Part 2:Research Aims and Objectives

1. Research Aim:

The research aim is to develop multimodal diagnostic system (FMDS) that takes into account structured clinical data and different skin types that improves the accuracy and objectivity of early skin cancer detection.

2. Research Objectives:

Objective 1: Familiarizing with the Lay of the Land of AI-Based Skin Cancer Detection.

Step one of this project is to become an expert on all of what's ever attempted in AI for skin cancer detection. This isn't a question of creating a list of what's come before, it's a question of creating an exhaustive study to examine how this technology evolved over time. I'll examine the evolution from the crude initial AI systems to the sophisticated ones being utilized today. I'll be interested in particular in what kind of data they were trained on and what preprocessing was performed on the data. The overriding purpose of this vigorous study is to uncover the significant weak spots and question why these powerful tools are not being relied upon in every doctor's office. My question will be motivated by two overriding areas of interest: first, the overriding issue of fairness, as numerous existing systems will not perform well on dark skin-toned patients, and this is a big issue for equal healthcare. Secondly, I'd be curious why these systems are so narrow and dependent on images when a human physician would be making a decision on a great amount of information.

Objective 2: Creating a New System That is Smarter and Fairer.

After identifying what's missing, comes the step of crafting a better solution from scratch. I will create a new and powerful diagnostic platform to be called the Fair Multimodal Diagnostic System. The guiding idea is to create an AI that acts more like a doctor by seeing the full picture of the patient rather than a snapshot. To do this, it will process simultaneously three different forms of information: the clinical skin picture, the patient's official medical data such as history and age, and the rich text of the doctor's case notes. Central to this system is a "Fairness by Design" idea. This means we are not trying to compensate for unfairness down the line with techniques to correct for it; we are building in fairness upfront by making the patient's skin type a key part of the input and using special techniques to ensure its diagnostic output is fair. This system won't be a dark "black box" either. It will have an Explainable AI componentuiltin whose job it is to give clear reasoning for its conclusions so a clinician can clearly see why the AI has come to a certain conclusion and trust its recommendation.

Objective 3: Demonstrating How This New Methodology is a Paradigm Shift.
The overriding objective is to present clearly and persuasively why this Fair Multimodal Diagnostic System represents a valuable and necessary improvement over existing approaches. This will be accomplished through demonstration of how its innovative design addresses critical problems of unfairness and inadequate data use that we uncovered in the

preliminary study. I hope to demonstrate that, through its bright idea of combining images and patient data with concise explanations, we are able to develop a diagnostic tool that is far superior and trustworthy. This is not a matter of simply achieving a higher accuracy score but of producing a trustworthy, fair, and understandable tool upon which a physician can comfortably rely when making critical health decisions. Ultimately, what is intended is to present this system as a superior model capable of serving as a benchmark through opening the way to subsequent study and refinements in the pursuit of developing improved AI suitable for real-world application to medicine.

3. Research Gaps:

Although deep learning models demonstrate significant success and high accuracy in skin cancer classification tasks, a review of the scientific literature reveals several gaps. These issues may create difficulties and errors in developing robust and fair systems ready for widespread clinical implementation. Our research aims to address the following limitations:

1. The problem of data fairness, diversity and bias. Most public datasets that serve as the basis for training modern models suffer from these types of biases:

- **Less data on different skin phototypes:** Most standard datasets, such as ISIC and HAM10000, consist primarily of images from stem-skinned, Europid, or US patients. Models trained on such data show significantly lower accuracy and reliability when working with images of patients with other skin types or races, making them unfair and limiting their global applicability.
- **Data imbalance:** In real clinical situations, as in datasets, benign lesions are more common than malignant ones. This imbalance leads to models more often and better predicting the most common class, ignoring rare but critical cases, which is unacceptable in medical diagnostics.

2. Limited use of patient metadata. The use of patient metadata has not yet become widespread. Most modern systems work with visual data, particularly the images being classified. However, these systems do not include relevant clinical information that dermatologists typically consider when making a diagnosis. Experiments have shown that incorporating patient metadata, such as age, gender, and anatomical location of the lesion, into the model can improve classification accuracy by more than 5%. Similarly, the use of disease taxonomies to clarify hierarchical relationships between diagnoses has also yielded important advances.

3. The Problem and Lack of Explainability (Explainable AI - XAI). Deep learning models are often criticized and misunderstood for their incomprehensible explanations of their decisions. In this case, physicians cannot blindly trust a diagnosis made by a deep learning model without understanding its basis. This is one of the most serious challenges for implementing AI in clinical practice. A paper by Layode et al. (2019) explicitly states that such non-interactive systems are of little use to dermatologists. While XAI technologies such as Grad-CAM and Saliency Maps already exist, they can visualize and show which areas of the image the model is focusing on when making its decision. Their use has not yet become widely accepted or standardized.

4. **There are issues with image quality and a lack of real-world experience and validation in real-world clinical settings.** Most studies use carefully curated and cleaned datasets. However, in reality, dermoscopic images often contain unwanted objects: hair, air bubbles, glare from lighting, and traces of marker and gel. These artifacts can lead to incorrect segmentation and misclassification. Furthermore, there are virtually no studies evaluating the performance of models in real time, in real hospitals, rather than on laboratory data.

Part 3: Proposing Research Paper Titles

A Fair Multimodal Deep Learning System for Skin Cancer Detection Across Diverse Skin Types.

Enhancing Diagnostic Accuracy and Fairness: A Hybrid Approach to Skin Cancer Classification Using Multimodal Data.

Beyond the Image: A Framework for a Fair and Explainable AI System for Skin Cancer Diagnosis.

Part 4:

1. Defining Key Terms

- Deep learning (DL): This is the part of machine learning that is required to use neural networks. Such networks consist of multiple layers. Specifically, they can detect complex patterns from data such as images, text, and audio. They perform well in tasks such as image classification and segmentation [1].
- Multimodal data: This helps to use different types of data in prediction. In medicine, it is important to use not only images, but also additional information such as the patient’s age, gender, and medical history.

- Fairness in artificial intelligence: For medical artificial intelligence to work fairly, the system must give the same results to all patients, regardless of their race, ethnicity, or skin type, which is a challenge. If fairness is not maintained, some groups may get wrong results and may cause harm to their health.

- Explainable AI (XAI): This is a set of techniques that explain to humans what decisions artificial intelligence has made. Since deep learning often works like a “black box,” XAI shows why the model came to the same conclusion. For example, it can identify areas of an image that are important for prediction. This improves the results to the maximum.

2. Describing the General Problem

Skin cancer is the most common type of cancer in the world, with millions of new cases and cases registered every year. Melanoma, although not the most common, is the most dangerous type of cancer and causes the majority of skin cancer deaths. Its early diagnosis is crucial to saving lives. In most cases, doctors visually examine the skin, sometimes using a device called a dermatoscope. However, such an assessment can be subjective, as it depends on the doctor's experience.

In recent years, deep learning has made great strides in medical image analysis. In particular, CNNs have shown excellent results in classifying skin lesions. In some studies, AI has even been shown to perform as well as or better than dermatologists [9, 11]. This method makes diagnosis faster, more accessible, and more consistent.

However, such models are still not widely used in clinical practice. One of the main reasons is the imbalance of data and the low number of . Many existing datasets focus primarily on light skin tones [6, 16]. As a result, AI may not be able to accurately detect lesions on darker skin, exacerbating health inequalities.

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