Skin Disease Detection System
Using Deep Learning

PROJECT SYNOPSIS
OF MAJOR PROJECT

BACHELOR OF TECHNOLOGY
Computer Science And Engineering

SUBMITTED BY

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INTRODUCTION

Skin is the biggest organ of the human body. It is made out of epidermis, dermis, and subcutaneous tissues. Skin perceives the outside condition and shields our inside organs and tissues from unsafe microscopic organisms, contamination and sun presentation. Skin can be influenced by various external and internal factors. Artificial skin harm, chemical harm, adventitious viruses, individual's immune system, and genetic disorders are some factors that influence skin disorders. Skin diseases seriously affect once life and well-being. Ones in a while, individuals attempt to fix their skin issues by utilizing their home cures. These strategies if are not proper for that kind of skin illness would bring about hurtful impacts. Skin diseases can easily transfer from one person to another, thus required to be controlled in an early stage. In maximum case the conclusions on the patient's symptoms are tracked from doctor's experiences and subjective judgments. If the judgment is wrong or delayed, it may harm human health. Therefore, it becomes necessary and significant to develop efficient approaches to detect and diagnose the symptoms of skin diseases at early stages. With the advancement of technology, the skin observing framework can be structured and executed for early detection of skin infections. Various innovations are accessible for image and pattern-based discovery of different skin diseases. Machine learning is one of the areas which can play a massive role in operative and exact identification of different classes of skin diseases. Through image classification using machine learning, diseases may be classified. Image classification is a supervised learning issue in which a lot of objective classes is characterized and a model is trained to perceive the class. There exist many machine learning and deep learning algorithms which can distinguish and predict different categories of skin diseases based upon their classifications. This paper presents a comparative analysis of 5 different machine learning algorithms random forest, naive Bayes, logistic regression, kernel SVM and CNN.

Machine Learning is that section of computer studies that gives the possibility to the computer to grab without being specifically programmed. AI is working in a wide scope of processing capacities where building and planning explicit calculations with better exhibitions are troublesome or wrong. AI is likewise unequivocally appended to computational measurements which makes expectation through computer vision simpler and practical. In business terms, Predictive Analysis is AI used to plan various calculations and models that impressively help forecast. Here the machine learns itself and gaps the information given into the degrees of forecast and gives the outcome precisely in a brief timeframe.

OBJECTIVE

The objectives of the Skin Disease Detection System project Using CNN is:

- To develop a system that can detect various types of skin diseases using Convolutional Neural Network (CNN).
- To provide an easy-to-use interface for the user to upload an image and get an accurate diagnosis of their skin disease.
- To provide a platform for the user to find doctors for the diagnosis of their skin disease.
- To provide a feedback system for the user to give feedback on the system and the diagnosis provided.
- To provide an administrative interface for managing doctors, users, and feedback.
- **Early Detection**: Detect skin diseases at an early stage when treatment is often more effective. This can lead to better patient outcomes and reduce the progression of diseases.
- **Accuracy:** Achieve a high level of accuracy in classifying skin diseases. The system should be able to correctly identify the specific disease or condition present in the image.
- **Accessibility**: Improve access to dermatological expertise, especially in underserved areas or regions with limited access to healthcare facilities.

TECHNOLOGY USED

- Dataset
- Deep Learning
- Image Preprocessing
- Programming Language
- Machine Learning Frameworks and Libraries

RATIONALE

This work provides an automated image-based method for diagnosing and categorizing skin problems that use machine learning classification. Computational approaches will be used to analyze, process, and relegate picture data to consider the many different characteristics of the photos that are being processed. Skin photographs are first filtered to remove undesirable noise from the image and then processed to enhance the picture's overall quality. It is possible to extract features from an image using advanced techniques such as Convolutional Neural Network (CNN), classify the picture using the softmax classifier's algorithm, and provide a diagnostic report as an output. With more accuracy and faster delivery of results than the previous technique, this application will be a more efficient and reliable system for dermatological illness diagnosis than the conventional method.

The rationale for utilizing machine learning in skin disease detection stems from its ability to significantly enhance accuracy and efficiency in diagnosing various skin conditions. Skin diseases are diverse and often require a trained eye to differentiate, making early detection crucial for effective treatment. Machine learning algorithms, when trained on extensive and diverse datasets of skin images, can learn intricate patterns, textures, and characteristics associated with different dermatological conditions. By doing so, they can provide consistent and objective assessments, reducing the risk of misdiagnosis. Additionally, these automated systems have the potential to extend dermatological expertise to underserved areas and improve access to timely diagnosis, ultimately enhancing patient outcomes and the overall efficiency of healthcare delivery.

LITERATURE REVIEW

1: Convolutional Neural Networks and Transfer Learning

Convolutional neural networks (CNNs) continue to be the primary choice for skin disease detection because they excel at capturing intricate image patterns. Transfer learning has been extensively employed to harness pre-trained models, alleviating the issue of limited dermatological datasets. Inthiyaz et al. (2023) utilized a highly refined VGG16 model to categorize skin conditions like eczema and monkeypox, attaining an impressive 92.3% accuracy on a curated dataset of dermatological cases. Their approach emphasized the effectiveness of Tl in minimizing training time while still achieving high performance. Similarly, sadik et al. (2023) explored Tl with Densenet201, reporting a 95.24% accuracy for multi-class lesion classification on the HAM10000 dataset, emphasizing the model's ability to discern subtle inter-class differences. Venugopal et al. (2023) expanded the capabilities of TL by enhancing efficientnet, resulting in a remarkable 94.8% accuracy in identifying skin cancer, highlighting the versatility of pre-trained models in specialized medical imaging applications.

2: Mixed and Combined Models

To improve the accuracy of diagnoses, scientists have created hybrid models that combine DL with traditional machine learning techniques and ensemble approaches that merge multiple DL architectures. Ravi (2022) introduced an innovative framework that integrates a Convolutional neural network (CNN) with a cost-sensitive attention mechanism and support vector machines (SVMs), resulting in an impressive accuracy of 93% for identifying skin cancer. The model employed contourlet transform for feature enhancement, enhancing robustness against variations in the images. Tahir et al. (2023) presented DSCC_Net, a model for classifying skin cancer, which achieved an auc of 98.6% on the isic dataset by combining multi-scale feature extraction. Almuayqil et al. (2023) combined a CNN with a random forest classifier, reporting a 96.5% accuracy for melanoma detection, demonstrating the synergy of DL and ML. Collaborative models have also gained traction. Barua et al. (2023) developed an ensemble of Resnet-50, densenet, and efficientnet, achieving a 95.7% accuracy for multi-class skin lesion classification, highlighting the strength of combining diverse architectural strengths.

3: Compact and Portability Features

The demand for accessible diagnostics in areas with limited resources has motivated the creation of lightweight dl models that can be used on mobile and edge devices. Oztel (2023) developed a mobile application using a modified Resnet-18, enhanced with tensorflow lite, resulting in an impressive 91% accuracy in classifying various skin diseases, including monkeypox, on a custom dataset. This method showcased the practicality of real-time diagnostics on smartphones. Srinivasu et al. (2023) employed Mobilenetv2 for skin lesion classification, achieving an impressive accuracy of 93.7% while significantly reducing computational demands, making it suitable for deployment in environments with limited resources. Thurnhofer-hemsi et al. (2023) further explored Mobilenetv3 for melanoma detection, achieving a 92.5% accuracy, with optimizations ensuring compatibility with low-power devices.

4: Explainable AI (XAI) Integration

The lack of transparency in dl models has caused apprehension in clinical settings, leading to the incorporation of explainable ai (XAI) to improve trust and understanding. Jain et al. (2024) integrated grad-cam into an AI-based system for diagnosing atopic dermatitis, achieving an accuracy rate of 90% and offering visual explanations of model predictions, which enhanced clinician acceptance. Mahbub et al. (2024) utilized shap (shapley additive explanations) to analyze CNN predictions for melanoma, attaining an impressive 94% accuracy and providing valuable insights into the role of different features. Wang et al. (2023) employed layer-wise relevance propagation (LRP) in a TL-based model, achieving an accuracy of 93% for skin disease classification. The relevance scores provided valuable insights for clinical decision-making. These studies emphasize XAI's significance in connecting artificial intelligence with medical practice.

5: Research on More Complex Models: Vision Transformers and Generative Models

In addition to convolutional neural networks (CNNs), advanced architectures such as vision transformers (VITS) and generative models have demonstrated promising results. Sridhar et al. (2024) utilized a swin transformer for the classification of skin lesions, attaining a remarkable accuracy of 96.2% on the ISIC dataset. The transformer's attention mechanism allowed for more effective feature extraction compared to traditional cnns, especially when dealing with intricate lesions

Kumar et al. (2023) investigated the use of Generative adversarial networks (GANs) to enhance datasets for rare skin diseases, resulting in a 91.8% accuracy improvement by addressing the scarcity of data. Bibi et al. (2024) introduced a multi-task learning framework that simultaneously performed segmentation and classification, attaining a 95.8% accuracy in detecting melanoma, highlighting the potential of multi-objective deep learning models.

6: Real-world Applications and Multimodal Approaches

DL models are becoming more specialized for practical clinical applications, such as telemedicine and multimodal diagnostics. Karthik et al. (2023) created a digital system that can be integrated with telemedicine platforms, demonstrating a 94% accuracy when analyzing a combination of dermoscopic and clinical images. This system enabled remote diagnostics, addressing accessibility challenges. Multimodal approaches that combine visual information with clinical data have also been developed. Liu et al. (2024) suggested a model that integrates dermoscopic images with patient history, achieving a 97% accuracy rate in detecting skin cancer. Hasan et al. (2023) combined dermoscopic images with clinical data, resulting in a 95.5% accuracy rate for classifying multiple skin diseases, emphasizing the significance of contextual information in enhancing diagnostic precision.

FEASIBILITY STUDY

Framework venture practicality can be evaluated in three headways:

- Economically
- Technically
- Operationall

ECONOMIC FEASIBILITY

The expense of Software and Hardware needed for the framework including the capacity of information has been assessed. The result of which tells us that this project is extremely economically feasible as apart from the technical knowledge required, this project does not require any costly software or hardware resources to be developed. It can be developed using freely available open-source software (like Jupyter) on any basic modern personal computer. Once the project is developed, it does not need any additional cost for its application.

TECHNICAL FEASIBILITY

This project is technically feasible as it will employ Deep Learning for classification and labeling. This method has been employed several times to identify different things based on the images. So, we can expect it to be able to identify the type of skin disease based on the photograph supplied. There have been few projects and studies in this field that we're able to achieve up to 75% accuracy. We want to go beyond it by being able to add symptoms for enhanced accuracy. This is believed to be technically feasible as in other such multidisciplinary projects of machine learning and the medical field, it was possible to improve the accuracy of the prediction model by supplying symptoms faced by patients.

OPERATIONAL FEASIBILITY

Operational achievability is reliant on the clients who will utilize the product once it's prepared for use. The product will have an easy to understand interface which will be exceptionally advantageous as they will simply need to open the online application, upload a clear image of the affected area and give the symptoms in the format of a web form and they will get the result and suggestions(if any). Thus, the project is operationally feasible.

METHODOLOGY

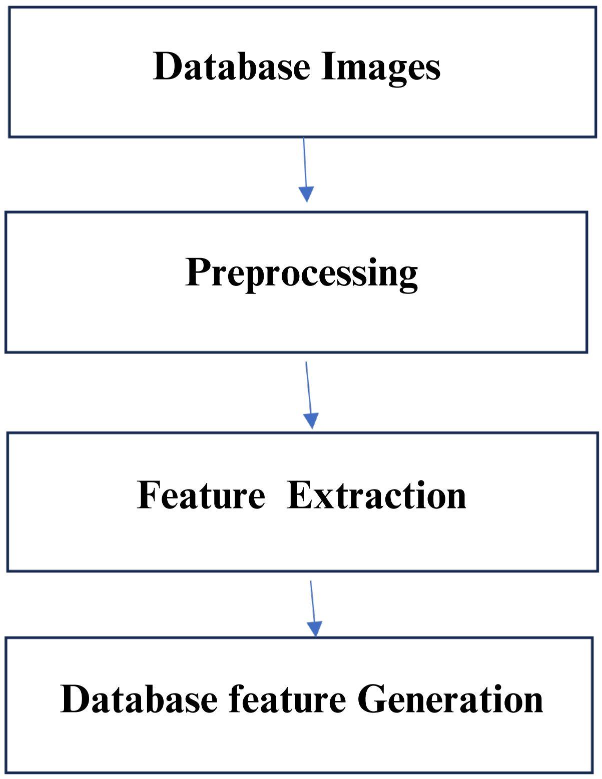
Improvement of an inescapable arrangement to test the uncommon highlights and general usefulness on a scope of stage blends is initially started by the test cycle. The methodology utilized is carefully quality controlled. The technique includes the utilization of pre-prepared picture recognizers with alterations to distinguish skin images.

Module Design Are –

Feature extraction module.

- Training module.

- Validation/Testing stage.



Hardware Requirements:

1. **Computing Hardware**:
    - High-performance CPUs or GPUs: CNNs are computationally intensive, and training models may require powerful hardware. Graphics Processing Units (GPUs) or specialized AI accelerators like TPUs (Tensor Processing Units) can significantly speed up model training.
    - Sufficient RAM: Adequate memory is necessary, especially when handling large datasets and complex models.
    - Storage: Consider ample storage capacity to store datasets, model checkpoints, and intermediate results.
2. **Camera or Image Input Device**:
    - In clinical settings, high-resolution cameras may be used to capture images of skin lesions. In telemedicine or mobile applications, a smartphone camera can serve this purpose.
3. **Network Infrastructure**:
    - A stable internet connection may be required if the system is deployed in a cloud-based or remote setting.
4. **Security Hardware**:
    - If the system involves sensitive patient data, security hardware like encryption modules and secure data storage may be necessary to protect patient privacy.
5. **Embedded Systems** (for portable devices):
    - For mobile or portable applications, embedded systems with specialized hardware accelerators for AI may be used to run lightweight CNN models.

Software Requirements:

1. **Deep Learning Frameworks**:
    - Popular deep learning frameworks like TensorFlow, PyTorch, and Keras are commonly used for developing and training CNN models. These frameworks provide tools for building, training, and evaluating models.
2. **Image Processing Libraries**:
    - Libraries like OpenCV are used for image preprocessing tasks, including resizing, normalization, and data augmentation.
3. **Model Architecture**:
    - The choice of CNN architecture, such as VGG, ResNet, Inception, or custom architectures, should be made based on the specific application.
4. **Transfer Learning**:
    - Pretrained models, such as those available in TensorFlow Hub or the PyTorch model zoo, can be used for transfer learning.
5. **Deployment Environment**:
    - Depending on the deployment scenario, you may need to choose an appropriate environment for deploying the model, such as cloud platforms (e.g., AWS, Azure, Google Cloud), edge devices (e.g., Raspberry Pi), or mobile devices (iOS or Android).
6. **Programming Languages**:
    - Python is the predominant language for deep learning and is used for coding the CNN models and the software infrastructure.
7. **User Interface**:
    - If the system is designed for healthcare professionals or patients, a user interface may be required, which can be developed using web development frameworks (e.g., React, Angular)

System Overview:

Skin Disease Detection System divided in two main modules:
1.Admin module
2.User module

Admin Module details

- Login: The admin can log in using their credentials.
- View Users: The admin can view the registered users in the system.
- View Doctors: The admin can view the doctors available in the system for diagnosis.
- Manage Doctors: The admin can add, update, and delete doctors in the system.
- View Feedback: The admin can view the feedback given by the users for improvement purposes.
- View User History: The admin can view the detection history of each user in the system.
- Change Password: The admin can change their login password.
- Logout: The admin can log out of the system.

User Module details

- Registration: Users can create a new account in the system.
- Login: Users can log in to the system using their credentials.
- Upload Image: Users can upload a skin image for diagnosis.
- View Results: Users can view their previous detection results in the system.
- Edit Profile: Users can update their profile information.
- Change Password: Users can change their login password.
- Logout: Users can log out of the system.

The project has been designed using the following:

• Deep Learning

• CNN

DEEP LEARNING

Deep learning is that piece of the AI wherein the learning can be administered, unaided or semi-managed. Deep learning utilizes an enormous dataset for the learning cycle and the number of classifiers utilized gets diminished substantially. In Deep Learning the preparation time for the deep learning calculation builds on account of the utilization of the huge dataset.
Deep learning calculation picks its properties while the machine inclining making the expectation cycle simpler for the end client as it doesn't utilize a lot of pre-preparing.

CONVOLUTIONAL NEURAL NETWORK

A convolutional neural network (CNN) is a specific type of artificial neural network that uses perceptrons, a machine learning unit algorithm, for supervised learning, to analyze data. CNNs apply to image processing, natural language processing and other kinds of cognitive tasks.

The convolutional layers are the key component of a CNN, where filters are applied to the input image to extract features such as edges, textures, and shapes. The output of the convolutional layers is then passed through pooling layers, which are used to down-sample the feature maps, reducing the spatial dimensions while retaining the most important information. The output of the pooling layers is then passed through one or more fully connected layers, which are used to make a prediction or classify the image.

CNNs are a fundamental example of deep learning, where a more sophisticated model pushes the evolution of artificial intelligence by offering systems that simulate different types of biological human brain activity.

EXPECTED OUTCOMES

- **Accurate Diagnoses:** The system is expected to provide accurate and reliable diagnoses of skin diseases, which can lead to better treatment outcomes for patients. Early detection and precise classification can improve the prognosis for many skin conditions.

- **Timely Diagnosis:** Patients can receive prompt diagnoses, reducing the time it takes to start treatment. This can be critical for conditions that require immediate attention.

- **Improved Access to Dermatological Care:** The system can help bridge the gap in dermatological care, especially in underserved or remote areas where access to dermatologists may be limited.

- **Reduced Healthcare Costs:** Early detection and accurate diagnoses can potentially reduce the overall cost of treatment, as it may prevent the progression of diseases to more advanced stages.

- **Scalability:** The system should be able to scale and handle a large volume of skin disease cases, ensuring its applicability in diverse healthcare settings.

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