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SURVEY

Unveiling the Spectrum of UV-Induced DNA Damage in Melanoma: Insights From AI-Based Analysis of Environmental Factors, Repair Mechanisms, and Skin Pigment Interactions

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ABSTRACT Melanoma, a global health concern, undergoes a transformative shift in early diagnosis through the integration of artificial intelligence (AI) and environmental factors. Exposure to UVB is the main cause of DNA deterioration in skin cells. The DNA molecules absorb UVB photons, which causes the creation of photoproducts such as pyrimidine (6-4), pyrimidone photoproducts (6-4PPS), and cyclobutane pyrimidine dimers (CPDs). These photoproducts alter important genes, including those that control cell development and apoptosis. These genetic changes accumulate over time as a result of UV-induced DNA damage to melanocytes, turning normal cells into malignant melanoma cells. This study explores the incorporation of ultraviolet (UV) radiation, DNA damage, UV signature mutations, skin pigmentation, melanin biochemistry, and gene-environment interactions into AI-powered melanoma identification systems. The analysis highlights the importance of these factors, contributing to the intricacies of melanoma and emphasizing their critical inclusion in predictive models. Design goals for AI systems prioritize accuracy, customization, comprehensibility, and ethical adherence. AI emerges as a potent ally in reshaping public health initiatives, identifying high-risk areas and populations, redefining early detection, and preventing melanoma on a population-wide scale. The increased incidence of melanoma cases globally can be attributed to overexposure to ultraviolet (UV) radiation. As a significant risk component, this environmental factor is responsible for the startling increase in melanoma incidence that has been occurring since the mid-1960s. The digital dermoscopy in conjunction with AI and environmental factors has demonstrated potential to support early melanoma detection. This study underscores the potential of AI to revolutionize melanoma research, leveraging insights from UV radiation, DNA damage, UV signature mutations, skin pigmentation, melanin biochemistry, and their interactions for enhanced diagnostic capabilities and improved public health outcomes.

INDEX TERMS Skin cancer, ultraviolet (UV) radiation, environment, melanoma, analysis, detection, classification.

I. INTRODUCTION

Melanoma is an aggressive and life-threatening form of skin cancer that originates from melanocytes, the specialized cells responsible for producing the pigment melanin [1], [2]. It is regarded as the most severe type of skin cancer due to its propensity to metastasize, or spread fast to other locations inside the body, if it is not identified and treated at an early stage [3]. According to Statista, it was predicted that in 2023 there would be a total of 97,610 new melanoma skin

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cancer cases, of which 10,950 would occur in California. This statistic shows the estimated number of new cases of melanoma of the skin in the U.S. in 2023, by state [4]. In 2020, 4.77 men and 2.69 women per 100,000 population died as a result of malignant melanomas of the skin in England. The North East had the highest mortality rate for men in this year, with 5.85 men per 100,000 population dying from malignant melanomas, while the highest rate for women was in the South West at 3.22 deaths per 100,000 [5]. Exposure to ultraviolet (UV) radiation, which can come from both natural and artificial sources, is the main risk factor for melanoma. Melanoma risk can be raised by prolonged and strong exposure to UV rays from sunshine and by using indoor tanning beds. UV radiation causes DNA damage in skin cells, which results in genetic mutations that can cause malignant growths to develop [6]. Moles or pigmented skin lesions with uneven borders and asymmetry are frequent signs of melanoma. These lesions can differ from ordinary moles in terms of color, size, and shape. Although innocuous moles can occasionally resemble melanoma, this emphasizes the significance of attentive self-examination and routine skin exams by dermatologists for early detection. Effective treatment of melanoma depends on early diagnosis. Melanoma is frequently treatable with surgical removal of the malignant tissue when discovered in its early stages. Melanoma can be extremely difficult to treat and perhaps deadly if it spreads to other organs or lymph nodes as it advances [7], [8], [9].

The stage and severity of the disease determine the melanoma therapy options. In situations of advanced illness, various therapies such radiation therapy, immunotherapy, and targeted therapy may be used. Surgery is the main treatment for localized melanoma. These therapies try to destroy cancer cells, improve immune system response, or focus on particular genetic abnormalities that fuel the development of the cancer [10], [11], [12]. Figure 1 shows the origination of melanoma through melanocytes and it also shows that melanoma can spread to other locations inside the body through metastasis. The risk of melanoma can be significantly reduced through prevention. This entails engaging in sun-safe practices including using sunscreen with a high SPF, using protective gear like wide-brimmed hats and long sleeves, looking for cover during the height of the sun's rays, and refraining from indoor tanning [13], [14]. People with a history of melanoma in their families or those who have a lot of moles should be very careful to check their skin and have regular skin inspections by medical professionals [15], [16].

Melanoma is significantly influenced by environmental factors as reflected from Figure 2. UV radiation, which is produced by both natural sources like sunlight and artificial ones like tanning beds, is one of the main environmental variables associated with melanoma. Long-term, high-intensity UV radiation exposure is a recognized risk factor for developing melanoma [17], [18]. Melanocytes, the skin's pigment-producing cells, are susceptible to DNA damage from UV radiation when exposed, and this damage can result in genetic abnormalities that cause malignant growths [19], [20]. A person's geographic location and local climate have an impact on their chance of developing melanoma. Melanoma is frequently more prevalent in areas with high UV exposure levels, such as those nearer the equator or at higher elevations. Increased UV exposure in these regions, which can be brought on by elements like lower atmospheric ozone and more intense sunlight, is one reason for this geographic variance [21], [22], [23]. Lifestyle decisions and practices connected to sun exposure can have a big impact on melanoma risk. Melanoma risk can be increased by practices including tanning, long periods spent outside without protection, and sunbathing [24]. On the other hand, melanoma risk can be decreased by engaging in sun-safe behaviors including putting on sunscreen with a high sun protection factor (SPF), wearing protective clothes (such as wide-brimmed hats and long sleeves), seeking cover during peak sun hours, and refraining from indoor tanning. The interaction between environmental factors and melanoma is nuanced, with lifetime cumulative UV exposure being a key determinant. Excessive sunburns, especially in infancy or adolescence, are linked to a higher chance of developing melanoma in later life. People who work outside or participate in outdoor recreational activities are also more susceptible to UV radiation and its possible negative effects on health [25], [26].

Artificial intelligence (AI)-based melanoma detection and classification is a promising area of innovation in the healthcare industry. AI has the ability to enhance the effectiveness and precision of melanoma diagnosis and it provides a lifeline to early detection [27], [28], [29]. Convolutional neural networks (CNNs) are the foundation of deep learning algorithms employed in melanoma detection and classification systems [30]. These algorithms can learn to recognize minor patterns and traits connected to melanoma since they have been trained on enormous datasets of dermatoscopic pictures [31]. AI's primary strength is its capacity to quickly and consistently process and interpret enormous amounts of visual data. Human dermatologists may encounter fatigue, cognitive bias, and subjective variability in their judgments, whereas AI systems are not susceptible to these limitations. This objectivity reduces the possibility of missed diagnoses or false positives, strengthening the validity of AI-driven assessments. AI has the ability to offer dermatologists priceless assistance in their clinical work. Dermatologists can have the facility to examine patients with greater confidence when using AI algorithms for quick analysis and examination of skin lesion images [32], [33]. In circumstances where dermatologists are overworked, the inclusion of AI into clinical operations helps hasten the diagnosing process. However, the availability and caliber of data also play a role in how well AI detects and categorizes melanoma. To correctly train AI models, a wide variety of representative datasets are necessary. In order to be current and flexible to changing melanoma characteristics, it is also a problem to make sure that AI systems are regularly updated with new data. Researchers are

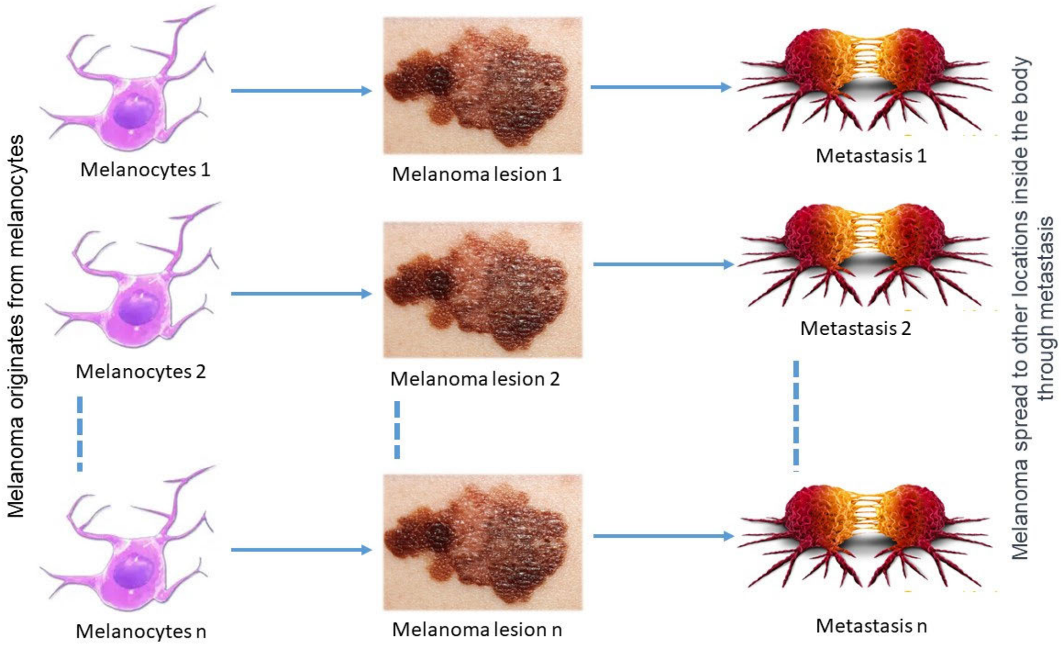

FIGURE 1. **Origination and spread of melanoma disease.**

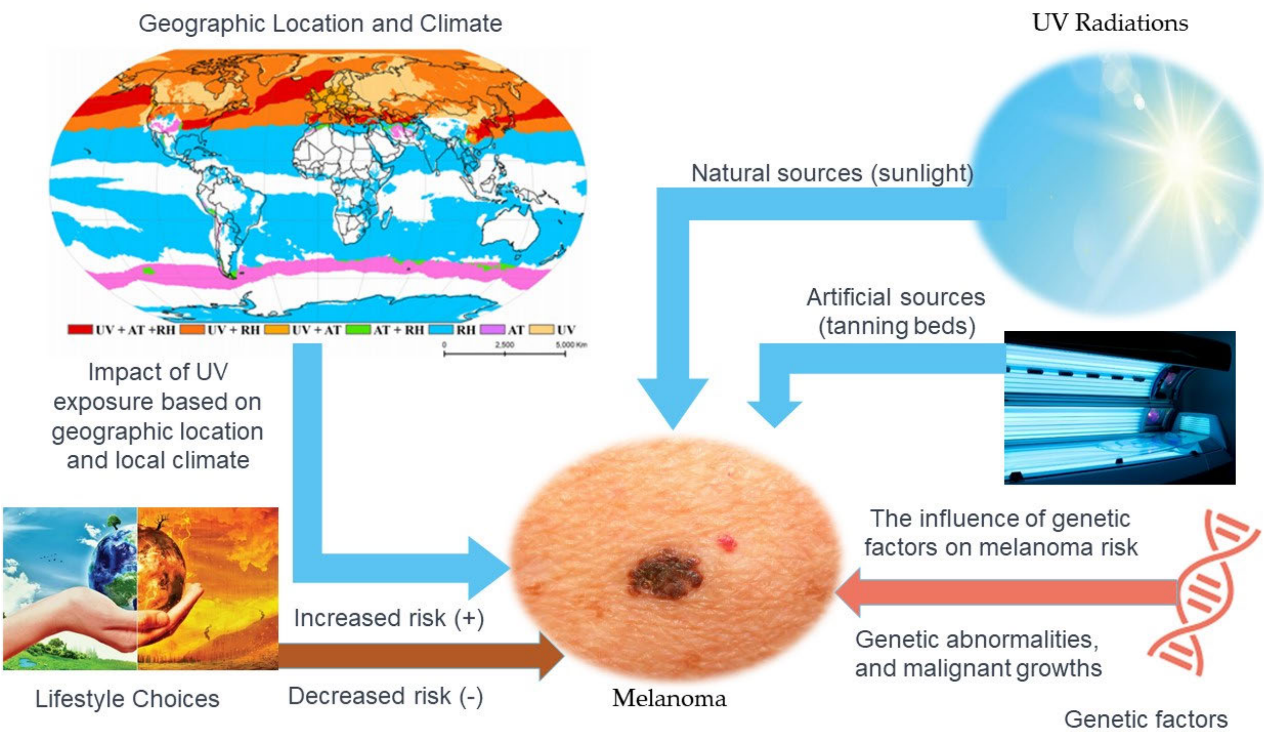

FIGURE 2. **Melanoma influenced by environmental factors.**

investigating the integration of environmental components into the AI models to improve the capabilities of AI in the detection of melanoma [27]. The effectiveness of melanoma risk assessment can therefore be increased by accounting for environmental factors like geographic location and UV radiation exposure, since AI algorithms perform well when large amounts of relevant data are available [27], [34].

Impact of environmental factors on the diagnosis and classification of the disease using artificial intelligence (AI) is an important part of melanoma research and treatment [35]. AI has a lot of potential to increase the accuracy of melanoma diagnosis, even if incorporating environmental data into AI models can add a context layer that can enhance the precision and relevance of melanoma assessments [36], [37].

It is important to recognize that exposure to ultraviolet (UV) radiation has a substantial impact on the emergence of melanoma. Excessive UV exposure come from both natural sources like sunlight and artificial ones like tanning beds is a well-known risk factor for melanoma. DNA in skin cells are damaged by UV light, leading to genetic defects that promote the development of malignant melanoma cells [38], [39], [40], [41]. An AI system may consider a person's outdoor activities, level of sun protection, and the UV index in their area when evaluating skin lesions. AI can be used to examine satellite-based data and estimate UV radiation levels across various geographies. This data can be used to identify high-risk areas and correlate them with melanoma incidence rates, enabling focused public health initiatives and awareness raising efforts [42]. Personalized risk evaluations are also made possible by the inclusion of environmental elements in AI models. AI can offer more individualized suggestions for early detection and prevention by taking into account a person's particular combination of genetic predisposition and environmental exposures [43]. There are still difficulties in gathering precise and thorough environmental data for AI models. Researchers and healthcare professionals face a number of obstacles, including the necessity for reliable data sources, data privacy concerns, and the requirement for ongoing upgrades and calibration of AI systems with changing environmental elements [44], [45], [46].

A. RESEARCH GOALS

The following are the research goals of the proposed study:

- This study aims to integrate environmental factors including geographic location and UV exposure, into AI-driven systems for melanoma detection and classification while analyzing and synthesizing existing methods.
- This study aims to identify the inadequacies and difficulties with current AI-based melanoma detection and classification models by considering environmental factors and offer possible remedies.
- This study aims to offer design guidelines for the creation of melanoma detection and classification systems powered by AI that takes into consideration environmental aspects into account.
- This study aims to utilize environmental data as a fundamental component in the algorithmic framework, to investigate fresh methodologies and AI techniques for the identification of melanoma.
- This study aims to assess the impact of AI-driven melanoma detection and classification, focusing on personalized risk assessments, early intervention, and enhanced patient outcomes.

B. RESEARCH MOTIVATION

The importance of proposed study lies in its potential to improve public health outcomes and medical procedures by deepening our understanding of the important connection between early diagnosis, melanoma illness, and environmental factors. The significance of this research is highlighted by a few significant points:

- Incidence rates for melanoma have been rising substantially in recent years. Investigating the impact of environmental factors in detection can help inform preventive efforts and shed light on how melanoma is evolving.
- Insights from this study can help preventive measures, such promoting sun-safe habits, targeted to individuals' environmental exposures, thereby lowering the risk of developing melanoma.
- Appropriate early detection and categorization using AI can optimize the distribution of healthcare resources, ensuring that people at higher risk receive screenings and interventions in a timely manner and possibly lowering healthcare expenditures.
- By incorporating environmental data into AI-driven melanoma diagnosis, it is possible to provide more individualized risk assessment and prevention advice based on each person's particular profile.
- Enhanced melanoma diagnosis and risk assessment has wider-ranging effects on public health, including decreased healthcare costs, enhanced quality of life for melanoma survivors, and raised awareness of the need for sun protection.
- As melanoma is a worldwide problem, knowledge of the environmental factors that influence its identification can be useful and applicable in a variety of locations with various UV radiation exposure levels.

The remaining sections of this article are organized as follows: We will discuss surveys and relevant literature in Section II. Section III will explain the intricate interactions between melanoma and the environment and go into how factors like UV radiation exposure, regional influences, and climate affect the growth of melanoma. Convolutional neural networks (CNNs) and other machine learning techniques will be highlighted in Section IV as it delves into the area of AI techniques used for melanoma detection and classification. Section V presents the detail of integration of environmental factors into AI-based detection and classification of melanoma. The design goals for creating AI-powered melanoma detection systems will be highlighted in Section VI. The current research concerns and challenges will be examined in Section VII to identify areas that require further research. Finally, Section VIII offers a conclusion that highlights the significance of considering environmental factors in the context of melanoma detection and classification using AI.

II. EXISTING SURVEYS

AI has brought about significant advancements in the fields of technology and medicine by enabling computers to think and act like humans. This is having a significant impact on the detection and diagnosis of melanoma. This section reviews the existing literature to explore how AI is assisting medical professionals in identifying and diagnosing melanoma.

We gain further insights into how AI can improve the detection and prevention of melanoma disease in the context of environmental factors.

A review study was conducted on a dangerous tumor called cutaneous melanoma (CM) develops from the skin's pigment-producing melanocytes [47]. The study shows that the frequency of CM has been rising over the last few decades, which presents a concerning picture of its prevalence. There were 351,880 new cases recorded globally in 2015, and this worrying trend continued in 2019 with about 96,000 new cases. This increasing burden highlights the important need for a thorough understanding of the early identification and treatment of CM, especially in light of the disease's well-known high death rate—especially when it reaches the metastatic stage. Successful therapy depends on early discovery, but the traditional diagnostic method, which uses histology, has drawbacks of its own. As a result, this paper emphasizes how important early diagnosis and treatment are to raising patient survival rates. It also emphasizes how important such information is for both quickly detecting metastases and assisting in the creation of cutting-edge treatment approaches. This article essentially acts as a compass, guiding readers through the terrain of early cancer diagnosis and treatment while providing ideas that may point the way toward a more optimistic and bright future in the fight against this aggressive cancer. A review study was conducted on the risk factors connected to cutaneous melanoma [48]. Through a thorough search of reputable resources like PubMed, Science Direct, Medline, Scopus, Scholar Google, and ISI Web of Knowledge, the authors have found relevant papers that provide insight into the complex field of melanoma risk. The increased incidence of melanoma cases globally can be attributed, in part, to overexposure to ultraviolet (UV) radiation. As a significant risk factor, this environmental factor is responsible for the startling increase in melanoma incidence that has been occurring since the mid-1960s. The review has a broad perspective, investigating the impact of individual characteristics, such as skin type, lifestyle choices, vitamin D levels, and the function of antioxidants in protecting against melanoma, as well as geographical factors, such as latitude. The integration of novel biomarkers holds the potential to unveil the complex mechanisms that underlie the pathogenesis of melanoma and individual vulnerability, thereby paving the way for the development of more efficacious preventive and therapeutic measures. This analysis emphasizes how important it is to understand the complex network of variables driving the rise in cutaneous melanoma cases while also providing hope for better targeted treatments in the ongoing fight against this deadly illness.

It is commonly known that dermoscopy can improve the accuracy of melanoma diagnoses [49]. More recently, digital dermoscopy in conjunction with artificial intelligence (AI) has demonstrated potential to support melanoma detection [50]. Nevertheless, there is not enough solid data to compare dermoscopy with AI's diagnostic accuracy in this particular situation. This study set out to assess the diagnostic accuracy of digital dermoscopy with artificial intelligence (AI) and dermoscopy in the detection of melanoma. The study also sought to examine the efficacy of several AI and dermoscopic algorithms in melanoma detection. In order to do this analysis, a comprehensive literature search was carried out using different databases, covering dermoscopy and digital dermoscopy with AI for melanoma diagnosis. Using a pre-established evaluation form, the titles and abstracts of the retrieved articles were used to filter them. To further evaluate the caliber of the studies incorporated into the analysis, a quality rating form was created. The degree of heterogeneity between the studies was assessed, and meta-analytic techniques were applied to the data in order to make comparisons between various diagnostic techniques. Thirty papers out the 765 articles that were first retrieved satisfied the requirements to be included in the meta-analysis. It was discovered that the pooled sensitivity for AI was marginally greater than that for dermoscopy (91% vs. 88%). On the other hand, dermoscopy showed noticeably higher pooled specificity than AI (86% vs. 79%). Yet, there was no discernible difference between dermoscopy and AI when looking at the diagnostic odds ratio, which offers a comprehensive assessment of diagnostic performance (51.5 vs. 57.8). No discernible variations were found in the diagnostic odds ratios across the different dermoscopic diagnostic techniques. This study indicates that for the diagnosis of melanocytic skin lesions, dermoscopy and artificial intelligence work similarly well. Moreover, no discernible differences in diagnostic efficacy across various dermoscopic techniques were found. Interestingly, some dermoscopic methods showed higher diagnostic odds ratios: the three-point checklist, the seven-point checklist, and the Menzies score. However, these results need to be confirmed A study was conducted in [51] that covers the most recent research on the genetic and behavioral risk factors for melanoma as well as strategies for improving diagnosis and lowering risk. Melanoma is a dangerous skin cancer, with an anticipated 106,110 new cases predicted in 2021 and rising incidence rates. This emphasizes how urgently preventative efforts need to be improved. Sunscreen, UV protection gear, protective clothes, and chemopreventive medications are all included in these strategies. The effectiveness of these actions is still unknown, though. The available information on preventative measures is examined in this review together with the genetic components of melanoma. To find pertinent clinical trials, observational studies, and meta-analyses about the incidence and prevention of melanoma, we carried out a thorough assessment of the literature. Information on clinical trials and epidemiology was gathered by searching online resources. There is evidence to back up community-based melanoma prevention measures, appropriate sunscreen use, and population-wide screening programs. The majority of recommended preventative medications have scant but developing clinical evidence. For continuous advancements in melanoma prevention, more study on these medications is necessary, as is the development of artificial intelligence and imaging methods for melanoma screening.

The discipline of artificial intelligence (AI), which aims to develop computer programs that simulate human intelligence, is expanding quickly and has a significant impact on many facets of our life [35]. Its uses are numerous and include everything from boosting search engines to powering electric vehicles to simplifying and streamlining difficult jobs. Interestingly, artificial intelligence has advanced significantly in the field of medicine, especially in oncology. The potential of AI to support cancer patients' clinical and therapeutic management has been highlighted by recent research. ''Intelligent'' devices and customized software are supplementing clinical judgments in certain medical settings to help medical practitioners with the complex patient care process. Clinical management of melanoma, a very complex and heterogeneous malignancy impacted by several hereditary and environmental variables, is still difficult, especially when the disease is advanced. Treatment choices are made more difficult by the fact that therapies are frequently limited by the emergence of innate or acquired resistance mechanisms. In this regard, an increasing amount of evidence indicates that AI, through the analysis of large datasets, can benefit the treatment of patients with advanced melanoma, even though further study is necessary. AI has the ability to save patients from needless, unsuccessful treatments by helping clinicians make the best therapeutic decisions. The purpose of this study is to examine the most recent uses of AI in relation to melanoma, with an emphasis on how it might completely transform the way medication is administered. The field of melanoma management stands to gain from better informed and personalized therapeutic decisions by utilizing AI's power and capacity to process and interpret large volumes of data. This will ultimately provide hope for improved outcomes for patients battling this difficult cancer.

Unrepaired DNA damage in skin cells causes genetic abnormalities that can result in malignant growths, making skin cancer a serious and potentially fatal disease [52]. Early skin cancer detection is essential since the disease is easier to treat when discovered early. The need of early diagnosis is underscored by the rising incidence rates of skin cancer, the high death rate that is connected with it, and the significant expenses of healthcare. Researchers have been working hard to create a variety of early skin cancer detection methods in order to overcome these issues. Frequently, these methods depend on examining lesion characteristics, such as symmetry, color, size, and form, in order to distinguish between benign skin disorders and malignant melanoma. Deep learning techniques have drawn a lot of attention as one of the more sophisticated approaches being investigated for early detection because of its capacity to automatically extract complex patterns and features from medical pictures, including skin lesions. The use of deep learning algorithms for skin cancer early detection is reviewed in-depth and methodically in this research. The evaluation includes research articles on skin cancer diagnostics that have been published in credible publications. The study provides a synthesis of research findings through a detailed analysis and presents insights in a variety of formats, including tools, graphs, tables, methodologies, and frameworks, to help readers better grasp the state of the art in deep learning-based skin cancer detection. Through the utilization of deep learning and the abundance of data found in medical photographs, this study adds to the current endeavors to enhance the early detection of skin cancer. The fight against this deadly and pervasive disease has the potential to improve patient outcomes, save treatment costs, and ultimately save lives through early detection.

As the skin tumor that causes the greatest number of deaths in Germany, malignant melanoma is a serious health concern [53]. Effective melanoma treatment depends on early detection. The nation's skin cancer screening program has drawn criticism, nevertheless, since death rates from malignant melanoma have not decreased despite a rise in melanoma diagnoses since it was implemented. This raises the prospect of over-diagnosis, in which lesions that might not have presented a major risk to health are identified. Differentiating benign from malignant tumors can be difficult for a number of reasons. Certain lesions may exhibit ambiguous biological behavior, placing them in a gray region. Furthermore, several lesions that are currently considered malignant could not have posed a risk to the patient's life because of their slow growth. Because there are currently no reliable indicators, it is challenging to diagnose these ''indolent'' melanomas. Moreover, it is impossible to predict with accuracy whether an in-situ melanoma will develop into an invasive tumor. Over-diagnosis can raise therapy costs and cause needless psychological and physical hardship for those who are afflicted. On the other hand, under-diagnosis, in which melanomas go unnoticed, can have a detrimental effect on patient outcomes and necessitate more aggressive treatment plans. Novel diagnostic approaches that can decrease over-diagnosis and under-diagnosis and increase objective evaluations in instances that are borderline are desperately needed. Making use of AI-based diagnostic tools is one possible strategy that has produced encouraging outcomes in preliminary tests. These instruments improve the precision of melanoma diagnosis and lessen the subjectivity involved in human evaluations. Although there is still work to be done in order to integrate these AI applications into clinical and pathology practice, this is an exciting opportunity to enhance the precision and efficacy of melanoma diagnosis and treatment in Germany and other countries.

Artificial intelligence (AI) has been applied to melanoma in recent years, which accounts for most mortality due to skin cancer [54]. No systematic research has been conducted to provide a thorough overview of AI's application in melanoma. The objective of this research is to examine the many uses of artificial intelligence in melanoma through a methodical evaluation of previously published works. 51 papers were considered in this evaluation, which was conducted using the search phrases ''artificial intelligence'' and ''melanoma'' in the PubMed database as of August 1, 2020. The assessment of dermoscopic pictures, image segmentation and processing, and the creation of AI-based diagnostic tools are the main uses of artificial intelligence in melanoma. AI has also shown useful in melanoma prognosis evaluation, medication response forecasting, and metastasis prediction. The study also examines the cooperative potential of human-AI collaborations in melanoma detection and treatment, emphasizing the significance of taking patients' viewpoints on AI into account. It is important to note that this review did not look at all algorithms created without publishing. Artificial intelligence seems to function satisfactorily in the setting of melanoma, and there are a plethora of potential uses in the future. Artificial intelligence has potential in the treatment of melanoma, with applications ranging from prognosis and diagnosis to medication reactions and patient views. There is a great deal of room for improvement in this area, indicating a promising future for the use of AI to melanoma research and clinical settings [54]. Convolutional Neural Network (CNN)-based classifiers have become the go-to option for melanoma detection in recent years. CNN classifiers have been shown to be able to classify skin cancer photos on par with dermatologists, which could lead to quicker and potentially life-saving diagnoses [55]. With an emphasis on the binary classification of melanoma, this paper offers a comprehensive evaluation of the most recent studies on melanoma classification using CNN. It investigates CNN classifiers, evaluates their accuracy against unpublished datasets, and looks at current research trends, obstacles, and possibilities in the diagnosis of melanoma. Through a methodical search of databases like IEEE, Medline, ACM, Springer, Elsevier, and Wiley, the review found pertinent material. 55 reputable papers were chosen for examination out of the 5112 studies that were first found. The goal of the project is to gather and disseminate cutting-edge research on CNN for melanoma diagnosis. It outlines current research directions and points out obstacles as well as openings in this important field. The paper also suggests a taxonomy for melanoma detection that summarizes the wide range of current approaches. Finally, it offers a model for melanoma identification that addresses obstacles and capitalizes on opportunities, providing insightful information for anyone studying this area [55].

Melanoma identification using CNN-based classifiers is a major improvement in medical imaging and diagnosis. In addition to reviewing the state of the field, this study provides a framework for comprehending present approaches and tackling upcoming opportunities and problems. It is well-positioned to support current initiatives to improve the precision and efficacy of melanoma diagnosis, possibly resulting in life-saving early identification and treatment [55].

Skin cancer is a serious and common health issue. Conventional skin cancer diagnostic techniques can be expensive, time-consuming, and need specialized training [29]. Artificial intelligence (AI) tools, such as deep neural networks and machine learning-based techniques, have surfaced in response to these difficulties and can help in the identification and categorization of skin cancer. The numerous AI-based technologies used for skin cancer detection and classification are to be identified and categorized in this study. It also investigates the relationship between the size of the dataset, the number of diagnostic classes, and the performance metrics used to assess AI models in order to determine how reliable the chosen research papers are. The Institute of Electrical and Electronics Engineers (IEEE) Xplore, Association for Computing Machinery Digital Library (ACM DL), and Ovid MEDLINE databases were searched systematically for pertinent papers in accordance with the Preferred Reporting Items for Systematic Reviews and Meta-Analyses Extension for Scoping Reviews (PRISMA-ScR) guidelines. Papers that met the eligibility requirements required to be specifically about skin cancer, use AI technology for classification or detection, and satisfy further requirements. Results: Data extraction and study selection were carried out by two separate reviewers. A narrative structure was employed to synthesis the extracted data, and studies were categorized according to the AI diagnostic methods and assessment metrics that were employed. Nine hundred and sixty-six papers were obtained from the three databases; fifty-three of them satisfied the requirements to be reviewed. Out of them, 39 research used deep AI-based techniques, and 14 studies used shallow AI-based techniques. The chosen studies evaluated their AI models using up to 11 different measures; 39 of the research utilized accuracy as the main evaluation indicator. Interestingly, research using smaller datasets tended to show greater accuracy scores. However, there were doubts about the dependability of models that scored higher on accuracy, particularly those that were trained on tiny datasets with few diagnostic classes. This analysis emphasizes the necessity for uniformity in assessment measures and datasets while highlighting the heterogeneous landscape of AI-based skin cancer diagnosis algorithms. Variability in these parameters makes it difficult to compare different approaches directly and casts doubt on the validity of models that appear to have high accuracy scores. Addressing these issues will be essential to improving the precision and efficacy of skin cancer diagnosis and categorization as the field of AI in dermatology develops.

In the field of cutaneous oncology, melanoma detection, prognosis, and therapy pose significant obstacles that have a significant impact on patient outcomes and healthcare costs [56]. There are now more options for resolving these issues because to the quick development of artificial intelligence (AI) applications in various fields. Using clinical imaging, dermoscopic pictures, and histopathologic tissues, advanced neural networks are being used to classify pigmented lesions. These endeavors may culminate in dependable prognostication and therapeutic response prediction, along with earlier and more precise melanoma identification. In this sense, melanoma detection and therapy are greatly advancing due to artificial intelligence. AI-powered algorithms analyze clinical imaging, dermoscopic pictures, and histopathologic material for assistance in the classification of pigmented lesions. AI has the potential to predict melanoma prognosis and therapy response, providing intelligent data. It is used to guide medical decisions and improve patient outcomes. AI holds a lot of promise for melanoma detection and therapy, but there are still a number of problems that required to be addressed. Creating legal frameworks and incorporating AI into clinical practice continue to be challenging tasks. As the field of melanoma continues to advance, it will be important to address such challenges in order to fully realize AI's potential for the purpose of improving patient treatment.

Deep learning has become more important in recent time and has shown to be an effective technique specifically in the field which are complicated and require prior knowledge [57]. One such area that is now having difficulties due to a lack of medical resources is biomedicine. In this sense, the use of deep learning for diagnosing diseases is an important area of research. The article aims to give a broad overview of the characteristics of skin lesions, the state of image technology, and the status of research on deep learning-based classification of skin diseases. The study examines the features of skin disorders and evaluates earlier research that classified skin conditions using deep learning. This test covers a wide range of subjects, including classification schemes, datasets, data processing techniques, and evaluation criteria. The overview highlights the evolution of the subject and describes the key factors and processes influencing dermatological diagnosis. It also enumerates the current issues and possibilities this industry is experiencing. Notably, the study confirms that deep learning-based techniques for identifying skin diseases can, in certain situations, perform better than dermatologists with extensive training experience.

Skin lesion picture assessment by hand has long been a laborious and time-consuming procedure for the diagnosis of skin cancer, especially melanoma [58]. Machine learning and deep learning algorithms have been developed to evaluate these photos due to recent technological and computing resource breakthroughs. Although these models have demonstrated potential, the distinct and intricate characteristics of skin lesion images continue to provide difficulties. The goal of this thorough investigation is to present a current overview of methods used to identify skin cancer from photographs of skin lesions. The authors tried to create effective algorithm that can reliably and automatically identify melanoma from images. There are following five sections of their proposed algorithm [58]:

- **Finding Difficulties:** The first section lists the difficulties in identifying melanoma from photos of skin lesions, such as problems with feature extraction, dataset size, and image quality.
- **Pre-processing and Segmentation:** In order to improve skin lesion photos for analysis, pre-processing and segmentation techniques are covered in detail in the second part.
- **Comparative analysis:** Assessing the advantages and disadvantages of cutting-edge techniques, this section compares and contrasts them.
- **Classification Methods**: In the fourth section, the various classification methods used to group skin lesions into distinct skin cancer classifications are discussed.
- **Performance Analysis:** The last section looks at how well cutting-edge techniques performed when used to tackle skin lesion image analysis problems, especially those from the International Skin Imaging Collaboration (ISIC) in 2018 and 2019. The study emphasizes that better classification results for skin lesion photos are obtained by using ensemble deep learning models on carefully segmented and preprocessed images.

Melanoma has a high death rate, which emphasizes the significance of early detection and appropriate treatment [59]. Numerous researchers have worked to create intelligent tools that can aid in the early detection and diagnosis of diseases of this nature, realizing the necessity for precise computer-aided diagnosis systems. The thorough overview of current developments in cancer prediction is presented in this research, with a particular emphasis on the use of artificial intelligence, especially neural network-based systems, for melanoma diagnosis. For dermatologists, these systems are thought of as intelligent support systems. Both theoretical and applied contributions are included in the paper, with a focus on new developments in decision-fusion-based multiple neural network designs.

The review in [59] focused on the years 2018–2021 in order to identify emerging patterns, taking into account the most representative papers that were presented at high-impact conferences and publications between 2015 and 2021. The main databases that are used to train neural networks to identify melanomas are also examined in this study. The review offers insightful information about the subject of neural network-based melanoma detection. It draws attention to the advancements made recently, particularly with regard to the creation of sophisticated neural network designs. In order to further the area, the report also analyzes research trends and proposes a research agenda [59]. All things considered, the application of artificial intelligence—in particular, neural networks—shows promise in terms of melanoma early diagnosis and detection, which is vital for improving patient outcomes and lowering death rates. Table 1 shows the comparison of existing work in terms of domain, main focus and key findings.

The existing work surveys have concluded with the following findings as reflected from Table 1:

- Environmental Variables and the Risk of Melanoma [48]: Melanoma is mostly associated with ultraviolet (UV) radiation exposure. Since the mid-1960s, the incidence of malignant melanoma has grown, in part because of increased UV exposure.
- Individual and Geographic Variables [48]: Melanoma risk can be influenced by geographical factors, such as

TABLE 1. Comparison of existing surveys.

Ref	Domain	Focus	Findings
[48]	Early CM Diagnosis & Management	Prevalence, diagnosis, and management	Urgent need for early diagnosis, AI's potential in improving patient outcomes
[49]	Risk Factors Associated with Melanoma	Risk factors including UV radiation, genetics, and lifestyle	Environmental and genetic factors contribute to melanoma risk
[51]	Dermoscopy vs. AI in Melanoma Diagnosis	Comparison of diagnostic accuracy between dermoscopy and AI	Dermoscopy and AI perform equally well in diagnosing melanocytic skin lesions
[52]	Melanoma Prevention and Risk Reduction	Genetic factors, prevention methods, and clinical trials	Population-wide screening and sunscreen use are vital in prevention
[36]	AI in Melanoma Treatment	Applications of AI in melanoma treatment	AI aids in patient care, therapy decisions, and personalized treatment
[53]	Early Detection Techniques for Skin Cancer	Various early detection techniques	Deep learning enhances skin cancer detection using lesion parameters
[54]	Melanoma Diagnosis Challenges in Germany	Challenges in distinguishing benign from malignant lesions	AI-based tools can enhance accuracy and objectivity in borderline cases
[55]	AI in Melanoma: A Systematic Review	Overview of AI applications in melanoma	AI's diverse applications include diagnosis, prognosis, and drug response prediction
[56]	CNN-Based Melanoma Classification	Classification of melanoma using CNN	CNN classifiers can classify skin cancer images similarly to dermatologists
[29]	AI-Based Skin Cancer Detection	AI's role in skin cancer detection	The need for standardization in evaluation metrics and datasets is emphasized
[57]	AI for Melanoma Diagnosis and Management	AI applications in melanoma diagnosis and management	AI can improve early detection, prognosis, and therapeutic decision-making
[58]	Deep Learning for Skin Disease Classification	Deep learning's role in skin disease classification	Deep learning methods have the potential to outperform dermatologists in certain scenarios
[59]	AI for Detecting Melanoma from Skin Lesion Images	Detecting melanoma from skin lesion images using AI	Ensemble deep learning models enhance classification performance for skin lesion images
[60]	AI for Melanoma Prediction	Melanoma prediction using neural network-based AI	AI shows promise in early detection and diagnosis of melanoma

latitude. Skin type, lifestyle decisions, vitamin D levels, and antioxidants are among the individual factors that influence the risk of melanoma.

- Sunburn and Environmental Factors [48]: Melanoma risk may be increased by sunburn episodes and exposure to a variety of environmental factors, such as cosmetics and photosensitizing medications.
- Genetic Factors [48]: The genetic foundations of melanoma risk include both common polymorphism genes and uncommon high-risk susceptibility genes.

- Dermoscopy vs. AI Accuracy [50]: Both Dermoscopy and AI are equally effective in identifying skin lesions that are melanocytic. Better diagnostic odds ratios are demonstrated by specific dermoscopic techniques.
- Prevention and Risk Reduction [51]: Sunscreen, UV protection, protective clothing, and chemopreventive drugs are among methods for preventing melanoma. There is evidence to promote population-wide screening initiatives and the preventative use of sunscreen.
- AI in the Treatment of Melanoma [35]: AI may help physicians avoid treating patients with advanced melanoma with inadequate therapies by assisting them in selecting the best course of action.
- Deep Learning for Early diagnosis [52]: By examining lesion parameters, deep learning approaches show promise for early skin cancer diagnosis. From medical photos, these methods may automatically extract complex patterns.
- AI-Based Diagnostic Tools for Germany [53]: In circumstances when melanoma diagnosis is borderline, AI-based diagnostic tools can improve the objectivity and accuracy of the diagnosis. AI has the potential to decrease both over- and underdiagnoses.
- AI's Potential in Melanoma Management [56]: • There is potential for using AI in the diagnosis and treatment of melanoma. In order to integrate AI, large, carefully selected datasets and potential biases must be addressed.
- CNN-Based Melanoma Classification [55]: Skin cancer photos can be classified using convolutional neural network (CNN) classifiers in a manner that is comparable to that of dermatologists. CNNs are an effective tool for quick, potentially life-saving diagnoses.
- AI for Skin Cancer Detection [29]: The dependability of AI models depends on standardization in assessment measures and datasets. Direct comparisons between approaches are impacted by the variability in these parameters.
- AI's Function in Prompt Detection [57]: Deep learning techniques may prove to be more effective than dermatologists in particular situations. AI can enhance early diagnosis and detection, which is essential for improving patient outcomes.

Table 2 shows some facts and findings based on the existing surveys. These findings highlight the complex relationship between environmental, genetic, and lifestyle factors and melanoma. They also emphasize how important AI and deep learning are to improving the detection and treatment of melanoma, raising the prospect of better patient outcomes and lower death rates.

III. MELANOMA AND ENVIRONMENTAL FACTORS

Environmental factors are one of many elements that have a significant impact on melanoma [48]. This section explores the complex interaction between melanoma and the environment, illuminating the effects of factors including ultraviolet (UV) radiation exposure, geographic influences, and climate on the growth of this cancer.

A. EXPOSURE TO ULTRAVIOLET (UV) RADIATION

A well-known environmental component that considerably aids in the growth of melanoma is ultraviolet (UV) radiation [60]. In this section we explore the complex relationship between exposure to UV radiation and melanoma, showing the processes by which UV radiation affects the development and spread of this illness.

There are three types of UV radiation: UVA, UVB, and UVC, with UVB being the most biologically active [61]. DNA deterioration in skin cells, particularly in melanocytes, is predominantly caused by UVB exposure. This damage results from DNA molecules absorbing UVB photons, which causes the creation of photoproducts such pyrimidine (6-4) pyrimidone photoproducts (6-4PPS) and cyclobutane pyrimidine dimers (CPDs) [62]. These photoproducts have the potential to alter important genes, such as those that control cell development and apoptosis. These genetic changes may accumulate over time as a result of UV-induced DNA damage to melanocytes, turning normal cells into malignant melanoma cells. The "UV signature" refers to this gradual accumulation of mutations during melanoma growth [63]. Repeated and excessive UV exposure, particularly in childhood and adolescence, can raise the chance of developing melanoma in later life. Sunburns, especially painful ones, are closely linked to a higher risk of developing melanoma, and getting one when someone is young increases that risk. The fact that extreme UV radiation-induced DNA damage, like that found in sunburns, can result in more dramatic genetic alterations highlights the connection between sunburns and melanoma. Therefore, minimizing exposure to UV radiation and adopting sun-safe practices are important for lowering the chance of developing melanoma [64]. Sunlight from the sun and artificial UV radiation from sunlamps and tanning beds both increase the risk of melanoma. UVA radiation from tanning beds primarily damages DNA and speeds up the aging process of the skin by penetrating deep into the skin. An increased risk of melanoma has been linked to prolonged and regular use of tanning beds, particularly in younger people [65], [66].

B. GEOGRAPHIC INFLUENCES

The prevalence of melanoma is greatly dependent on geographic location [67]. In this section, we explored the geographic factors as given in Figure 3 that affect the risk of melanoma occurrence, such as latitude, altitude, and regional variations.

One of the primary geographic factors influencing melanoma risk is latitude. The chance of getting melanoma varies significantly with distance from the equator. More direct sunlight is experienced by regions closer to the equator, which raises UV radiation levels. This enhanced UV exposure is mostly responsible for the higher melanoma

TABLE 2. Facts and findings based on the existing surveys.

Ref	Area	Facts
[48]	Cutaneous Melanoma (CM)	CM is a dangerous tumor originating from melanocytes in the skin. There were 351,880 new cases recorded in 2015, and around 96,000 in 2019.
[49]	Risk Factor	Overexposure to UV radiation is a significant risk factor for melanoma.
[51]	Dermoscopy and AI in Melanoma Detection	AI combined with digital dermoscopy shows potential enhance melanoma diagnoses but requires more data.
[52]	Prevention	Melanoma prevention strategies include sunscreen and protective gear. Preventative medications need further development.
[36]	AI in the Field of Melanoma	AI supports clinical and therapeutic management in melanoma.
[54]	Over-diagnosis and Under-diagnosis in Melanoma	Over-diagnosis and under-diagnosis of melanoma can be problematic. AI-based diagnostic tools can be useful to improve accuracy and reduce subjectivity.
[57]	Deep Learning for Skin Lesion Classification	Deep learning is commonly used for classification of skin lesions efficiently. Ensemble deep learning models on preprocessed images can provide better results.
[58]	AI for Melanoma Detection and Diagnosis	AI tools are helpful in early detection and diagnosis of melanoma. Neural network-based systems show promise and are considered intelligent support systems.

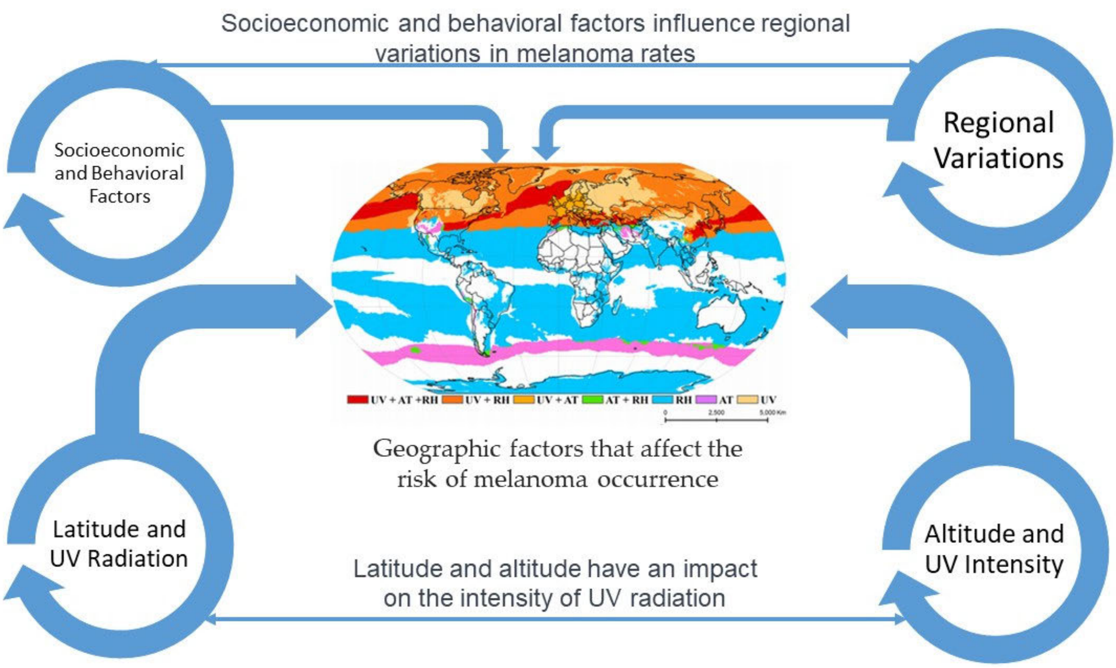

FIGURE 3. Geographic factors that affect the risk of melanoma occurrence.

incidence observed in these areas. However, UV radiation is lower in regions farther from the equator due to the angle at which sunlight enters the Earth's atmosphere. Higher latitude regions consequently often have lower rates of melanoma occurrence. The ''latitude gradient'' in melanoma incidence refers to this latitude-dependent pattern [68]. Altitude is another geographical element that affects melanoma risk. As atmospheric filtering decreases with altitude, UV intensity rises. Individuals are exposed to increased UV radiation levels in high-altitude places, such as mountainous regions.

Even though these regions are found at higher latitudes, the increased UV exposure can contribute to a higher risk of melanoma [67]. Regional variations can have a substantial impact on melanoma incidence rates within nations or regions. Latitude, altitude, and other environmental conditions, as well as human demographics and behaviors, all have an impact on these variances. For instance, coastal areas frequently have higher rates of melanoma due to increased sun exposure brought on by outdoor activities and way of life close to water bodies [69]. Socioeconomic and behavioral factors also have an impact on geographic variations in melanoma incidence. Greater levels of wealth in a region may encourage more people to travel to warm climates, increasing UV exposure and melanoma risk. The prevalence of melanoma can also vary across different geographical areas due to lifestyle factors including outdoor jobs and sunbathing habits [70], [71].

C. CLIMATE AND ENVIRONMENTAL FACTORS

The development and spread of melanoma are significantly influenced by climate and environmental factors as shown by Figure 4, which include temperature, humidity, and regional weather patterns [72]. This section investigates the complicated interactions between these factors and the risk of developing melanoma.

Sun exposure behavior and temperature are closely related. Climates that are warmer frequently promote outdoor activities and attire that exposes more flesh to the sun. In warm climes, prolonged and frequent sun exposure can raise the risk of UV radiation exposure, which is known to contribute to the development of melanoma. The increased accessibility of outdoor activities may also encourage physical fitness and healthy practices that reduce melanoma risk, therefore the relationship between temperature and melanoma is complex [73]. Humidity levels in a particular climate might have an effect on skin health. Dryer skin may be more vulnerable to UV radiation damage in low humidity settings, which are typical of arid climates. The skin's natural defenses against damaging UV radiation might be compromised by dry skin. As a result, people who reside in low-humidity environments may need to exercise more caution when shielding their skin from the sun [74]. Melanoma incidence rates can be impacted by seasonal changes in the climate. The summer months, when individuals spend more time outdoors and UV radiation levels are normally greater, are when many places see an increase in melanoma diagnoses. On the other hand, as a result of reduced sun exposure during the winter, melanoma diagnoses may rise. These seasonal fluctuations highlight the significance of year-round awareness and the necessity of increased summertime UV protection [75]. Local weather patterns, including cloud cover and air circumstances, can have an impact on the UV radiation's strength. UV rays may be partially blocked by cloud cover, lowering exposure. On cloudy days, people could underestimate the need for sun protection, which could increase their risk. Monitoring the UV Index, which takes weather-related elements into account, can offer advice on the daily requirement for sun protection [76].

D. THE INTERACTION OF GENETIC AND ENVIRONMENTAL FACTORS

Melanoma is influenced by both genetic predisposition and environmental variables [77]. This section explored the complex interaction between genetics and environment in the melanoma formation process as given in Figure 5. It emphasizes how environmental exposures can either initiate or aggravate genetic predisposition.

Significant proportion of melanoma instances are caused by genetic factors. A person is said to be genetically predisposed to the disease if they have a family history of melanoma or certain genetic alterations, such as those in the CDKN2A or CDK4 genes. These genetic risk factors can enhance the possibility that melanoma will develop, thus high-risk people must perform routine skin checks and use attentive sun protection [78]. Environmental triggers can cause melanoma in those who are genetically predisposed to cancer, even though genetic predisposition is still a major component [79]. When the skin is still forming during childhood and adolescence, excessive UV exposure can have a significant impact on melanoma risk later in life. Early UV exposure may more easily activate genetic markers that promote melanoma risk, therefore sun protection and sunburn prevention are significant during these formative years [80]. Genetic alterations brought on by exposure to UV radiation frequently result in a recognizable "UV signature" in melanoma tumors. These mutations are distinct from those discovered in melanomas that arise in locations that are not exposed to sunlight, emphasizing the connection between melanoma formation and UV exposure. The existence of the UV signature supports the idea that environmental variables play a role in the development of melanoma [81]. High-risk people who have a family history of melanoma or known genetic abnormalities ought to get regular dermatologist skin checks. They should also take careful sun protection measures to reduce their exposure to UV rays [26].

The relationship between melanoma and environmental factors emphasizes the important role that outside forces play in the emergence of this potentially fatal skin disease. UV radiation exposure, whether from the sun or artificial sources like tanning beds, continues to be a major risk factor. Melanoma susceptibility is increased over time by cumulative UV exposure. The direct relationship between UV exposure and melanoma incidence is highlighted by geographic variations in melanoma rates, with higher incidence closer to the equator. Temperature, humidity, and altitude are climate-related variables that are also connected to melanoma risk; areas with greater temperatures and lower humidity have higher incidence rates. Importantly, because these environmental factors might influence genetic predisposition, it is important to comprehend how genes and the environment

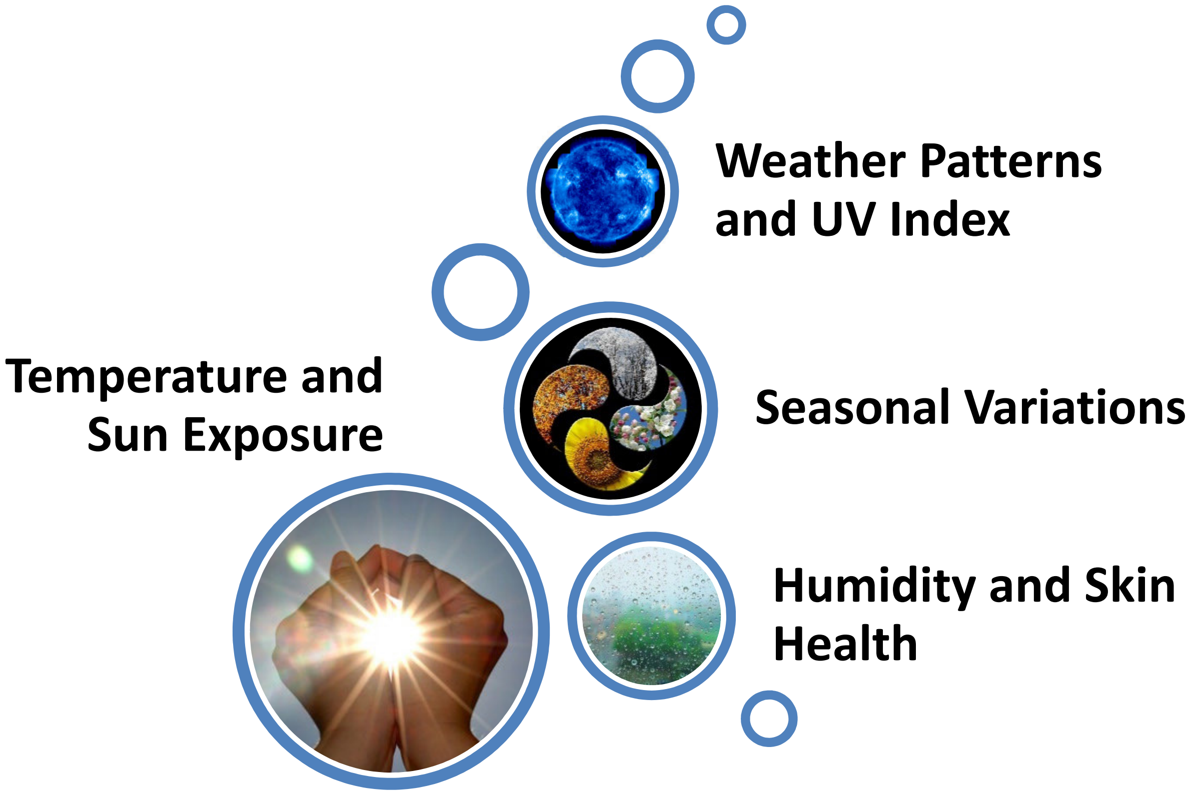

FIGURE 4. Spread of melanoma influenced by climate and environmental factors.

interact. Prevention strategies, such sun protection and skin checks, are still essential for lowering risk and promoting early detection. However, further study is required to fully understand the complex interactions between genetics and environmental factors, thereby improving our capacity to successfully prevent and treat melanoma.

IV. AI TECHNIQUES FOR MELANOMA DETECTION AND CLASSIFICATION WITH TAXONOMY

This section presents the taxonomy and description of AI techniques used for melanoma detection and classification.

A. TAXONOMY OF AI TECHNIQUES FOR MELANOMA DETECTION AND CLASSIFICATION

Detection and classification of melanoma have been significantly impacted by AI. Taxonomy for AI techniques used in melanoma detection and classification can be categorized into several key areas as shown in Figure 6. This section examines the cutting-edge AI methodologies and strategies created to enhance the precision and effectiveness of melanoma diagnosis and support medical professionals in early detection and classification [82].

B. CONVOLUTIONAL NEURAL NETWORKS (CNNS) IN MELANOMA DETECTION

Convolutional Neural Networks (CNNs) have transformed the precision and effectiveness of diagnosis in the field of melanoma detection. Due to the fact that these deep learning architectures were created expressly for image analysis tasks, they are ideally suited for the classification of dermatoscopic images, where they excel at spotting minute patterns and features suggestive of melanoma. The function of CNNs in melanoma detection is examined in this section, as well as the underlying mechanisms that support their effectiveness [83], [84], [85].

CNNs are a subclass of artificial neural networks that take their cues from how the human brain processes visual information. They are made up of several layers, each of which is intended to carry out a certain image analysis task:

- Convolutional Layers Convolutional layers enable feature extraction by applying filters (also known as kernels) to the input image. Convolutional filters look for edges, forms, and textures in the image.
- Pooling Layers: The feature maps produced by convolutional layers are downsample using pooling layers. The two most common pooling processes are average-pooling and max-pooling, which compute the average value and keep the maximum value in a region, respectively.
- Fully Connected Layers Fully Connected Layers: These layers carry out categorization functions and are frequently seen near the end of a CNN. They use the features that were collected and base their predictions on them.

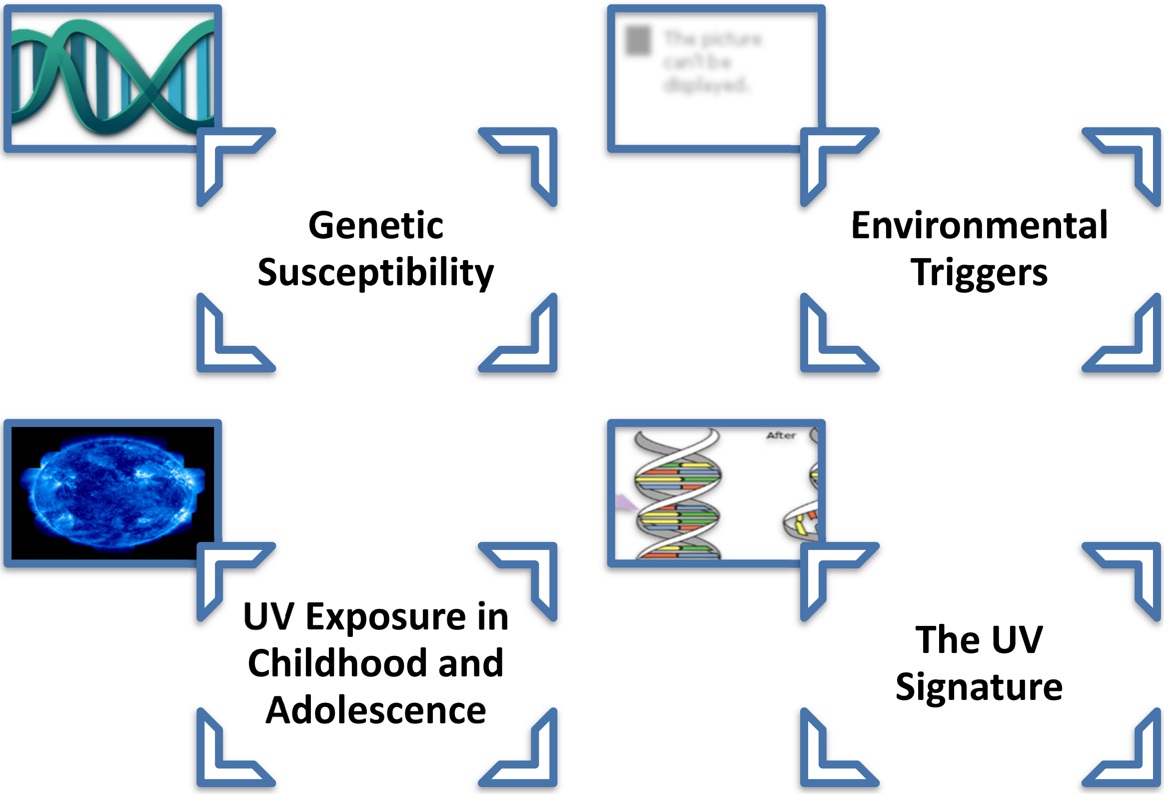

FIGURE 5. Interaction between genetics and environment in the melanoma formation process.

CNNs are excellent at extracting features, which is important for melanoma identification. Skin lesions can appear complex in dermatoscopic images in ways that the human eye might not be able to see. From these photographs, CNNs automatically detect and learn the following features:

- Color Distribution: CNNs are able to identify color changes throughout the lesion, which may be a sign of malignancy. Asymmetrical or variegated color patterns are examples of irregular color patterns that could be signs of melanoma.
- Texture analysis: Texture characteristics, such as tiny granular textures, may hold important information about melanoma. These minor textures can be captured by CNNs and used for categorization.
- Shape and asymmetry: Characteristics of the lesions' form and asymmetry are important. CNNs evaluate asymmetry and recognize irregular forms, two important characteristics in the diagnosis of melanoma.

The process of teaching CNNs to identify melanoma entails providing them with a sizable collection of tagged dermatoscopic pictures. To reduce classification errors, the network learns to modify its internal parameters (weights and biases). The process of fine-tuning frequently involves transferring knowledge from dermatoscopic pictures to general image databases, such ImageNet, using pre-trained CNN models. This transfer learning strategy expedites model training and improves output. Although CNNs have demonstrated amazing success in melanoma detection, difficulties still exist. The requirement for broad and representative datasets, potential biases in training data, and the interpretability of AI-generated outcomes are a few of these. These problems are being addressed in ongoing research in order to increase the clinical usefulness and robustness of CNN-based melanoma detection systems.

C. MELANOMA IMAGE PREPROCESSING IN DETECTION

In the use of artificial intelligence (AI) techniques, such as Convolutional Neural Networks (CNNs), for melanoma identification, image preprocessing is an essential step. In order to increase image quality, model performance, and facilitate precise diagnosis, a number of actions are done on dermatoscopic pictures before analysis. The importance of picture preprocessing and the specific methods used in the context of melanoma detection are covered in this section [86], [87], [88]. Several important functions of image preprocessing in melanoma detection include:

- Noise reduction: Artifacts and speckle noise are two types of noise that can be present in dermatoscopic images. Preprocessing methods eliminate or lessen this noise to guarantee that AI models assess correct and clean data.
- Standardization: By altering variables like brightness, contrast, and color balance during preprocessing,

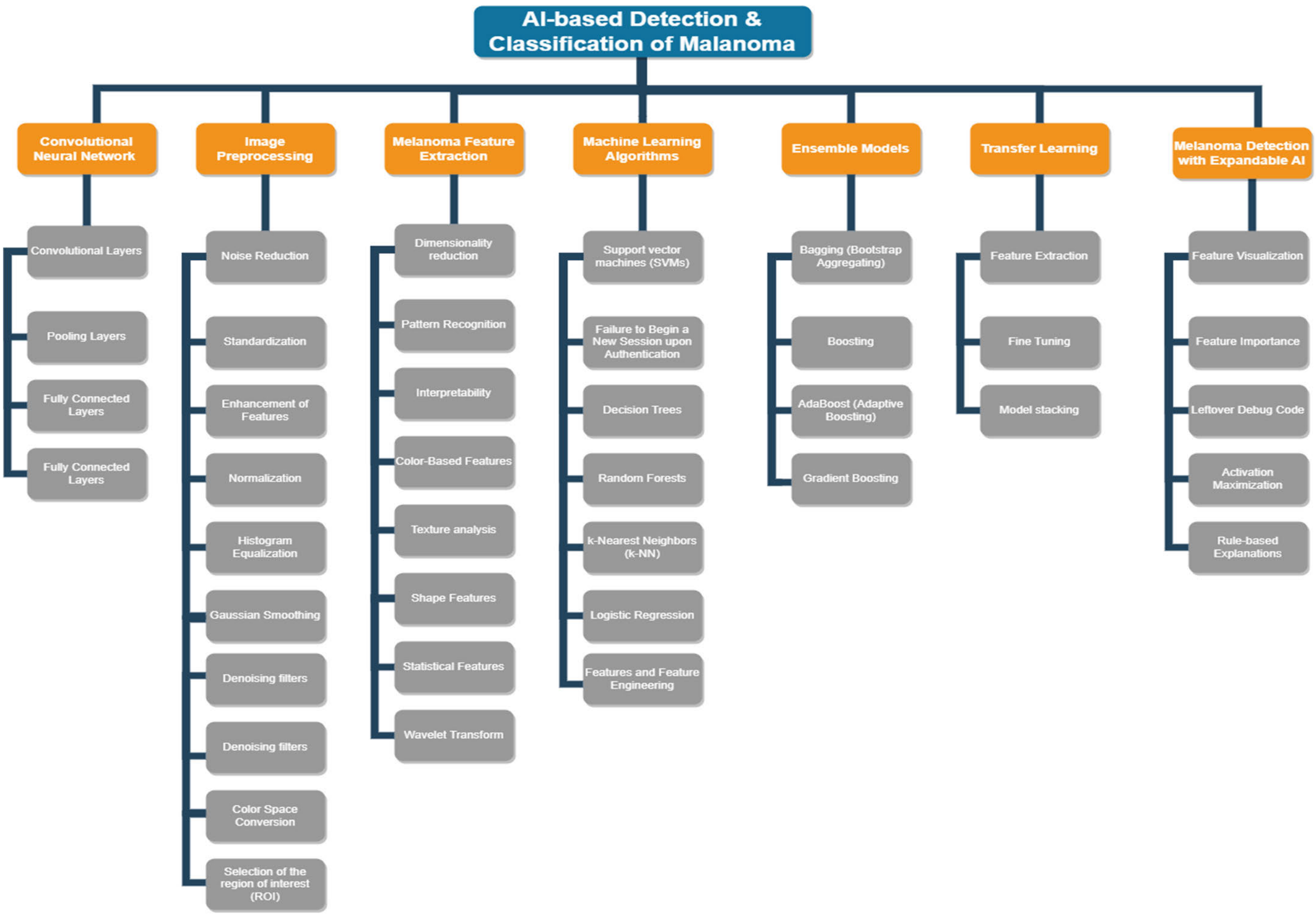

FIGURE 6. AI Techniques for melanoma detection and classification.

photographs can be made more uniform. This standardization guarantees that input data for AI models is consistent, enhancing their dependability and generalizability.

- Enhancement of Features: A few preprocessing methods, like contrast enhancement and sharpening, can draw attention to certain features inside skin lesions. This can help AI algorithms recognize subtle patterns and structures melanoma-specific.

Common methods for image processing: Melanoma detection uses several popular picture preparation techniques, including:

- Normalization: To remove fluctuations in image intensity, normalization scales pixel values to a defined range (for example, 0 to 1). This guarantees that AI models handle all photos equally.
- Histogram Equalization: Histogram equalization spreads out pixel values over a wider intensity range, improving visual contrast. When applied to photographs with poor contrast, it is quite helpful.
- Gaussian Smoothing: To eliminate high-frequency noise from an image, a Gaussian filter is applied. It subtly distorts the image while keeping key information.
- Denoising filters: The removal of salt-and-pepper noise and speckle from images is assisted by denoising filters such as median and mean filters. These filters swap out individual pixel values for the weighted average of nearby pixels.
- Color Space Conversion: Converting images between color spaces might improve some aspects or make image analysis easier (e.g., RGB to grayscale or LAB).
- Selection of the region of interest (ROI): The region of interest (ROI) for melanoma detection frequently correlates to the skin lesion itself. Segmenting and removing the lesion from the surrounding skin are two image preprocessing procedures that may be used. Due to the ability to concentrate solely on the pertinent area, computational overhead is decreased, and accuracy is increased.

D. MELANOMA FEATURE EXTRACTION IN DETECTION

In the use of artificial intelligence (AI) methods, such as Convolutional Neural Networks (CNNs) for melanoma diagnosis, feature extraction is an important step. Within dermatoscopic images of skin lesions, pertinent traits or patterns are automatically recognized and chosen. These collected properties provide the foundation for AI algorithms to distinguish between benign and malignant melanomas with accuracy. The importance of feature extraction and the methods used in the context of melanoma detection are examined in this section [87], [89], [90]. Feature Extraction's Function: For a number of reasons, feature extraction is important in the detection of melanoma.

- Dimensionality reduction: Dermatoscopic images might have a lot of data, which makes it difficult and expensive to perform direct analysis. Through the selection of the most useful and discriminating features, feature extraction lowers the dimensionality of the data.
- Pattern Recognition: The diagnosis of melanoma depends on the recognition of particular structures and patterns inside skin lesions. AI models can spot these patterns due to feature extraction, which improves the precision of their diagnosis.
- Interpretability: Extracted features frequently match traits that can be seen and understood by the human eye, like color changes, texture, and shape. This improves the clarity and interpretability of diagnoses produced by AI.

Common Methods for Feature Extraction: Melanoma detection uses several popular feature extraction techniques, including:

- Color-Based Features: Color features record changes in how colors are distributed inside a skin lesion. Color histograms, color moments, and color texture descriptors are a few examples of these properties. Unlike benign lesions, melanomas frequently have uneven or unbalanced color patterns.
- Texture analysis: The fine-grained structures of a picture are characterized by texture features. Techniques like Local Binary Patterns (LBP) and Gray-Level Co-occurrence Matrix (GLCM) can capture textural characteristics, like uneven granularity or roughness, which are symptomatic of melanoma.
- Shape Features: Shape-based features measure the geometric characteristics of a skin lesion. These characteristics can be used to describe melanoma-related characteristics like asymmetry, irregularity, and the presence of particular forms (such as spicules or notches).
- Statistical Features: The distribution of pixel intensities and color values inside a picture can be understood using statistical features such as mean, standard deviation, skewness, and kurtosis.
- Wavelet Transform: A wavelet transform extracts characteristics at various degrees of detail by dissecting an image into numerous sizes and orientations. This can be especially useful for dermatoscopic images that capture both fine and coarse features.

E. MACHINE LEARNING ALGORITHMS IN MELANOMA DETECTION

In order to improve the precision and effectiveness of diagnosis, deep learning methods like Convolutional Neural Networks (CNNs) and machine learning algorithms are essential tools in the field of melanoma detection. The function of machine learning algorithms, their advantages and uses, and their significance in the context of melanoma detection are covered in this section [91], [92], [93], [94]. Machine learning algorithms—including both conventional and cutting-edge methods—play a vital role in the identification of melanoma. These algorithms identify patterns, features, and discriminative traits that distinguish between benign and malignant skin lesions by training them on vast datasets of dermatoscopic images. Machine learning models can extrapolate from training data to produce predictions about dermatoscopic images that have not yet been viewed. This feature is essential for real-world clinical applications where different skin lesions could be seen. By allocating weights to various features, many machine learning models produce findings that are understandable, enabling doctors to comprehend the factors that go into the diagnosis of melanoma. The following machine learning techniques have been used to diagnose melanoma:

- Support vector machines (SVMs): For binary classification problems like melanoma detection, SVMs are frequently used. They identify an ideal hyperplane that maximizes the margin between classes and is useful for separating benign from malignant lesions [95].
- Decision Trees: Using a tree-like structure, decision trees are simple models that depict decision-making processes. To increase classification accuracy, they are frequently used in conjunction with ensemble techniques like Random Forests [96].
- Random Forests: These ensemble learning techniques mix different decision trees to produce predictions that are more reliable and precise. They excel in managing large, complicated datasets with several attributes [96].
- k-Nearest Neighbors (k-NN): In feature space, k-NN algorithms classify samples according to the dominant class among those of their k-nearest neighbors. Both classification and regression jobs can benefit from them [96].
- Logistic Regression: The likelihood that a sample belongs to a specific class is modeled using logistic regression. It is a straightforward technique that works well for binary classification issues like melanoma detection [96].
- Features and Feature Engineering: Feature engineering frequently determines whether machine learning methods for melanoma diagnosis are successful. From dermatoscopic images, feature engineers choose and extract pertinent traits such color distributions, texture patterns, and form features. Machine learning models use these traits as input so they can be more informed in their decisions.

F. ENSEMBLE MODELS IN MELANOMA DETECTION

In the realm of melanoma detection, ensemble models have become important because they provide a potent method for enhancing the precision, robustness, and dependability of diagnostic tools. In the context of melanoma detection, this section examines the significance of ensemble models, their applications, and their effects [97], [98], [99], [100].

Overfitting, bias, and model variance are some prominent problems in melanoma detection that ensemble models address. They use numerous base models' predictions (often referred to as weak learners) to integrate them into a final judgment that is typically more accurate and stable than the judgment of the individual models. Ensemble models combine the predictions of many models, each trained on different subsets of data or with various parameter settings, reducing the danger of overfitting. Ensemble models become more robust to noise and outliers in the data by averaging out errors or disputes among base models. By harnessing the collective intelligence of various models, ensemble approaches can improve classification accuracy. Melanoma detection employs a number of ensemble approaches, including:

- Bagging (Bootstrap Aggregating): Training numerous instances of the same base model on various bootstrap samples (randomly resampled sections of the training data) is known as bagging (Bootstrap Aggregating). The final prediction is then calculated by averaging or aggregating the results of different models.
- Boosting: Boosting is the process of training multiple base models successively while increasing the weights assigned to cases that the prior models incorrectly categorized. With this iterative process, a robust ensemble model is produced.
- AdaBoost (Adaptive Boosting): It is a well-known boosting algorithm that is employed in the identification of melanoma. Training examples are given variable weights, with misclassified cases receiving larger weights. Weak students are taught to fix the errors of their elders.
- Gradient Boosting: Gradient Boosting sequentially constructs an ensemble of decision trees. Every new tree is taught to fix the flaws of the older trees. When used for melanoma detection among other machine learning applications, gradient boosting has demonstrated astounding results.

G. TRANSFER LEARNING IN MELANOMA DETECTION

In the realm of melanoma detection, transfer learning is a cutting-edge method that offers a potent way to use pre-trained artificial intelligence models for increased effectiveness and efficiency. In the context of melanoma detection, this section examines the significance of transfer learning, its applications, and its effects [101], [102], [103]. The necessity for huge annotated datasets and the computational resources necessary for building deep neural networks from scratch are two issues that transfer learning solves in melanoma diagnosis. Transfer learning's primary function is the transfer of information from one task or domain (such as generic picture recognition) to another, related task (such as melanoma detection). This strategy has the following benefits: Transfer learning enables the bootstrapping of the learning process using pre-existing huge datasets for generic applications, such as ImageNet. As a result, there is less need for detailed labeled data unique to melanoma. Transfer learning speeds up model training by beginning with pre-trained models. Less iterations are needed for fine-tuning on melanoma data than for training from scratch. Models that have learned features from a wide range of source domain images typically generalize to melanoma detection tasks better. In order to identify melanoma, several transfer learning approaches are used:

- Feature Extraction: In this method, fixed feature extractors are created using pre-trained models (such as CNNs like VGG16 or ResNet). The top layers of the network are eliminated or adjusted for melanoma-specific categorization, while the lower layers, which are in charge of low-level characteristics like edges and textures, are left in place.
- Fine Tuning: Training a previously trained model on melanoma data while maintaining some of the acquired weights is known as fine-tuning. To adjust the model to melanoma detection, the higher-level features, which are more task-specific, can be fine-tuned.
- Model stacking: Model stacking is the act of combining several previously trained models into an ensemble in which each model handles the input data in a unique way. The final prediction is then created by combining the results of several models, which offers a variety of views on the data.

H. MELANOMA DETECTION WITH EXPLAINABLE AI (XAI)

Explainable AI (XAI), which provides transparency and interpretability in AI-driven diagnostics, has become a vital component in the field of melanoma detection. In this section, we examine the importance of XAI, its uses, and its effects with regard to the identification of melanoma [104], [105], [106]. Explainable AI addresses an important issue in melanoma detection, as the clinical acceptability and trust of AI-generated diagnoses depend critically on their interpretability. The main function of XAI in melanoma detection is to explain the rationale behind the choices made by AI models, increasing their transparency and assisting doctors in comprehending and validating the diagnosis. Key advantages of XAI are as follows:

- Clinical Transparency: XAI approaches increase the clarity of AI choices by visualizing or explaining the features and patterns that went into a given diagnosis. Clinicians are better able to comprehend and justify these choices.
- Error detection: XAI makes it possible to locate potential biases or faults in AI models. Clinicians can identify instances when unexpected or confusing circumstances may have led the model to make erroneous diagnoses.
- User Trust: XAI's transparency and interpretability help users have more confidence in AI systems, which promotes their application in therapeutic contexts.

The following XAI methods are used in the detection of melanoma:

- Feature Visualization: Feature visualization techniques create heatmaps or visualizations highlighting the areas of an image that the model considered to be most important. This aids clinicians in comprehending the characteristics (such as color or texture) that contributed to the diagnosis.
- Feature Importance: Methods like SHAP (SHapley Additive exPlanations) and LIME (Local Interpretable Model-agnostic Explanations) assign importance ratings to certain features in order to quantify how much of an impact they have on the model's output.
- Activation Maximization: Activation maximization techniques modify input images in order to enhance the activity of particular neurons or model features. This sheds light on the patterns the model searches for when melanoma is detected.
- Rule-based Explanations: XAI approaches that are based on rules produce human-readable rules or decision trees that imitate the way AI models make decisions. Clinicians can quickly interpret these rules.

Melanoma illness identification and classification by AI show considerable improvements in early diagnosis and classification precision. The ability of AI-based systems, in particular deep learning models like Convolutional Neural Networks (CNNs), to discern between benign and malignant skin lesions has been impressively proven. To produce extremely precise predictions, these systems take advantage of variables like color patterns, texture, and shape properties. Utilizing pre-trained models is now possible due to transfer learning approaches, which also result in a decrease in training time and data needs. Furthermore, AI-generated diagnoses are now more transparent and trustworthy due to explainable AI (XAI) techniques, which has facilitated their acceptance in clinical contexts. The clinical integration of AI tools has demonstrated potential for enhancing patient care, simplifying processes, and giving dermatologists useful decision help. Despite these successes, issues with data privacy, legal compliance, and user education continue to exist and demand continual attention. Overall, the use of AI in melanoma diagnosis is a game-changing advancement in healthcare with the potential to increase the rate of early detection and eventually save lives.

V. INTEGRATING ENVIRONMENTAL FACTORS INTO AI-BASED DETECTION AND CLASSIFICATION OF MELANOMA

A complex interaction of hereditary and environmental variables affects the development of melanoma as shown in Figure 7. The development of melanoma is significantly influenced by environmental factors, especially ultraviolet (UV) radiation exposure, even if genetic predisposition is a known risk factor.

An essential first step in improving the precision and efficacy of early diagnosis and risk assessment is the integration of environmental elements into AI-based melanoma detection and classification [34], [107], [108], [109], [110]. It is important to incorporate environmental elements into AI-driven melanoma diagnosis for a number of reasons.

Going beyond genetics alone, the inclusion of environmental data enables a more thorough assessment of melanoma risk. Predictions may be more accurate as a result of this comprehensive approach. AI models that take environmental aspects into account can offer individual recommendations for sun protection and skin monitoring, enhancing preventative actions for people. By identifying high-risk areas and groups, environmental data, such as UV exposure history, geographic location, and climate information, can aid in early detection efforts. Environmental factors are incorporated using a variety of techniques into AI-based melanoma detection and classification:

- Environmental information can be turned into useful properties that AI models can utilize to make predictions, such as UV index, latitude, and weather conditions.
- To get a more complete dataset, environmental and genetic data can be combined. Then, AI models can be trained using this combined data.
- AI hybrid models can give a more comprehensive picture of melanoma risk by combining genetic and environmental factors. Both deep learning and conventional machine learning methods may be applied in these models.
- Geographic information systems (GIS) and spatial analysis are able to pinpoint where melanoma instances are concentrated geographically and their relationships to environmental variables.

Adding environmental elements to AI-based melanoma detection presents a number of difficulties. Reliable projections require accurate, current, and high-quality environmental data. It is important to safeguard patient information when using environmental data. To comply with data privacy laws, strict steps must be taken. When environmental and genetic data are combined, the complexity of AI models can increase, making it difficult to maintain model interpretability while preserving predictive ability. It takes sophisticated modeling methods and interdisciplinary cooperation to fully comprehend the complex interactions between genetics and the environment.

Future success of AI-based melanoma detection depends greatly on the incorporation of environmental factors. With the help of this integration, more individualized preventative and treatment plans based on a person's genetic makeup and environmental risk factors would be possible. AI is able to pinpoint high-risk areas and populations, enabling tailored public health campaigns and early detection initiatives. Ongoing research will concentrate on creating more complicated AI models that can handle intricate interactions between genes and environments. To smoothly integrate environmental data into electronic health records (EHRs) and clinical workflows, healthcare systems will need to change.

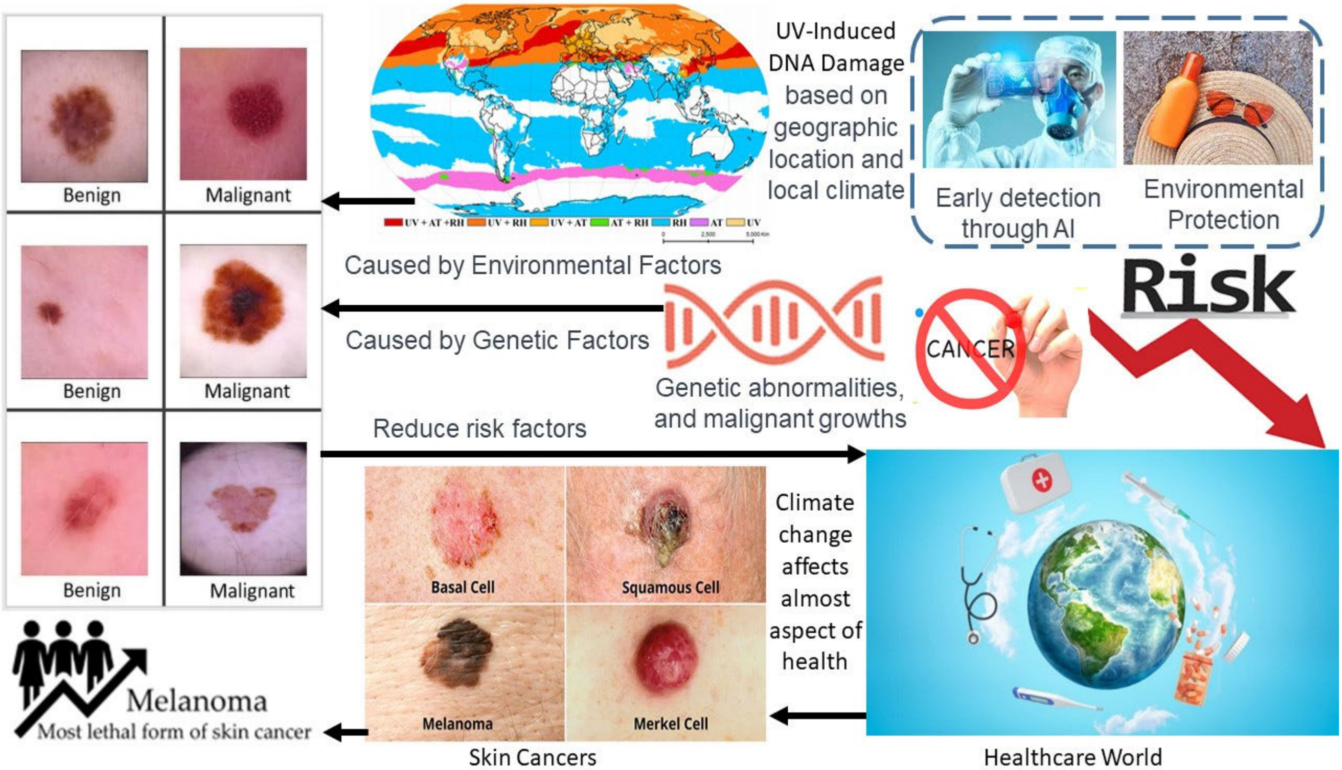

FIGURE 7. Unveiling the spectrum of UV-induced DNA damage in melanoma and its AI-based analysis of environmental factors.

VI. DESIGN GOALS

Designing an artificial intelligence (AI) system for the detection and categorization of melanoma in the context of environmental factors necessitates careful consideration of a number of aims to guarantee the performance and utility of the system [27], [34], [43], [111]. Following are a few design goals:

- Accuracy with variety of data: The main objective is to detect and classify melanoma with high accuracy. To ensure accurate diagnoses, the AI system require reduce false positives and false negatives. This goal can be achieved by adding the variety in dataset with integration of environmental factors.
- Personalization with environmental information: It is require to make the AI system relevant to each patient by taking into account their particular contextual circumstances, genetic makeup, and skin features. Individualized risk analyses and recommendations can improve early detection and prevention.
- Interpretability: It is require to design the AI system to be able to be understood by dermatologists and other healthcare experts so that they can comprehend the elements driving its forecasts. It is important to use explainable AI (XAI) tools to offer clear, comprehensible explanations for diagnoses.
- Efficiency with larger datasets: It is require to ensure that the AI system uses resources and processes large data in an effective manner. For prompt decision-making, it should be able to handle massive datasets and deliver findings in real-time or very near real-time.
- Scalability: Design the system to be scalable so that it can be integrated into a variety of healthcare environments, from small dermatology practices to bigger healthcare networks. As the system gains more widespread adoption, it should be able to handle an expanding amount of patient data.
- Data privacy: Implement strong data privacy and security procedures to safeguard patient data and adhere to data protection laws. Make sure that private medical and environmental data is handled securely.
- Cross-Platform Compatibility: Make sure the AI system can be easily connected with electronic health records (EHRs) and other regularly used healthcare information systems by healthcare providers.
- User-Friendly Interface: Create a user-friendly interface so dermatologists and other healthcare professionals can easily communicate with the AI system. Patient information, predictions made by AI, and explanations should all be accessible through the UI with ease.
- Continuous Learning: Allow the AI system to learn and adapt continuously to changing environmental circumstances, fresh scientific discoveries, and advancements in AI algorithms. An aspect of the system's architecture should include frequent updates and retraining.

- Cost-Effectiveness: Consider aspects including installation costs, patient outcomes, and the use of healthcare resources when assessing the AI system's cost-effectiveness.
- Feedback Loop: Create a feedback loop so that healthcare professionals may give feedback on how well the system is working, how easy it is to use, and where it needs to be improved.

VII. OPEN RESEARCH CHALLENGES AND PROBLEMS

Improvements in melanoma detection and classification using AI in conjunction with environmental factors show significant potential, however, there are still a number of research obstacles and problems. To further enhance the efficiency and moral considerations of such systems, these issues must be addressed. The following are some active research problems and issues [34], [43], [112], [113], [114], [115], [116], [117]:

- Data Quality and Diversity: Limited availability to complete environmental and genetic information in high-quality, diverse datasets continues to be a major concern. To create reliable models, researchers must address the problems of data imbalance and shortage.
- Interpretable AI: It might be difficult to strike a compromise between high accuracy and model interpretability. It is difficult to create AI models that are accurate and give clear justifications for their choices, especially when dealing with complicated gene-environment interactions.
- Generalization across populations: AI models must be able to generalize over a variety of populations and geographical areas. It is difficult to take into account differences in the environment, genetic makeup, and skin types.
- Overfitting and Bias: It is important to reduce overfitting and bias in AI models. Unbalanced datasets can introduce bias, and overfit models may not translate well to fresh data. It is necessary to conduct more research on methods to assure fairness and reduce bias.
- Healthcare system integration: Technical and interoperability hurdles must be overcome in order to smoothly integrate AI systems into the current healthcare infrastructure, including electronic health records (EHRs) and clinical workflows.
- Cost-Effectiveness: More research is needed to evaluate the cost-effectiveness of AI-based melanoma detection and classification, including the financial impact on healthcare systems and patients.
- Long-Term Monitoring: AI systems should be made to be able to track the risk of melanoma over time and change with the environment and a patient's health.

VIII. CONCLUSION

A promising area in dermatology and healthcare is the incorporation of environmental elements into AI-based melanoma diagnosis and classification. The complex interactions between genetics, environmental exposures, and skin cancer risk are acknowledged by this holistic approach. In this thorough examination, we have looked at the importance, approaches, difficulties, and potential outcomes of this integration. Important discoveries have emphasized how important it is to comprehend environmental factors—in particular, ultraviolet (UV) radiation exposure, geographic impacts, climate, and gene-environment interactions—affect the development of melanoma. It is imperative to acknowledge these factors in order to provide precise risk evaluation, timely identification, and customized mitigation tactics. Several important conclusions are reached after a thorough investigation of melanoma detection and categorization in conjunction with environmental factors:

- Melanoma risk is significantly influenced by environmental factors, specifically UV radiation exposure, geographic impacts, and climate conditions. These variables compound the hereditary propensity, adding to the disease's complexity.
- Personalizing melanoma risk assessments and recommendations based on unique genetic and environmental profiles should be the goal of AI-based solutions. One-size-fits-all strategies might not work.
- One of the most important challenges in AI modeling is striking a balance between interpretability and accuracy. Transparent justifications for AI system judgments are crucial, particularly in intricate scenarios involving gene-environment interactions.
- It is important to protect the quality and privacy of data, particularly genetic and environmental data. It's still difficult to protect patient data while maintaining its relevance and accuracy.
- Thorough clinical validation is necessary to prove AI-driven melanoma detection systems' practical efficacy and safety. In this process, working together with healthcare professionals is essential.
- Medical devices that use artificial intelligence (AI) and incorporate environmental data are subject to shifting regulatory regimes. Finding the ideal balance between patient safety and innovation is a critical problem.
- Precision medicine is where melanoma treatment is headed. Systems powered by AI will make it possible to develop individualized preventative and treatment plans based on each person's particular risk factors.
- Artificial intelligence (AI) has the potential to transform public health programs pertaining to melanoma prevention and early diagnosis by identifying high-risk areas and populations.
- In order to use and understand AI-driven melanoma detection systems successfully, healthcare professionals and AI practitioners must get education and training.
- Fairness, accountability, and openness are just a few of the ethical factors that must influence the creation and application of AI in the healthcare industry.

Design objectives for AI-driven systems have emphasized the importance of precision, adaptability, comprehensibility, effectiveness, and moral implications. The intricacy of gene-environment interactions, data quality, and privacy must all be addressed in order to achieve these aims. Despite the possible advantages, there are still a lot of problems and obstacles with open research. Significant obstacles include data diversity and quality, ethical issues, clinical validation, and regulatory frameworks. Researcher collaboration, healthcare provider collaboration, and policymaker collaboration will be necessary to overcome these obstacles. Precision medicine will be a major area of study in the future since AI-driven systems make it possible to create individualized treatment and preventative plans based on patient risk factors. AI will be used in public health projects to pinpoint high-risk areas and demographics and enable focused treatments. This study also aims to extend the role of artificial tanning instruments in conjunction with demographic information being the risk factors for skin cancer.

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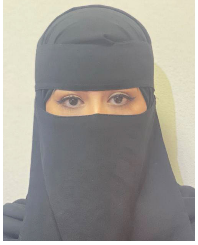

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