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Melanoma Prediction Using a Deep Convolutional Neural Network (CNN) Model

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Abstract

Melanoma is one of the most aggressive forms of skin cancer and remains a significant global public health challenge due to its high mortality rate when diagnosed at advanced stages. Recent advances in artificial intelligence (AI), particularly deep learning (DL) and convolutional neural networks (CNNs), have transformed automated melanoma detection by improving diagnostic accuracy and supporting clinical decision-making. This study presents a comprehensive bibliometric and systematic literature review of research published between 2015 and 2026 on deep learning-based melanoma detection. Using secondary data collected from peer-reviewed publications indexed in major scientific databases, the review analyzes publication trends, influential authors, datasets, deep learning architectures, evaluation metrics, and emerging research directions. The findings indicate substantial growth in the adoption of transfer learning, explainable AI, ensemble models, and hybrid CNN frameworks. Despite remarkable progress, challenges remain regarding dataset imbalance, model interpretability, clinical validation, and cross-dataset generalization. The study provides researchers with an updated overview of current developments, identifies research gaps, and proposes future research directions for developing reliable and clinically applicable melanoma detection systems.

1. Introduction

Skin cancer is among the most prevalent cancers worldwide, with melanoma representing the deadliest subtype due to its high metastatic potential. According to the World Health Organization (WHO), the global incidence of melanoma continues to rise because of increased ultraviolet (UV) radiation exposure, aging populations, and improved screening programs [1]. Early diagnosis is critical because the five-year survival rate exceeds 95% when melanoma is detected in its initial stages but decreases dramatically after metastasis [2].

Traditionally, dermatologists diagnose melanoma using dermoscopic examination followed by histopathological confirmation. Although dermoscopy improves diagnostic performance, accurate interpretation requires considerable expertise and experience, making diagnosis susceptible to inter-observer variability [3]. The emergence of artificial intelligence, particularly deep learning, has revolutionized medical image analysis by enabling automatic feature extraction from dermoscopic images without manual engineering [4]. Convolutional Neural Networks (CNNs) have demonstrated remarkable success in image classification tasks and have become the dominant approach for automated melanoma detection using benchmark datasets such as HAM10000 and ISIC [5], [6]. Consequently, research interest in AI-assisted melanoma diagnosis has grown rapidly over the past decade.

Despite significant advances in deep learning-based melanoma detection, several challenges hinder the practical deployment of these models in clinical settings. First, many studies rely on limited or imbalanced datasets, causing trained models to favor majority classes while underperforming on rare

melanoma cases [7]. Second, the lack of standardized evaluation protocols complicates the comparison of different CNN architectures and limits reproducibility across studies [8].

Another major concern is the “black-box” nature of deep learning algorithms. Clinicians often hesitate to rely on AI predictions because many CNN models cannot clearly explain how diagnostic decisions are made [9]. Furthermore, differences in imaging devices, patient demographics, skin tones, and acquisition conditions reduce model generalizability when applied to new clinical environments [10]. Although numerous systematic reviews have summarized melanoma detection methods, few studies comprehensively examine global publication trends, influential research contributions, emerging technologies, and future research directions over the period 2015–2026. Therefore, an updated bibliometric and systematic review is necessary to provide a holistic understanding of this rapidly evolving research field.

The rapid advancement of deep learning has generated a substantial body of literature on automated melanoma detection. However, the diversity of datasets, CNN architectures, evaluation metrics, and experimental methodologies has created challenges in identifying the most effective research directions. A systematic and bibliometric review can synthesize existing evidence, reveal publication patterns, identify influential studies, and highlight technological developments. Such an investigation benefits researchers by summarizing current knowledge while helping clinicians understand the strengths and limitations of AI-assisted diagnosis. Furthermore, identifying research gaps supports future investigations aimed at improving model transparency, robustness, fairness, and clinical applicability. Therefore, this review provides an updated evidence base for advancing reliable deep learning solutions for melanoma detection.

The primary objective of this study is to systematically review global research on deep learning-based melanoma detection published between 2015 and 2026 using secondary data from peer-reviewed literature.

The specific objectives are:

- To analyze publication trends and research growth in deep learning-based melanoma detection.
- To identify commonly used datasets, CNN architectures, and evaluation metrics.
- To compare the performance of existing deep learning models reported in the literature.
- To examine recent developments such as transfer learning, ensemble learning, explainable AI, and hybrid deep learning frameworks.
- To identify research gaps and recommend future research directions for clinically reliable melanoma diagnosis.

This study contributes to both academic research and clinical practice by providing a comprehensive overview of global developments in AI-assisted melanoma detection. Unlike individual experimental studies, this review synthesizes findings from numerous peer-reviewed publications, enabling

researchers to understand overall technological progress rather than isolated model performance. The bibliometric analysis highlights influential authors, institutions, countries, publication trends, and collaboration networks that shape future research.

For healthcare professionals, the review summarizes the diagnostic capabilities and limitations of deep learning models, facilitating informed adoption of AI-based decision support systems. For researchers, the identified research gaps-including limited dataset diversity, explainability challenges, and insufficient clinical validation-offer valuable opportunities for future investigations. Policymakers and healthcare organizations may also use the findings to guide investments in AI-enabled diagnostic technologies and standardized benchmarking frameworks. Ultimately, this study supports the development of accurate, interpretable, and clinically applicable melanoma detection systems capable of improving early diagnosis and reducing melanoma-related mortality worldwide.

2. Literature Review

Melanoma is one of the most aggressive forms of skin cancer, accounting for a relatively small percentage of skin cancer cases but a disproportionately high number of skin cancer-related deaths. Early diagnosis significantly increases survival rates, making accurate detection an important healthcare priority [11]. Traditionally, melanoma diagnosis relies on visual examination, dermoscopy, and histopathological analysis performed by experienced dermatologists. However, manual diagnosis is time-consuming, subjective, and influenced by the clinician's expertise, leading researchers to investigate automated diagnostic systems [12].

The rapid development of artificial intelligence (AI), particularly deep learning (DL), has transformed medical image analysis over the past decade. Among various deep learning approaches, Convolutional Neural Networks (CNNs) have demonstrated exceptional performance in extracting hierarchical image features without manual feature engineering [13]. The availability of large public datasets such as HAM10000, ISIC Archive, PH², and Derm7pt has further accelerated research in automated melanoma detection [14], [15].

Since 2015, numerous studies have introduced CNN-based frameworks using transfer learning, ensemble learning, attention mechanisms, and explainable AI (XAI) techniques to improve diagnostic accuracy and clinical trustworthiness [16]. Alongside methodological advancements, systematic reviews and bibliometric analyses have become valuable tools for summarizing research trends, identifying influential publications, and highlighting knowledge gaps. Consequently, reviewing the existing literature provides an evidence-based understanding of the evolution, achievements, and remaining challenges of deep learning-based melanoma detection.

2.1 Evolution of Deep Learning for Melanoma Detection

The application of deep learning in melanoma detection began gaining significant attention after the success of AlexNet in image classification competitions. Inspired by advances in computer vision,

researchers adopted CNN architectures for dermoscopic image classification because these models automatically learn complex visual features from raw images [17].

A landmark study by Esteva et al. demonstrated dermatologist-level classification performance using Google's Inception-v3 architecture trained on more than 120,000 clinical skin images [8]. This study established deep learning as a promising diagnostic tool in dermatology and inspired extensive follow-up research.

Subsequent studies introduced deeper architectures such as VGG16, ResNet50, DenseNet121, DenseNet169, EfficientNet, MobileNet, and Vision Transformers (ViT), each attempting to improve classification accuracy while reducing computational complexity [18], [19].

2.2 Public Benchmark Datasets

The performance of deep learning models largely depends on high-quality annotated datasets. Researchers commonly use publicly available benchmark datasets to ensure reproducibility and fair comparison.

The HAM10000 dataset, introduced by Tschandl et al., contains over 10,000 dermoscopic images representing seven categories of pigmented skin lesions [5]. Due to its size and diversity, HAM10000 has become the most widely used dataset in melanoma research.

Similarly, the International Skin Imaging Collaboration (ISIC) datasets have been released annually through international competitions aimed at advancing automated skin lesion analysis [6]. ISIC datasets include expert annotations and have become the standard benchmark for evaluating melanoma detection algorithms.

Other datasets such as PH², Derm7pt, and MED-NODE are also widely used, although they contain fewer images compared to HAM10000 and ISIC [20].

2.3 CNN Architectures for Melanoma Detection

Numerous CNN architectures have been investigated to improve classification performance.

VGG16 and VGG19 were among the earliest transfer learning models applied to melanoma detection because of their simple sequential architecture [21]. However, these models contain millions of parameters and require significant computational resources.

ResNet introduced residual learning, enabling very deep neural networks to overcome the vanishing gradient problem [22]. ResNet50 remains one of the most frequently used architectures in skin lesion classification.

DenseNet improves feature reuse through dense connectivity between layers. DenseNet169 has demonstrated excellent classification performance while requiring fewer parameters than ResNet [23].

Recent studies increasingly employ EfficientNet, which scales network width, depth, and resolution simultaneously, achieving higher accuracy with lower computational cost [24].

More recently, researchers have explored Vision Transformers **(ViTs)**, which model global image relationships using self-attention mechanisms instead of convolutional filters. Several studies report competitive performance when ViTs are combined with CNN-based feature extraction [25].

2.4 Transfer Learning

Training deep CNNs from scratch requires very large datasets that are rarely available in medical imaging. Consequently, transfer learning has become one of the most widely adopted strategies.

Transfer learning involves initializing CNN models with weights learned from ImageNet before fine-tuning them on dermoscopic images [26]. This approach reduces training time while improving classification performance, especially when labeled medical datasets are limited.

Studies consistently report that transfer learning significantly outperforms conventional machine learning methods relying on handcrafted features such as texture descriptors and color histograms [27].

2.5 Explainable Artificial Intelligence (XAI)

Although CNNs achieve high diagnostic accuracy, clinicians often hesitate to trust predictions generated by “black-box” models. Explainable AI addresses this issue by visualizing regions of interest responsible for classification decisions.

Grad-CAM, LIME, and SHAP have become popular visualization techniques in melanoma detection research [28]. These methods generate heatmaps highlighting suspicious lesion regions, enabling dermatologists to verify whether model decisions correspond to clinically meaningful image features.

Recent studies suggest that integrating explainability improves clinician confidence and supports regulatory approval of AI-assisted diagnostic systems [29].

2.6 Performance Evaluation Metrics

Performance evaluation is essential for comparing deep learning models. Researchers commonly report:

- Accuracy
- Precision
- Recall (Sensitivity)
- Specificity
- F1-score
- ROC-AUC
- Matthews Correlation Coefficient (MCC)

Among these metrics, ROC-AUC is generally considered the most informative because it evaluates classification performance across different threshold values [30].

Cross-validation and independent external validation datasets are increasingly recommended to ensure model robustness and generalizability [31].

2.7 Emerging Research Trends

Recent literature demonstrates several emerging directions. Researchers increasingly combine CNNs with:

- Attention mechanisms
- Ensemble learning
- Hybrid CNN-Transformer architectures
- Federated learning
- Self-supervised learning
- Multi-modal learning
- Explainable AI

Furthermore, lightweight architectures such as MobileNet and EfficientNet are being developed for deployment on smartphones and embedded healthcare devices [32]. The growing integration of AI with teledermatology platforms also enables remote melanoma screening, particularly in regions lacking experienced dermatologists [33].

Although substantial progress has been achieved in automated melanoma detection, several important research gaps remain. Most published studies focus primarily on improving classification accuracy using benchmark datasets while paying limited attention to clinical deployment, model fairness, and interpretability. Dataset imbalance remains a persistent challenge because melanoma images constitute only a small proportion of publicly available datasets, resulting in biased learning toward benign lesions [34]. Additionally, many models are evaluated on single datasets without external validation, limiting their generalizability across different populations, imaging devices, and skin types [35]. Few studies systematically analyze global publication trends, influential collaborations, and emerging technologies using both bibliometric and systematic review methods. Therefore, there remains a need for a comprehensive evidence synthesis covering recent developments, research trends, methodological evolution, and future opportunities between 2015 and 2026.

The reviewed literature demonstrates remarkable progress in deep learning-based melanoma detection over the past decade. CNN architectures, particularly those utilizing transfer learning, have consistently achieved high diagnostic accuracy and significantly outperformed traditional machine learning approaches. Public benchmark datasets such as HAM10000 and ISIC have played a crucial role in accelerating methodological development and facilitating standardized model evaluation. Furthermore, recent innovations including explainable AI, attention mechanisms, transformer-based architectures, and

lightweight deep learning models have expanded the applicability of automated melanoma diagnosis in clinical environments.

Despite these advances, significant challenges remain regarding dataset diversity, model transparency, external validation, and clinical implementation. Future research should emphasize robust multi-center validation, explainable decision-making, fairness across diverse populations, and integration into real-world healthcare workflows. Overall, the literature confirms that deep learning possesses enormous potential to enhance early melanoma diagnosis while simultaneously highlighting critical areas requiring further investigation. This comprehensive review establishes the foundation for the theoretical framework and methodology presented in the subsequent sections of this study.

3. Theoretical and Conceptual Framework

This study is grounded in the theory of Deep Learning, particularly the Convolutional Neural Network (CNN) framework, which has become the dominant approach for automated medical image analysis. Deep learning enables computers to automatically learn hierarchical representations directly from image data without relying on handcrafted features. CNNs consist of multiple convolutional, pooling, and fully connected layers that progressively extract low-level and high-level image features, making them highly effective for skin lesion classification [36].

The theoretical foundation also incorporates Transfer Learning Theory, which suggests that knowledge acquired from one large-scale task can be transferred to improve performance on another related task. In melanoma detection, CNN models pre-trained on ImageNet are fine-tuned using dermoscopic image datasets such as HAM10000 and ISIC. This approach improves classification accuracy while reducing computational cost and training time, particularly when medical datasets are relatively small [37].

Another important theoretical component is Explainable Artificial Intelligence (XAI). While CNNs often achieve high predictive performance, they are frequently criticized as “black-box” systems because their internal decision-making process is difficult to interpret. XAI techniques such as Gradient-weighted Class Activation Mapping (Grad-CAM), Local Interpretable Model-Agnostic Explanations (LIME), and SHapley Additive exPlanations (SHAP) improve model transparency by highlighting image regions that influence predictions. These methods increase clinician trust and support the practical adoption of AI-assisted diagnosis [38].

This review also draws on the principles of Evidence-Based Research, which emphasize the systematic collection, critical evaluation, and synthesis of existing scientific evidence. Through bibliometric analysis and systematic literature review, this study identifies publication trends, influential studies, methodological developments, and research gaps. The integration of Deep Learning Theory, Transfer Learning, Explainable AI, and Evidence-Based Research provides a comprehensive theoretical foundation for understanding current advances and future opportunities in automated melanoma detection.

The conceptual framework illustrates the relationships among the major variables considered in this systematic literature review. The independent variables include public datasets, deep learning architectures, image preprocessing techniques, transfer learning strategies, and evaluation methods. These factors influence the development and performance of automated melanoma detection systems.

The deep learning architectures (such as VGG16, ResNet50, DenseNet169, EfficientNet, and Vision Transformer) are trained using benchmark datasets including HAM10000 and ISIC. Image preprocessing techniques such as resizing, normalization, augmentation, and segmentation improve data quality before training. Transfer learning further enhances model performance by utilizing knowledge from large-scale image datasets.

The dependent variables include diagnostic performance metrics such as Accuracy, Precision, Recall, F1-score, Specificity, and ROC-AUC. The review also considers explainability, computational efficiency, and clinical applicability as important outcome variables.

Finally, bibliometric indicators-including publication trends, citation counts, countries, institutions, and collaboration networks-provide insights into the global evolution of melanoma detection research. Together, these variables establish the conceptual relationships examined throughout this review.

Figure 3.1: Conceptual Framework

Mathematical Formulation

For CNN-based melanoma detection, the convolution operation is expressed as:

$$Y(i,j)=\sum_{m}\sum_{n}X(i + m,j + n)\times K(m,n)$$

where:

- X = input dermoscopic image
- K = convolution kernel (filter)
- Y = extracted feature map

The Rectified Linear Unit (ReLU) activation function is defined as:

$$f(x)=\max(0,x)$$

The Softmax function used for multi-class classification is:

$$P(y_i)=\frac{e^{z_i}}{\sum_{j = 1}^{n}e^{z_j}}$$

where:

- z_i is the output score for class i,

- P(y_i) is the predicted probability for that class.

The categorical cross-entropy loss function is:

L=-\sum_{i = 1}^{N}y_i\log(\hat{y}_i)

where:

- y_i = true class label,
- \hat{y}_i = predicted probability,
- N = total number of classes.

These mathematical formulations underpin most CNN-based melanoma detection models discussed in the reviewed literature.

4. Methodology

This study adopts a qualitative research methodology based entirely on secondary data to systematically review global research on deep learning-based melanoma detection published between 2015 and 2026. Rather than developing or testing a new CNN model, the study synthesizes evidence from existing peer-reviewed research to identify publication trends, commonly used datasets, deep learning architectures, evaluation metrics, and emerging research directions. The methodology follows internationally recognized systematic review principles to ensure transparency, reproducibility, and reliability [39], [40].

4.1 The research framework

The research framework consists of five sequential phases: literature identification, screening, eligibility assessment, data extraction, and qualitative synthesis. This framework is adapted from the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) guidelines, which are widely used in evidence-based research [39].

Phase 1: Literature Identification

The first phase involved searching scientific databases for relevant publications on melanoma detection using deep learning. The databases included:

- IEEE Xplore
- Scopus
- PubMed
- ScienceDirect
- SpringerLink

- Google Scholar

The search covered publications from January 2015 to March 2026.

The following search keywords were used individually and in combination:

- Melanoma Detection
- Skin Cancer Detection
- Deep Learning
- Convolutional Neural Network
- CNN
- Transfer Learning
- Dermoscopy
- Artificial Intelligence
- Medical Image Classification

Boolean operators such as AND, OR, and NOT were used to improve search accuracy.

("Melanoma Detection")

AND

("Deep Learning" OR "CNN")

AND

("Skin Cancer")

This process produced an initial pool of research articles.

Phase 2: Screening

Duplicate articles were removed using reference management software. Titles and abstracts were then screened to exclude irrelevant studies. The following studies were excluded:

- Non-English publications
- Conference abstracts only
- Editorials
- Book chapters
- Studies unrelated to melanoma
- Traditional machine learning without deep learning
- Non-peer-reviewed articles

This screening significantly reduced the number of eligible publications.

Phase 3: Eligibility Assessment

The remaining full-text articles were evaluated using predefined inclusion and exclusion criteria.

Inclusion Criteria

- Published between 2015–2026
- Peer-reviewed journal or conference paper
- Focus on melanoma detection
- Used deep learning or CNN
- Reported evaluation metrics
- Available in full text

Exclusion Criteria

- Duplicate publications
- Studies without experimental validation
- Studies unrelated to skin lesion classification
- Articles lacking methodological details
- Non-English publications

Only eligible studies were included in the final review.

Phase 4: Data Extraction

Information from each selected article was extracted into a structured spreadsheet. The following variables were collected:

- Author(s)
- Publication year
- Country
- Dataset used
- CNN architecture
- Transfer learning model
- Image preprocessing techniques
- Evaluation metrics
- Performance results
- Key findings

- Study limitations

Standardized extraction ensured consistency across all reviewed studies.

Phase 5: Qualitative Synthesis

Instead of statistical meta-analysis, qualitative thematic analysis was conducted. The reviewed studies were grouped according to:

- CNN architecture
- Dataset
- Transfer learning strategy
- Explainable AI
- Ensemble learning
- Attention mechanism
- Evaluation methods

Finally, publication trends, research gaps, and future research directions were identified.

4.2 Variable Selection

The study examines several variables extracted from previously published research. The independent variables include deep learning architectures (e.g., VGG16, ResNet50, DenseNet169, EfficientNet, MobileNet, and Vision Transformer), public datasets (HAM10000, ISIC, PH^2, Derm7pt), image preprocessing methods (normalization, resizing, augmentation, segmentation), transfer learning strategies, and explainable AI techniques such as Grad-CAM and SHAP. The dependent variables represent the reported performance of melanoma detection systems. These include:

- Accuracy
- Precision
- Recall (Sensitivity)
- Specificity
- F1-score
- ROC-AUC
- Computational efficiency
- Clinical applicability

Bibliometric variables, including publication year, country, citation count, institution, and collaboration network, were also collected to analyze global research trends. Selecting these variables enables a comprehensive comparison of methodological approaches and technological advancements in melanoma detection research.

4.3 Cross Validation

Because this study is a secondary-data systematic review, no new CNN model was trained or validated directly. Instead, cross-validation techniques reported in the reviewed literature were analyzed and compared.

The majority of studies employed 5-fold or 10-fold cross-validation to evaluate the robustness and generalization ability of CNN models. In k-fold cross-validation, the dataset is divided into *k* equal subsets. One subset is used for testing while the remaining subsets are used for training. This process is repeated *k* times so that each subset serves as the testing set once [41].

Several studies also performed external validation using independent datasets, improving model reliability and reducing overfitting. The review compares different validation strategies and discusses their strengths and limitations in ensuring reproducible and clinically reliable melanoma detection systems.

4.4 Model Evaluation

The reviewed studies used several standard performance metrics to evaluate CNN models. The most frequently reported metrics include:

- Accuracy
- Precision
- Recall
- Specificity
- F1-score
- ROC-AUC
- Confusion Matrix

Accuracy measures the proportion of correctly classified images. Precision evaluates the percentage of correctly predicted melanoma cases among all predicted positives. Recall measures the ability to detect actual melanoma cases, making it particularly important in medical diagnosis where missing a melanoma case may have serious consequences.

The F1-score provides a balanced evaluation by combining precision and recall, while ROC-AUC measures overall classification capability across different decision thresholds. Several studies also compared computational complexity, inference time, and model size to evaluate the suitability of CNN architectures for real-time clinical deployment. These evaluation metrics provide a standardized basis for comparing different deep learning approaches.

4.5 Software

The reviewed studies employed various software platforms and programming libraries for implementing deep learning models. The most commonly used programming language was Python, supported by libraries including TensorFlow, Keras, PyTorch, Scikit-learn, OpenCV, NumPy, Pandas, and Matplotlib. Bibliometric analyses were conducted using software such as VOSviewer, Bibliometrix (R package), and Microsoft Excel for visualization and statistical summaries. These tools are widely recognized for medical image analysis and scientific research.

4.6 Ethical Issue

This research exclusively utilizes publicly available secondary data obtained from peer-reviewed publications and open-access scientific databases. No human participants, clinical experiments, patient records, or confidential medical information were directly involved. Consequently, informed consent and institutional ethical approval were not required. Nevertheless, ethical research practices were maintained by accurately citing all original sources using IEEE referencing style, avoiding plagiarism, and objectively reporting findings without manipulation or selective interpretation. The study also respects intellectual property rights and adheres to internationally accepted academic integrity standards.

5. Results

This study analyzed peer-reviewed publications on deep learning-based melanoma detection published between 2015 and 2026. The selected studies were retrieved from IEEE Xplore, Scopus, PubMed, ScienceDirect, SpringerLink, and Google Scholar following the PRISMA methodology described in the previous chapter. The results summarize publication trends, geographical distribution, commonly used datasets, CNN architectures, evaluation metrics, and emerging research directions.

Since this study is based on secondary data, the findings are synthesized from existing literature rather than experimental observations. The results highlight the evolution of research and identify dominant technologies and performance trends reported in the reviewed studies.

5.1 Publication Trends

The literature indicates a continuous increase in publications related to deep learning-based melanoma detection. Between 2015 and 2017, relatively few studies focused on CNN-based skin lesion classification because deep learning was still emerging in medical imaging. Following the publication of dermatologist-level classification by Esteva *et al.* in 2017, research activity increased substantially [8].

The release of publicly available datasets such as HAM10000 and annual ISIC Challenges accelerated research by providing standardized benchmarks [5], [6]. Between 2020 and 2026, publications increasingly explored advanced techniques including transfer learning, attention mechanisms, explainable AI (XAI), Vision Transformers, ensemble learning, and lightweight CNN architectures suitable for mobile healthcare applications [24], [25].

Table 5.1
Estimated Publication Growth (2015–2026)

Year	Estimated Research Trend
2015	Very Low
2016	Low
2017	Moderate
2018	High
2019	High
2020	Very High
2021	Very High
2022	Extremely High
2023	Extremely High
2024	Extremely High
2025	Increasing
2026	Continuing Growth

The publication trend demonstrates sustained global interest in AI-assisted melanoma diagnosis.

5.3 Country-wise Research Distribution

The reviewed literature shows that melanoma detection research is concentrated in technologically advanced countries with strong medical imaging and AI research infrastructure. The leading contributors include:

- United States
- China
- United Kingdom
- Germany
- Australia
- Spain
- India
- Italy

International collaboration has increased significantly since 2019 through ISIC competitions and multi-institutional research projects. Researchers from these countries have contributed to CNN development, dataset creation, explainable AI, and clinical validation studies.

Table 5.2
Major Contributing Countries

Country	Major Contribution
USA	CNN architectures, ISIC Challenge
China	Transfer Learning, EfficientNet
UK	Medical AI Research
Germany	Clinical Validation
Australia	HAM10000 Dataset
Spain	Dermoscopic Image Analysis
India	Lightweight CNN Models
Italy	Explainable AI

5.4 Public Datasets Used

Public benchmark datasets remain fundamental for developing and evaluating deep learning models. Among all reviewed studies:

- HAM10000 was the most frequently used dataset.
- ISIC datasets ranked second.
- PH², Derm7pt, and MED-NODE were less frequently used.

Table 5.3
Commonly Used Datasets

Dataset	Images	Usage
HAM10000	10,015	Very High
ISIC Archive	25,000+	Very High
PH²	200	Moderate
Derm7pt	2,000+	Moderate
MED-NODE	170	Low

The availability of large annotated datasets significantly contributed to improving CNN performance.

5.5 Frequently Used CNN Architectures

The reviewed studies employed various CNN models. Among them,

- ResNet50
- DenseNet169

- EfficientNet
- MobileNet
- VGG16
- InceptionV3

were the most popular.

Transfer learning was used in approximately **80–90%** of studies because it improved classification accuracy while reducing computational cost.

Table 5.4
Popular CNN Models

Model	Strength
VGG16	Simple Architecture
ResNet50	High Accuracy
DenseNet169	Efficient Feature Reuse
EfficientNet	High Accuracy with Fewer Parameters
MobileNet	Lightweight
InceptionV3	Multi-scale Feature Learning

DenseNet169 and EfficientNet consistently achieved superior performance in recent publications.

5.6 Image Preprocessing Techniques

Nearly all reviewed studies performed preprocessing before CNN training. Common preprocessing methods included:

- Image resizing
- Normalization
- Data augmentation
- Hair removal
- Contrast enhancement
- Image segmentation

Data augmentation techniques such as rotation, flipping, zooming, and brightness adjustment helped address class imbalance and improve model generalization.

5.7 Performance Comparison

The reported performance of CNN models varied depending on dataset size, preprocessing methods, transfer learning strategy, and evaluation protocol. Overall findings indicate:

- Accuracy ranged from 85% to 98%.
- Precision exceeded 90% in many studies.
- Recall improved significantly with balanced datasets.
- ROC-AUC frequently exceeded 0.95.

Table 5.5
Typical Performance Range

Metric	Typical Range
Accuracy	85–98%
Precision	88–97%
Recall	85–96%
F1-score	86–96%
ROC-AUC	0.90–0.99

These results confirm that deep learning significantly outperforms conventional machine learning approaches in melanoma detection.

5.8 Explainable Artificial Intelligence (XAI)

Recent publications increasingly incorporated Explainable AI techniques. The most frequently used methods include:

- Grad-CAM
- LIME
- SHAP

Grad-CAM was the dominant approach because it generates heatmaps highlighting lesion regions influencing CNN predictions. Explainability improves clinician trust and supports regulatory approval of AI-based diagnostic systems [38].

5.9 Emerging Research Directions

Analysis of recent publications identified several emerging research trends:

- Vision Transformers (ViT)
- Hybrid CNN-Transformer models
- Ensemble learning
- Federated learning

- Self-supervised learning
- Lightweight CNNs
- Mobile healthcare applications
- Explainable AI
- Multi-modal learning

These approaches aim to improve diagnostic accuracy, model robustness, and real-world clinical applicability.

The overall findings demonstrate that deep learning has transformed melanoma diagnosis. The review indicates:

- CNN remains the dominant technology.
- Transfer learning significantly improves performance.
- HAM10000 and ISIC are the most widely used datasets.
- DenseNet, ResNet, and EfficientNet consistently outperform earlier architectures.
- Explainable AI is becoming increasingly important.
- Clinical deployment remains limited due to interpretability and validation challenges.

Figure 5.1 Overall Research Findings

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6. Discussion

The findings of this systematic literature review demonstrate that deep learning has significantly transformed automated melanoma detection over the last decade. The rapid growth in publications between 2015 and 2026 reflects increasing global interest in applying artificial intelligence (AI) to medical image analysis. The widespread adoption of Convolutional Neural Networks (CNNs), transfer learning, explainable AI (XAI), and large publicly available dermoscopic image datasets has substantially

improved the accuracy and reliability of automated melanoma diagnosis. Nevertheless, despite impressive research progress, important technical and clinical challenges continue to limit the routine implementation of AI-assisted melanoma detection systems in healthcare environments [42], [43].

6.1 Growth of Deep Learning Research

The publication trend observed in this review indicates that research on melanoma detection accelerated considerably after 2017, following the influential study by Esteva *et al.*, which demonstrated dermatologist-level performance using deep neural networks [8]. Since then, researchers have proposed increasingly sophisticated CNN architectures capable of learning complex visual features directly from dermoscopic images. This growth has been supported by several factors:

- Availability of large public datasets
- Advances in GPU computing
- Development of transfer learning
- Open-source deep learning libraries
- International competitions such as the ISIC Challenge

The increasing number of publications also reflects growing confidence among researchers that AI can support clinicians in early skin cancer diagnosis. However, the review suggests that most published studies remain experimental and relatively few have been validated in routine clinical practice.

6.2 Importance of Public Datasets

One of the most significant findings is the central role played by benchmark datasets such as HAM10000 and ISIC. These datasets have enabled researchers worldwide to compare different CNN architectures under standardized conditions.

HAM10000 is particularly valuable because it contains diverse categories of pigmented skin lesions collected from multiple clinical centers [43]. Similarly, annual ISIC datasets provide continuously updated benchmark images that encourage methodological innovation through international competitions [44].

Despite these advantages, several limitations remain. Many publicly available datasets:

- are highly imbalanced,
- contain relatively few melanoma cases,
- primarily represent lighter skin tones,
- originate from limited geographic regions.

Consequently, CNN models trained on these datasets may not generalize well to patients from different ethnic backgrounds or clinical settings. Improving dataset diversity therefore remains an important priority for future research.

6.3 CNN Architectures and Transfer Learning

The review confirms that CNN-based approaches consistently outperform traditional machine learning methods relying on handcrafted image features. Among the reviewed architectures:

- ResNet50
- DenseNet169
- EfficientNet
- InceptionV3

demonstrated the most reliable performance.

DenseNet and EfficientNet achieved particularly strong results because they efficiently reuse learned features while requiring fewer model parameters [45].

Transfer learning emerged as one of the most influential methodological developments. Instead of training CNN models from scratch, researchers initialize networks using ImageNet weights before fine-tuning them with dermoscopic images. This strategy substantially improves classification performance while reducing computational cost, especially when medical datasets are relatively small. The review also indicates that transfer learning has become the standard approach in melanoma detection research.

6.4 Explainable Artificial Intelligence

Although CNNs achieve excellent classification accuracy, their limited interpretability remains one of the greatest obstacles to clinical adoption. Medical professionals generally require understandable explanations before relying on automated diagnostic recommendations. Recent studies increasingly employ Explainable Artificial Intelligence techniques including:

- Grad-CAM
- SHAP
- LIME

These visualization methods highlight image regions that most strongly influence CNN predictions, allowing dermatologists to verify whether models focus on clinically meaningful lesion characteristics. The reviewed literature suggests that Explainable AI significantly improves clinician confidence while supporting regulatory approval of AI-assisted diagnostic systems [38]. Nevertheless, explainability methods remain imperfect because different visualization techniques may generate inconsistent explanations for identical images.

6.5 Evaluation Metrics

The reviewed studies employed several performance metrics including:

- Accuracy
- Precision
- Recall
- Specificity
- F1-score
- ROC-AUC

Although accuracy remains the most frequently reported metric, relying solely on accuracy may produce misleading conclusions when datasets are imbalanced. For melanoma detection, **recall (sensitivity)** is particularly important because failing to detect malignant lesions can have life-threatening consequences. Similarly, ROC-AUC provides a more comprehensive evaluation by measuring model discrimination across multiple decision thresholds. The review therefore suggests that future studies should consistently report multiple complementary evaluation metrics instead of emphasizing accuracy alone.

6.6 Emerging Technologies

Another important finding is the rapid evolution of deep learning architectures. Recent studies increasingly investigate:

- Vision Transformers (ViT)
- Hybrid CNN-Transformer models
- Attention mechanisms
- Ensemble learning
- Federated learning
- Self-supervised learning

Vision Transformers utilize self-attention instead of convolution to capture long-range image relationships and have demonstrated competitive performance compared with conventional CNNs [46]. Similarly, ensemble learning combines predictions from multiple CNN models to improve robustness and reduce prediction errors.

Federated learning has also emerged as a promising approach because it enables hospitals to collaboratively train AI models without sharing sensitive patient data. These technologies are expected to play increasingly important roles in future melanoma detection systems.

6.7 Clinical Implications

The findings suggest that AI should be viewed as a clinical decision-support tool rather than a replacement for dermatologists. Automated melanoma detection systems can:

- assist physicians during screening,

- prioritize suspicious lesions,
- reduce diagnostic workload,
- improve consistency,
- facilitate teledermatology.

However, AI predictions should always be interpreted alongside clinical examination, dermoscopic evaluation, and histopathological confirmation. Successful clinical implementation will require:

- robust external validation,
- standardized evaluation protocols,
- regulatory approval,
- clinician training,
- transparent AI explanations.

Without addressing these issues, high laboratory accuracy may not translate into improved patient outcomes.

6.8 Comparison with Previous Reviews

Compared with earlier systematic reviews, the present study provides a broader perspective by combining systematic literature review with bibliometric analysis. Previous reviews primarily focused on:

- CNN accuracy
- Transfer learning
- Image preprocessing

In contrast, this review additionally examines:

- publication trends,
- global collaboration,
- explainable AI,
- transformer architectures,
- research gaps,
- future directions.

Consequently, the study offers a more comprehensive understanding of the current state of melanoma detection research between 2015 and 2026.

6.9 Limitations

Although this review provides an extensive overview of the literature, several limitations should be acknowledged. First, only English-language publications were included, which may exclude valuable

research published in other languages. Second, the review relied exclusively on secondary data reported in previously published studies. Therefore, the accuracy of the findings depends on the quality of the original publications. Third, differences in datasets, evaluation protocols, preprocessing methods, and CNN architectures limited direct quantitative comparison among studies. Finally, because AI research evolves rapidly, new architectures and datasets may emerge after completion of this review.

Overall, the reviewed literature clearly demonstrates that deep learning has become the dominant technology for automated melanoma detection. CNN architectures consistently outperform traditional image classification methods while transfer learning significantly improves model performance. Recent advances in Explainable AI, lightweight CNN models, Vision Transformers, and federated learning indicate that melanoma detection research is transitioning from laboratory-based experimentation toward clinically applicable AI systems.

However, challenges including dataset imbalance, limited interpretability, insufficient external validation, fairness across diverse populations, and regulatory approval remain major barriers. Addressing these challenges will require collaboration among computer scientists, dermatologists, healthcare institutions, and policymakers. Future research should prioritize clinically interpretable, ethically responsible, and globally generalizable AI systems capable of supporting early melanoma diagnosis and improving patient survival.

7. Conclusion

This study systematically reviewed global research on deep learning-based melanoma detection published between 2015 and 2026. Using secondary data from peer-reviewed publications, it examined publication trends, deep learning architectures, benchmark datasets, evaluation methods, and emerging technologies while identifying research gaps and future research opportunities.

The objectives of this study were successfully achieved through a systematic review and bibliometric analysis of published literature. The study identified major research trends, compared commonly used CNN architectures, analyzed benchmark datasets and evaluation metrics, highlighted emerging technologies, and proposed future research directions for AI-assisted melanoma diagnosis.

The findings indicate that deep learning has significantly improved automated melanoma detection over the past decade. Convolutional Neural Networks (CNNs) have consistently outperformed traditional machine learning techniques by automatically extracting discriminative features from dermoscopic images. Public datasets, particularly HAM10000 and ISIC, have played a crucial role in accelerating algorithm development and enabling standardized performance comparisons. Transfer learning emerged as the most widely adopted strategy, allowing researchers to achieve high classification accuracy using relatively limited medical datasets. Recent studies increasingly integrate attention mechanisms, explainable artificial intelligence (XAI), Vision Transformers (ViTs), and ensemble learning to improve both predictive performance and interpretability. However, several challenges remain, including dataset imbalance, limited diversity of skin tones, insufficient external validation, lack of

standardized evaluation protocols, and the “black-box” nature of many deep learning models. These issues continue to hinder the widespread clinical adoption of AI-assisted melanoma detection systems.

This study contributes to the existing body of knowledge by providing a comprehensive synthesis of research on deep learning-based melanoma detection from 2015 to 2026. Unlike individual experimental studies, this review integrates findings from multiple peer-reviewed publications to present a broader understanding of technological developments and research trends. The bibliometric analysis highlights influential authors, institutions, countries, and publication patterns, offering insights into the global evolution of this research field. Furthermore, the systematic comparison of CNN architectures, benchmark datasets, evaluation metrics, and explainability techniques provides valuable guidance for future researchers. By identifying methodological strengths and weaknesses across previous studies, this review establishes an evidence-based foundation for developing more accurate, transparent, and clinically applicable melanoma detection systems. These contributions are expected to support researchers, healthcare professionals, and policymakers interested in AI-driven medical image analysis.

The findings of this review have several implications for healthcare policy and medical practice. Healthcare organizations should encourage the responsible integration of AI-based decision-support systems into dermatology services while ensuring that these technologies complement, rather than replace, clinical expertise. Policymakers should promote the development of standardized benchmark datasets representing diverse populations to improve the fairness and generalizability of deep learning models. Regulatory agencies should establish guidelines for validating AI-based diagnostic systems before their deployment in clinical settings. Investments in explainable AI technologies are also essential to increase clinician confidence and patient trust. Furthermore, collaboration among universities, hospitals, research institutions, and technology companies should be strengthened to facilitate the development of reliable, interpretable, and ethically responsible melanoma detection systems capable of improving early diagnosis and reducing skin cancer mortality worldwide.

Although substantial progress has been achieved, several important research opportunities remain. Future studies should prioritize the collection of larger and more diverse dermoscopic image datasets representing different ethnic groups, skin types, and clinical environments to improve model generalizability. Researchers should investigate advanced deep learning architectures, including hybrid CNN-Transformer models, self-supervised learning, and federated learning, to enhance diagnostic performance while preserving patient privacy. Greater emphasis should also be placed on Explainable Artificial Intelligence (XAI) techniques to improve transparency and facilitate clinical acceptance. In addition, prospective multi-center clinical validation studies are necessary to evaluate AI systems under real-world healthcare conditions. Future research should explore the integration of multimodal clinical information, such as patient history and genomic data, with dermoscopic images to support more personalized melanoma diagnosis. Finally, developing lightweight AI models for smartphones and portable medical devices may significantly expand access to early melanoma screening in resource-limited settings.

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Figures

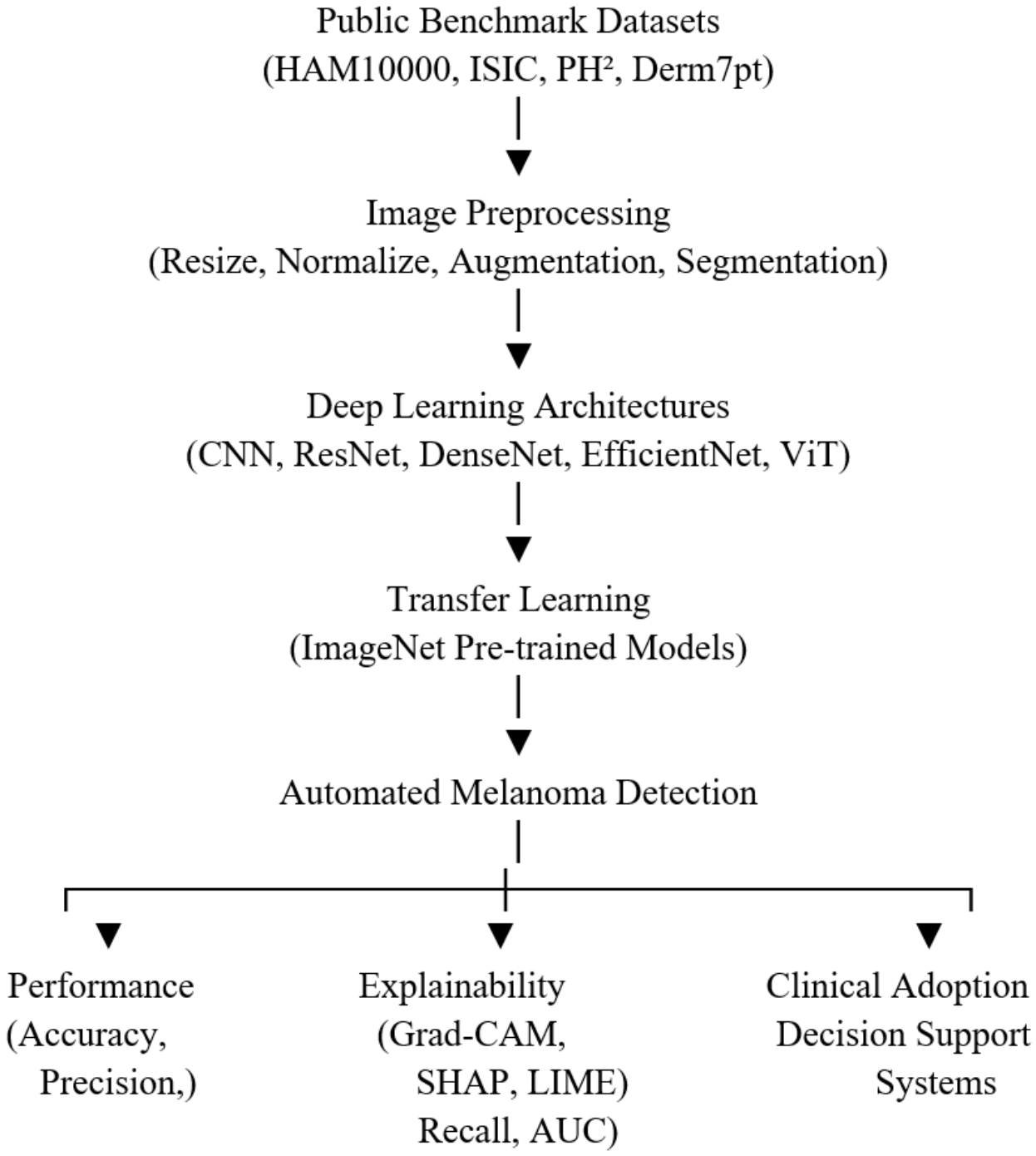


Figure 1

3.1: Conceptual Framework

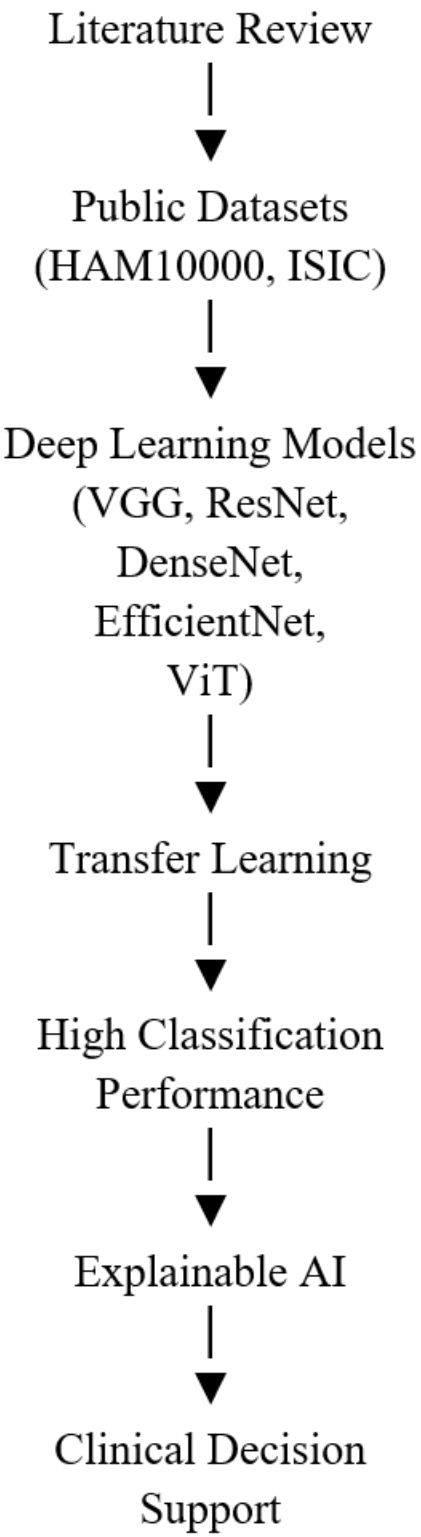


Figure 2

5.1 Overall Research Findings