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Skin Lesion Detection

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Problem Definition

Early detection of skin cancer, particularly malignant lesions such as melanoma, is critical for improving patient survival rates. However, accurate diagnosis remains challenging due to subtle visual differences between benign and malignant lesions, variability in lesion size, shape, and color, and the presence of artifacts such as hair and shadows in dermoscopic images. Manual diagnosis by dermatologists is time-consuming and prone to inter-observer variability, leading to potential inconsistencies in clinical assessment.

In India, although skin cancer incidence is relatively lower compared to Western countries, it has been steadily increasing in recent years. According to the National Cancer Registry Programme (ICMR-NCRP 2024), non-melanoma skin cancers account for approximately 0.5–1% of all cancers, while melanoma cases are rising at an estimated 3–5% annually, particularly in states with higher UV exposure. Reports indicate that around 25,000–30,000 new cases of skin cancer are diagnosed each year across the country, with a concerning trend of late-stage detection, which significantly reduces survival outcomes.

While deep learning–based automated detection systems have demonstrated promising results, they often face significant challenges, including class imbalance, limited generalization across diverse datasets, and difficulty in providing interpretable outputs that can be trusted in clinical practice.

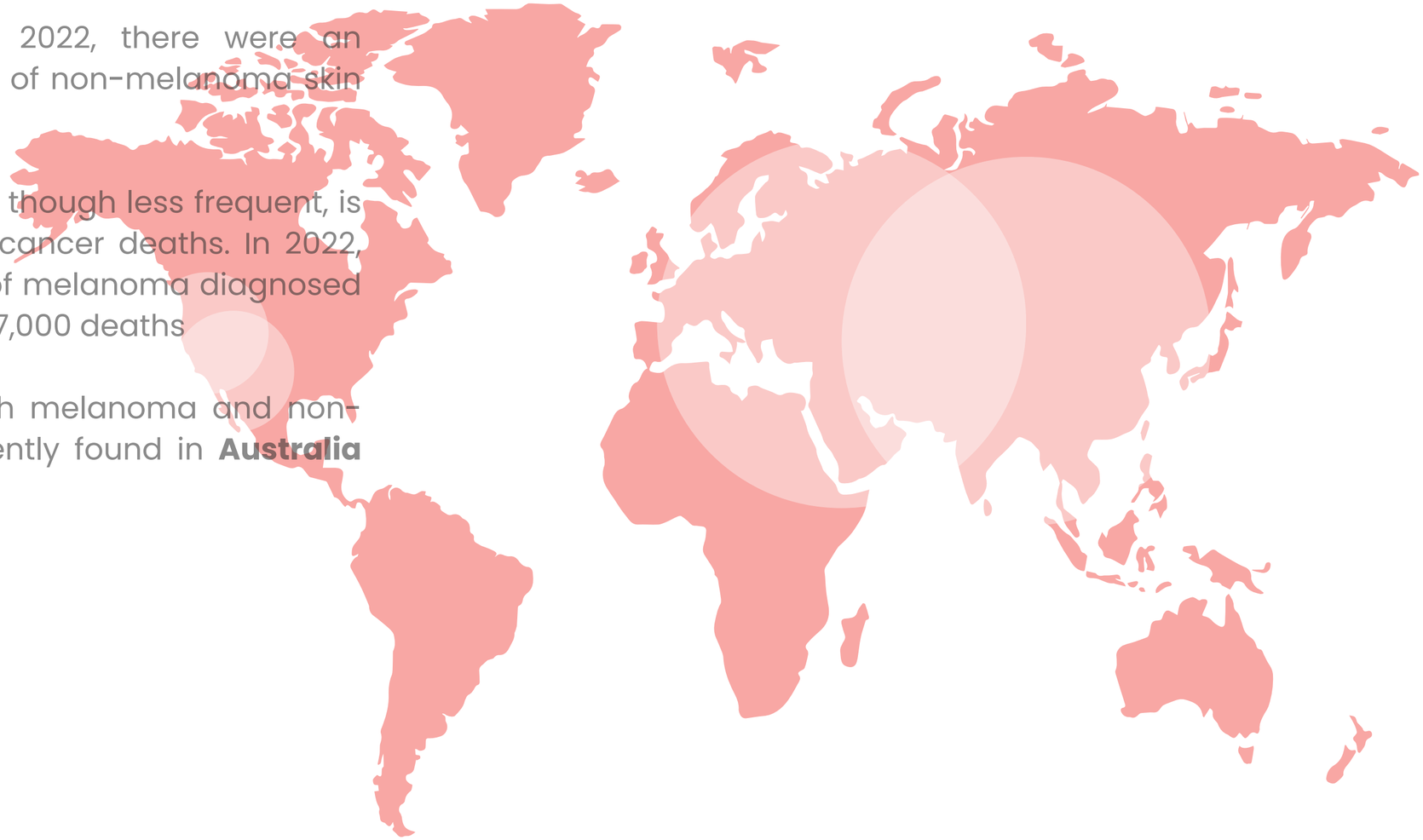
This project aims to develop an automated skin lesion detection and classification system capable of accurately identifying and classifying multiple types of skin lesions from dermoscopic images. The proposed system seeks to address key challenges such as data imbalance, feature variability, and clinical interpretability, ensuring high diagnostic accuracy and reliability to assist dermatologists in real-world decision-making and help improve early detection rates in the Indian healthcare context.

Stastical Data

Non-Melanoma Skin Cancer : In 2022, there were an estimated over 1.2 million new cases of non-melanoma skin cancer worldwide.

Melanoma Skin Cancer : Melanoma, though less frequent, is responsible for the majority of skin cancer deaths. In 2022, there were over 324,000 new cases of melanoma diagnosed globally, resulting in approximately 57,000 deaths

The highest incidence rates for both melanoma and non-melanoma skin cancer are consistently found in **Australia** and **New Zealand.**



Literature Survey

https://docs.google.com/spreadsheets/d/1bsLe53xOCE4ymTlOb0VeEF54mKuaJHhqK69MpgTsm7I/edit?usp=sharing

Our Solution

- **Hybrid Deep Learning Model:**
  - Develop an Automated Multi-Class Skin Lesion Detection system using a Hybrid CNN–Transformer architecture.
  - Combine CNN layers for extracting local features (texture, color, border details) with Transformer modules for capturing global context and long-range dependencies.
- **Multi-Class Classification:**
  - Accurately classify multiple skin lesion types such as melanoma, basal cell carcinoma, squamous cell carcinoma, and benign lesions.
- **Data Imbalance Handling:**
  - Apply advanced data augmentation techniques (rotation, flipping, color adjustments) to increase diversity in underrepresented classes.
  - Use class-weighted loss functions to balance model training and improve prediction accuracy across all lesion categories.
- **Transfer Learning & Fine-Tuning:**
  - Utilize pre-trained deep learning models to leverage existing feature knowledge and enhance generalization on Indian and global datasets.
  - Fine-tune the hybrid model for improved performance on real-world dermoscopic images.
- **Explainable AI Integration:**
  - Implement Grad-CAM or similar visualization techniques to highlight the regions of the lesion image that influence model predictions.
  - Provide dermatologists with interpretable outputs to build clinical trust and support decision-making.
- **Optimized End-to-End Pipeline:**
  - Include preprocessing steps for noise removal, color normalization, and artifact reduction (e.g., hair removal).
  - Design for real-time deployment, enabling scalability in hospitals and tele-dermatology applications.
- **Indian Healthcare Relevance:**
  - Tailor the system to address the growing incidence of skin cancer in India (approx. 25,000–30,000 new cases per year) and the need for early detection in resource-constrained settings.

Research Gaps

Data-Centric Gaps

- Existing datasets are biased toward lighter skin tones → poor performance on Indian populations.
- Images often contain artifacts (e.g., hair) that confuse models.
- Narrow focus: most datasets cover only a few diseases, ignoring other common malignancies.
- Strong class imbalance (some lesion types overrepresented, rare ones ignored).

- Use DermaCon-IN[11] dataset (Indian skin tones, diverse conditions) + transfer learning.
- Preprocessing pipeline (artifact removal: hair, noise).
- Expand scope to multi-class classification (melanoma, BCC, SCC).
- Handle imbalance using augmentation & class-weighted loss.

Algorithmic Gap

- Simple models (CNN-only) are fragile, learn spurious correlations.
- Off-the-shelf bias-mitigation often fails in medical imaging.

- Propose Hybrid CNN–Transformer model.
- CNN → captures local features (texture, borders).
- Transformer → captures global context.
- More robust and domain-specific architecture.

Generalization Gap

- Models perform well in labs but fail in real clinics (different populations, imaging devices).
- Accuracy and fairness do not transfer across settings.

- Use transfer learning & fine-tuning on Indian + global datasets.
- Adapt model for real-world dermoscopy images.
- Ensures reliable deployment in diverse clinical settings.

Interpretability Gap

- Black-box AI → dermatologists cannot trust decisions.
- Lack of transparency blocks clinical adoption.

- Integrate Explainable AI (XAI) with Grad-CAM.
- Highlight lesion regions influencing prediction.
- Build clinical trust and support decision-making.

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Thank You