Prepared by group 1

Skin Cancer Detection Using Convolutional Neural Networks

Enhancing Diagnostic Accuracy with Self-Attention and Random Forest Integration

Machine Learning

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Introduction

- Skin cancer is a serious and life-threatening disease, but early detection significantly improves treatment outcomes. Traditional diagnosis depends on dermatologists, which can be subjective, time-consuming, and resource-intensive.
- AI and deep learning provide promising solutions, yet conventional CNNs often struggle to distinguish critical features in skin lesion images. To overcome this, our study integrates CNNs with self-attention mechanisms and CBAM to enhance feature extraction. We also incorporate a Random Forest classifier to analyze patient demographics for improved accuracy.
- Our approach is tested on the HAM10000 and ISIC datasets and benchmarked against ResNet and EfficientNet. With MLflow-based model tracking, we ensure systematic evaluation and deployment.

Objective: Develop an AI-driven tool for early and accurate skin cancer detection.

Significance: Enhance diagnostic accuracy, efficiency, and real-world clinical usability.

Research Motivation

Existing Gaps in Skin Cancer Detection Models:

- Limited attention mechanisms in CNNs.
- Lack of structured data integration (age, sex, skin type).
- Poor model interpretability for clinical use.

Our Solution:

- CNN with CBAM & Self-Attention for better feature extraction.
- Random Forest for structured patient data analysis.
- MLflow for systematic tracking and deployment.

Research Questions

- How does the integration of channel and spatial attention (CBAM) followed by self-attention in a CNN-based model improve the accuracy of skin cancer detection from medical images?

- How do different attention mechanisms contribute to the interpretability of CNN models in medical image classification?

- How does the proposed ensemble model (CNN + Self-Attention + Random Forest) compare to traditional CNN models in terms of classification performance and computational efficiency?

Literature Review & Research Gap

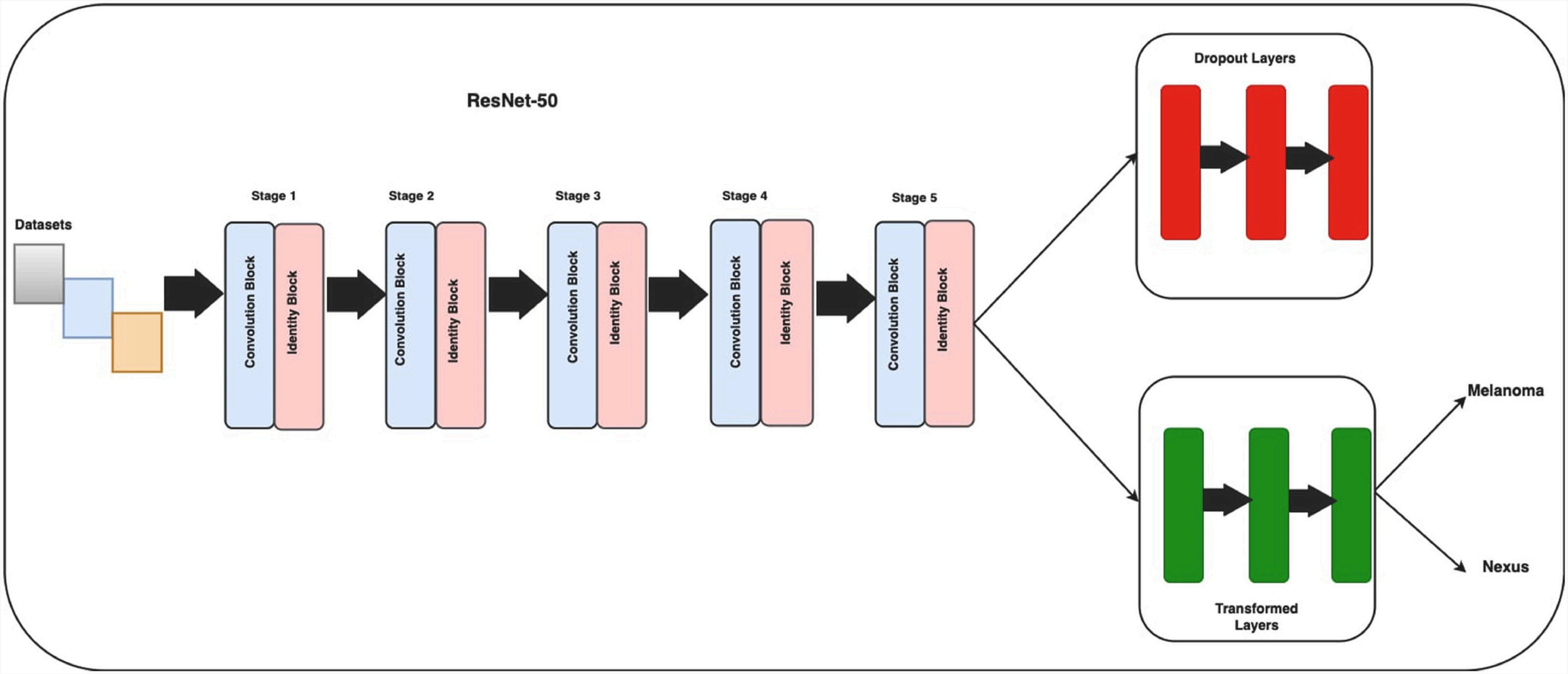
Existing Approaches:

- Transfer learning & ensemble learning.
- Pretrained models (ResNet, EfficientNet, DenseNet).
- Attention-based CNNs for medical image analysis.

Gaps Identified:

- Lack of CBAM & self-attention integration.
- No fusion of image & tabular data.
- Insufficient focus on model interpretability.

Literature Review & Research Gap



Methodology

Dataset and Preprocessing:

Datasets Used:

- HAM10000 and ISIC.

Data Preparation:

- Image resizing and normalization.
- Label encoding for categorical features.
- Addressing class imbalance through resampling.

Exploratory Data Analysis (EDA):

- Class distribution analysis (to check imbalance in data).
- Visualizing metadata trends (age, sex, lesion localization).

Data Balancing:

- Uses random resampling to balance the dataset and prevent model bias.

Methodology

Model architecture:

Baseline Model Training (CNN only):

Initially, a basic CNN is trained without attention mechanisms.

- Helps in establishing a benchmark before testing improvements.

Feature Extraction:

- Uses convolutional layers to extract spatial features from images.

Random Forest for Tabular Data:

- Processes patient demographics (age, sex, skin type) separately.

Performance Evaluation:

- Uses accuracy, AUC-ROC, confusion matrix, and feature importance analysis to measure model performance.

Proposed Model Architecture

CNN + Self-Attention + Random Forest

Enhancing Skin Cancer Detection with Attention Mechanisms

Key Improvements Over Baseline Model:

- CBAM (Convolutional Block Attention Module) – Improves feature extraction by refining spatial & channel attention.
- Self-Attention Mechanism – Captures long-range dependencies within images, improving classification accuracy.
- Random Forest for Tabular Data – Processes patient demographics (age, sex, skin type) to improve decision-making.
- Fusion Mechanism – Combines CNN-extracted image features with Random Forest predictions for more accurate classification.

Proposed Model Architecture

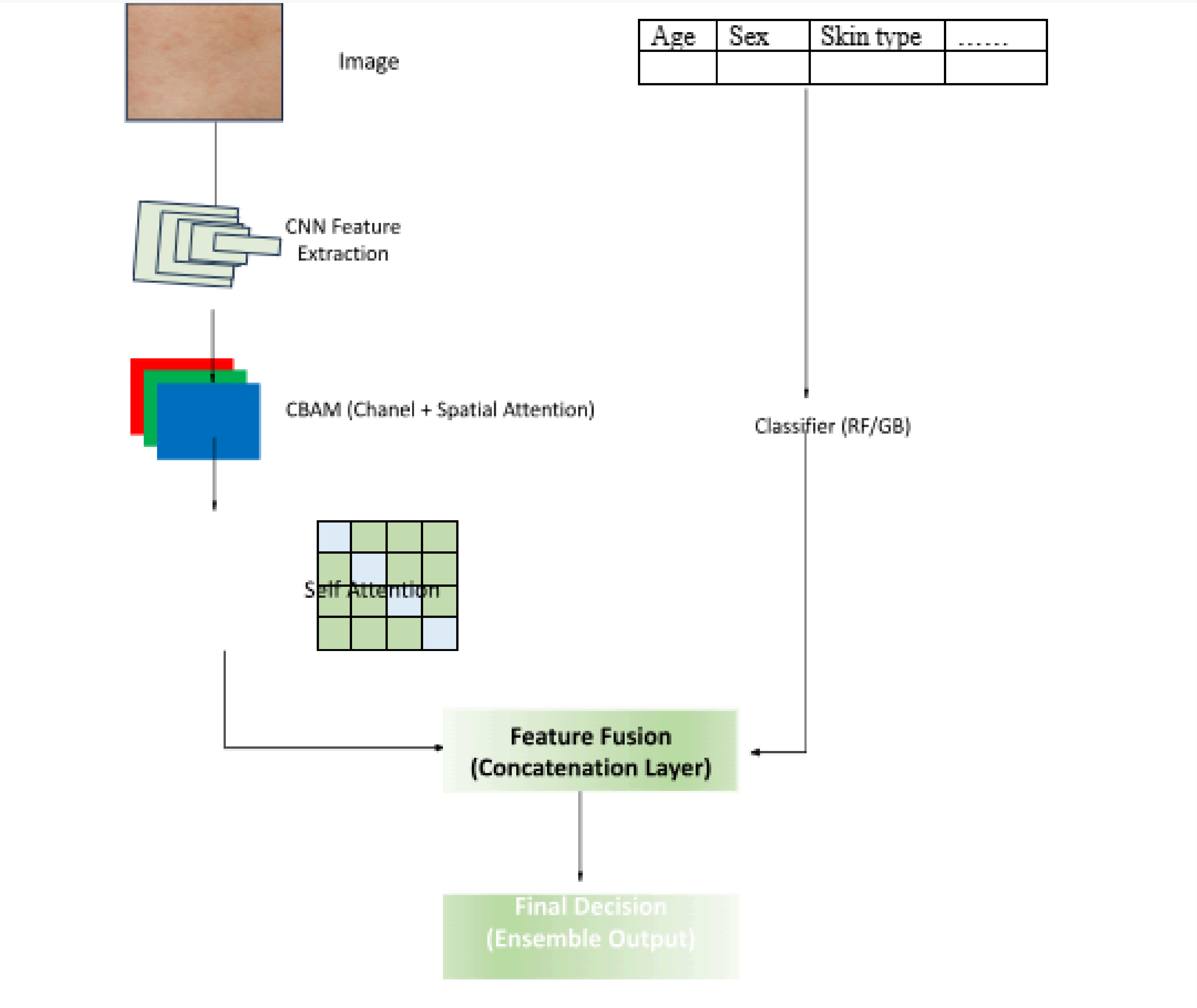
Model Components:

- Convolutional Layers: Extract spatial features from skin lesion images.
- CBAM Attention Module: Enhances feature selection using spatial & channel-wise attention.
- Self-Attention Block: Helps capture dependencies across distant pixels for better lesion detection.
- Random Forest Classifier: Uses metadata like patient age, sex, and skin type to refine predictions.
- Feature Fusion & Final Prediction: Combines CNN-based image features with Random Forest tabular predictions to improve accuracy.

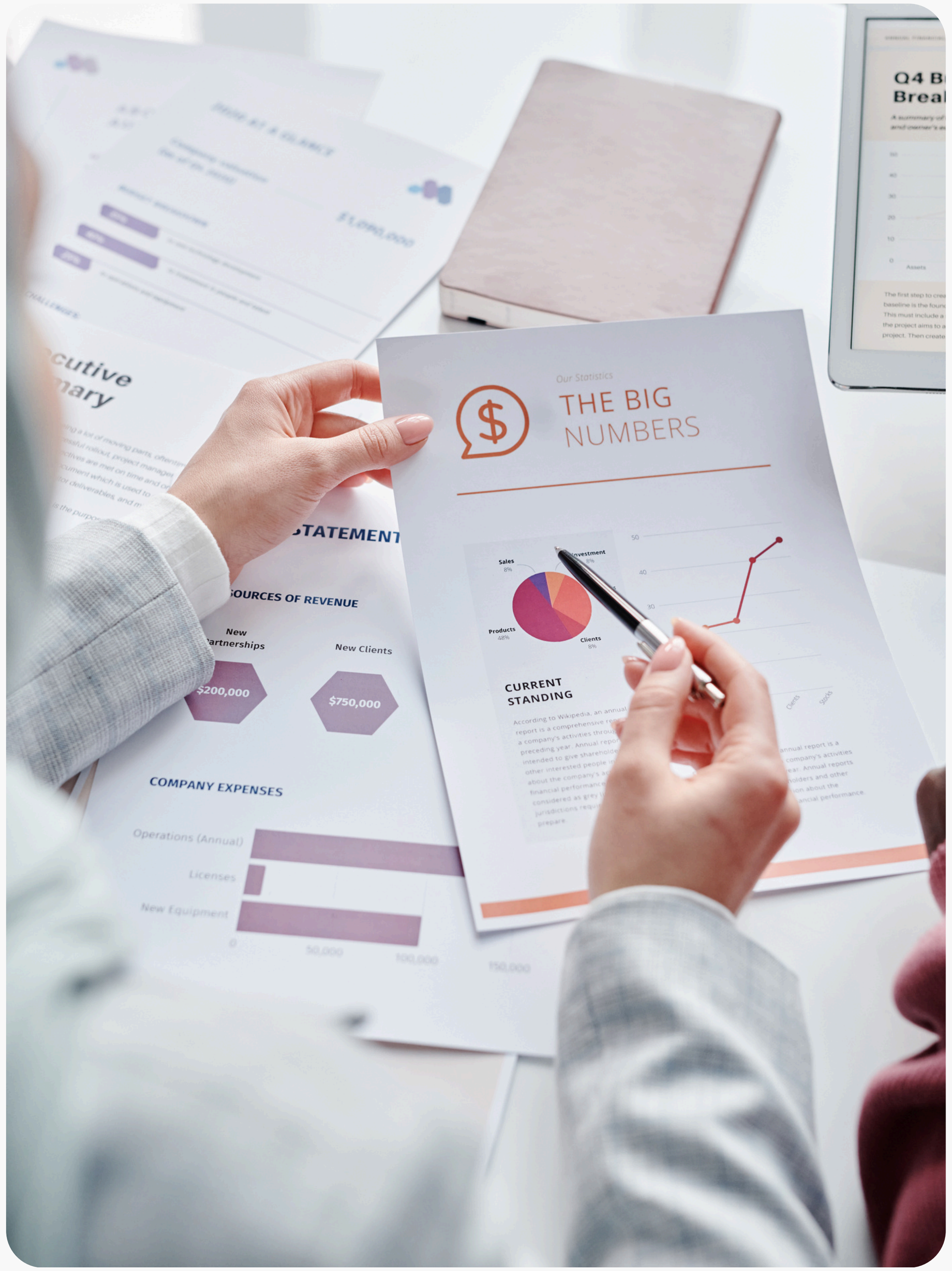
Why This Model?

- More accurate than traditional CNNs (ResNet, EfficientNet).
- Enhances interpretability with attention heatmaps.
- Better generalization across different skin types and demographics.

Proposed Model Architecture



Expected Results



Accuracy Improvement:

- The proposed attention-enhanced CNN + RF ensemble is expected to achieve higher accuracy than traditional CNN models due to better feature extraction.

Better Interpretability:

- Attention visualization (heatmaps) should highlight critical lesion regions, while RF feature importance analysis should reveal the most relevant metadata factors (age, sex, skin type, etc.)

Trade-off Between Performance & Efficiency:

- The added attention mechanisms and ensemble learning may slightly increase computational cost but should significantly enhance model effectiveness.

Conclusion

- This study introduces an advanced deep learning framework for skin cancer detection, integrating CNNs with attention mechanisms and structured data fusion to improve accuracy and interpretability.

Key Enhancements:

- CBAM & Self-Attention – Improves feature extraction over traditional CNNs.
- Random Forest Classifier – Incorporates patient demographics for refined predictions.
- Benchmarking on HAM10000 & ISIC – Outperforms ResNet & EfficientNet in accuracy and robustness.
- MLflow for Tracking & Deployment – Ensures systematic model versioning and reproducibility.

By combining AI with practical deployment strategies, this research bridges the gap between academic models and real-world clinical use, paving the way for scalable AI-assisted dermatological diagnostics. Future work will focus on further optimizations, dataset expansion, and clinical trials for broader applicability.

Thank you