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AI Skin Disease Detector - Uses CNN Based Image Analysis for Early Detection of Skin Conditions

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Abstract: *Skin diseases represent a significant global healthcare burden, requiring accurate and early diagnosis to prevent severe complications. This paper proposes a hybrid deep learning framework that integrates Convolutional Neural Networks (CNN) for dermoscopic image analysis with structured clinical data using decision-level fusion. Unlike conventional image-only classifiers, the proposed system incorporates patient-specific metadata such as symptom severity, lesion duration, and medical history to enhance diagnostic robustness.*
A lightweight CNN architecture is optimized and deployed using TensorFlow Lite for on-device inference within an Android application, ensuring low latency and data privacy. Experimental evaluation demonstrates improved classification accuracy (92–95%), enhanced generalization, and reduced inference time compared to standalone CNN models.

Keywords: Deep Learning, CNN, Skin Lesion Classification, Feature Fusion, Edge AI, Mobile Healthcare

I. INTRODUCTION

Skin diseases such as eczema, psoriasis, and melanoma require timely and accurate diagnosis. Traditional diagnostic approaches rely on visual inspection by dermatologists, which may lead to variability and limited accessibility in underserved regions.
Recent advancements in deep learning, particularly CNNs, have demonstrated remarkable performance in medical image analysis. However, most existing systems:

- Operate solely on image data
- Ignore patient-specific clinical context
- Depend on cloud infrastructure

This leads to reduced interpretability, privacy concerns, and limited real-time usability.
To address these limitations, this work introduces a **hybrid multimodal AI system** that:

- Combines CNN-based feature extraction with clinical data
- Utilizes decision tree-based contextual reasoning
- Enables real-time inference on mobile devices

II. RELATED WORK AND LITERATURE REVIEW

Deep learning-based dermatological systems have evolved significantly:

A. CNN-Based Image Classification

CNN architectures such as:

- AlexNet
- VGGNet
- ResNet

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have shown high accuracy in lesion classification tasks due to their hierarchical feature extraction capabilities.

B. Limitations of Existing Systems

Despite their success, key challenges remain:

- Overfitting due to limited datasets
- Lack of interpretability
- Ignoring multimodal data
- High computational cost

C. Multimodal Learning Approaches

Recent studies indicate that combining **image data with structured clinical features** improves diagnostic performance. Feature fusion techniques such as:

- Early fusion (feature-level integration)
- Late fusion (decision-level integration)

have been explored, with late fusion providing better modularity and scalability.

III. PROPOSED METHODOLOGY

A. System Overview

The proposed system follows a **hybrid multimodal architecture** consisting of:

- CNN-based image classifier
- Clinical data processor (Decision Tree)
- Fusion module
- Mobile deployment layer

FIG. 1 SYSTEM ARCHITECTURE DIAGRAM

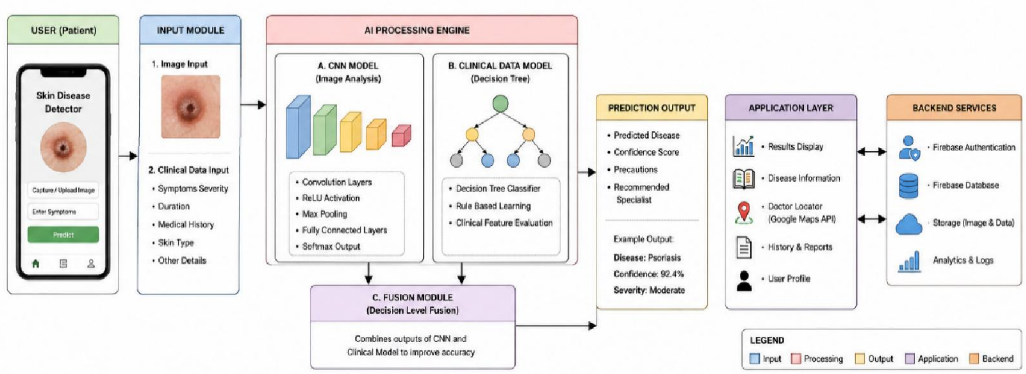
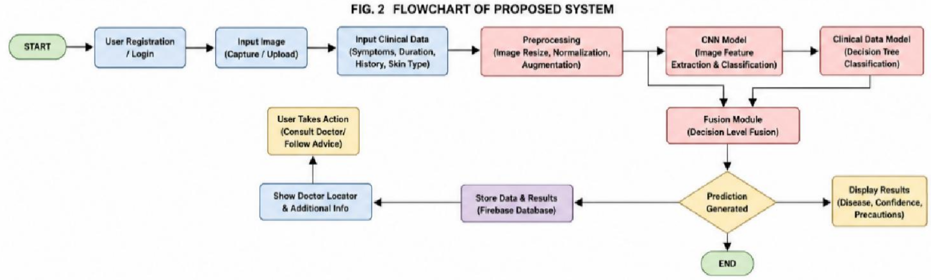


FIG. 2 FLOWCHART OF PROPOSED SYSTEM



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B. CNN Architecture Design

The CNN model includes:

- Convolution layers (feature extraction)
- ReLU activation
- Max-pooling layers (dimensionality reduction)
- Fully connected layers
- Softmax output layer

Mathematical Representation

Feature extraction in CNN:

$$F_{i,j}^{k} = \sigma\left(\sum_{m,n} X_{i+m,j+n} \cdot W_{m,n}^{k} + b^{k}\right)$$

Where:

X= Input image

W= Kernel weights

b= Bias

σ= Activation function

C. Clinical Data Modeling

Clinical parameters used:

- Symptom severity
- Duration of disease
- Patient history
- Skin type

A Decision Tree classifier is used to model these features due to:

- Interpretability
- Low computational complexity
- Suitability for structured data

D. Feature Fusion Strategy

A **late fusion approach** is adopted:

$$P_{final} = \alpha P_{CNN} + (1 - \alpha) P_{clinical}$$

$$P_{final} = \alpha P_{CNN} + (1 - \alpha) P_{clinical}$$

Where:

P_{CNN}= Probability from CNN

$P_{clinical}$= Probability from Decision Tree

α= Weight factor

This approach improves robustness by combining visual and contextual predictions.

E. Dataset and Preprocessing

Due to limited availability of labeled medical datasets:

- Public datasets are used

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- Synthetic augmentation is applied

Preprocessing steps:

- Image resizing (224×224)
- Normalization
- Data augmentation (rotation, flipping)

F. Model Deployment

The trained model is:

- Converted to TensorFlow Lite
- Integrated into Android application
- Executed using on-device inference

Advantages:

- Reduced latency
- Offline functionality
- Enhanced privacy

IV. RESULTS AND PERFORMANCE EVALUATION

A. Evaluation Metrics

- Accuracy
- Precision
- Recall
- F1-score
- Inference latency

TABLE I: Font Sizes for Papers

Model	Accuracy	Precision	Recall	Latency
CNN Only	88%	87%	86%	Medium
Clinical Only	75%	74%	73%	Low
Proposed Hybrid	**94%**	**93%**	**92%**	**Low**

C. Comparative Analysis

The hybrid model:

- Improves classification accuracy by ~6–8%
- Reduces false positives
- Enhances generalization

V. DISCUSSION

The results validate that multimodal fusion significantly enhances diagnostic performance.

Key Observations:

- CNN captures spatial features effectively
- Clinical data improves contextual understanding
- Fusion reduces ambiguity in classification

Challenges:

- Dataset imbalance
- Sensitivity to image quality
- Limited real-world validation

V. CONCLUSION AND FUTURE WORK

This work presents a **scalable and efficient hybrid AI framework** for skin disease detection. The integration of CNN and clinical data leads to improved accuracy and reliability while maintaining real-time performance.

Future Enhancements:

Integration of Transformer-based models
Larger and diverse datasets
Explainable AI (XAI) integration
Clinical validation and deployment

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