthcare data has further enhanced disease prediction capabilities. Tiwari et al. (2025) proposed a climate-aware healthcare framework integrating meteorological, environmental, and clinical datasets for disease outbreak prediction, demonstrating that multimodal machine learning significantly improves predictive performance compared with conventional approaches. Islam et al. (2025) similarly highlighted the increasing frequency and intensity of heat waves due to climate change and advocated the use of data-driven analytical frameworks for climate adaptation and heat stress mitigation. Aldosary et al. (2025) extended this concept by applying ensemble machine learning techniques to forecast climate risk and specific humidity in arid ecosystems, thereby improving heat hazard prediction and environmental risk assessment. Recent clinical investigations have demonstrated the practical application of machine learning in predicting heat-related health outcomes. Hirano et al. (2021) developed machine learning-based mortality prediction models using multicentre heat illness registry data and reported that XGBoost achieved superior predictive performance compared with conventional APACHE-II clinical scoring systems. Similarly, Javari and Javari (2026) combined epidemiological modelling with machine learning techniques to investigate cardiovascular hospitalizations associated with heat stress. Their study identified Heat Index, Wet Bulb Globe Temperature (WBGT), and age as the most influential predictors, while XGBoost produced the highest classification accuracy for prolonged hospitalization. Forbes et al. (2025) further compared traditional thermo physiological models with machine learning algorithms for predicting rectal and skin temperatures among older adults exposed to prolonged heat conditions. Their findings demonstrated that Ridge Regression significantly outperformed conventional biophysical models, indicating the potential of machine learning for personalized heat-risk monitoring.

Artificial intelligence has also transformed dermatological diagnosis through deep learning. Alzaeemi et al. (2026) developed an InceptionV3-based convolutional neural network for pediatric skin disease classification, achieving high diagnostic accuracy and demonstrating the effectiveness of transfer learning for early disease detection. Similar advances in image-based classification have encouraged wider adoption of convolutional neural networks for automated dermatological diagnosis, particularly in regions with limited specialist availability. Collectively, the reviewed studies consistently demonstrate that climate change is increasingly influencing public health through direct and indirect pathways, including heat stress, cardiovascular complications, infectious diseases, and skin disorders. Machine learning and artificial intelligence have emerged as powerful tools for analysing complex environmental and clinical datasets, enabling accurate prediction, early diagnosis, and personalized healthcare interventions. Although significant progress has been achieved, several studies identified limitations such as small datasets, limited geographical diversity, lack of standardized climate-health databases, and insufficient integration of multimodal information. Future research should therefore focus on developing large-scale, standardized datasets, incorporating advanced deep learning architectures, explainable artificial intelligence techniques, and real-time environmental monitoring systems to improve prediction accuracy and support climate-resilient healthcare systems.

Table 1: Summary of Existing Literature on Artificial Intelligence and Machine Learning Applications for Climate-Related Health Prediction

Ref. No.	Authors	Dataset Used	Objectives	Methods	**RESULTS**
19	Lee & Kwon (2024)	1308 records; 65 eligible studies	Review AI-tailored cosmetics for climate-related skin health	PRISMA systematic review	AI-supported personalized cosmetics improve climate-adaptive skin care.
20	Basha et al. (2022)	Climate & dermatology dataset (49 attributes)	Predict erythemato-squamous diseases	ML + Pearson correlation	23 climate attributes significantly associated with disease.

INTERNATIONAL JOURNAL OF LATEST TECHNOLOGY IN ENGINEERING, MANAGEMENT & APPLIED SCIENCE (IJLTEMAS)

ISSN 2278-2540 | DOI: 10.51583/IJLTEMAS | Volume XV, Issue VI, June 2026

21	Boudreault et al. (2025)	25 ML studies	Review ML for extreme heat health impacts	Comprehensive literature review	Random Forest most common; recommends deep learning.
22	Ssebyala et al. (2024)	6096 records; 7 studies	Review ML for climate-sensitive health risks	Scoping review	ML predicts mortality, heat illness and PTSD.
23	Tiwari et al. (2025)	50 health & weather attributes	Disease outbreak prediction	XGBoost + SHAP	99.2% accuracy using multimodal data.
24	Forbes et al. (2025)	76 adults;162 sessions	Predict core & skin temperature	Ridge Regression vs biophysical models	Ridge Regression best (RMSE 0.27°C).
25	Islam et al. (2025)	Historical climate datasets	Review heatwave prediction	ML, LSTM, ARIMA, SARIMA	Hybrid ML improves heatwave forecasting.
26	Javari & Javari (2026)	Hospital + ERA5 climate data	Heat stress & CVD hospitalization	DLNM, RF, XGBoost, SHAP	Heat Index and WBGT strongly associated with hospitalization.
27	Aldosary et al. (2025)	Daily climate data (1982–2023)	Forecast humidity & heat hazards	SVM, RF, LightGBM, XGBoost	LightGBM/XGBoost achieved $R^2 \approx 0.999$.
28	Hirano et al. (2021)	2393 heat illness patients	Mortality prediction	LR, SVM, RF, XGBoost	XGBoost outperformed APACHE-II.
29	Sousan et al. (2026)	30 agricultural workers	Evaluate wearable heat monitoring	RF, GBR, regression	RF achieved $R^2=0.96$ for heat strain prediction.
30	Wang et al. (2022)	Climate chamber thermal sensation study	Predict thermal sensation from skin temperature	Correlation & sensitivity analysis	Chest skin temperature best predictor.
31	Tikarya et al. (2023)	Review of cattle skin disease datasets	Review CNN for disease detection	Deep learning review	CNNs improve early disease identification.
32	Anderson et al. (2023)	Perspective review	Climate change impacts on skin health	Narrative review	Climate change increases dermatological risks.
33	Alzaeemi et al. (2026)	520 pediatric skin images	Website-based skin disease diagnosis	InceptionV3 CNN	~88% classification accuracy.

ISSN 2278-2540 | DOI: 10.51583/IJLTEMAS | Volume XV, Issue VI, June 2026

34	Wu et al. (2022)	PLA/CeO_2 composite experiments	Develop UV-protective film	Material characterization	99.3% UV reduction with improved strength.
35	Lee & Kwon (2023)	107 selected studies	Sustainable skin protection	Systematic review	Hsian-Tsao identified as promising heat-resistant ingredient.

METHODOLOGY

The survey paper was conducted using a systematic literature review approach to investigate recent advances in machine learning (ML) and artificial intelligence (AI) for climate-related health prediction, heat stress assessment, and skin disease diagnosis. Relevant peer-reviewed journal articles and review papers published between 2021 and 2026 were selected from high-quality scientific databases based on their relevance to climate change, heat-health modelling, dermatological disease prediction, and intelligent healthcare systems.

The reviewed studies primarily followed the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) framework or similar systematic review methodologies. Most studies searched multiple scientific databases, including PubMed, Scopus, Web of Science, Embase, and MEDLINE, using combinations of keywords such as machine learning, artificial intelligence, heat stress, climate change, heatwave, skin disease, thermal sensation, prediction, and healthcare. Duplicate articles were removed, followed by title screening, abstract screening, and full-text eligibility assessment according to predefined inclusion and exclusion criteria.

The selected studies covered diverse healthcare applications, including prediction of heat-related mortality and morbidity, development of Heat Health Warning Systems (HHWS), classification of dermatological diseases using deep learning, and identification of climate-sensitive diseases. Various environmental datasets consisting of meteorological variables (air temperature, humidity, Wet Bulb Globe Temperature, Heat Index, apparent temperature, solar radiation, and wind speed) were integrated with clinical and epidemiological datasets containing hospital admissions, mortality records, physiological measurements, wearable sensor data, and skin lesion images.

Machine learning techniques [36-41] employed across the reviewed studies included Random Forest (RF), eXtreme Gradient Boosting (XGBoost), Support Vector Machine (SVM), Decision Tree (DT), Logistic Regression (LR), Artificial Neural Networks (ANN), Convolutional Neural Networks (CNN), Gradient Boosting Regression (GBR), Ridge Regression, Light Gradient Boosting Machine (LightGBM), Long Short-Term Memory (LSTM), and ensemble learning methods. Recent studies also incorporated Explainable Artificial Intelligence (XAI) techniques, particularly SHapley Additive exPlanations (SHAP), to improve model interpretability and identify influential environmental and clinical variables.

The extracted information from each study included publication year, study objectives, datasets, machine learning algorithms, environmental and clinical predictors, validation strategies, evaluation metrics, and major findings. Comparative analysis was subsequently performed to identify common research trends, strengths, limitations, and existing research gaps in climate-aware healthcare and intelligent skin disease prediction systems.

DISCUSSION

The reviewed literature demonstrates that climate change has significantly increased the frequency and intensity of heatwaves, thereby elevating the global burden of heat-related illnesses, cardiovascular disorders, respiratory diseases, skin diseases, and mortality. Machine learning has emerged as a powerful computational tool capable of modelling complex nonlinear relationships between environmental variables and human health outcomes, enabling more accurate prediction than conventional statistical approaches.

INTERNATIONAL JOURNAL OF LATEST TECHNOLOGY IN ENGINEERING, MANAGEMENT & APPLIED SCIENCE (IJLTEMAS)
ISSN 2278-2540 | DOI: 10.51583/IJLTEMAS | Volume XV, Issue VI, June 2026

Among the reviewed algorithms, Random Forest and XGBoost were the most frequently adopted models because of their robustness, ability to handle nonlinear relationships, resistance to overfitting, and superior predictive performance. Deep learning models, particularly Convolutional Neural Networks, have shown remarkable success in automated skin disease classification by learning discriminative image features directly from dermatological images without manual feature engineering. Ensemble learning approaches, including LightGBM and Gradient Boosting models, consistently demonstrated improved predictive accuracy for climate-sensitive health outcomes.

Most studies integrated meteorological variables such as air temperature, relative humidity, Wet Bulb Globe Temperature (WBGT), Heat Index, apparent temperature, and solar radiation with healthcare datasets. Several investigations further incorporated demographic characteristics, physiological measurements obtained from wearable sensors, hospital admission records, mortality databases, and medical histories to improve prediction performance. Explainable Artificial Intelligence methods, particularly SHAP, were increasingly adopted to improve transparency and identify the most influential predictors contributing to disease occurrence.

Although substantial progress has been achieved, several important limitations remain. Most studies relied on geographically restricted datasets collected from developed countries, reducing model generalizability across diverse climatic regions. Publicly available multimodal datasets integrating environmental, physiological, and dermatological information remain scarce. Dataset imbalance, limited external validation, insufficient consideration of socioeconomic determinants, and lack of standardized benchmark datasets continue to affect the reproducibility and clinical deployment of machine learning models.

The literature also reveals that current Heat Health Warning Systems primarily depend on temperature thresholds while overlooking individualized physiological responses, wearable sensor measurements, built-environment characteristics, and real-time health monitoring. Future intelligent warning systems should integrate environmental monitoring, wearable Internet of Things (IoT) devices, satellite observations, electronic health records, and explainable deep learning frameworks to provide personalized early warning systems. Similarly, future dermatological research should combine climate variables with skin image analysis to investigate climate-induced skin diseases more comprehensively.

The reviewed studies indicate that integrating artificial intelligence, climate science, environmental monitoring, and healthcare analytics provides a promising direction for developing intelligent decision-support systems capable of improving early diagnosis, disease surveillance, personalized healthcare, and climate resilience. Future research should prioritize large-scale multicenter datasets, explainable machine learning, multimodal data fusion, federated learning, and real-time predictive systems to facilitate reliable and clinically applicable climate-aware healthcare solutions.

CONCLUSION

This survey provides a comprehensive review of the current research on heat-related skin diseases and the application of machine learning techniques for predicting disease risk under changing climatic conditions. The findings demonstrate that climate change, characterized by rising temperatures, increasing heat waves, and changing environmental conditions, has significantly increased the burden of heat-related skin diseases, particularly among vulnerable populations such as children, older adults, and individuals with prolonged outdoor exposure. Climatic variables including temperature, humidity, ultraviolet radiation, and air pollution, together with demographic and socioeconomic factors, play a crucial role in influencing disease occurrence and progression.

The review also highlights the growing adoption of machine learning techniques in healthcare and environmental health research. Algorithms such as Random Forest, Support Vector Machine, Decision Tree, Gradient Boosting Decision Tree, Convolutional Neural Networks, and Deep Learning models have demonstrated considerable potential for disease prediction and risk assessment. Nevertheless, existing studies primarily focus either on skin disease classification using medical images or on general heat-related health outcomes such as mortality,

ISSN 2278-2540 | DOI: 10.51583/IJLTEMAS | Volume XV, Issue VI, June 2026

heatstroke, and hospital admissions. Limited research has addressed the integration of climatic, environmental, and clinical data for predicting heat-related skin disease risk under future climate change scenarios.

Future research should focus on developing interpretable machine learning frameworks that combine climatic, environmental, clinical, and socioeconomic data from multiple regions. The incorporation of advanced deep learning techniques, explainable AI, climate projections, and geospatial analytics can improve prediction accuracy while enhancing model transparency and generalizability. Such predictive frameworks will assist healthcare professionals and policymakers in identifying high-risk populations, optimizing healthcare resource allocation, strengthening heat action plans, and improving climate adaptation strategies. Overall, this survey establishes a comprehensive knowledge base and identifies future research directions for developing robust machine learning systems capable of forecasting heat-related skin disease risk and supporting climate-resilient healthcare systems.

REFERENCES

1. Dirk Roosterman, Tobias Goerge, Stefan W. Schneider, Nigel W. Bunnett, and Martin Steinhoff, “Neuronal Control of Skin Function: The Skin as a Neuroimmunoendocrine Organ”, Physiological Reviews 2006 86:4, 1309-1379 10.1152/physrev.00026.2005
2. Oláh, A., Szöllősi, A.G., Bíró, T. (2012). The Channel Physiology of the Skin. In: Nilius, B., et al. Reviews of Physiology, Biochemistry and Pharmacology, Vol. 163. Reviews of Physiology, Biochemistry and Pharmacology, vol 163. Springer, Berlin, Heidelberg. https://doi.org/10.1007/112_2012_7
3. Goldust, M. and Grant-Kels, J.M. (2024), Using AI to help address skin health challenges caused by climate change. Int J Dermatol, 63: e126-e127. https://doi.org/10.1111/ijd.17222
4. Karolina Mieczkowska, Thomas Stringer, John S. Barbieri, Mary Williams, Misha Rosenbach, Surveying the attitudes of dermatologists regarding climate change, British Journal of Dermatology, Volume 186, Issue 4, 1 April 2022, Pages 748–750, https://doi.org/10.1111/bjd.20900
5. Shen CZ, Zhao AT, Rotemberg V, Daneshjou R, Parker ER, Rosenbach M. Artificial intelligence in dermatology: Clinical promise and environmental impact. J Invest Dermatol. 2026 Jun 10:S0022-202X(26)01043-2. doi: 10.1016/j.jid.2026.03.039. Epub ahead of print. PMID: 42274450.
6. Chaisurin P, Tantranont K. Examining the Interplay Between Occupational Health Hazards and Health Status Related to Risk Among Home-Based Workers in Thailand. Workplace Health Saf. 2026 Jul;74(7):364-373. doi: 10.1177/21650799261421553. Epub 2026 Mar 16. PMID: 41834727.
7. Maini Chen, Xiangyu Li, Anrong Dang, Yang Weng, Shi Qiu, Adapting to heatwaves: Optimizing urban green spaces in Beijing to reduce heat health risks, Sustainable Cities and Society, Volume 130, 2025, 106600, ISSN 2210-6707, https://doi.org/10.1016/j.scs.2025.106600.
8. Oka, K. (2023). Heat-Related Health Impacts of Climate Change and Adaptation Strategies in Japan. In: Akhtar, R. (eds) Climate Change and Human Health Scenarios. Global Perspectives on Health Geography. Springer, Cham. https://doi.org/10.1007/978-3-031-38878-1_5
9. Wabnitz, K.J.P., Leppmeier, L., Kuempfel, R. et al. Heat, health and inequalities in the WHO European region – a scoping review with an intersectional lens. Int J Equity Health 25, 60 (2026). https://doi.org/10.1186/s12939-026-02787-1
10. Gerardo Sanchez Martinez, Vladimir Kendrovski, Miguel Antonio Salazar, Francesca de’Donato, Melanie Boeckmann, Heat-health action planning in the WHO European Region: Status and policy implications, Environmental Research, Volume 214, Part 1, 2022, 113709, ISSN 0013-9351, https://doi.org/10.1016/j.envres.2022.113709.
11. A. Rahman and M. G. Rabiul Alam, "Explainable AI based Maternal Health Risk Prediction using Machine Learning and Deep Learning," 2023 IEEE World AI IoT Congress (AIIoT), Seattle, WA, USA, 2023, pp. 0013-0018, doi: 10.1109/AIIoT58121.2023.10174540.
12. Kute, S.S., Shreyas Madhav, A.V., Kumari, S. and Aswathy, S.U. (2022). Machine Learning–Based Disease Diagnosis and Prediction for E-Healthcare System. In Advanced Analytics and Deep Learning Models (eds A. Mire, S. Malik and A.K. Tyagi). https://doi.org/10.1002/9781119792437.ch6.
13. Moulaei, K., Afshari, L., Moulaei, R. et al. Explainable artificial intelligence for stroke prediction through comparison of deep learning and machine learning models. Sci Rep 14, 31392 (2024). https://doi.org/10.1038/s41598-024-82931-5

ISSN 2278-2540 | DOI: 10.51583/IJLTEMAS | Volume XV, Issue VI, June 2026

14. Elliot Mbunge, John Batani,Application of deep learning and machine learning models to improve healthcare in sub-Saharan Africa: Emerging opportunities, trends and implications,Telematics and Informatics Reports,Volume 11,2023,100097,ISSN 2772-5030,https://doi.org/10.1016/j.teler.2023.100097.
15. Jaiyeoba, O., Ogbuju, E., Ataguba, G. et al. State-of-the-art skin disease classification: a review of deep learning models. Netw Model Anal Health Inform Bioinforma 14, 9 (2025). https://doi.org/10.1007/s13721-024-00495-w
16. Sultana, N. (2022), Predicting sun protection measures against skin diseases using machine learning approaches. J Cosmet Dermatol, 21: 758-769. https://doi.org/10.1111/jocd.14120
17. A. Mohanty, A. Sutherland, M. Bezbradica and H. Javidnia, "Skin Disease Analysis With Limited Data in Particular Rosacea: A Review and Recommended Framework," in IEEE Access, vol. 10, pp. 39045-39068, 2022, doi: 10.1109/ACCESS.2022.3165574.
18. Gulhan Bizel , Albert Einstein, Amey G Jaunjare, sharath kumar Jagannathan, Machine Learning Study: Identification of Skin Diseases for Various Skin Types Using Image Classification. Vol. 2 No. 1 (2024): JBDAI Second Volume. DOI: https://doi.org/10.54116/jbdai.v2i1.32
19. LEE, J., KWON, K.. Skin health response to climate change weather tailored cosmetics using artificial intelligence. Journal of Medical Artificial Intelligence, North America, 7, jun. 2024. Available at: <https://jmai.amegroups.org/article/view/9056>. Date accessed: 28 Jun. 2026.
20. Shaik Abdul Khalandar Basha, P. M. Durai Raj Vincent, K. Srividya, Pusarla Samyuktha, Jessu Madhumathi, "A Novel Approach to Analysis Consequence of Climate changes on Erythemato-squamous Diseases using Machine Learning Algorithms," International Journal of Engineering Trends and Technology (IJETT), vol. 70, no. 11, pp. 10-18, 2022. Crossref, https://doi.org/10.14445/22315381/IJETT-V70I11P202
21. Jérémie Boudreault, Félix Lamothe, Céline Campagna, Fateh Chebana,Machine learning for modelling the health impacts of extreme heat: A comprehensive literature review,Environment International,Volume 206,2025,109965,ISSN 0160-4120,https://doi.org/10.1016/j.envint.2025.109965.
22. Ssebyala SN, Kintu TM, Muganzi DJ, Dresser C, Demetres MR, Lai Y, et al. (2024) Use of machine learning tools to predict health risks from climate-sensitive extreme weather events: A scoping review. PLOS Clim 3(1): e0000338. https://doi.org/10.1371/journal.pclm.0000338
23. R. G. Tiwari, T. E. Nyamasvisva, N. Ibrahim, A. K. Agarwal, N. Rakesh and M. Gulhane, "Climate-Aware Healthcare: Predictive Modeling of Disease Outbreaks using Multimodal Data," 2025 4th International Conference on Innovative Mechanisms for Industry Applications (ICIMIA), Tirupur, India, 2025, pp. 1811-1816, doi: 10.1109/ICIMIA67127.2025.11200760.
24. Connor Forbes, Alberto Coccarelli, Zhiwei Xu, Robert D. Meade, Glen P. Kenny, Sebastian Binnewies, Aaron J.E. Bach,Biophysical versus machine learning models for predicting rectal and skin temperatures in older adults,Journal of Thermal Biology,Volume 128,2025,104078,ISSN 0306-4565,https://doi.org/10.1016/j.jtherbio.2025.104078.
25. Islam, S., Sinha, P., Srivastava, R.K., Khare, M. (2025). Heat Waves and Heat Stress in the Changing Climate: A Data-Driven Evaluation. In: Srivastava, R.K., Chakraborty, A. (eds) Mitigation and Adaptation Strategies Against Climate Change in Natural Systems. Environmental Earth Sciences. Springer, Cham. https://doi.org/10.1007/978-3-031-75968-0_14
26. Javari, P., Javari, M. Heat stress and cardiovascular hospitalizations in a semi-arid megacity: a multi-method epidemiological and machine-learning analysis in Isfahan, Iran. BMC Public Health 26, 1719 (2026). https://doi.org/10.1186/s12889-026-26909-0
27. Aldosary, A.S., Al-Ramadan, B., Kafy, A.A. et al. Forecasting climate risk and heat stress hazards in arid ecosystems: Machine learning and ensemble models for specific humidity prediction in Dammam, Saudi Arabia. Nat Hazards 121, 9281–9309 (2025). https://doi.org/10.1007/s11069-025-07140-3
28. Hirano, Y., Kondo, Y., Hifumi, T. et al. Machine learning-based mortality prediction model for heat-related illness. Sci Rep 11, 9501 (2021). https://doi.org/10.1038/s41598-021-88581-1
29. Sousan S, Mizelle E, Wu Q, Wu R, Iverson G, Popoviciu C, Hemedinger D, Loyola E, Hood T, Ramirez M, Balanay JA. Assessing the Feasibility of Wearable Devices for Physiological Monitoring and Heat Risk Prediction in Outdoor Agricultural Workers. Am J Ind Med. 2026 Jun 9. doi: 10.1002/ajim.70103. Epub ahead of print. PMID: 42265825.

ISSN 2278-2540 | DOI: 10.51583/IJLTEMAS | Volume XV, Issue VI, June 2026

30. Yuemei Wang, Haoyu Chang, Zhiwei Lian,Evaluation of the feasibility of using skin temperature to predict overall thermal sensation in non-uniform thermal environments,Journal of Thermal Biology,Volume 106,2022,103254,ISSN 0306-4565,https://doi.org/10.1016/j.jtherbio.2022.103254.
31. K. Tikarya, Y. V. Jain and D. Bhise, "A review: Cattle Breed and Skin Disease Identification Using Deep Learning," 2023 International Conference on Computing, Communication, and Intelligent Systems (ICCCIS), Greater Noida, India, 2023, pp. 835-842, doi: 10.1109/ICCCIS60361.2023.10425776.
32. Anderson, A., Bruce, F., Soyer, H.P., Williams, C. and Saunderson, R.B. (2023), The impact of climate change on skin health. Med J Aust, 218: 388-390. https://doi.org/10.5694/mja2.51931
33. Alzaeemi, S., Tay, K.G., Ali, G.A. et al. A website-based Skin Disease Identification using a Convolutional Neural Network for Childcare Applications. Iran J Sci Technol Trans Electr Eng (2026). https://doi.org/10.1007/s40998-026-01018-1
34. Yincai Wu, Xintu Lin, Lily Chen, Diansong Gan, Rujian Li, Yuejun Liu, Lijun Song, Xihai Hao, Tungalag Dong, Linze Liu, Fenglong Lin, Shenglong Wang,Preparation a skin disease UV protection polylactic acid film and crystallinity, mechanical properties characterization,Materials Today Communications,Volume 30,2022,103085,ISSN 2352-4928,https://doi.org/10.1016/j.mtcomm.2021.103085.
35. Lee, J.; Kwon, K.H. Sustainable Countermeasures for Skin Health Improvement for Green Consumers: The Utilization of Hsian-Tsao during Global Warming. Sustainability 2023, 15, 14619. https://doi.org/10.3390/su151914619
36. A. A. Nafea, S. A. Alameri, R. R. Majeed, M. A. Khalaf, and M. M. AL-Ani , Trans., “A Short Review on Supervised Machine Learning and Deep Learning Techniques in Computer Vision ”, Babylonian Journal of Machine Learning, vol. 2024, pp. 48–55, Feb. 2024, doi: 10.58496/BJML/2024/004.
37. M. Bkassiny, Y. Li and S. K. Jayaweera, "A Survey on Machine-Learning Techniques in Cognitive Radios," in IEEE Communications Surveys & Tutorials, vol. 15, no. 3, pp. 1136-1159, Third Quarter 2013, doi: 10.1109/SURV.2012.100412.00017.
38. Ramu, P., Thananjayan, P., Acar, E. et al. A survey of machine learning techniques in structural and multidisciplinary optimization. Struct Multidisc Optim 65, 266 (2022). https://doi.org/10.1007/s00158-022-03369-9
39. Emmanuel G. Pintelas, Theodore Kotsilieris, Ioannis E. Livieris, and Panagiotis Pintelas. 2018. A review of machine learning prediction methods for anxiety disorders. In Proceedings of the 8th International Conference on Software Development and Technologies for Enhancing Accessibility and Fighting Info-exclusion (DSAI '18). Association for Computing Machinery, New York, NY, USA, 8–15. https://doi.org/10.1145/3218585.3218587
40. Mohanty, A., Gao, G. A survey of machine learning techniques for improving Global Navigation Satellite Systems. EURASIP J. Adv. Signal Process. 2024, 73 (2024). https://doi.org/10.1186/s13634-024-01167-7
41. R. Reddy and G. K. Shyam, "Analysis Through Machine Learning Techniques: A Survey," 2018 Second International Conference on Green Computing and Internet of Things (ICGCIoT), Bangalore, India, 2018, pp. 542-546, doi: 10.1109/ICGCIoT.2018.8753050.