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DEVELOPMENT OF A MACHINE LEARNING BASE PREDICTION SYSTEM FOR SKIN DISEASES USING IMAGES

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ABSTRACT

The proposed project is aimed at the creation of a CNN rule-based model for predicting skin diseases based on machine learning (ML) methods. Skin diseases are a significant health issue and diagnosis must be delivered in time and correctly to avoid complications. Current diagnostic systems are still based on traditional manual evaluation by the dermatologists which is subject to human error. To this end, the system combines C and ML.NET to develop the system, and data of the medical images are stored and managed in SQL server to ensure their security.A hybrid architecture that had Convolutional Neural Networks (CNNs) and a rule-oriented classifier was adopted to enhance prediction accuracy. The system is based on Object-Oriented Programming, which guarantees easy maintenance, scalability and modularity. Data preprocessing techniques such as cleaning, normalization, resizing, and augmentation were afterward used to improve the quality and variety of the images and then divided into training and testing sets. The accuracy, precision, recall, and F1-score have been used to assess performance achieving 91, 89, 91, and 90 percent respectively which are a strong predictive capability with low error rates.The findings indicate that the system enhances diagnostic efficiency and minimizes the number of manual work, and aids clinical decision-making. It shows the possibilities of ML in the medical field and lays the basis of its further improvements, such as bigger datasets, support of mobile applications, and explainable AI, which will enhance its usability and improve trust levels.

INTRODUCTION

Skin infections is affecting millions of individuals across all age groups and significantly impacting quality of life because of climate change and other factors. Therefore, early detection is crucial for effective treatment, prevention of disease progression, and minimizing psychosocial effects. Traditional diagnosis of skin conditions relies heavily on the expertise of dermatologists who manually examine the skin and, in some cases, perform biopsies, a process that is time-consuming, subjective, and prone to human error. Machine learning (ML) and deep learning (DL) algorithms offer a significant advantage by automating image-based analysis, thereby improving diagnostic accuracy and reducing the burden on healthcare professionals (Michalek et al., 2017).

The detection and classification of skin diseases present a classical machine learning image classification challenge. Our work addresses this challenge by implementing a predictive system capable of analyzing skin lesion images for acne, eczema, psoriasis, and melanoma. Recent progress in machine learning, especially in image-based classification techniques, has demonstrated strong potential in automatically identifying complex patterns in skin images, differentiating between benign and malignant lesions, and enabling early disease detection (Karimkhani et al., 2017; Ojie et al, 2023; Okpor et al 2024a; Okofu et al 2024b; Mega et al. 2024). In skin disease determination, the machine algorithms enhance diagnostic accuracy, reduce variability caused by human assessment, and provide scalable solutions for regions with limited access to dermatologists. By training on extensive image datasets, machine learning algorithms improve prediction performance and patient outcomes (Idiodi et al 2025; Oboro, and Akazue 2025; Aghware et al 2025; Okofu et al 2024a; Okpor et al. 2024b; Akazue et al 2024).

The determination of skin infection's type has traditionally depended on the visual expertise of dermatologists, supplemented by biopsies and histological analysis when necessary. This process, is however, subjective to differences in individual expertise. In recent years, advancements in machine learning (ML) and deep learning (DL) have shown substantial potential in enhancing the accuracy, consistency, and efficiency of predicting skin infections through automated analysis of medical images (idiodi et al, 2025; Okofu et al. 2023; Ikem and Akazue 2025).

Machine learning algorithms are fundamental in data analysis, enabling computers to recognize patterns, classify information, and make predictions with minimal human intervention (Okitikpi et al, 2025; Yoro et al. 2025).

Transfer learning has become a crucial approach in the field of skin disease diagnosis, given the scarcity of labeled medical images. Models pre-trained on extensive image datasets like ImageNet are fine-tuned using smaller, domain-specific datasets, significantly enhancing the diagnostic performance of ML models in dermatology (Esteva *et al*., 2017). Additionally, the integration of ML algorithms into mobile applications has democratized access to dermatological care (Fitzpatrick *et al*., 2019; Kassianos *et al*., 2021).

As machine learning models become more integrated into healthcare, there is a growing emphasis on transparency and explainability. Explainable AI (XAI) techniques are being developed to provide insights into how models make decisions, which is crucial for gaining the trust of healthcare professionals and patients alike (Holzinger *et al*., 2019; Okofu et al 2023). Recent studies have introduced visualization methods such as Gradient-weighted Class Activation Mapping (Grad-CAM) and Layer-wise Relevance Propagation (LRP), which highlight specific regions of an image that influenced the model's prediction, making diagnostic decisions more interpretable to clinicians (Samek *et al*., 2022).

Despite these advancements, several challenges remain. Variability in image quality, differences in lighting conditions, and the presence of artifacts can affect the performance of ML models. Data augmentation techniques, including image rotation, cropping, and normalization, are increasingly being used to address these challenges by enhancing dataset diversity and improving model robustness (Wibowo, 2024). Furthermore, ethical considerations, including data privacy, potential algorithmic bias, and the need for regulatory approval, must be addressed to ensure safe and effective deployment (Char *et al*., 2018). Algorithmic bias, in particular, poses a significant risk when models are trained on datasets lacking demographic diversity, potentially leading to reduced accuracy for underrepresented populations (Ojei et al 2023; Oweimieotu et al 2024; Akazue et al 2024b; Ako et al 2024**)**. Addressing these concerns requires not only technical solutions but also compliance with international health data standards (Patel & Kumar, 2024).

Choy et al. (2023) used traditional machine learning models, such as Support Vector Machines (SVM) for skin disease diagnosis. develop an automated skin disease diagnosis system using traditional machine learning models, such as Support Vector Machines (SVM), to improve diagnostic accuracy and reduce manual effort in disease identification. The research applied traditional machine learning algorithms, such as Support Vector Machines (SVM), for image classification tasks. The system Struggles with high-dimensional dermoscopic images; suffers from limited, imbalanced, and non-diverse datasets.

Adarsh et al. (2023) applied CNN model for skin disease prediction using HAM-10000 dataset, CNN Model was used to classify multiple skin conditions. It has poor generalization, dataset imbalance, privacy concerns, and clinical integration issues.

Ashwini et al. (2023) applied machine learning algorithm and deep learning algorithm to classify, detect, and recommend skin diseases treatments and solutions. There is lacked handling of image variations and consistency across diverse populations

Malik et al. (2024) developed an efficient convolutional neural network for early and accurate diagnosis of skin diseases using dermoscopic images. Compared traditional ML models, CNNs, and hybrid models to determine the most precise approach. Empirical performance comparisons show practical gains. The study did not clearly explain how the model makes its decisions, and it is uncertain how well it would perform in real-world medical settings

Skin diseases encompass a wide range of conditions that affect the skin, the body's largest organ. Figure 1.2 shows that these conditions can vary greatly in symptoms and severity, ranging from mild irritations to severe, chronic diseases that significantly impact quality of life. Recent advancements in dermatology have improved our understanding and treatment of these diseases, but challenges remain, particularly in early detection and diagnosis. According to Patel and Kumar (2024) in their article Advances in Dermatological Diagnostics and Treatment, integrating machine learning with clinical practice offers solutions for improving skin disease management and patient outcomes.

Types of Skin Diseases

i. Infectious Skin Diseases: These are caused by pathogens such as bacteria, viruses, fungi, or parasites. Common examples include bacterial infections like impetigo, viral infections like herpes simplex, fungal infections like ringworm, and parasitic infestations like scabies (Brown, 2020).

ii. Inflammatory Skin Diseases: Conditions like psoriasis, eczema (atopic dermatitis), and rosacea fall under this category. These diseases are characterized by inflammation, redness, and itching. The exact cause of many inflammatory skin diseases is unknown, but they often involve an abnormal immune response (Boehncke and Schön, 2015).

iii. Allergic Skin Diseases: Allergic reactions can lead to skin conditions such as contact dermatitis and urticaria (hives). These reactions are often triggered by exposure to allergens like certain foods, medications, or chemicals (Johansen *et al*., 2015).

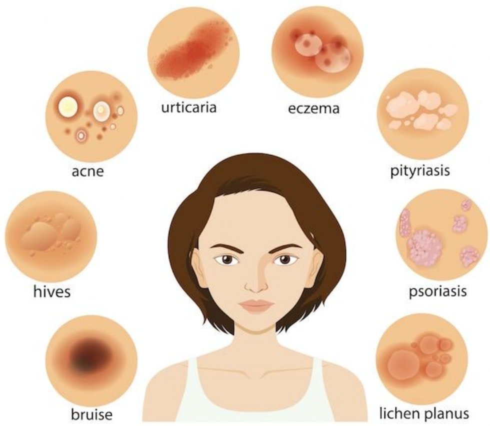

Figure 2.2: Skin Disease ((Liu *et al*., 2023)

Analysis of the Existing System

The system developed by Choy (2023) uses traditional machine learning methods, mainly Support Vector Machines (SVM), to diagnose skin diseases from images. It works by first extracting features from the images manually, such as color, texture, or shape, and then using those features to classify the type of skin condition. While this method can perform well on small or simple datasets, it has major limitations when dealing with high-dimensional images like dermoscopic skin images. These images contain complex patterns that traditional models like SVM cannot easily capture. Also, because the system depends on handcrafted features and often uses small or unbalanced datasets.

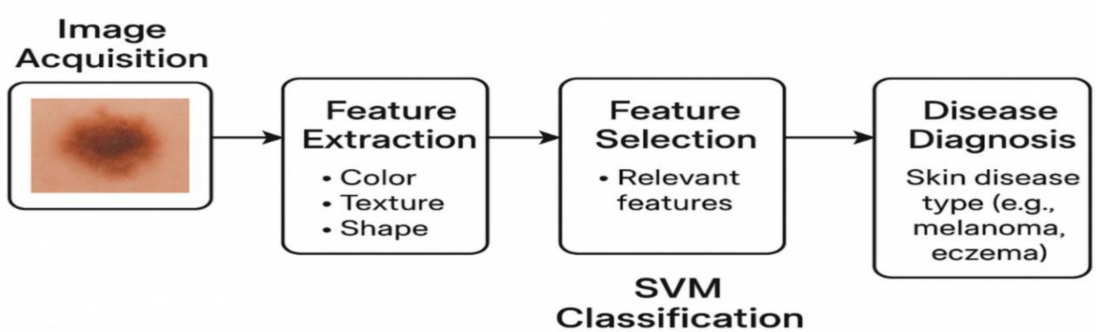

Figure 1.1: Traditional machine learning approach

MATERIALS AND METHODS

This study developed a machine learning-based predicting system for skin diseases using images. The resources were C# and ML.NET programming languages, SQL Server to store data, a webcam and a personal computer, and a labeled dataset pro procedure entailed data gathering, pre-processing (data cleaning, data normalization, data resizing, data augmentation), and division into a training and testing set. The architectural design of a hybrid system that is a Convolutional Neural Network (CNN) along with a rule-based classifier was realized to enhance the prediction accuracy as per the concept of object-oriented programming to enhance modularity and scalability. Measures were used to train, evaluate and validate the model including accuracy, precision, recall, F1-score, and confusion matrix. Lastly, it was incorporated into a desktop application which allows one to upload or take pictures to make predictions in real time.

The Object-Oriented Methodology (OOM) and the Convolutional Neural Network (CNN) mathematical model were adopted for this work. The CNN acts as a function that takes an input image and predicts the category it belongs to, such as eczema, melanoma, psoriasis, or normal skin. Mathematically, this can be expressed as:

$$f(x; \emptyset) = y$$

Where **x** is the input image, y is the predicted class, and θ represents the learnable parameters (weights and biases) that the network adjusts during training.

Each layer of the CNN performs a specific mathematical task that contributes to accurate prediction:

Convolutional Layer: This layer scans the image with small filters to detect features like edges, 1 shapes, or color intensity. The operation is mathematically expressed as:

$$(I * K)(x, y) = \sum_m \sum_n I(x - m, y - n)K(m, n) \qquad 2$$

Where;

I is the input image, and **K** is the kernel or filter. Activation Function: Introduces non-linearity using the Rectified Linear Unit (ReLU) defined as:

$$f(x) = \max(0, x) \qquad 3$$

This allows the model to learn complex, non-linear relationships between pixels.

Pooling Layer: Reduces the spatial dimensions of the feature maps while retaining the most important features, commonly using max pooling:

$$y = \max(x_1, x_2, \ldots\ldots, x_n) \qquad 4$$

Fully Connected Layer: Combines all extracted features and performs the final classification using a linear transformation: $y = Wx + b$. Where; W represents the weights and b the bias term.

Softmax Function: Converts the output scores into probabilities for multi-class classification:

$$P(y_i) = \frac{e^{z_i}}{\sum_j e^{z_j}}$$

RESULTS AND DISCUSSION

The output of this study indicate that the developed CNN model yielded a total accuracy of 91.11, a precision of 89.13, a recall of 91.11, and F1-score of 90.01, which is a good and balanced outcome in an overall classification of the skin disease in a multi-class system.

Table 4.1: Model Performance table

Model	Accuracy	Precision	Recall	F1-score.	Training time

Table 4.2: Comparison Table for the Results

Metric	**Existing System**	**CNN Model**

Machine Learning Model (CNN)	91%	89.0%	91%	90%	5 mins

Accuracy	85%	91.00%
Precision	80%	89.00%
Recall	72%	88.00%
F1 Score	87%	89.00%
Training Time	10mins	5mins

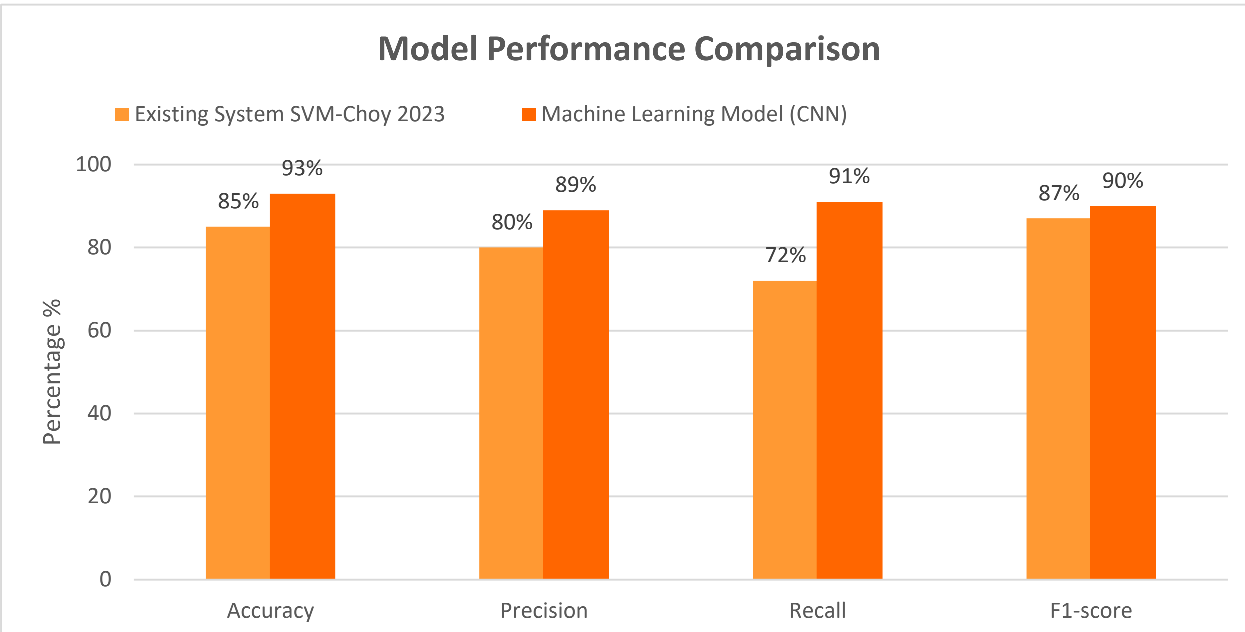

Figure 4.1: Comparison Chart Between the existing System and Develop System

The login module: this is where a user is allowed access into the system in a secure way. It verifies the users without any access to the functionality of the system, including uploading or taking of skin pictures to be predicted.

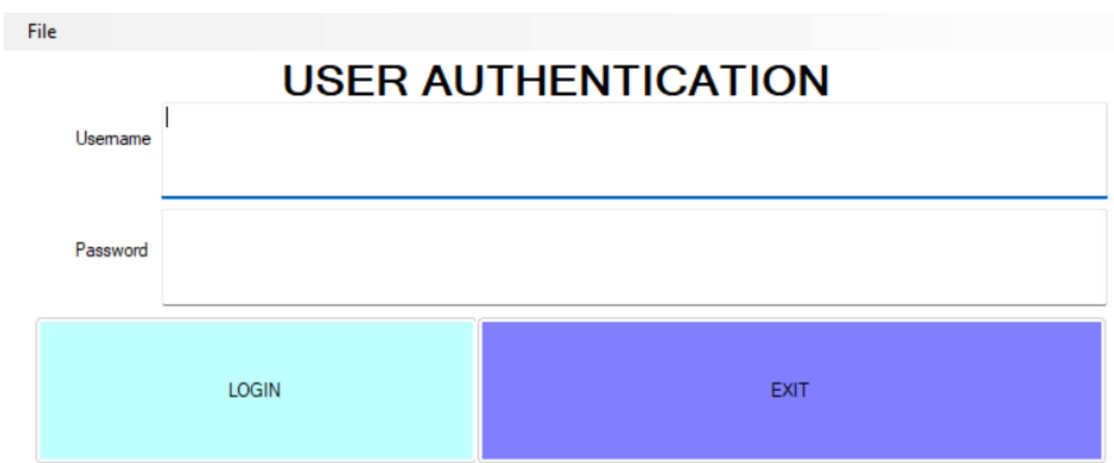

Plate 4.1: Login Module

The Training Module: This module is used by the administrator for training the system which in turn enables him to manage the entire system The Training Module serves as a fundamental component for refining the proficiency of systems embedded with machine learning capabilities. Its primary objective involves optimizing algorithms or models by exposing them to diverse datasets for iterative learning and improvement.

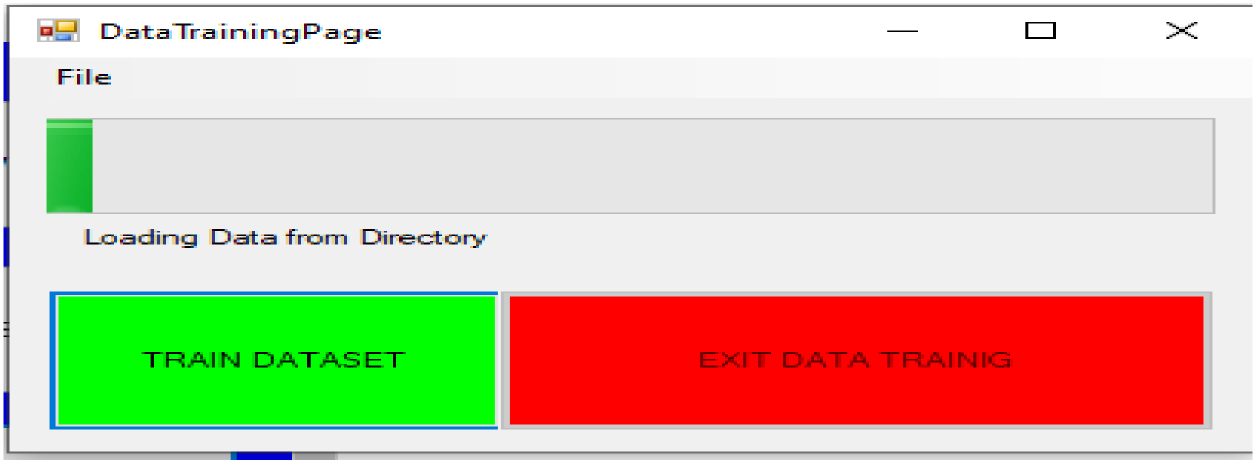

Plate 4.2: Demographic Data Training

Plate 4.3: Image Upload Page Function

Image Upload Page Function, this Page enables a user to upload the skin pictures to be automatically predicted to have a disease. Its primary role is to offer a user friendly interface where the user could choose an image in their device or take a live image with a connected web camera. After the image is uploaded, the page allows the user to preview the image and then send them to the trained CNN-rule-based model to analyze them. The outcome of the process is a displayed predicted skin disease and a confidence score. This page is the main point of interaction between users to test the system, thus the diagnosis process is quick, reliable and convenient.

Table 1: Test Result Data

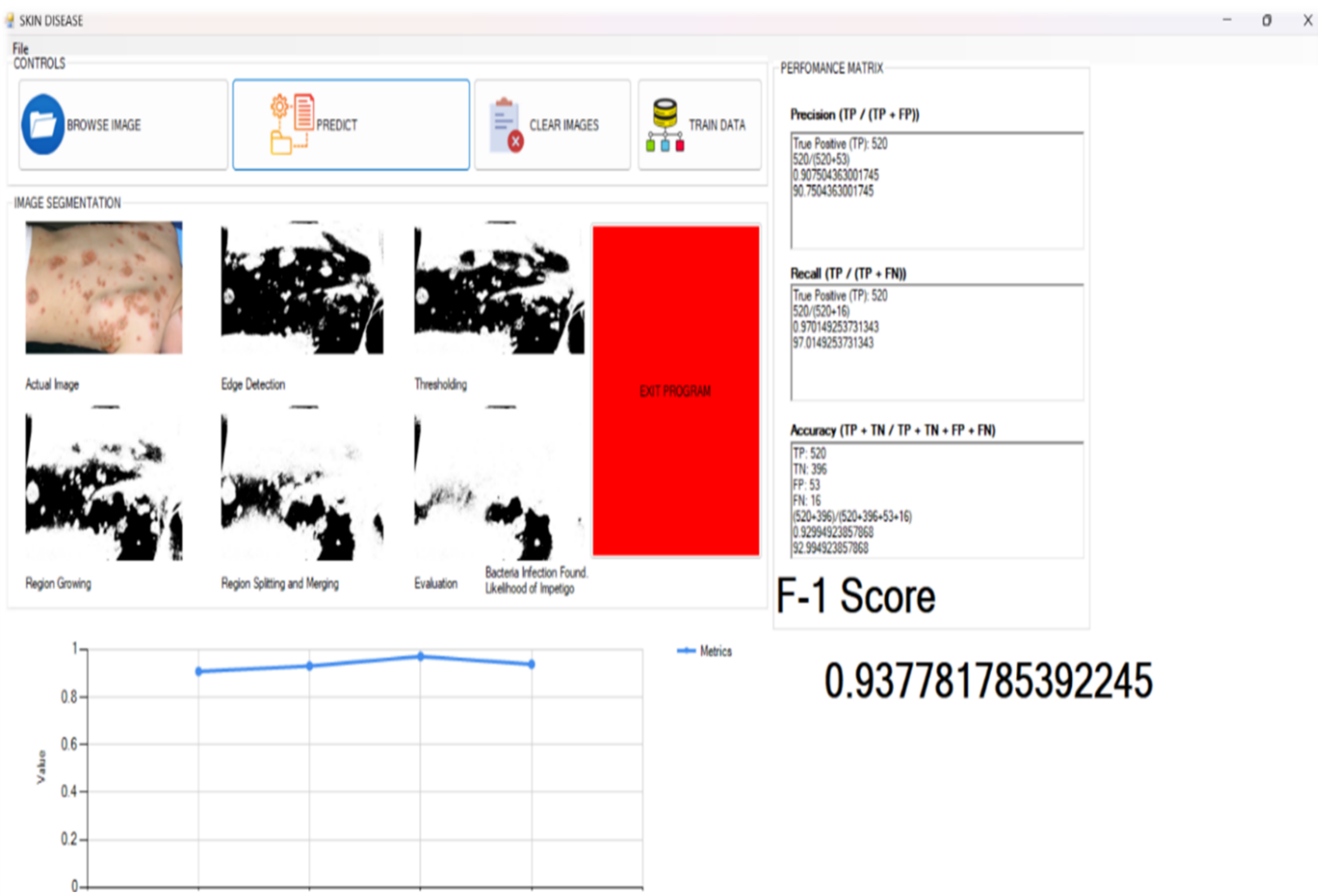

Plate 4.4: Application interface for skin diseases prediction

Test Condition	Input Mode	Prediction	Severity	System Message
Test 1, Normal Skin	Uploaded Image	Normal	None	Skin in good state
Test 2, Disease Skin	Uploaded Image	Impetigo	Mild	Bacteria infection found, Likehood of Impetigo.
Test 3, Disease Skin	Uploaded Image	Tinea	Severe	Fungal infection found. Likehood of Tinea
Test 4 Disease Skin	Uploaded Image	Cellultis	Mild	Bacteria infection found. Like hood of Cellultis
Test 5 Disease Skin	Live Cam	Follicultis	Moderate	Bacteria infection found. Like hood of Follicultis
Test 4 Disease Skin	Uploaded Image	Cellultis	Mild	Bacteria infection found. Like hood of Cellultis
Test 5 Disease Skin	Uploaded Image	Follicultis	Severe	Bacteria infection found. Like hood of Follicultis

The following table shows the sample test results of the skin disease prediction system. A row corresponds to a test case, so it implies the kind of skin (normal or diseased), the source of an image (uploaded image or live camera), and diagnosed illness. It also demonstrates the level of severity (mild, moderate, severe) and gives some other diagnostic data, including the type of infection (bacterial or fungal) and the probability of the forecasted state.

Performance Matrix and Evaluation:

The table describes the quantitative measures used to assess a model's performance and effectiveness.

Metric	Value
True Positives	82
True Negatives	80
False Positives	10
False Negatives	8
Evaluation	
Accuracy	91.11%
Precision	89.13%
Recall	91.11%
F-1 Score	90.01%

System Evaluation:

The analysis area displays the possible good results of the performance, such as Accuracy, Precision, Recall, and F1-score that show the relatively high effectiveness of skin disease prediction. Nevertheless, it does not provide the background on the dataset that was used to assess it and its possible biases and its extrapolation to different populations, which may compromise the quality of the findings. The system description and the development process, based on the use of the Visual Studio C+, EMGU profiler, and MS SQL server, shows that a thorough approach to software development was taken. Altogether, although the proposal fills an essential gap in the healthcare delivery and provides a potentially ground-breaking solution, a more thorough assessment and description of the system methodology would contribute to the validity and practicality of the proposed solution.

The evaluation parameters and Definition are as follows:

Accuracy : The proportion of correct predictions made by the model.

$$AC = \frac{TP + TN}{TP + TN + FP + FN} * 100$$

Precision : Indicates how many of the samples predicted as positive are actually positive.

$$PR = \frac{TP}{TP + FP} * 100$$

Recall : Measures the model's ability to correctly identify all positive cases.

$$RC = \frac{TP}{TP + FN} * 100$$

F1-score : is a **performance metric** that combines **precision** and **recall** into a single value

$$F1 = 2 * \frac{Precision * Recall}{Precision + Recall}$$

CONCLUSION AND RECOMMENDATIONS

The developed system demonstrates the potential of machine learning in automating the predictions of skin diseases, providing high accuracy, precision, and recall to support healthcare professionals with minimal intervention. It offers a fast, reliable, and scalable solution for clinical environments, enhancing patient care through early detection of skin conditions. To further improve its effectiveness, it is recommended that the system be expanded with larger and more diverse datasets and tested in real-world clinical settings to assess its practicality, robustness, and overall performance in routine healthcare practice.

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