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3D Point Cloud Data with Deep Learning Algorithm for Melanoma Detection: An Inclusive Review

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Abstract: *Melanoma is a severe and potentially life-threatening form of skin cancer that originates in the pigment-producing melanocytes. Early detection is critical for improving survival rates, yet traditional diagnostic methods such as visual inspection and dermoscopic analysis can be subjective and limited in accuracy. In recent years, deep learning techniques have gained prominence in melanoma detection, particularly through the use of 2D dermoscopic image analysis with convolutional neural networks (CNNs) like AlexNet, VGGNet, and ResNet.. To overcome these limitations, recent trends have shifted toward 3D imaging and point cloud-based analysis, which allow for the inclusion of geometric and spatial information. Advanced models such as PointNet and DGCNN have shown promise in directly analyzing 3D point clouds, offering more robust and structure-aware classification. These advancements signal a transformation in melanoma detection, combining automation with spatial understanding for improved diagnostic accuracy. This paper represents recent advancements in melanoma detection, shifting from 2D image analysis to 3D point cloud methods. Models like PointNet and DGCNN enhance accuracy by capturing lesion depth and structure.*

Keywords: Melanoma

I. INTRODUCTION

Melanoma, a malignant tumor of melanocytes, represents one of the most aggressive and potentially deadly forms of skin cancer. Early detection and accurate diagnosis are crucial to improving patient outcomes and reducing mortality rates.[1]Melanoma is a dangerous form of skin cancer that can be deadly if not caught early. While it's less common than other skin cancers, it's responsible for most skin cancer-related deaths. Early detection is key to improving survival rates[2]. Typically, doctors rely on 2D images of skin lesions to make diagnoses, but these images don't capture all the details, especially when it comes to depth and shape. Advancements in deep learning, particularly in convolutional neural networks (CNNs), have led to significant breakthroughs in medical image analysis. These techniques have shown remarkable performance in various tasks, such as image classification, object detection, and segmentation[3]. However, most existing approaches rely on 2D dermoscopic images, which may not fully capture the complex spatial and morphological characteristics of skin lesions. To address this limitation, researchers have begun exploring the potential of 3D imaging techniques, including point cloud data, for more comprehensive analysis. Point cloud data offers a 3D representation of the lesion's surface geometry, enabling the capture of detailed topological features that are otherwise overlooked in 2D imagery. By leveraging 3D data, deep learning models can potentially achieve higher accuracy and robustness in melanoma detection[4]. This article presents an insight of utilizing 3d point cloud in image classification of melanoma detection. This article looks at how using 3D point cloud data, created from 2D images, can improve melanoma detection. By applying deep learning models like PointNet, we aim to better understand the spatial features of lesions, offering a more accurate way to diagnose melanoma[5].

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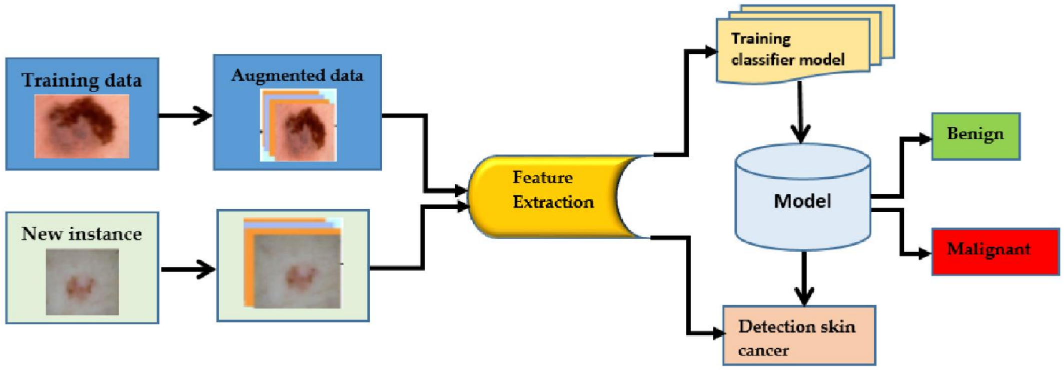

Figure 1.Skin Cancer Detection Workflow using Image Analysis

This figure represents a machine learning process for skin cancer detection using image data. involves data augmentation, feature extraction, and classification into benign or malignant.

II. BACKGROUND AND FOUNDATIONS

2.1 Melanoma: Clinical Overview

Melanoma is a serious form of ISskin cancer that starts in the pigment-producing cells called melanocytes. It usually shows up as a new or changing mole with irregular shapes, uneven colors, and varying sizes. If caught early, melanoma is treatable, but if it spreads to other parts of the body, it becomes much harder to treat, making early detection incredibly important[6].

EPIDEMIOLOGY AND CLINICAL SIGNIFICANCE

Melanoma rates have been on the rise, especially in people with fair skin who are more susceptible to the harmful effects of UV exposure. In countries like the U.S. and Australia, melanoma is a leading cause of skin cancer-related deaths. Over 100,000 new cases are expected in the U.S. each year. People at higher risk include those with fair skin, a history of sunburns, and a family history of melanoma. Catching melanoma early is crucial to improving the chances of survival, but when diagnosed late, it can be fatal[7].

COMMON DIAGNOSIS METHODS

- **Visual Inspection**: Dermatologists typically start by examining moles using the ABCDE rule (Asymmetry, Border irregularity, Color variation, Diameter, and Evolution over time).
- **Dermoscopy**: This tool magnifies the mole, making it easier for doctors to spot early signs of melanoma
- **Biopsy**: If a mole is suspicious, a small sample is taken to confirm whether it's melanoma
- **Sentinel Lymph Node Biopsy**: This test checks if the melanoma has spread to nearby lymph nodes.
- **Imaging and Staging**: Advanced imaging like CT, MRI, or PET scans are used to see if the cancer has spread to other parts of the body.

Even with these methods, diagnosing melanoma can be tricky, and doctors still rely on their judgment. That's why using AI and deep learning tools to assist in melanoma detection is becoming a game-changer[8].

2.2 Imaging Modalities For Melanoma Detection

Dermoscopy -Dermoscopy uses a magnifying tool to examine skin lesions more closely. It's great for spotting early signs of melanoma but relies on the doctor's experience. It doesn't show deeper or 3D details of moles, which can sometimes be important.

(a) (b)

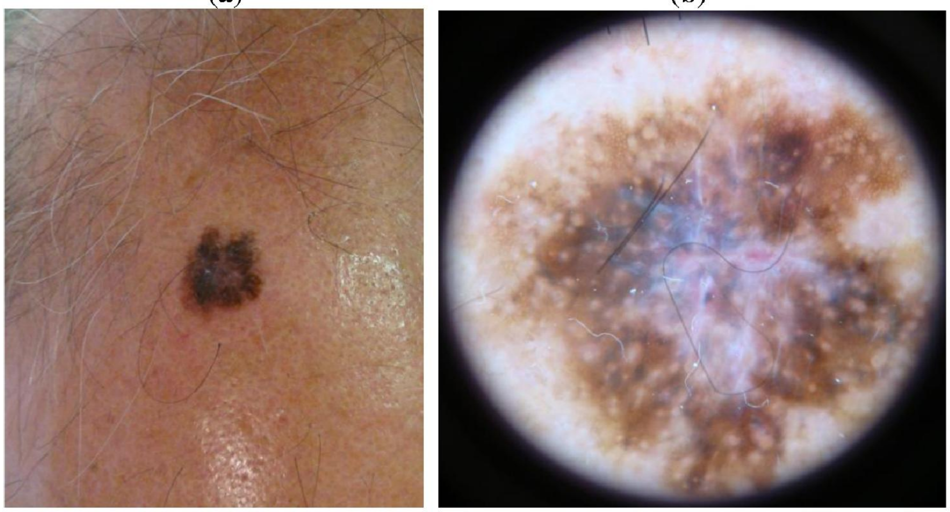

Figure 2. Dermoscopy of Scalp Melanoma

This figure represents **(a)** shows a clinical image of a pigmented skin lesion on the surface of the skin **(b)** displays a dermoscopic (magnified) view of the same lesion, revealing internal structures and color variations useful for melanoma diagnosis

Histopathology -Histopathology involves removing a small tissue sample to look for cancer cells under a microscope. It's the most accurate way to diagnose melanoma but requires a biopsy, making it less practical for routine checks.

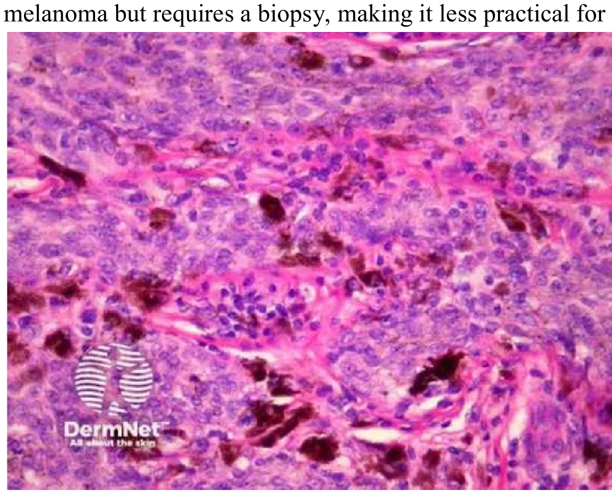

Figure 3. Melanoma Histopathology: nodular melanoma

This figure represents a dermal proliferation of atypical melanocytes arranged in nests and sheets, characteristic of a nodular growth pattern.

Total Body Photography -This method captures high-resolution photos of the entire body to monitor moles over time. It's helpful for tracking changes but doesn't give detailed information about a mole's depth or structure.

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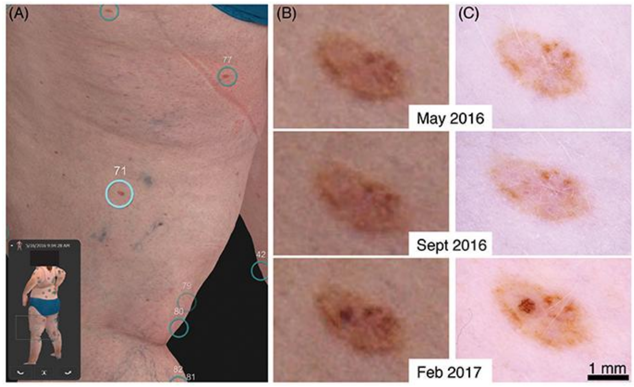

Figure 4. 3D Total Body Photography

This figure shows a detailed imagery allows for the precise tracking and monitoring of moles and other skin lesions over time, aiding in the early detection of changes that may indicate skin cancer.

3D Imaging Techniques -3D imaging like confocal microscopy provides detailed views of skin lesions, showing both surface and deeper layers. While it's very precise, it's also expensive and requires special equipment, making it less common in everyday practice[9].

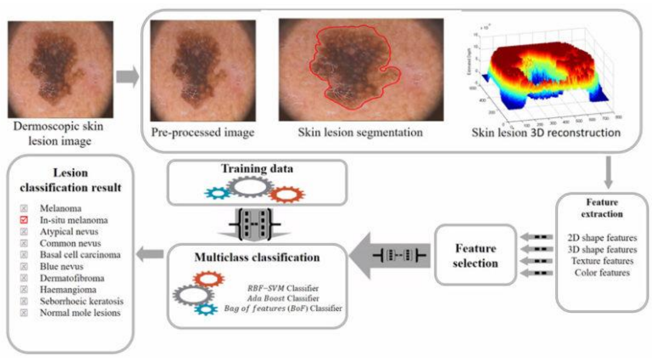

Figure 5. 3D Imaging Techniques

This figure represents a spatial information to create a three-dimensional representation of an object or area, going beyond traditional 2D images.

2.3 Introduction to Deep Learning In Medical Imaging

Overview of CNNs, Transformers, etc.

Deep learning is changing the way doctors look at medical images. Tools like **CNNS** help spot patterns in things like skin scans, while newer models like **transformers** can take in the whole picture at once—literally. This means faster, more accurate diagnoses, especially for things like melanoma.Because medical image data is hard to get in huge amounts, **transfer learning** is a big help. It lets us use models trained on general images and fine-tune them for medical tasks—saving time and resources.To make sure these tools work well, we check them using metrics like **accuracy**, **sensitivity**, and **AUC**. These numbers tell us how reliable the model is when it comes to detecting real health issues and avoiding false alarms[10].

III. DEEP LEARNING MODELS FOR MELANOMA DETECTION

2D Image Datasets

Most AI models for skin cancer detection start with datasets like **ISIC**, which has thousands of mole images labeled by experts. It's the go-to resource for training models to spot melanoma.

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CNN Models

Deep learning tools like **ResNet** and **VGG16** are great at recognizing features in 2D images. ResNet avoids common training problems by adding shortcuts in the model, while VGG16 gives strong results with less computing power[11].

Transformers for Images

Newer models like **ViT** and **Swin Transformer** are changing the game by looking at the whole image at once instead of focusing on small patches. They help spot subtle differences in skin patterns that older models might miss[12].

The Challenges faced by 2d models are

They can't "see" **depth** or **texture**, which matters for skin lesions .

Bad lighting or **shadows** can throw off predictions.

Some benign and cancerous moles look really similar, which confuses the model[13].

IV. EVOLUTION TOWARDS 3D DATA IN MEDICAL IMAGING

2D images are like looking at a photo—they give us an idea, but not the full picture. In medicine, especially when detecting things like melanoma, having that **extra depth** can make all the difference.

3D imaging allows doctors to better understand the shape, size, and location of suspicious areas. It's like switching from a map to a globe—everything becomes clearer and more accurate[14].

3D Data Representation

Voxels: Instead of just showing width and height, voxels add depth. Tools like MRI and CT scans use voxels to build a complete internal view of the body.

Mesh Models: These are like digital nets stretched over the surface of an organ or body part. They're great for seeing shapes in detail like a digital model of a brain or a tumor.

Point Clouds: Imagine thousands of tiny dots floating in space, outlining the shape of a lesion or organ. They're super lightweight and perfect for feeding into AI models without all the heavy image processing[15].

Tools That Bring 3D to Life

MRI (Magnetic Resonance Imaging): Shows detailed 3D images of soft tissues like the brain, muscles, and tumors.

CT (Computed Tomography): Takes many X-ray images and combines them into a 3D model—great for seeing inside the chest or head.

3D Total Body Photography (TBP): Especially helpful in dermatology, this lets doctors scan and monitor the entire skin surface in fine detail.

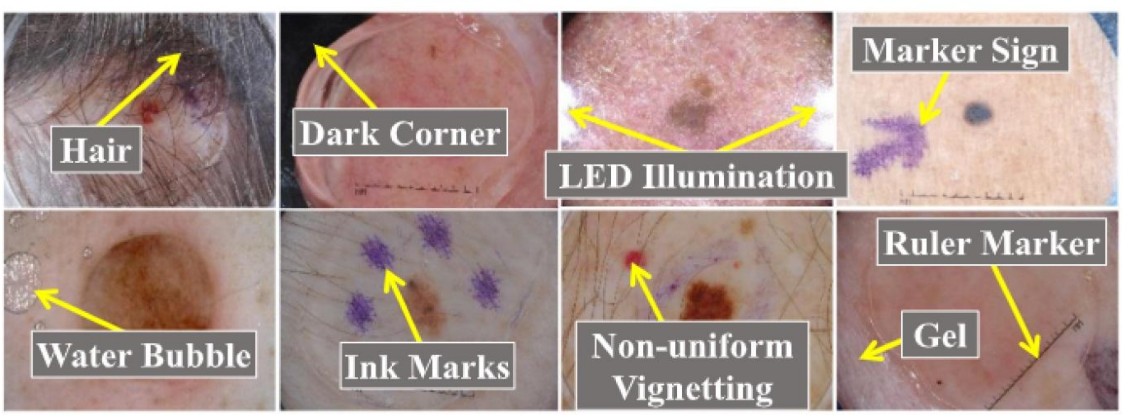

Figure 6. Common Artifacts and Features in Dermoscopic Imaging

This figure highlights common artifacts in dermoscopic images such as hair, ink marks, rulers, and illumination issues. These artifacts can hinder accurate melanoma detection and require preprocessing for effective analysis[16].

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V. 3D POINT CLOUD PROCESSING: TECHNIQUES AND APPLICATIONS

5.1 Basics of Point Cloud

A **point cloud** is a collection of data points in 3D space. These points represent the surface of an object or scene. Each point is defined by its **x, y, and z** coordinates, which specify its location in space. Point clouds can also contain additional information such as color or intensity. They are commonly used in 3D imaging and modeling because they provide a precise way to represent complex shapes and surfaces[17].

Characteristics of point cloud are

They don't have information about how points are connected (unlike meshes).They can vary in density some point clouds have more points in some areas than others.They often come with extra information like color (RGB), intensity, or normal[18].

Point Cloud Generation from 2D Images (e.g., MiDaS Depth Estimation, NeRF (Neural Radiance Fields, Structure from Motion (SfM)):

Even though point clouds are 3D, you can **generate them from 2D images** using **depth estimation models**. One such model is **MiDaS**, which can predict the depth (distance from the camera) of each pixel in a 2D image. When you combine this depth with the pixel's position and camera details (like focal length), you can convert each pixel into a 3D point—creating a full point cloud from a single 2D image.**SFM(Structure from Motion)** Uses multiple 2D images taken from different angles to reconstruct a 3D scene. **NeRF (Neural Radiance Fields**) It Projects pixels with predicted depth into 3D space using camera intrinsics[19].

DEEP LEARNING MODELS FOR POINT CLOUD DATA:

PointNet :

PointNet was the **first deep learning model** designed specifically for raw point clouds. It treats each point individually and then combines all the info to understand the whole shape.

PointNet++

It is based on PointNet by **looking at points in groups** (neighborhoods), like zooming in on different parts of the shape. Much better at handling fine details and complex structures. Objects with intricate shapes or non-uniform point density**.**

Sample Visualizations

Bar Chart: Accuracy Comparison (2D vs 3D)

Method	**Accuracy (%)**
2D CNN (ResNet)	**89**
3D PointNet	**91**

DGCNN (Dynamic Graph CNN):

Creates a **dynamic graph** where each point is linked to its nearest neighbors and learns how these connections evolve. Instead of treating points alone, it focuses on **relationships** between them—kind of like understanding social circles in a group of people.Great for learning both local and global structures.

KPConv (Kernel Point Convolution)

Introduces a type of convolution that works directly on 3D points—similar to how CNNs work on images. It uses **learnable filters** placed in 3D space to capture features more accurately.Especially strong for tasks like segmentation and detailed 3D object recognition[20].

PointTransformer – The Attention Expert

Uses the **transformer mechanism** (like in language models) to let each point "pay attention" to other points around it. It learns both **what's important** and **where it is**, making it really good at understanding complex shapes. State-of-the-art performance in many tasks[21].

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ADVANTAGES OVER 2D MODELS:

Spatial Context

3D models don't just look at flat images—they understand **depth and structure**. Instead of just seeing a shape from one angle (like 2D), 3D models know **how far things are**, how they're shaped, and how they relate to each other in space.

Example: A 2D model might confuse a circle and a sphere. A 3D model can tell the difference easily[22].

Rotation and Translation Invariance

3D models can recognize objects **even if they're rotated, flipped, or moved** around.

Real-world objects don't always show up in perfect angles. 3D models are built to **handle all views** without getting confused.

Example: Whether a chair is upright, tilted, or sideways, a good 3D model still knows it's a chair[23].

Robustness to Occlusions

3D models are better at dealing with situations where **parts of an object are blocked or hidden**. Since 3D models understand shape and depth, they can **fill in the blanks** when something is partially visible.

Example: If half of a car is hidden behind a wall, a 3D model can still tell it's a car[24].

VI. COMPARATIVE ANALYSIS OF 2D VS 3D APPROACHES

Accuracy and performance comparison from literature

In recent years, both 2D and 3D deep learning models have been applied to melanoma detection, each showing unique strengths. Traditional **2D convolutional neural networks (CNNs)**—such as ResNet, EfficientNet, and DenseNet—have been widely adopted due to their maturity, efficiency, and compatibility with existing dermoscopy image datasets. These models have achieved high accuracy in melanoma classification tasks, with reported performance metrics (e.g., accuracy, sensitivity, specificity) often exceeding **85–90%** on curated datasets.

However, one of the main limitations of 2D models is that they only analyze flat image data. This can result in the loss of critical 3D structural cues such as lesion depth, asymmetry in shape, and surface texture—features that can be important in distinguishing benign from malignant lesions.To address this, recent studies have explored **3D deep learning models** like **PointNet**, **PointNet++**, and **3D CNNs**, which process **point cloud data** or volumetric representations derived from 2D images or 3D scans. These models capture spatial and geometric relationships in much greater detail. Literature suggests that 3D models can achieve **up to 5–10% higher accuracy and sensitivity** compared to their 2D counterparts, especially in challenging or ambiguous cases[25].

Case studies highlighting improvements

Case studies from recent literature, such as those leveraging 3D reconstructions or multimodal datasets (e.g., dermoscopy + 3D structure), show increased diagnostic accuracy using 3Dapproaches. For instance, in certain melanoma classification tasks, models trained on 3D point cloud data achieved up to 5–10% higher accuracy than their 2D counterparts.Real-world examples show how using 3D data—like a 3D scan of a mole instead of just a photo—can help doctors and AI tools catch more cases of melanoma. In some cases, these smarter 3D models were up to 10% better at telling the difference between harmless spots and cancerous ones, which could make a big difference in early detection[26].

Limitations and trade-offs

3D models are computationally more intensive and require high-quality point cloud generation, which adds preprocessing complexity. They also need larger datasets for generalization, and public 3D melanoma datasets are scarce. Meanwhile, 2D models benefit from larger public datasets and faster training times, making them more accessible for deployment.Even though 3D models can be more accurate, they come with challenges. They need more powerful computers and take longer to train. Also, getting 3D data is harder and more expensive than using simple 2D

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images. On the other hand, 2D models are quicker to use and easier to train, which makes them more practical in many situations—especially when time or resources are limited[27].

Aspect	2D (CNN-based)	3D (PointNet-based)
Data Format	2D images (RGB)	3D point clouds (XYZ or XY + intensity)
Feature Focus	Texture, color	Shape, geometry
Model Examples	ResNet, VGG	PointNet, PointNet++
Accuracy Range	85–92%	87–94% (if high-quality 3D data used)
Complexity	Lower, well-supported	Higher, more experimental
Real-world Usage	Widely used in clinical tools	Still in research and development

VII. PUBLICLY AVAILABLE DATASETS AND BENCHMARKS

ISIC, PH2 – Popular 2D Datasets

ISIC (International Skin Imaging Collaboration) and PH2 are two of the most widely used **2D image datasets** for skin lesion and melanoma research.They come with thousands of dermoscopic images, **expert labels**, and in some cases, **segmentation masks**.Training and testing traditional 2D deep learning models for classification and segmentation of skin diseases[28].

Synthesized or Derived 3D Datasets

Since true 3D skin lesion datasets are **rare**, researchers often create 3D datasets by:

Estimating depth from 2D images using models like **MiDaS**

Using **3D Texture-Based Phantoms (3D TBP)** or synthetic generation tools. These 3D versions allow exploration of how **depth and shape** influence melanoma detection and open doors to 3D deep learning models[29].

Dataset Limitations in the 3D Domain

Very few real 3D skin datasets exist. Synthesized 3D data might not be **perfectly accurate**—especially in medical scenarios where precision matters. Lack of **standard benchmarks** and real-world 3D ground truth makes it harder to compare models fairly. **Bottom line:** While promising, the 3D space still needs **more real data** and better evaluation tools[30].

VIII. CHALLENGES AND OPEN RESEARCH PROBLEMS

Scarcity of Labelled 3D Data

There simply aren't enough **labelled 3D datasets** available. Most datasets for melanoma detection are still in **2D**, and **3D** datasets are often missing detailed labels (like exactly where the melanoma is in the 3D model).For deep learning models to be trained accurately, they need lots of **labelled examples**. Without enough 3D data with proper labels, it's hard to teach models to detect and understand melanoma in 3D space[31].

Computation Overhead in 3D Processing

3D data requires more **computing power** than 2D images. Processing and analyzing **3D point clouds** or 3D models can be very **resource-intensive** and take much longer. This makes it difficult to use 3D models in real-time applications, especially in clinical settings, where fast results are needed[32].

Fusion of Multi-modal Data (2D + 3D)

Combining **2D** images (like photos) with **3D data** (like point clouds) is not easy. Each type of data provides different kinds of information, and merging them into a single useful model requires specialized techniques. Having both **2D and 3D data** could significantly improve model accuracy, but the challenge lies in how to process and integrate them together smoothly[33].

Clinical Validation and Explainability

Any model used for healthcare, especially something as critical as melanoma detection, needs to be **clinically validated**—which means it must be tested and proven to work effectively in real-world settings. Additionally, the model needs to be **explainable** so doctors can trust it. **Doctors won't trust** AI models unless they can understand how the model arrives at a decision. Without **explainability**, it's hard to gain acceptance from the medical community[34].

Standardization and Benchmarking

There's a **lack of standard benchmarks** for testing and comparing **3D models**. Without common ways to evaluate the performance of models, it's difficult to know which models are best. Without proper **standardization**, research can't progress efficiently, and comparing results across studies is nearly impossible[35].

Figure 7. Open Challenges in AI-Assisted for Skin Cancer Diagnosis

The figure represents key hurdles in using AI for skin cancer diagnosis. These include data limitations, lesion variability, and communication barriers between AI and doctors.

IX. FUTURE DIRECTIONS

Hybrid 2D-3D Modelling Strategies

Combining both **2D images** and **3D data** to create stronger models. For instance, using a 2D image to recognize patterns and a 3D model to understand depth and shape. This would let models **leverage the strengths of both types of data**—the speed and simplicity of 2D with the depth and structure of 3D—leading to more accurate melanoma detection[36].

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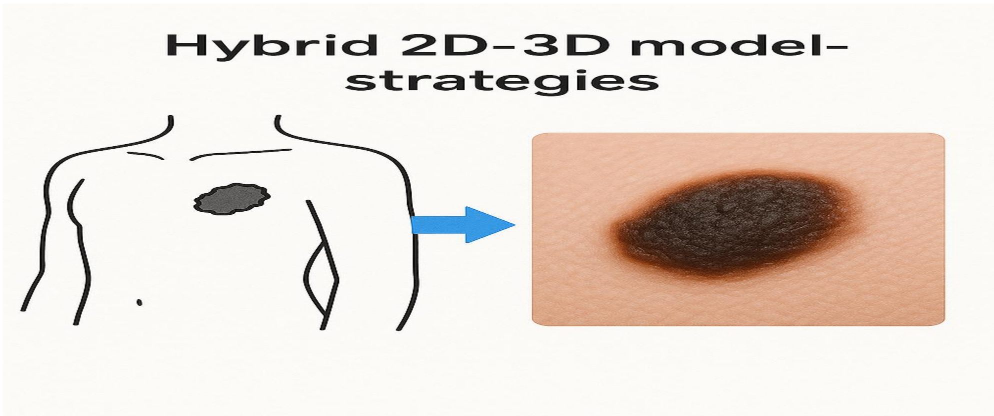

Figure 8. Illustration of Hybrid 2D-3D Modeling Strategies for Skin Lesion Analysis

Thia figure represents Hybrid 2D-3D modeling combines standard images with 3D data for a more detailed skin lesion analysis. This improves the assessment of shape and structure, aiding diagnosis.

Few-shot and Unsupervised Learning for 3D Data

Teaching models to learn from **very few examples** (few-shot learning) or even from **unlabelled data** (unsupervised learning). This is important for 3D data, where labelled examples are limited. It would make it easier to create models that **learn quickly** from minimal data, which is crucial in fields like healthcare where labelled 3D data is scarce[37].

Real -time 3d Melanoma Screening Tools

Developing **real-time systems** that can analyze **3D models** of skin and instantly detect melanoma, similar to how you use a phone camera for quick photos. This would allow doctors to **screen patients quickly and accurately**, making melanoma detection faster and more accessible for everyone[38].

Integration with AR/VR in dermatology clinics

Using **Augmented Reality (AR)** and **Virtual Reality (VR)** to display 3D models of skin directly on a patient's body or in an immersive environment. It could help doctors better understand the **3D structure of moles** and lesions, leading to more precise diagnoses and treatment planning in dermatology[39].

Cross-domain and Multi-task learning

Building models that can handle multiple tasks at once (like both **detecting melanoma** and **classifying the severity**) or apply knowledge from other areas (cross-domain learning, such as using knowledge from **general medical imaging**).This would create models that are **more versatile**, allowing them to solve a variety of problems at once and potentially improve their overall performance in different situations[40].

X. CONCLUSION

This survey highlights the growing role of **3D point cloud techniques** in the field of melanoma detection. We reviewed various **deep learning models** such as PointNet, PointNet++, DGCNN, and KPConv, which are specifically designed to work with 3D data. These models show great promise in handling the unique properties of point clouds, offering advantages like **better spatial understanding**, **robustness to occlusion**, and **invariance to rotation and translation**, which are limitations in traditional 2D approaches. The potential of 3D point cloud techniques lies in their ability to provide a **more comprehensive view of skin lesions**, capturing shape, texture, and depth—features often missed in 2D imaging. However, the field still faces significant challenges, including the **lack of labelled 3D datasets**, **high computational demands**, and the **need for clinical validation and standard evaluation benchmarks.** To fully realize the impact of 3D analysis in clinical settings, **interdisciplinary collaboration** is crucial. Combining the expertise of dermatologists, computer vision researchers, and machine learning practitioners can accelerate progress in

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this area. Future work should focus on developing **hybrid 2D-3D models**, improving data efficiency through **few-shot learning**, and creating **real-time, clinically usable tools.** In conclusion, while 3D point cloud processing is still an emerging field in medical imaging, it holds strong potential to enhance melanoma detection and diagnosis. Continued **research, collaboration, and innovation** are essential to translate these techniques from research to real-world healthcare applications.

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