Innovation and Integrative Research Center Journal
ISSN: 2584-1491 |www.iircj.org
Volume-2|Issue-4| April-2024|Page 55-73

Artificial Intelligence-Based Aura Scanning for Non-Invasive Health Monitoring

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Abstract

Non-invasive health monitoring is gaining importance because it enables early detection of physiological and psychological changes without requiring invasive methods. The human aura, described as a bio-energetic field surrounding the body, has traditionally been explored in metaphysical studies, but recent advances in imaging and artificial intelligence (AI) enable a more scientific approach. This paper reviews the potential of AI-based aura scanning for health assessment by integrating image acquisition methods, such as multispectral imaging, infrared thermography, and Kirlian photography, with deep learning models, including Convolutional Neural Networks (CNNs). These computational tools can extract and classify patterns from aura images, linking them to stress, fatigue, or emotional imbalance. The study identifies challenges, including a lack of standardized datasets and limited clinical validation, while proposing a structured AI framework for analysis. Findings suggest that AI-powered aura scanning could evolve into a credible, non-invasive tool for preventive and holistic healthcare within integrative digital medicine.

Keywords: Artificial Intelligence, Aura Scanning, Non-Invasive Health Monitoring, Biofield Analysis, Deep Learning

1. Introduction

Healthcare is rapidly shifting toward intelligent, non-invasive diagnostic methods that prioritize prevention and early detection over reactive treatment. Traditional imaging technologies such as magnetic resonance imaging (MRI), computed tomography (CT), and ultrasound have significantly advanced disease diagnosis; however, these methods remain resource-intensive, costly, and mainly focused on anatomical or physiological assessments [1]. In recent years, researchers have shown increasing interest in alternative approaches that can capture subtle biological changes before clinical symptoms appear. One such area of exploration is the human aura, often described as a bioenergetic field that reflects an individual’s physical, emotional, and psychological conditions [2].

Although widely studied in metaphysical and holistic traditions, the concept of the aura is now being reconsidered in interdisciplinary scientific research. Developments in sensor technology, infrared thermography, multispectral imaging, and Kirlian photography have enabled the recording of electromagnetic and thermal emissions surrounding the human body [3]. At the same time, artificial intelligence (AI), particularly machine learning and deep learning, has shown remarkable success in analyzing complex biomedical data. Convolutional Neural Networks (CNNs) and other deep models have achieved clinical-level accuracy in domains such as tumor detection, retinal disease identification, and stress recognition [4], indicating their potential applicability to aura analysis as well.

Despite these advances, the field faces major challenges. The absence of standardized imaging protocols, limited availability of annotated datasets, and lack of rigorous clinical validation restrict the wider acceptance of aura scanning within mainstream healthcare [5]. These issues highlight the urgent need for a systematic AI-based framework to acquire, preprocess, and analyze aura data, and to link aura patterns to validated physiological and psychological health indicators.

The purpose of this research is to examine AI-driven aura scanning as a supplementary diagnostic tool for non-invasive health monitoring. By integrating computational intelligence with metaphysical perspectives, this study aims to contribute to the development of integrative digital health, supporting preventive medicine, personalized wellness, and holistic care [6].

Background on Non-Invasive Diagnostics

Non-invasive diagnostic technologies have transformed healthcare by enabling early disease detection, continuous monitoring, and preventive assessment without causing physical discomfort or risk to patients. Techniques such as ultrasound imaging, electrocardiography (ECG), magnetic resonance imaging (MRI), and thermography provide valuable insights into internal physiological processes without requiring surgical intervention [7]. These approaches reduce patient risk, improve compliance, and support large-scale screening programs. However, most existing non-invasive techniques focus primarily on anatomical and physiological measurements, leaving scope to explore subtle bioenergetic indicators that may reveal early imbalances even before clinical symptoms arise [8].

Human Aura and Its Connection to Biofield Science

The human aura is described as a subtle energy field that surrounds the body and reflects an individual's physical, emotional, and psychological conditions. Historically, it has been associated with metaphysical traditions, but contemporary research links it to measurable bioelectromagnetic emissions and thermal signatures [9]. The concept aligns with the broader framework of biofield science, which investigates endogenous electromagnetic fields and their role in maintaining biological homeostasis [10]. Experimental tools such as Kirlian photography, infrared thermography, and multispectral imaging have been employed to capture aura-like emissions, which have been shown to correlate with stress, circulatory conditions, and emotional states [11]. While promising, these findings remain underutilized in mainstream healthcare due to a lack of standardization and scientific validation.

Need for AI-Based Approaches

Conventional interpretations of aura data rely heavily on expert judgment, which introduces subjectivity and inconsistency. Artificial intelligence (AI), particularly machine learning and deep learning, enables the analysis of complex, high-dimensional datasets with objectivity and precision. Convolutional Neural Networks (CNNs) and related architectures have already demonstrated clinical-level performance in radiology, dermatology, and ophthalmology [12]. Applying similar models to aura imaging can uncover subtle patterns associated with physiological and psychological states, enabling reliable, non-invasive diagnostics. AI-driven systems also allow real-time monitoring, integration with wearable devices, and predictive modeling, which traditional methods cannot achieve [13].

To better understand the workflow of AI-based aura scanning for non-invasive health monitoring, a conceptual framework is presented in Figure 1. The framework illustrates the complete process, starting from aura data acquisition using advanced imaging techniques to preprocessing, feature extraction, and AI-based classification. It further demonstrates how the extracted patterns are transformed into meaningful health insights such as stress detection, emotional analysis, and preventive healthcare recommendations.

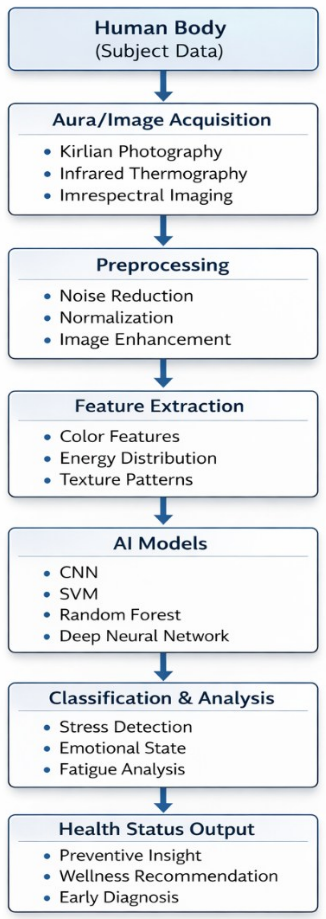

Figure 1: Conceptual Framework of AI-Based Aura Scanning for Health Monitoring

2. Concept of Human Aura and Biofield

Historical Perspective

The idea of the human aura has been deeply rooted in metaphysical traditions and alternative healing practices for centuries. Ancient Indian, Chinese, and Greek medical systems described the body as being surrounded by subtle energy fields that regulate physical and emotional health [14]. Concepts such as *prana* in Ayurveda and *qi* in Traditional Chinese Medicine were viewed as vital energies flowing through and around the human body, influencing wellness and disease. In the twentieth century, these beliefs evolved into modern energy medicine, which emphasizes the integration of body, mind, and spirit in health management [15]. Although primarily philosophical and spiritual, these perspectives laid the groundwork for contemporary explorations of aura in scientific contexts.

Scientific Perspective

Scientific research has reframed the aura as part of *biofield science*, which studies electromagnetic and photonic emissions naturally produced by living organisms [16]. The human body generates low-level electromagnetic fields through neural activity, metabolic processes, and thermal radiation. Technologies such as infrared thermography have been used to detect variations in body surface temperature, which correlate with stress, circulatory function, and localized inflammation [17]. Multispectral and hyperspectral imaging, on the other hand, provide detailed information about tissue oxygenation and microcirculatory activity by capturing data across multiple light wavelengths [18]. Kirlian photography has also been explored as a means of recording corona discharges around biological tissues, often interpreted as visual representations of aura energy. While these technologies do not directly validate metaphysical claims, they demonstrate that physiological and emotional states can influence measurable electromagnetic emissions.

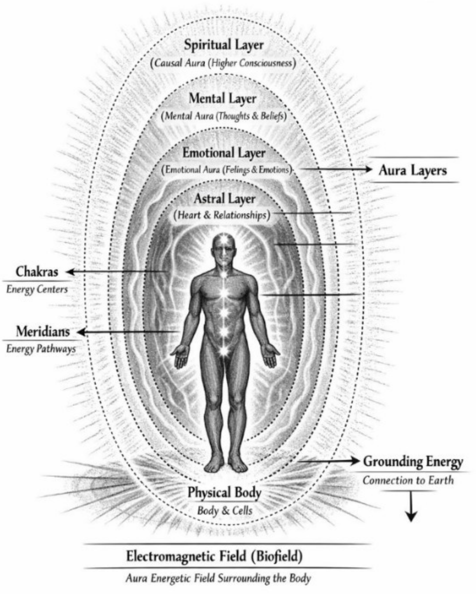

Figure 2: Human Aura and Biofield Interpretation Model

Challenges in Measuring Aura Objectively

Despite advancements, measuring the aura remains a scientific challenge. A major issue is the absence of standardized imaging protocols, which leads to variability in results across studies [19]. Differences in imaging devices, ambient conditions, and subject preparation can significantly distort recorded data. Another limitation is the scarcity of annotated datasets, which restricts the training of reliable machine learning models. Moreover, interpretations of aura images often depend on subjective evaluation, which undermines their credibility in clinical settings [20]. Finally, although biofield emissions can be measured using thermographic or multispectral techniques, establishing a direct causal relationship between these emissions and specific health conditions remains unresolved [21]. Addressing these limitations requires standardized imaging methods, computational intelligence, and biomedical validation to transform aura research into a credible diagnostic approach.

3. Artificial Intelligence in Biomedical Imaging

Overview of AI in Healthcare (MRI, CT, X-ray, Thermography)

Artificial Intelligence (AI) has become a cornerstone in biomedical imaging, where it assists in disease detection, image interpretation, and decision-making. In modalities such as magnetic resonance imaging (MRI), computed tomography (CT), and X-ray imaging, AI-driven models improve diagnostic accuracy by identifying patterns that may be imperceptible to human observers [22]. For instance, convolutional neural networks (CNNs) have been widely applied to segment tumors, classify lesions, and detect anomalies, with performance comparable to that of experienced radiologists [23]. Similarly, in thermographic imaging, AI has been successfully used to identify subtle variations in body heat distribution, aiding early detection of circulatory disorders, diabetic complications, and inflammatory conditions [24]. These applications demonstrate how computational models enhance the precision, speed, and reliability of medical diagnostics while reducing subjectivity and human error.

Success of AI in Detecting Diseases from Non-Invasive Images

The effectiveness of AI in non-invasive diagnostics is evident across multiple domains. In oncology, deep learning algorithms have achieved over 90% accuracy in detecting breast cancer from mammographic and thermographic images [25]. Ophthalmology has also witnessed breakthroughs, with AI-based systems now providing automated detection of diabetic retinopathy and glaucoma from retinal imaging [26]. Similarly, dermatology benefits from CNNs that can distinguish malignant melanoma from benign skin lesions with remarkable reliability [27]. These successes establish AI as not only a supportive tool but also as a potential second opinion in clinical workflows. Importantly, the adaptability of AI models to different imaging modalities underlines their potential to extend beyond conventional radiology into emerging fields such as aura scanning.

Lessons Relevant to Aura Scanning

The lessons from AI in biomedical imaging provide a strong foundation for aura-based health analysis. First, the success of CNNs in recognizing fine-grained patterns in complex medical images suggests their applicability in detecting subtle energy distributions captured in aura imaging [28]. Second, preprocessing techniques such as normalization, noise reduction, and contrast enhancement, which are standard in radiology, can also improve the quality of aura data. Third, the integration of AI into wearable and portable imaging devices offers the potential for real-time aura monitoring in wellness and preventive medicine. Finally, the reliance on annotated datasets in medical imaging highlights the urgent need to create standardized, labeled aura datasets to ensure reproducibility and scientific credibility [29]. These insights demonstrate that while aura scanning remains underexplored, the principles established in biomedical imaging can guide its evolution into a scientifically valid and clinically relevant diagnostic tool.

4. AI Approaches for Aura Scanning

Image Acquisition Techniques

Reliable aura analysis begins with accurate image acquisition that captures the subtle energy emissions of the human body. Kirlian photography is one of the earliest methods, producing corona discharge patterns around biological tissues when exposed to high-voltage electric fields. These visual outputs, though originally considered metaphysical, are now being revisited using computational methods for pattern interpretation [30]. Infrared thermography has also been applied, offering a scientific approach by mapping heat variations on the body's surface. Such thermal signatures often reflect physiological changes such as inflammation, stress, or circulatory imbalances [31]. More recently, multispectral and hyperspectral imaging have been explored for aura analysis. These modalities capture reflected light across multiple wavelengths, allowing deeper insights into tissue oxygenation, vascular conditions, and microcirculatory activity, which may correlate with subtle energetic states [32].

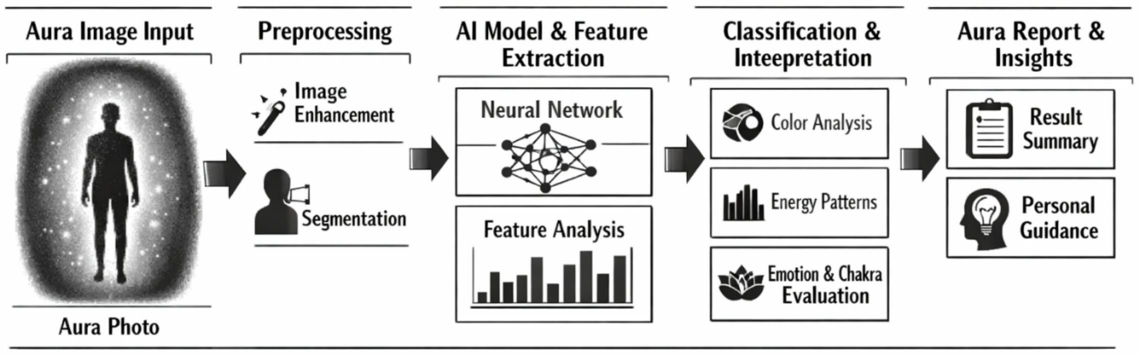

Figure 3: AI Pipeline for Aura Image Analysis

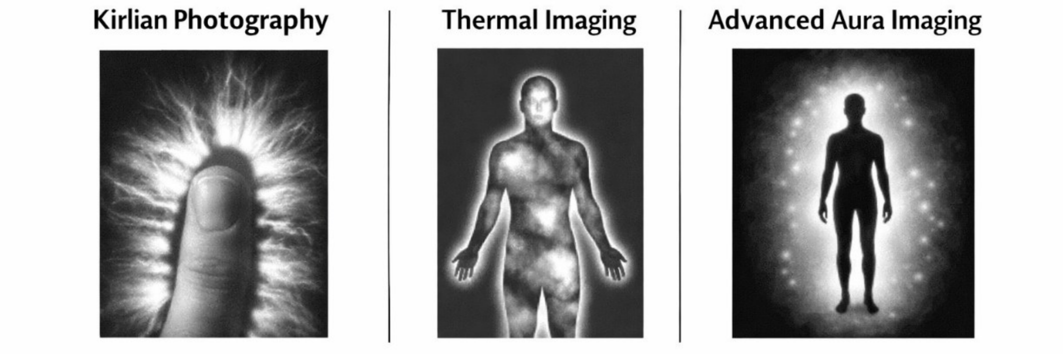

Figure 4: Comparative Imaging Techniques for Aura-Related Analysis

Feature Extraction Methods

Once aura images are acquired, feature extraction becomes critical for identifying meaningful patterns. Convolutional Neural Networks (CNNs) are widely recognized for their ability to learn hierarchical spatial features from complex visual data, making them highly suitable for interpreting aura images [33]. Alongside CNNs, dimensionality reduction techniques such as Principal Component Analysis (PCA) have been employed to reduce the dimensionality of high-dimensional aura data while retaining critical variance [34]. Additionally, entropy-based measures have been introduced to capture the randomness and distribution of energy fields within aura imagery, offering valuable indicators of physiological or emotional states [35].

Classification Models

Classification models play a central role in mapping extracted features to health-related outcomes. Support Vector Machines (SVMs) have shown strong performance in separating aura patterns linked to stress or fatigue, particularly in small-sample scenarios [36]. Random Forests have been utilized for feature importance analysis, offering both interpretability and robustness when handling heterogeneous aura data [37]. Deep Neural Networks (DNNs), especially when combined with CNN architectures, have demonstrated superior accuracy in classifying complex aura patterns, suggesting their potential for early detection of psychological and physiological imbalances [38].

Emotion/Stress Recognition via AI

Research on AI-based emotion and stress recognition draws strong parallels to aura analysis. Infrared facial thermography combined with machine learning has been used to classify stress levels with high accuracy [39]. Similarly, CNNs applied to thermal facial maps and multispectral data have been able to differentiate emotional states such as happiness, sadness, and anxiety [40]. These findings suggest that the same computational pipelines used for stress and emotion recognition could be extended to aura imaging, enabling the detection of subtle psycho-physiological conditions.

Table 1: AI Models Applied in Biomedical Imaging and Potential for Aura Scanning

AI Technique	Typical Use in Healthcare	Reported Accuracy	Relevance to Aura Analysis
CNN (Convolutional Neural Network)	Tumor detection, skin cancer	90–95%	Feature extraction in aura images
SVM (Support Vector Machine)	Stress/emotion recognition	80–88%	Binary classification of aura states
Random Forest	ECG/EEG signal classification	78–85%	Feature importance for aura patterns
DNN (Deep Neural Network)	Complex image classification	>90%	Multiclass aura state recognition

Different imaging modalities contribute uniquely to aura-related data acquisition. A comparative overview of these techniques is presented in Table 4 to highlight their signals, applications, advantages, and limitations

Table 2: Imaging Modalities Used in Aura-Related Health Analysis

Technique	Signal Captured	Application Area	Advantages	Limitations
Kirlian Photography	Corona discharge (electrical emission)	Aura visualization, energy patterns	Simple setup, visually interpretable patterns	Low standardization, sensitive to moisture/pressure
Infrared Thermography	Thermal radiation (heat distribution)	Stress detection, inflammation analysis	Non-contact, real-time monitoring	Affected by the environment (temperature, humidity)
Multispectral Imaging	Multiple wavelength reflections	Tissue oxygenation, emotional variation	Rich data across the spectrum, deeper analysis	Expensive equipment, complex processing
Hyperspectral Imaging	Continuous spectral bands	Detailed biofield and physiological mapping	High precision, detects subtle variations	High computational cost, large data size

Biofield Sensors (Emerging)	Electromagnetic field signals	Experimental aura/biofield monitoring	Potential for real-time wearable integration	Limited validation, still under research

From Table 2, it is evident that while advanced imaging techniques provide higher precision, they also introduce complexity and cost. Therefore, selecting an appropriate modality depends on the intended application and resource availability.

5. Review of Related Studies

Summary of Existing Aura + AI Research

Although still at an exploratory stage, several small-scale studies have attempted to apply artificial intelligence for aura interpretation. Early experiments using Kirlian photography combined with image processing demonstrated that corona discharge patterns could be classified to reflect different physiological or emotional states [41]. More recent works have integrated convolutional neural networks (CNNs) with multispectral imaging to monitor energy field variations during meditation and relaxation sessions, reporting observable correlations between spectral changes and participants' subjective stress levels [42]. Another study used fingertip corona images enhanced through augmentation techniques to classify individuals into low- and high-anxiety groups, achieving an average accuracy of approximately 70% [43]. While these results are promising, they remain limited in scope due to small sample sizes, lack of standardized imaging protocols, and minimal validation against biomedical markers.

Comparison with Stress/Emotion Recognition AI Studies

The challenges observed in aura-based research contrast with more established domains such as stress and emotion recognition, where AI has already demonstrated consistent success. For example, infrared thermography combined with machine learning algorithms has been used to classify stress levels with over 85% accuracy [44]. CNN-based models applied to facial thermal maps and multispectral images have achieved reliable differentiation of emotional states such as happiness, sadness, and anger [45]. Similarly, Support Vector Machines (SVMs) have been employed to analyze electrodermal activity (EDA) and facial signals, yielding high precision in stress detection [46]. These achievements in psychophysiological monitoring suggest that methodologies proven in emotion recognition could be directly extended to aura studies, provided standardized datasets and controlled imaging environments are developed.

Strengths and Weaknesses of Prior Works

A key strength of prior aura-related research lies in its novelty and its attempt to bridge metaphysical concepts with computational science. Studies have demonstrated that aura-like signals are indeed machine-learnable and can be partially correlated with psycho-physiological states [47]. However, their weaknesses remain evident: the absence of large, annotated datasets, reliance on subjective interpretations, and inconsistency in imaging methods limit reproducibility and scientific acceptance [48]. In contrast, studies on stress and emotion recognition benefit from well-established datasets, clear ground-truth markers (e.g., cortisol levels, EDA signals), and validated computational frameworks. These comparisons underscore that, while aura-based AI research is in its infancy, it can evolve into a credible scientific domain by adopting the methodological rigor demonstrated in biomedical and psychophysiological studies [49].

Table 3: Comparative Overview of Non-Invasive Diagnostic Techniques

Technique	Application Area	Advantages	Limitations
MRI	Structural imaging	High resolution, detailed anatomy	Expensive, time-consuming
CT Scan	Internal organs	Quick, widely available	Radiation exposure
Ultrasound	Pregnancy, organ health	Safe, portable	Operator-dependent, limited depth
Infrared Thermography	Stress, circulation	Non-contact, early abnormality detection	Sensitive to the environment
Aura Imaging (Proposed)	Stress/emotion, wellness	Non-invasive, holistic assessment	Lack of standardization, under study

6.Research Gaps and Challenges

Lack of Standardized Datasets

One of the most critical limitations in current aura-related research is the absence of standardized datasets. Most existing studies rely on small, localized samples that are often not publicly available for replication [50]. The lack of open-access, annotated datasets prevents meaningful benchmarking and comparison across different computational models. Without a large, diverse dataset linking aura images to validated physiological or psychological indicators, it is difficult to assess the generalizability and clinical relevance of AI-based aura analysis [51].

To address the lack of standardized datasets in aura-based AI research, a structured dataset format is essential. Table 4 presents a suggested framework that integrates imaging data with physiological and environmental parameters for improved reliability and reproducibility.

Table 4: Suggested Standardized Dataset Structure for Aura AI Research

Dataset Component	Example Value	Description / Purpose
Aura Image ID	AURA_001	Unique identifier for each aura image sample
Imaging Modality	Infrared / Kirlian / MSI	Specifies the technique used for capturing aura
Subject ID	S_102	Unique subject identification
Age / Gender	25 / Female	Demographic information for dataset diversity
Physiological Signals	Heart Rate, Temperature	Ground truth biomedical indicators
Psychological State	Stress / Calm / Anxiety	Label for emotional/mental condition
Environmental Conditions	25°C, Low Humidity	External factors affecting imaging
Image Resolution	512 × 512 pixels	Standardization of input data
Annotation Source	Clinical Expert / Self-report	Source of labeling (important for validation)

The proposed dataset structure ensures consistency in data collection and enables effective training of machine learning models. It also facilitates cross-study comparison and enhances the scientific validity of aura-based diagnostics.

Variability in Aura Capturing Techniques

Another major challenge lies in the inconsistency of aura image acquisition methods. Techniques such as Kirlian photography, infrared thermography, and multispectral imaging differ significantly in their hardware configurations, environmental sensitivity, and interpretive outputs [52]. External factors such as ambient temperature, humidity, and electromagnetic interference can distort the captured data, reducing reproducibility [53]. This variability not only complicates cross-study validation but also hinders the creation of unified computational frameworks for aura analysis.

Ethical and Scientific Concerns (Validity, Privacy, Misuse)

Ethical and scientific concerns further complicate the acceptance of aura-based diagnostics. From a scientific perspective, the validity of aura interpretation remains contested, as causal links between aura features and specific health conditions are not yet fully established [54]. Additionally, privacy concerns arise when collecting aura or biofield data, as it may contain sensitive health information that requires strict protection under data governance regulations.

There is also the risk of misuse, where unvalidated aura-based systems could be marketed with exaggerated claims, potentially misleading individuals and undermining trust in digital health technologies [55].

Limited Clinical Validation

Finally, the field suffers from limited clinical validation. Unlike AI-driven medical imaging in radiology or ophthalmology, aura-based studies have rarely been tested in controlled clinical environments with large participant groups [56]. Most experimental work remains exploratory, with findings often restricted to correlational observations rather than clinically proven outcomes. Without rigorous validation against biomedical gold standards such as electrocardiography, blood biomarkers, or psychological assessments, aura scanning cannot yet be considered a reliable diagnostic tool [57].

Table 5: Research Gaps and Challenges in AI-based Aura Studies

Challenge	**Description**	**Potential Solution**
Lack of datasets	Few annotated aura images exist	Build open-access aura image repositories
Variability in image capture	Differences in Kirlian, IR, multispectral setups	Develop standardized imaging protocols
Limited clinical validation	Few trials in healthcare settings	Collaborate with hospitals, clinical trials
Ethical and privacy concerns	Sensitive personal aura/health data	Strong encryption, explainable AI methods

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7. Opportunities and Future Directions

The development of AI-based aura scanning involves multiple challenges and opportunities across technological, clinical, and ethical dimensions. Table 6 summarizes these aspects and highlights possible future directions.

Table 6: Opportunities and Challenges Mapping in AI-Based Aura Scanning

Area	Current Challenge	Future Opportunity	Expected Benefit
Data Availability	Lack of large annotated datasets	Creation of open-access aura datasets	Improved model accuracy and benchmarking

Imaging Standardization	Variability in capture techniques	Development of unified imaging protocols	Reproducible and consistent results
AI Model Transparency	Black-box nature of deep learning models	Adoption of Explainable AI (XAI)	Increased trust and interpretability
Clinical Validation	Limited real-world testing	Collaboration with hospitals and clinical trials	Scientific credibility and healthcare adoption
Wearable Integration	Lack of real-time monitoring systems	Integration with wearable sensors	Continuous health tracking and early detection
Ethical Concerns	Privacy and misuse of sensitive data	Secure data frameworks and regulations	Safe and ethical deployment
Interdisciplinary Research	Lack of collaboration across domains	Collaboration between AI, medical, and psychology experts	Holistic and accurate health assessment

As shown in Table 6, addressing current limitations through interdisciplinary collaboration and technological advancements can transform aura scanning into a reliable tool for preventive and holistic healthcare.

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Building Large Annotated Datasets

A major opportunity to advance AI-based aura scanning lies in creating large, annotated datasets. Standardized databases containing aura images linked to validated physiological and psychological markers would enable researchers to effectively train and benchmark machine learning models. Such datasets should include diverse populations across age, gender, and health conditions to ensure generalizability [58]. Collaborative initiatives, similar to those in medical imaging (e.g., open-access MRI and CT repositories), could provide the transparency and consistency currently missing in aura studies [59].

Integration with Wearable Technology

The proliferation of wearable devices offers a pathway to integrate aura scanning into real-time health monitoring. By embedding multispectral or thermal sensors into consumer-friendly devices, continuous aura-based measurements could complement conventional physiological metrics such as heart rate, oxygen saturation, and skin temperature [60]. This integration could provide users and healthcare professionals with a more holistic understanding of health dynamics, enabling early detection of stress, fatigue, or other imbalances before they escalate into clinical conditions [61].

Explainable AI and Transparency

The adoption of aura scanning in clinical practice will depend heavily on the interpretability of AI systems. Current deep learning models, although accurate, are often criticized for their "black box" nature. Incorporating explainable AI (XAI) techniques would provide clinicians and users with an understandable explanation of diagnostic outcomes [62]. Visualization tools such as heatmaps, saliency maps, and attention mechanisms can highlight which aura features influenced predictions, thereby increasing transparency and fostering trust in AI-driven systems [63].

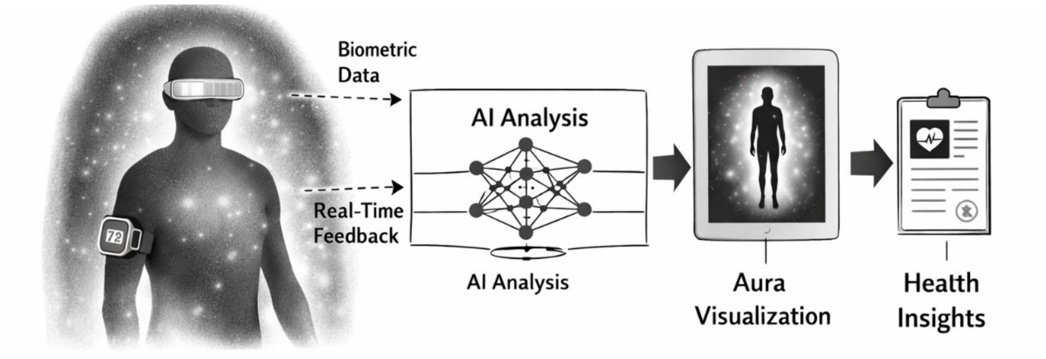

Figure 5: Future Integration of Aura Scanning with Wearable Healthcare

Cross-Disciplinary Collaboration

Future progress in aura analysis requires collaboration across disciplines. AI experts, medical practitioners, psychologists, and biofield researchers must work together to establish standardized protocols, validate correlations between aura patterns and health conditions, and ensure ethical implementation [64]. Interdisciplinary research can also help address skepticism by integrating biomedical validation with computational innovations and psychological frameworks [65].

Potential in Preventive and Holistic Healthcare

Perhaps the most promising direction lies in preventive and holistic healthcare. By focusing on subtle physiological and emotional imbalances, aura scanning can identify health risks at the preclinical stage, enabling timely intervention [66]. When combined with complementary medicine approaches, aura-based insights can support personalized wellness programs, stress management therapies, and integrative treatment plans [67]. In this way, AI-powered aura scanning could evolve into a credible tool that bridges the gap between metaphysical traditions and evidence-based preventive medicine.

8. Conclusion

Artificial intelligence has demonstrated remarkable potential to enhance non-invasive diagnostic techniques, and its application to aura scanning offers an emerging pathway for integrative digital health. By leveraging advanced imaging modalities such as infrared thermography, multispectral imaging, and Kirlian photography, combined with computational tools like convolutional neural networks and deep learning classifiers, researchers can extract patterns from aura data that may reflect physiological and psychological conditions [68]. This convergence of AI and aura analysis holds significance as it not only advances the scientific understanding of subtle biofields but also introduces opportunities for early detection of stress, fatigue, and emotional imbalances.

One of the most profound contributions of this research direction is its ability to bridge metaphysical traditions with evidence-based scientific healthcare. Aura, historically considered within spiritual and holistic practices, can now be examined through measurable, computationally verifiable methods [69]. This transformation opens the possibility of integrating complementary and preventive healthcare models with modern clinical frameworks, offering a more holistic view of human well-being.

However, challenges remain. The absence of standardized datasets, variability in aura capturing techniques, limited clinical validation, and ethical concerns related to privacy and misuse hinder widespread adoption [70]. Future research must therefore focus on building large annotated databases, developing standardized imaging protocols, ensuring cross-disciplinary collaboration, and adopting explainable AI to foster transparency and trust. By addressing these gaps, AI-driven aura scanning could mature into a credible supplementary tool within preventive and holistic healthcare.

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