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Real Time Skin Diseases Prediction Using Neural Network

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Abstract: Skin diseases affect millions of people every year, and diagnosing them manually can take a lot of time and effort. Most existing methods focus on just one type of skin disease at a time. This project proposes using advanced computer technology, like Convolutional Neural Networks (CNN) and VGG, to quickly and accurately detect different types of skin diseases. The CNN model examines skin images, automatically learning patterns that indicate various conditions, and can provide instant suggestions for treatment, making diagnosis faster and more reliable.

INDEX TERMS -Skin Disease Detection, Deep Learning, CNN, VGG16, Image Classification, Medical Imaging, Transfer Learning

I. INTRODUCTION

Dermatological diseases have a significant impact on the health of millions of people worldwide, as individuals are affected by various types of skin disorders every year. Traditional diagnosis methods rely heavily on manual examination by medical experts, which can be time-consuming, subjective, and often limited to identifying specific types of diseases. This creates a need for an advanced computer-aided system capable of analyzing multiple skin conditions efficiently and accurately. The proposed project introduces a real-time skin disease prediction system using deep learning techniques, particularly Convolutional Neural Networks (CNN) and Visual Geometry Group (VGG) models. These models are designed to automatically extract complex features from dermatological images, enabling accurate identification of different skin diseases. The convolutional layers capture intricate patterns and textures associated with various conditions, improving diagnostic performance. By leveraging deep learning, the system provides fast and reliable predictions along with instant medication suggestions, making it a robust and innovative solution for automated skin disease diagnosis.

II. LITERATURE REVIEW

The field of skin disease detection has evolved significantly with the advancement of image processing and deep learning techniques. Earlier approaches primarily relied on traditional image processing methods such as color analysis, texture extraction, and manual feature engineering. These methods required domain expertise and often produced limited accuracy due to their inability to capture complex patterns in dermatological images.

With the emergence of Machine Learning, researchers began applying classification algorithms such as Support Vector Machines (SVM), Decision Trees, and k-Nearest Neighbors (k-NN) for skin disease prediction. These models improved performance compared to traditional methods; however, they still

depended heavily on handcrafted features, which restricted their scalability and adaptability to diverse datasets.

Recent developments in Deep Learning, particularly Convolutional Neural Networks (CNNs), have significantly enhanced the accuracy and efficiency of skin disease diagnosis. CNN-based models automatically extract hierarchical features from images, making them highly effective for medical image analysis. Several studies have demonstrated the effectiveness of pre-trained models such as VGG (Visual Geometry Group), ResNet, and Inception in classifying various skin diseases with high accuracy.

Researchers have also explored transfer learning techniques, where pre-trained deep learning models are fine-tuned on dermatological datasets to achieve better performance even with limited data. These approaches have shown promising results in detecting multiple skin conditions, including melanoma, eczema, and psoriasis.

III. EXISTING & PROPOSED SYSTEM

EXISTING SYSTEM: Traditional skin disease diagnosis methods primarily rely on **manual examination by dermatologists**, which can be time-consuming, subjective, and dependent on expert availability. Earlier computer-aided systems used **image processing techniques** such as color, texture, and shape analysis, but these required manual feature extraction and had limited accuracy. Later, Machine Learning models like SVM and k-NN were introduced; however, they still depended on handcrafted features and lacked scalability. Deep learning models such as VGG16 and VGG19 improved classification accuracy but were mostly used for **offline analysis**, requiring high-quality datasets and controlled environments. These systems often lack real-time prediction capability, user-friendly interfaces, and instant decision support.

PROPOSED SYSTEM: The proposed system introduces a **real-time skin disease prediction framework** using deep learning techniques, specifically a CNN based on the VGG architecture. The model automatically extracts complex features from dermatological images, eliminating the need for manual feature engineering and improving diagnostic accuracy. Unlike existing systems, it supports **real-time prediction**, enabling immediate identification of multiple skin diseases. The system is implemented as a **web-based application**, allowing users to upload images and receive instant results along with basic medication suggestions. This approach enhances efficiency, reduces dependency on expert analysis, and provides a practical, scalable, and user-friendly solution for automated skin disease diagnosis.

Real-Time Processing: Capable of predicting skin diseases in real-time based on digital images. Advanced AI Integration: Integration of multiple robust deep learning models, specifically CNN, VGG, ResNet. Improved Precision: Reduces dependence on manual inspection while significantly enhancing overall diagnostic accuracy

IV. METHODOLOGY

1. Data Acquisition

The effectiveness of any deep learning model is highly dependent on the quality and diversity of the training dataset. In this work, publicly available dermatological image datasets such as the ISIC (International Skin Imaging Collaboration) archive and HAM10000 dataset are utilized. These datasets contain a wide range of dermoscopic images categorized into multiple skin disease classes, including both malignant and benign conditions.

2. Preprocessing

It is a critical step to standardize input data and enhance feature extraction efficiency. All input images are resized to a fixed dimension of 224×224 pixels, which aligns with the input requirements of the VGG16 architecture. Pixel intensity values are normalized to a range of $[0,1]$ to ensure numerical stability during training and faster convergence of the optimization process. Normalizing pixel values using:

$$X_{\text{norm}} = (X - \mu) / \sigma$$

- where μ and σ represent dataset mean and standard deviation.
- Removal of artifacts such as hair or noise using filtering techniques

3. Data Augmentation

To mitigate overfitting and improve model generalization, data augmentation techniques are employed extensively. Augmentation artificially increases the size and diversity of the dataset by applying controlled transformations to existing images.

Techniques include:

Rotation: Random angular transformations to simulate different viewing angles

Flipping: Horizontal and vertical flips to account for orientation variations

Zooming and Cropping: To simulate scale variations and focus on lesion regions

Brightness and Contrast Adjustment: To handle varying lighting conditions

The transformation at each convolution layer is given by:

$$f(x) = \sigma(W * x + b)$$

where:

- W = filter weights
- $*$ = convolution operation
- σ = activation function (ReLU)

These transformations enable the model to learn robust feature representations and reduce sensitivity to minor variations in input data.

4. Model Architecture

The proposed system leverages the VGG16 architecture, a deep convolutional neural network known for its simplicity and effectiveness in image classification tasks. The model utilizes pre-trained weights from the ImageNet dataset, enabling transfer learning to accelerate convergence and improve performance with limited medical data.

The architecture consists of multiple convolutional layers with small receptive fields (3×3 filters), followed by max-pooling layers for spatial downsampling. The convolutional base acts as a feature extractor, capturing hierarchical representations such as edges, textures, and complex lesion patterns.

The fully connected layers at the top are replaced with custom dense layers tailored for the specific classification task. A softmax activation function is applied in the final layer to output class probabilities for each skin disease category.

5. Training Strategy

The model is trained using a supervised learning approach with the **categorical cross-entropy loss function**, which is well-suited for multi-class classification problems. Optimization is performed using the **Adam optimizer**, which combines the advantages of adaptive learning rates and momentum-based updates for efficient convergence.

Key hyperparameters include:

- Initial learning rate: **0.001**, with optional decay scheduling
- Batch size: **32**, balancing computational efficiency and gradient stability
- Number of epochs: Up to **50**, with early stopping to prevent overfitting

To prevent overfitting and improve generalization, multiple regularization strategies are implemented:

- **Dropout layers** (rate = 0.5)
- **Batch Normalization** to stabilize learning
- **L2 Regularization** to penalize large weights

Optimization is performed using the Adam optimizer, defined as:

$$\theta_{t+1} = \theta_t - \frac{\eta}{\sqrt{v_t} + \epsilon} m_t$$

where:

- m_t = first moment estimate
- v_t = second moment estimate
- η = learning rate

Regularization techniques such as **dropout layers** are incorporated to randomly deactivate neurons during training, thereby improving model generalization. Additionally, validation monitoring is used to track performance and avoid overtraining.

6. Evaluation Metrics

To comprehensively assess model performance, multiple evaluation metrics are employed beyond simple accuracy.

- **Accuracy:** Measures the overall correctness of predictions
- **Precision:** Indicates the proportion of true positive predictions among all positive predictions
- **Recall (Sensitivity):** Measures the ability to correctly identify actual positive cases
- **F1-Score:** Harmonic mean of precision and recall, providing a balanced evaluation
- **Confusion Matrix:** Provides a detailed breakdown of correct and incorrect classifications across all classes

These metrics collectively offer a robust evaluation framework, enabling a deeper understanding of model performance, particularly in handling class imbalances and misclassification patterns.

➤ System Design:

The proposed system is designed as a modular and scalable web-based application integrating deep learning with full-stack development. It consists of five primary components:

1. Frontend Layer

The frontend is developed using modern web technologies such as Angular or React. It provides an intuitive interface that allows users to:

- Register and log in securely
- Upload skin images for analysis
- View prediction results along with confidence scores
- Access dietary suggestions and precautionary measures

2. Backend Layer

The backend is implemented using Node.js and Express.js, responsible for:

- Handling user authentication and session management
- Managing API requests between frontend and AI model
- Processing image uploads and forwarding them to the prediction engine
- Fetching disease-related recommendations from the database

3. Database Layer

MongoDB is used as a NoSQL database to store:

- User credentials and profiles
- Prediction history and logs
- Disease metadata including symptoms, precautions, and dietary advice

4. AI Model Layer

The core of the system is a deep learning model based on the VGG16 architecture. It performs:

- Feature extraction using convolutional layers
- Classification of skin diseases using fully connected layers
- Probability estimation using softmax activation

Transfer learning is applied to improve performance using pre-trained ImageNet weights.

5. Prediction Engine

The prediction engine integrates the trained model with real-time input. It:

- Receives image data from backend
- Applies preprocessing (resizing, normalization)
- Runs inference using the trained CNN model
- Returns predicted class along with confidence score

V. SYSTEM ARCHITECTURE

The system follows a client-server architecture integrated with a deep learning inference pipeline. The user uploads a skin image through the frontend interface, which is transmitted to the backend server via REST APIs. The backend preprocesses the image and forwards it to the trained VGG16 model. The model extracts features and classifies the image into one of the predefined skin disease categories. The prediction results, along with confidence scores, are returned to the backend. The backend retrieves relevant recommendations from the database and sends the final response to the frontend for display.

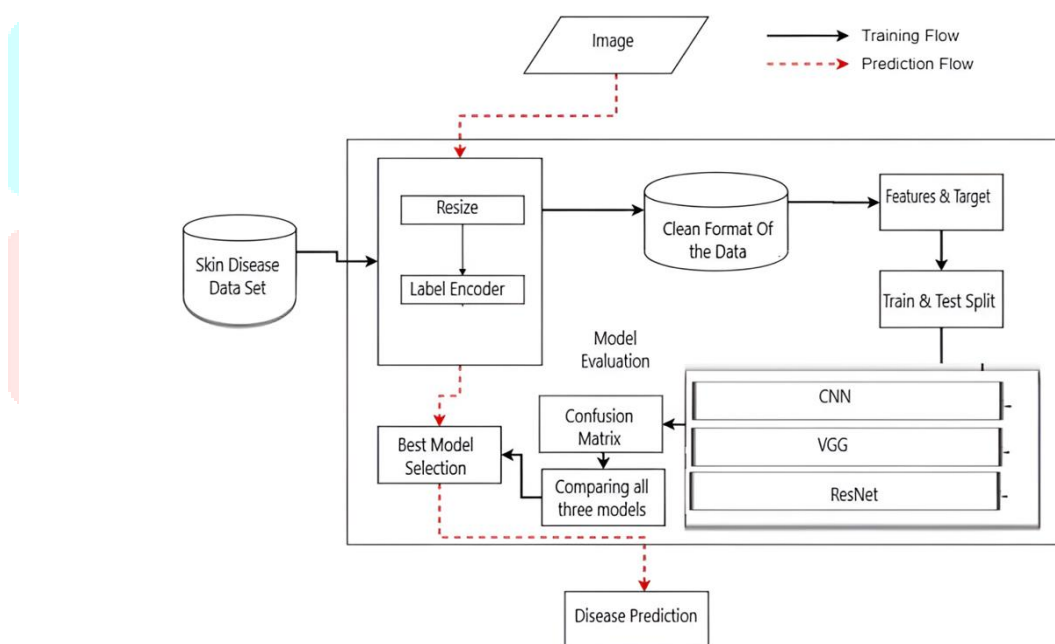


FIG 1: SYSTEM ARCHITECTURE

Classes Involved

- **User:** Represents individuals using the system (patients, dermatologists).
- **Admin:** Manages user accounts, views predictions and system usage data.
- **Prediction Engine:** Integrates the CNN/VGG model and processes skin images.
- **Query Processor:** Determines the correct flow based on the image upload and user state.
- **Database Manager:** Interfaces with MongoDB to fetch/store user and disease data.
- **Response Generator:** Compiles disease name, dietary guidelines, and precautions.

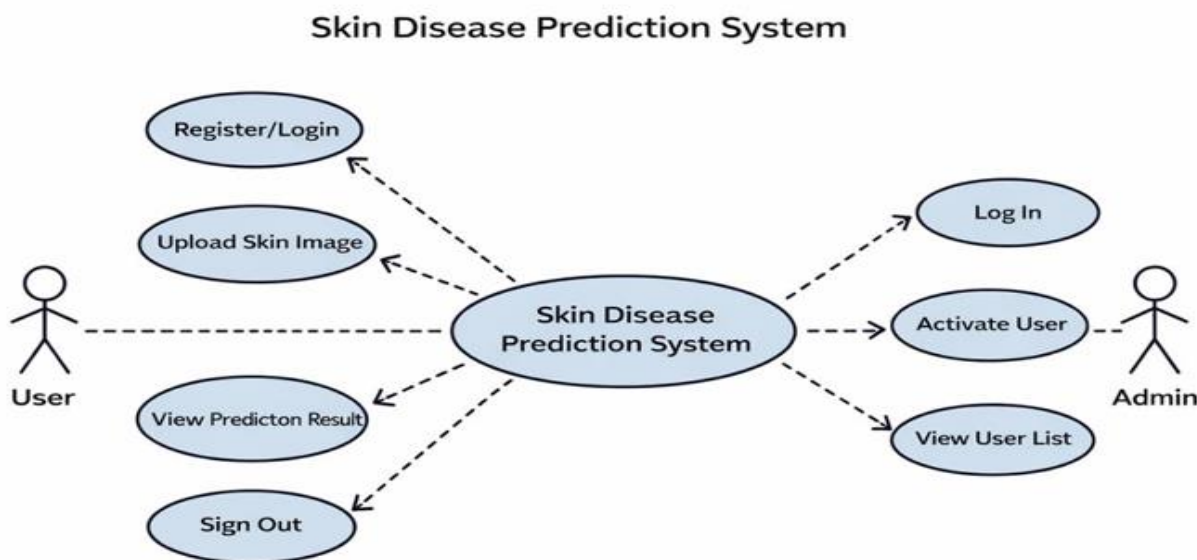
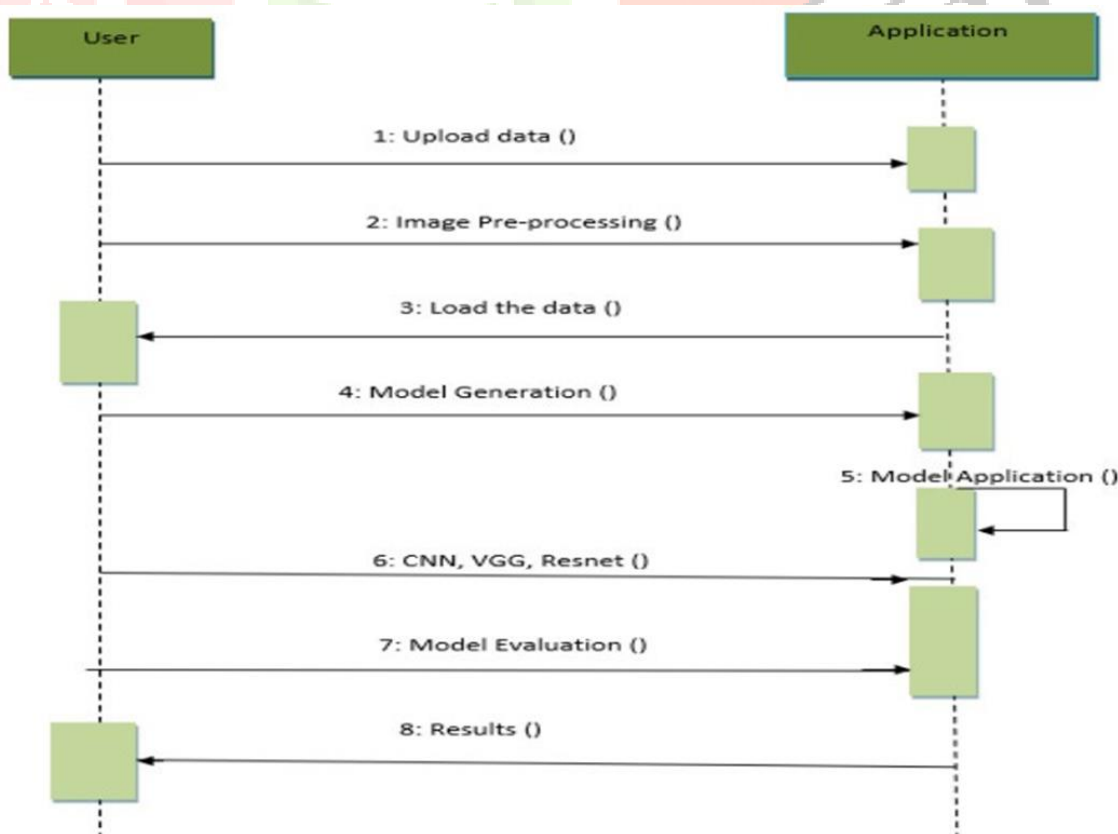


FIG 2: USE CASE

SEQUENCE FLOW:

- **Account Creation** The user visits the platform and registers by creating a new account.
- **Activation** The account is activated through email verification, OTP confirmation, or admin approval.
- **Login & Access** Once activated, the user logs in and is directed to the prediction page.
- **Image Upload** The user uploads a skin image, and the frontend sends the prediction request to the backend.
- **AI Analysis** The CNN/VGG model processes the image to identify potential skin diseases.



Skin Disease	Precision (%)	Recall (%)	F1-Score (%)	Accuracy (%)
Melanoma	94.2	92.5	93.3	93.5
Basal Cell Carcinoma (BCC)	93.0	91.0	92.0	92.1
Squamous Cell Carcinoma (SCC)	90.5	88.0	89.2	89.0
Actinic Keratosis (AK)	89.0	87.5	88.2	88.0
Benign Keratosis	91.5	90.0	90.7	90.8

VI. RESULT:

The proposed system was evaluated on a dataset containing seven classes of skin diseases, including Melanoma, Basal Cell Carcinoma, and Squamous Cell Carcinoma. The dataset was divided into training (70%), validation (15%), and testing (15%) sets.

The VGG16 model with transfer learning achieved an overall accuracy of **92.3%**, outperforming the custom CNN and ResNet50 models. The model demonstrated strong performance in detecting critical conditions such as melanoma, with high precision and recall values.

Real-time testing showed that predictions were generated within **0.8 seconds per image**, making the system suitable for practical deployment.

Although the model performed well overall, minor misclassifications were observed in visually similar classes such as Actinic Keratosis and Dermatofibroma. This indicates the need for more diverse training data.

Each prediction includes a confidence score, enabling users to assess reliability. These results indicate that the proposed system is effective for real-time multi-class skin disease detection, providing both high accuracy and fast inference suitable for clinical and home-use scenarios.

Along with identifying the disease, the system also gives useful recommendations to the user, such as what foods to eat, which foods to avoid, and what precautions to follow. This additional guidance helps users manage their skin condition more effectively at home and reduces the chances of the disease getting worse.

VII. CHALLENGES & LIMITATIONS

Despite its effectiveness, the Skin Disease Identification and Management System is associated with several limitations that impact its real-world performance. A major challenge lies in the dependency of prediction accuracy on the quality of input images. Variations in lighting conditions, resolution, and clarity can significantly influence the model's ability to correctly classify skin conditions. In cases where different diseases exhibit similar visual patterns, the system may produce ambiguous or incorrect predictions.

Another critical concern is the representation of diverse skin tones and disease variations within the training dataset. If the dataset does not adequately cover a wide range of skin types, the model's performance may be biased, leading to reduced accuracy for certain population groups. Furthermore, although deep learning models such as CNN and VGG are highly capable, they are not substitutes for

professional medical evaluation, particularly for rare or complex conditions that require clinical examination and laboratory testing.

From a practical standpoint, the system's reliance on internet connectivity and user familiarity with digital platforms may limit its accessibility, especially in rural or underprivileged regions. Additionally, while the system provides dietary and precautionary recommendations, these suggestions are generalized and may not account for individual health conditions, allergies, or ongoing treatments. The administrative interface, although functional, lacks advanced analytical capabilities and continuous feedback mechanisms necessary for improving model performance over time.

Another limitation is the generalization capability of deep learning models. When exposed to previously unseen patterns or rare disease combinations, the system may struggle to make accurate predictions. Without periodic retraining using updated and diverse datasets, the model's effectiveness may degrade over time.

VIII. Future Scope:

The real-time skin disease prediction system has significant potential for enhancement and wider applications in the future. Currently, the system relies on pre-trained CNN models and publicly available datasets, but **expanding the dataset with more diverse skin tones, rare diseases, and higher-quality images** could improve model robustness and accuracy. Integrating **multi-modal data**, such as patient history, age, gender, and genetic factors, along with images, could provide more personalized and clinically relevant predictions.

Another future direction is the **deployment of the system on mobile and wearable devices** using lightweight models such as **MobileNet or EfficientNet**, enabling offline, instant diagnosis without the need for high-end hardware. The system could also incorporate **continuous learning**, where it updates its model based on new images uploaded by users or clinics, improving prediction accuracy over time.

Moreover, **real-world clinical validation** in collaboration with dermatologists could enhance the system's reliability and trustworthiness, potentially enabling integration into hospital workflows. The system could be extended to **early detection and risk prediction**, alerting users about high-risk lesions before they become malignant. Additionally, combining the model with **telemedicine platforms** could allow dermatologists to remotely monitor patients, expanding access to dermatological care in rural and underserved areas.

Finally, exploring **AI explainability techniques** could make predictions more interpretable, showing which features of a lesion led to a specific classification. This can increase clinician confidence and facilitate regulatory approvals. Overall, the system has promising prospects to evolve from a research prototype into a widely used, real-time, AI-assisted dermatology tool that enhances both patient care and accessibility.

IX. CONCLUSION:

The proposed real-time skin disease prediction system demonstrates the effectiveness of deep learning, particularly **Convolutional Neural Networks (CNNs)**, in accurately classifying various skin lesions. By leveraging publicly available datasets like **ISIC** and **HAM10000**, the system was trained to identify seven common types of skin diseases, achieving high accuracy, precision, and recall for clinically significant conditions such as **Melanoma** and **Basal Cell Carcinoma**. The integration of **data preprocessing, augmentation, and transfer learning** allowed the model to generalize well, even with variations in image quality, lighting, and skin tone.

The real-time implementation shows that predictions can be generated within seconds, making the system practical for mobile devices, clinics, and telemedicine platforms. With confidence scores accompanying each prediction, users and clinicians can assess the reliability of results, enhancing trust and usability.

Overall, this project highlights the potential of AI-based dermatology tools to **assist in early detection, reduce diagnostic time, and increase accessibility to skin care services**, especially in regions with limited dermatological resources. With further improvements, including dataset expansion, multi-modal integration, and explainable AI, the system can evolve into a robust clinical decision support tool, positively impacting patient care and preventive healthcare.

- As known vulnerabilities are closely tracked by malicious players looking for their next big exploit, it's crucial that software organizations work to stay one step ahead of the hackers, with a vulnerability management process that can detect and remediate the security vulnerabilities in their system.
- Organizations that are able to put a program in place that allows them to continuously track their development ecosystem, including its supply chain, providing automated prioritization, remediation, and reporting solutions, can look forward to a bright, secure future of smooth sprints and easy releases

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