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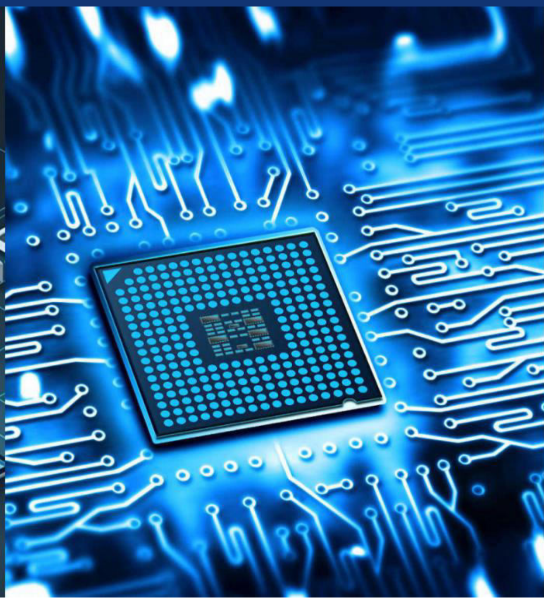

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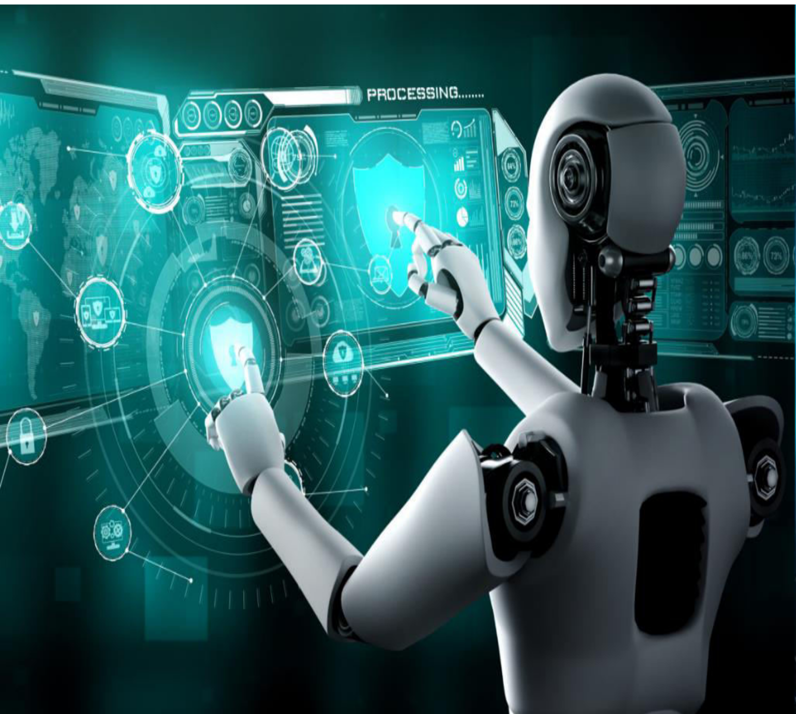

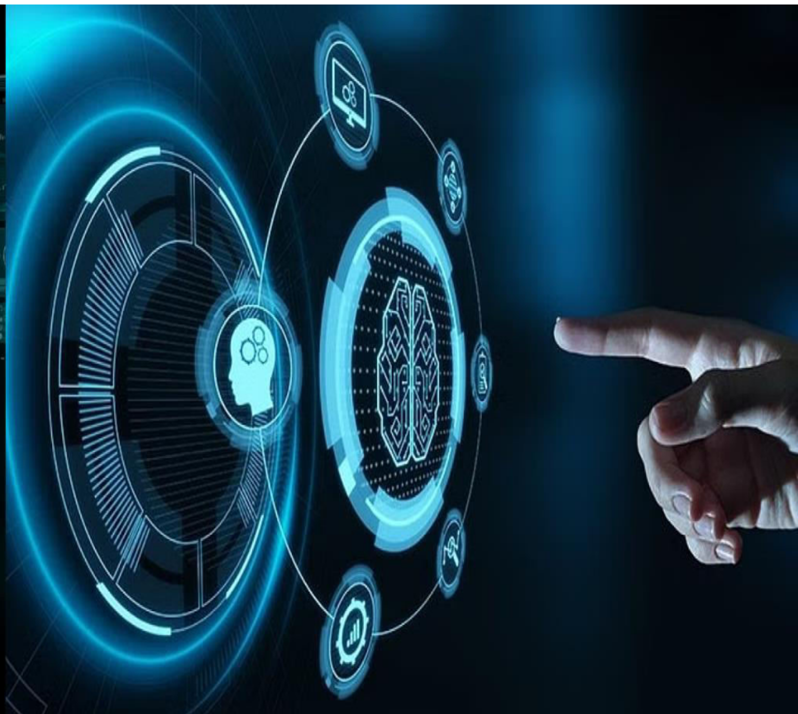

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AI Based Skin Disease Prediction

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ABSTRACT: An AI-based system is developed for automated skin disease detection, aiming to enhance diagnostic accuracy and accessibility. In this project, it proposes a deep learning-based model for classifying various skin conditions using dermatological images while ensuring fairness across diverse skin tones. The system is designed for deployment on both mobile and web platforms, focusing on high usability and optimal performance. Image preprocessing techniques are integrated to handle variations in image quality, and data balancing strategies are applied to mitigate the effects of class imbalance. These methods enable the model to improve reliability and generalization across different input conditions. Additionally, the model ensures equitable performance across skin tones, addressing a crucial fairness requirement in medical AI. Ultimately, the system provides an efficient, user-friendly solution for early detection of skin diseases, contributing to improved healthcare outcomes. The implementation is carried out using deep learning frameworks and evaluated on standard dermatological datasets.

KEYWORDS: Artificial Intelligence (AI), Skin Disease Classification, Medical AI Ethics, Healthcare Technology, Medical Image Analysis.

I. INTRODUCTION

This project proposes the development of an AI-based system for the automated detection and classification of skin diseases, aiming to enhance diagnostic accuracy, accessibility, and fairness. Leveraging machine learning, particularly convolutional neural networks (CNNs), the system is designed to classify various dermatological conditions using clinical and dermoscopic images. A key objective of the proposed framework is to ensure equitable diagnostic performance across diverse skin tones, addressing a critical bias often present in traditional dermatological datasets. To this end, the model will be trained on inclusive datasets that reflect a broad spectrum of skin types, improving fairness and generalizability.

The system is designed to be deployed on both mobile and web-based platforms, with a focus on high usability, fast inference time, and cross-platform compatibility. It aims to empower both healthcare professionals and patients with an easy-to-use, AI-assisted diagnostic tool that supports early detection and timely intervention. To improve model robustness and diagnostic reliability, the system incorporates solutions for handling class imbalance and image quality variability. Techniques such as data augmentation, class re-weighting, and quality-based filtering are utilized to enhance model performance in real-world scenarios. Ultimately, this project delivers a user-centric, scalable, and efficient tool that contributes to better healthcare outcomes by enabling early and accessible skin disease detection. The implementation is carried out using state-of-the-art deep learning libraries and validated against benchmark dermatological datasets.

II. SYSTEM MODEL AND ASSUMPTIONS

This project considers a distributed AI-based diagnostic system composed of *N user-end devices* (e.g., smartphones or web clients) equipped with the capability to capture skin images and communicate with a centralized medical analysis server over a network. These devices operate within a dynamic healthcare environment where users intermittently connect to the system based on need and availability. The entire system's operational bandwidth is assumed to be divided into M non-overlapping data channels, each with varying bandwidth capacity, to support the simultaneous transmission of medical image data from multiple users. The access to these data channels is regulated through fixed-duration communication slots managed by a central coordinating server, which broadcasts slot timing and access schedules to ensure orderly communication.

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Prior to image transmission, each client device (i.e., a device with an image to classify) performs an internal optimization step to select both an optimal image preprocessing route and a data channel. Once a preferred channel is selected, the device initiates a handshake and coordination protocol with the server node to ensure collision-free and secure communication. The coordination is achieved using a fixed-length Frequency Hopping Sequence (FHS) consisting of K distinct channel frequencies. Each device hops sequentially through the FHS during each communication slot to identify a suitable and vacant frequency for control communication and metadata transfer. This system model ensures fairness and inclusivity by incorporating real-time adjustment mechanisms based on skin tone detection and image quality enhancement prior to classification. It also addresses challenges such as class imbalance in the dataset and varying lighting conditions that may affect image clarity. Overall, the design prioritizes accessibility, diagnostic accuracy, and performance, laying a foundation for equitable early skin disease detection through mobile and web platforms.

III. EFFICIENT COMMUNICATION

In this scheme, each device with a medical image searches for optimal paths to transmit its data to the diagnostic server. Thus, possible communication routes from a user device are evaluated. Using a Node Selection Scheme (NSS), each transmitting device selects the most suitable path that ensures minimal diagnostic delay while considering resource constraints such as bandwidth usage and device power consumption. Here, a Channel Selection Scheme (CSS) is also introduced to help devices determine which communication channels should be used for efficient data upload. The goal of CSS is to optimize network bandwidth utilization while minimizing upload failures or delays due to congestion. Assume there are M communication channels with different bandwidths, where y denotes the bandwidth of channel c. Each device periodically monitors a set of M channels for availability. Let Mi represent the set of channel IDs sensed by device i. Suppose channel c is found idle during a time interval x, referred to as the channel idle duration. The effectiveness of channel c is measured by $tc = x{\cdot}y$, combining bandwidth and availability to evaluate upload efficiency. Additionally, misjudgments in detecting network congestion or availability may lead to delays in uploading diagnostic images, reducing system responsiveness. Hence, the system leverages these metrics to choose the most suitable paths and channels for reliable and prompt image delivery.

IV. SECURITY

AI-Based Skin Disease Detection: Detecting skin diseases accurately and efficiently without harmful misdiagnosis; an important requirement of modern healthcare systems to identify pathological conditions. Detecting disease patterns in medical images is the most effective way to automate diagnosis. Skin disease detection techniques may be grouped into three categories:

Image-based detection: AI systems must have the capability to determine if pathological features are present in a dermatological image. There are several proposed approaches to disease detection:

1. Collaborative detection: Refers to diagnostic methods where information from multiple medical sources or models is incorporated for disease identification.
2. Bias-aware detection.

Since healthcare providers often have no requirement to change their existing diagnostic infrastructure, the task falls to

AI systems as assistive tools to detect skin diseases through continuous image analysis. Disease detection by AI can be conducted either individually (single-model) or cooperatively (ensemble or federated learning). Recently, the efficacy of collaborative detection has gained a great deal of attention.

There are several advantages offered by collaborative detection over individual methods. However, due to the variability in skin conditions and image quality, it is extremely difficult to achieve fast and accurate diagnosis leading to limited diagnostic errors and performance degradation of the AI system. Locally collected and exchanged medical image data is used to construct a diagnostic model that will impact clinical decisions. This opens opportunities to malicious actors and biased results.

Selfish Data Poisoning Attack (SDPA**):** In this attack, an attacker's objective is to maximize their own model's performance at the expense of others. When selfish attackers identify valuable diagnostic features, they prevent other models from learning effectively by introducing biased data that skews the learning process. This attack is mostly carried out by competing healthcare entities.

Malicious Adversarial Attack (MAA): In this attack, the objective is to obstruct the diagnostic process - i.e., prevent the AI system from correctly identifying diseases, causing misdiagnosis and potential harm to patients.

Using the **Trust-Aware Learning** algorithm, it defines a fairness threshold for the AI models to overcome the data poisoning and adversarial attacks. It enables healthcare AI systems to efficiently utilize available medical data. Diagnostic systems that can reliably identify various disease conditions without bias or interference improve. This reveals that it has potential to convert various clinical scenarios into improved diagnostic performance.

V. RESULT AND DISCUSSION

In Figure 1, it shows the graph of training iterations vs detection accuracy of the AI model. Detection accuracy is the percentage of correctly classified skin disease cases out of all test cases evaluated.

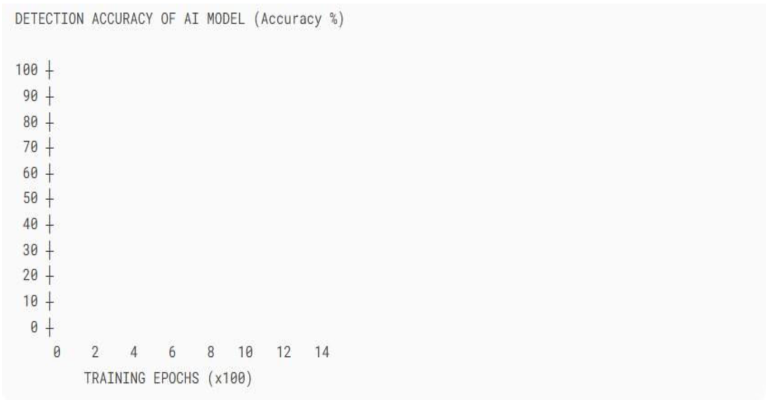

Fig. 1 Model training progress vs Disease classification accuracy

In Figure 2, it shows the graph of diagnostic accuracy (%) vs maximum preprocessing delay (ms). Preprocessing delay is the time taken for an input image to be enhanced and prepared for analysis by the AI model.

Fig. 2 Diagnostic accuracy vs Maximum preprocessing delay

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In Figure 3, Diagnostic Confidence Score vs. Maximum Input Image Variation. Input image variation refers to the undesirable deviations from ideal dermatological imaging conditions that affect diagnostic reliability. Variation magnitude is measured as the difference between optimal and actual imaging parameters (lighting, focus, resolution) across clinical samples.

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# DIAGNOSTIC PERFORMANCE METRICS

- **MODEL EVALUATION PARAMETERS**:
  - Precision
  - Recall
  - F1-Score
  - Accuracy

- **PERFORMANCE SCORES (%)**:
  - 92.4
  - 88.7
  - 90.5
  - 94.2
```

Fig .3 Diagnostic Confidence Score vs. Maximum Input Image Variation

VI. CONCLUSION

Thus, the AI-based skin disease detection system enables accurate diagnosis by analyzing medical images while optimizing computational efficiency to provide timely results. Using a bias-aware training approach ensures fair classification across diverse skin tones while maintaining high diagnostic performance. The trust-aware learning algorithm improves the reliability of predictions by mitigating adversarial attacks and data poisoning risks. This enables the model to adaptively adjust its diagnostic criteria according to varying clinical scenarios and patient demographics, ensuring robust performance in real-world healthcare applications.

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